Evaluation of Unsupervised Emotion Models to Textual Affect Recognition

Sunghwan Mac Kim
School of Electrical and Information Engineering
University of Sydney
Sydney, Australia
skim1871@uni.sydney.edu.au

Alessandro Valitutti
Department of Cognitive Science and Education
University of Trento
Trento, Italy
a.valitutti@email.unitn.it

Rafael A. Calvo
School of Electrical and Information Engineering
University of Sydney
Sydney, Australia
rafa@ee.usyd.edu.au

Abstract

In this paper we present an evaluation of new techniques for automatically detecting emotions in text. The study estimates categorical model and dimensional model for the recognition of four affective states: Anger, Fear, Joy, and Sadness that are common emotions in three datasets: SemEval-2007 “Affective Text”, ISEAR (International Survey on Emotion Antecedents and Reactions), and children’s fairy tales. In the first model, WordNet-Affect is used as a linguistic lexical resource and three dimensionality reduction techniques are evaluated: Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), and Non-negative Matrix Factorization (NMF). In the second model, ANEW (Affective Norm for English Words), a normative database with affective terms, is employed. Experiments show that a categorical model using NMF results in better performances for SemEval and fairy tales, whereas a dimensional model performs better with ISEAR.

1 Introduction

Supervised and unsupervised approaches have been used to automatically recognize expressions of emotion in text such as happiness, sadness, anger, etc... Supervised learning techniques have the disadvantage that large annotated datasets are required for training. Since the emotional interpretations of a text can be highly subjective, more than one annotator is needed, and this makes the process of the annotation very time consuming and expensive. For this reason, unsupervised methods are normally preferred in the realm of Natural Language Processing (NLP) and emotions.

Supervised and unsupervised techniques have been compared before. (Strapparava and Mihalcea 2008) describe the comparison between a supervised (Naïve Bayes) and an unsupervised (Latent Semantic Analysis - LSA) method for recognizing six basic emotions. These techniques have been applied to many areas, particularly in improving Intelligent Tutoring Systems. For example, (D’Mello, Craig et al. 2008) used LSA but for detecting utterance types and affect in students’ dialogue within Autotutor. (D’Mello, Graesser et al. 2007) proposed five categories for describing the affect states in student-system dialogue.

Significant differences arise not only between these two types of techniques but also between different emotion models, and these differences have significant implications in all these areas. While considering emotions and learning, (Kort, Reilly et al. 2001) proposed (but provided no empirical evidence) a model that combines two emotion models, placing categories in a valence-arousal plane. This mixed approach has also been used in other domains such as blog posts where (Aman and Szpakowicz 2007) studied how to identify emotion categories as well as emotion intensity. To date, many researchers have, however, utilized and evaluated supervised methods, mainly based on the categorical emotion model.

In this study, the goal is to evaluate the merits of two conceptualizations of emotions (a categorical model and a dimensional model) in which an unsupervised approach is used. The evaluation incorporates three dimensionality re-
duction methods and two linguistic lexical resources.

The rest of the paper is organized as follows: In Section 2 we present representative research of the emotion models used to capture the affective states of a text. Section 3 describes the techniques of affect classification utilizing lexical resources. More specifically, it describes the role of emotion models and lexical resources in the affect classification. In addition, we give an overview of the dimension reduction methods used in the study. In Section 4 we go over the affective datasets used. Section 5 provides the results of the evaluation, before coming to our discussion in Section 6.

2 Emotion Models

There are two significantly different models for representing emotions: the categorical model and dimensional model (Russell 2003).

The categorical model assumes that there are discrete emotional categories such as Ekman’s six basic emotions - anger, disgust, fear, joy, sadness, and surprise - (Ekman 1992). There are a number of primary and unrelated emotions in the model. Each emotion is characterized by a specific set of features, expressing eliciting conditions or responses. Some researchers have argued that a different set of emotions is required for different domains. For instance, the following emotion classes are used in the field of teaching and education: boredom, delight, flow, confusion, frustration, and surprise. The advantage of such a representation is that it represents human emotions intuitively with easy to understand emotion labels.

A second approach is the dimensional model, which represents affects in a dimensional form (Russell 2003). Emotional states are related each other by a common set of dimensions (e.g. valence or arousal) and are generally defined in a two or three dimensional space. Each emotion occupies some location in this space. A valence dimension indicates positive and negative emotions on different ends of the scale. The arousal dimension differentiates excited vs. calm states. Sometimes a third, dominance dimension is used to differentiate if the subject feels in control of the situation or not.

The categorical model and the dimensional model have two different methods for estimating the actual emotional states of a person. In the former, a person is usually required to choose one emotion out of an emotion set that represents the best feeling. On the other hand, the latter exploits rating scales for each dimension like the Self Assessment Manikin (SAM) (Lang 1980), which consists of pictures of manikins, to evaluate the degree of valence, arousal, and dominance.

3 Automatic Affect Classification

3.1 Categorical classification with features derived from WordNet-Affect

WordNet-Affect (Strapparava and Valitutti 2004) is an affective lexical repository of words referring to emotional states. WordNet-Affect extends WordNet by assigning a variety of affect labels to a subset of synsets representing affective concepts in WordNet (emotional synsets). In addition, WordNet-Affect has an additional hierarchy of affective domain labels. There are publicly available lists relevant to the six basic emotion categories extracted from WordNet-Affect and we used four of the six lists of emotional words among them for our experiment.

In addition to WordNet-Affect, we exploited a Vector Space Model (VSM) in which terms and textual documents can be represented through a term-by-document matrix. More specifically, terms are encoded as vectors, whose components are co-occurrence frequencies of words in corpora documents. Frequencies are weighted according to the log-entropy with respect to a tf-idf weighting schema (Yates and Neto 1999). Finally, the number of dimensions is reduced through the dimension reduction methods.

The vector-based representation enables words, sentences, and sets of synonyms (i.e. WordNet synsets) to be represented in a unifying way with vectors. VSM provides a variety of definitions of distance between vectors, corresponding to different measures of semantic similarity. In particular, we take advantage of cosine angle between an input vector (input sentence) and an emotional vector (i.e. the vector representing an emotional synset) as similarity measures to identify which emotion the sentence connotes.

3.2 Dimension Reduction Methods

The VSM representation can be reduced with techniques well known in Information Retrieval: LSA, Probabilistic LSA (PLSA), or the Non-negative Matrix Factorization (NMF) representations.

Cosine similarities can be defined in these representations, and here, as other authors have done, we use a rule that if the cosine similarity
does not exceed a threshold, the input sentence is labeled as “neutral”, the absence of emotion. Otherwise, it is labeled with one emotion associated with the closest emotional vector having the highest similarity value. We use a predetermined threshold (t = 0.65) for the purpose of validating a strong emotional analogy between two vectors (Penumatsa, Ventura et al. 2006).

If we define the similarity between a given input text, I, and an emotional class, $E_j$, as $\text{sim}(I, E_j)$, the categorical classification result, CCR, is more formally represented as follows:

$$\text{CCR}(I) = \begin{cases} \text{arg max} \left( \text{sim}(I, E_j) \right) & \text{if } \text{sim}(I, E_j) \geq t \\ \text{"neutral"} & \text{if } \text{sim}(I, E_j) < t \end{cases}$$

One class with the maximum score is selected as the final emotion class.

Dimensionality reduction in VSM reduces the computation time and reduces the noise in the data. This enables the unimportant data to dissipate and underlying semantic text to become more patent. We will review three statistical dimensionality reduction methods (LSA, PLSA, and NMF) that are utilized in a category-based emotion model.

Latent Semantic Analysis (LSA) is the earliest approach successfully applied to various text manipulation areas (Landauer, Foltz et al. 1998). The main idea of LSA is to map terms or documents into a vector space of reduced dimensionality that is the latent semantic space. The mapping of the given terms/document vectors to this space is based on singular vector decomposition (SVD). It is known that SVD is a reliable technique for matrix decomposition. It can decompose a matrix as the product of three matrices.

$$A = U \Sigma V^T \approx U_k \Sigma_k V_k^T = A_k$$

where $A_k$ is the closest matrix of rank $k$ to the original matrix. The columns of $V_k$ represent the coordinates for documents in the latent space.

Probabilistic Latent Semantic Analysis (PLSA) (Hofmann 2001) has two characteristics distinguishing it from LSA. PLSA defines proper probability distributions and the reduced matrix does not contain negative values. Based on the combination of LSA and some probabilistic theories such as Bayes rules, the PLSA allows us to find the latent topics, the association of documents and topics, and the association of terms and topics. In the equation (2), $z$ is a latent class variable (i.e. discrete emotion category), while $w$ and $d$ denote the elements of term vectors and document vectors, respectively.

$$P(d, w) = \sum_z P(z) P(w|z) P(d|z)$$

where $P(w|z)$ and $P(d|z)$ are topic-specific word distribution and document distribution, individually. The decomposition of PLSA, unlike that of LSA, is performed by means of the likelihood function. In other words, $P(z)$, $P(w|z)$, and $P(d|z)$ are determined by the maximum likelihood estimation (MLE) and this maximization is performed through adopting the Expectation Maximization (EM) algorithm. For document similarities, each row of the $P(d|z)$ matrix is considered with the low-dimensional representation in the semantic topic space.

Non-negative Matrix Factorization (NMF) (Lee and Seung 1999) has been successfully applied to semantic analysis. Given a non-negative matrix $A$, NMF finds non-negative factors $W$ and $H$ that are reduced-dimensional matrices. The product $WH$ can be regarded as a compressed form of the data in $A$.

$$A \approx WH = \sum WH$$

$W$ is a basis vector matrix and $H$ is an encoded matrix of the basis vectors in the equation (3). NMF solves the following minimization problem (4) in order to obtain an approximation $A$ by computing $W$ and $H$ in terms of minimizing the Frobenius norm of the error.

$$\min_{W,H} \| A - WH \|_F^2,$$  s. t. $W, H \geq 0$$

where $W$, $H \geq 0$ means that all elements of $W$ and $H$ are non-negative. This non-negative peculiarity is desirable for handling text data that always require non-negativity constraints. The classification of documents is performed based on the columns of matrix $H$ that represent the documents.

### 3.3 Three-dimensional estimation with features derived from ANEW

Dimensional models have been studied by psychologists often by providing a stimulus (e.g. a photo or a text), and then asking subjects to report on the affective experience. ANEW (Bradley and Lang 1999) is a set of normative emotional ratings for a collection of English words (N=1,035), where after reading the words, subjects reported their emotions in a three-dimensional representation. This collection provides the rated values for valence, arousal, and dominance for each word rated using the Self Assessment Manikin (SAM). For each word $w$, the normative database provides coordinates $\bar{w}$ in an affective space as:
\[ \bar{w} = (\text{valence}, \text{arousal}, \text{dominance}) = \text{ANEW}(w) \] (5)

The occurrences of these words in a text can be used, in a naive way, to weight the sentence in this emotional plane. This is a naive approach since words often change their meaning or emotional value when they are used in different contexts.

As a counterpart to the categorical classification above, this approach assumes that an input sentence pertains to an emotion based on the least distance between each other on the Valence-Arousal-Dominance (VAD) space. The input sentence consists of a number of words and the VAD value of this sentence is computed by averaging the VAD values of the words:

\[ \text{sentence} = \frac{\sum_{i=1}^{n} \bar{w}}{n} \] (6)

where \( n \) is the total number of words in the input sentence.

Since not many words are available in this normative database, a series of synonyms from WordNet-Affect are used in order to calculate the position of each emotion. These emotional synsets are converted to the 3-dimensional VAD space and averaged for the purpose of producing a single point for the target emotion as follows:

\[ \text{emotion} = \frac{\sum_{i=1}^{k} \bar{w}}{k} \] (7)

where \( k \) denotes the total number of synonyms in an emotion. Anger, fear, joy, and sadness emotions are mapped on the VAD space. Let \( A_e, F_e, J_e, \) and \( S_e \) be the centroids of four emotions. Then the centroids, which are calculated by the equation (7), are as follows: \( A_e = (2.55, 6.60, 5.05) \), \( F_e = (3.20, 5.92, 3.60) \), \( J_e = (7.40, 5.73, 6.20) \), and \( S_e = (3.15, 4.56, 4.00) \). Apart from the four emotions, we manually define neutral to be \( (5, 5, 5) \). If the centroid of an input sentence is the most approximate to that of an emotion, the sentence is tagged as the emotion (with the nearest neighbor algorithm). The centroid sentence might be close to an emotion on the VAD space, even if they do not share any terms in common. We define the distance threshold (empirically set to 4) to validate the appropriate proximity like the categorical classification.

### 4 Emotion-Labeled Data

Three emotional datasets, with sentence-level emotion annotations, were employed for the evaluation described in the next section. The first dataset is “Affective Text” from the SemEval 2007 task (Strapparava and Mihalcea 2007).\(^1\) This dataset consists of news headlines excerpted from newspapers and news web sites. Headlines are suitable for our experiments because headlines are typically intended to express emotions in order to draw the readers’ attention. This dataset has six emotion classes: anger, disgust, fear, joy, sadness and surprise, and is composed of 1,250 annotated headlines. The notable characteristics are that SemEval dataset does not only allow one sentence to be tagged with multiple emotions, but the dataset also contains a neutral category in contrast to other datasets.

We also use the ISEAR (International Survey on Emotion Antecedents and Reactions) dataset, which consists of 7,666 sentences (Scherer and Wallbott 1994), with regard to our experiments.\(^2\) The ISEAR dataset has six emotion classes: angry-disgusted, fearful, happy, sad, and surprised. There are 176 stories by three authors: B. Potter, H.C. Andersen, and Grimm’s. The dataset is composed of only sentences with affective high agreements, which means that annotators highly agreed upon the sentences (four identical emotion labels).

| Emotion   | SemEval | ISEAR  | Fairy tales | Total  |
|-----------|---------|--------|-------------|--------|
| Anger     | 62      | 2,168  | 218         | 2,448  |
| Fear      | 124     | 1,090  | 166         | 1,380  |
| Joy       | 148     | 1,090  | 445         | 1,683  |
| Sadness   | 145     | 1,082  | 264         | 1,491  |

Table 1: Number of sentences for each emotion

In our study, we have taken into account four emotion classes (Anger, Fear, Joy and Sadness) which are in the intersection among three datasets (SemEval, ISEAR and Fairy tales). The number of sentences for each emotion and each

---

1. The dataset is publicly available at [http://www.cse.unt.edu/~rada/affectivetext](http://www.cse.unt.edu/~rada/affectivetext).
2. Available at [http://www.unige.ch/fapse/emotion/databanks/isear.html](http://www.unige.ch/fapse/emotion/databanks/isear.html)
The dataset used in our experiment is shown in Table 1. In addition, sample sentences from the annotated corpus appear in Table 2.

| Emotion | Dataset | Sentences tagged with Sadness/Sad |
|---------|---------|----------------------------------|
| Anger   | SemEval | Bangladesh ferry sink, 15 dead.  |
|         | ISEAR   | When I left a man in whom I really believed. |
|         | Fairy tales | The flower could not, as on the previous evening, fold up its petals and sleep; it dropped sorrowfully. |

Table 2: Sample sentences labeled with sadness/sad from the datasets

5 Experiments and Results

The goal of the affect classification is to predict a single emotional label given an input sentence. Four different approaches were implemented in Matlab. A categorical model based on a VSM with dimensionality reduction variants, (LSA, PLSA, and NMF), and a dimensional model, each with evaluated with two similarity measures (cosine angle and nearest neighbor). Stopwords were removed in all approaches. A Matlab tool-kit (Zeimpekis and Gallopoulos 2005), was used to generate the term-by-sentence matrix from the text.

The evaluation in Table 3 shows Majority Class Baseline (MCB) as the baseline algorithm. The MCB is the performance of a classifier that always predicts the majority class. In SemEval and Fairy tales the majority class is joy, while anger is the majority emotion in case of ISEAR. The five approaches were evaluated on the dataset of 479 news headlines (SemEval), 5,430 responses to questions (ISEAR), and 1,093 fairy tales’ sentences. We define the following acronyms to identify the approaches:

- CLSA: LSA-based categorical classification
- CPLSA: PLSA-based categorical classification
- CNMF: NMF-based categorical classification
- DIM: Dimension-based estimation

The measure of accuracies used here were: Cohen’s Kappa (Cohen 1960), average precision, recall, and F-measure. While the kappa scores are useful in obtaining an overview of the reliability of the various classification approaches, they do not provide any insight on the accuracy at the category level for which precision, recall, and F-measure are necessary.

| Emotion | Dataset | Prec. | Rec. | F1   | Prec. | Rec. | F1   | Prec. | Rec. | F1   |
|---------|---------|-------|------|------|-------|------|------|-------|------|------|
| Anger   | SemEval | 0.000 | 0.000 | -    | 0.399 | 1.000 | 0.571 | 0.000 | 0.000 | -    |
|         | ISEAR   | 0.089 | 0.151 | 0.112 | 0.468 | 0.970 | 0.631 | 0.386 | 0.749 | 0.510 |
|         | Fairy tales | 0.169 | 0.440 | 0.244 | 0.536 | 0.397 | 0.456 | 0.239 | 0.455 | 0.313 |
|         |         | 0.294 | 0.263 | 0.278 | 0.410 | 0.987 | 0.579 | 0.773 | 0.560 | 0.650 |
|         |         | 0.161 | 0.192 | 0.175 | 0.708 | 0.179 | 0.286 | 0.604 | 0.290 | 0.392 |
| Fear    | SemEval | 0.000 | 0.000 | -    | 0.000 | 0.000 | -    | 0.000 | 0.000 | -    |
|         | ISEAR   | 0.434 | 0.622 | 0.511 | 0.633 | 0.038 | 0.071 | 0.710 | 0.583 | 0.640 |
|         | Fairy tales | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
|         |         | 0.525 | 0.750 | 0.618 | 0.689 | 0.029 | 0.056 | 0.704 | 0.784 | 0.741 |
|         |         | 0.404 | 0.404 | 0.404 | 0.531 | 0.263 | 0.351 | 0.444 | 0.179 | 0.255 |
| Joy     | SemEval | 0.309 | 1.000 | 0.472 | 0.000 | 0.000 | -    | 0.407 | 1.000 | 0.579 |
|         | ISEAR   | 0.455 | 0.359 | 0.402 | 0.333 | 0.061 | 0.103 | 0.847 | 0.637 | 0.727 |
|         | Fairy tales | 0.250 | 0.258 | 0.254 | 0.307 | 0.381 | 0.340 | 0.555 | 0.358 | 0.436 |
|         |         | 0.773 | 0.557 | 0.648 | 0.385 | 0.005 | 0.010 | 0.802 | 0.761 | 0.781 |
|         |         | 0.573 | 0.934 | 0.710 | 0.349 | 0.980 | 0.515 | 0.661 | 0.979 | 0.789 |
| Sadness | SemEval | 0.000 | 0.000 | -    | 0.000 | 0.000 | -    | 0.000 | 0.000 | -    |
|         | ISEAR   | 0.472 | 0.262 | 0.337 | 0.500 | 0.059 | 0.106 | 0.704 | 0.589 | 0.642 |
|         | Fairy tales | 0.337 | 0.431 | 0.378 | 0.198 | 0.491 | 0.282 | 0.333 | 0.414 | 0.370 |
|         |         | 0.500 | 0.453 | 0.475 | 0.360 | 0.009 | 0.017 | 0.708 | 0.821 | 0.760 |
|         |         | 0.647 | 0.157 | 0.253 | 0.522 | 0.249 | 0.337 | 0.408 | 0.169 | 0.240 |

Table 3: Emotion identification results
5.1 Precision, Recall, and F-measure

Classification accuracy is usually measured in terms of precision, recall, and F-measure. Table 3 shows these values obtained by five approaches for the automatic classification of four emotions. The highest results for a given type of scoring and datasets are marked in bold for each individual class. We do not include the accuracy values in our results due to the imbalanced proportions of categories (see Table 1). The accuracy metric does not provide adequate information, whereas precision, recall, and F-measure can effectively evaluate the classification performance with respect to imbalanced datasets (He and Garcia 2009).

As can be seen from the table, the performances of each approach hinge on each dataset and emotion category, respectively. In the case of the SemEval dataset, precision, recall and F-measure for CNMF and DIM are comparable. DIM approach gives the best result for joy, which has a relatively large number of sentences. In ISEAR, DIM generally outperforms other approaches except for some cases, whereas CNMF has the best recall score after the baseline for the anger category. Figure 1 indicates the results of 3-dimensional and 2-dimensional attribute evaluations for ISEAR. When it comes to fairy tales, CNMF generally performs better than the other techniques. Joy also has the largest number of data instances in fairy tales and the best recall ignoring the baseline and F-measure are obtained with the approach based on DIM for this affect category. CNMF gets the best emotion detection performance for anger, fear, and sadness in terms of the F-measure.

Figure 2 and Table 4 display results among different approaches obtained on the three different datasets. We compute the classification performance by macro-average, which gives equal weight to every category regardless of how many sentences are assigned to it. This measurement prevents the results from being biased given the imbalanced data distribution. From this summarized information, we can see that CPLSA performs less effectively with several low performances across all datasets. CNMF is superior to other methods in SemEval and Fairy tales datasets, while DIM surpasses the others in ISEAR. In particular, CPLSA outperforms CLSA and CNMF in ISEAR because their performances are relatively poor. The result implies that statistical models which consider a probability distribution over the latent space do not always achieve sound performances. In addition, we can infer that models (CNMF and DIM) with non-negative factors are appropriate for dealing with these text collections.

Another notable result is that the precision, recall, and F-measure are generally higher in fairy tales than in the other datasets. These sentences in the fairy tales tend to have more emotional terms and the length of sentences is longer. The nature of fairy tales makes unsupervised models yield better performance (see Table 2). In addition, affective high agreement sentence is another plausible contributing reason for the encouraging experimental results.

In summary, categorical NMF model and dimensional model show the better emotion identification performance as a whole.

5.2 Cohen's Kappa

The kappa statistic measures the proportion of agreement between two raters with correction for chance. The kappa score is used as the metric to compare the performance of each approach. Figure 3 graphically depicts the mean kappa scores and its standard errors obtained from the emotion classification. Comparisons between four approaches are shown across all three datasets. MCB is excluded in the comparison because the mean kappa score of MCB is 0.

Let $\text{MK}_{\text{CLSA}}, \text{MK}_{\text{CPLSA}}, \text{MK}_{\text{CNMF}},$ and $\text{MK}_{\text{DIM}}$ be the mean kappa scores of four methods. The highest score ($\text{MK}_{\text{CNMF}} = 0.382$) is achieved by the CNMF when the dataset is SemEval. In fairy tales, the CNMF method ($\text{MK}_{\text{CNMF}} = 0.652$) also displays better result than the others ($\text{MK}_{\text{CLSA}} = 0.506, \text{MK}_{\text{DIM}} = 0.304$). On the contrary, the achieved results are significantly different in the case of the ISEAR dataset in comparison with the aforementioned datasets. The DIM ($\text{MK}_{\text{DIM}} = 0.210$) clearly outperforms all methods. The kappa score of the CPLSA approach ($\text{MK}_{\text{CPLSA}} = 0.099$) is quantitatively and significantly higher than the CLSA ($\text{MK}_{\text{CLSA}} = 0.031$) and CNMF ($\text{MK}_{\text{CNMF}} = 0.011$). Kappa score for the NMF-based methods is remarkably lower than the other three approaches.

According to (Fleiss and Cohen 1973), a kappa value higher than 0.4 means a fair to good level of agreement beyond chance alone and it is
SemEval and Fairy tales datasets, while DIM surpasses the others in ISEAR dataset. Our PLSA conducted in all experiments is inferior to NMF, DIM as well as LSA. The result implies that statistical models which consider a probability distribution over the latent space do not always lead to sound performances. In addition, we can infer that models (NMF and DIM) with non-negative factors are appropriate for dealing with text collections. Another interesting notice from overall results is that the precision, recall, and F-measure are higher in fairy tales than in two other datasets. The sentences in fairy tales have ampler emotional terms and the length of sentences is longer in comparison with those in other datasets. The nature of fairy tales makes unsupervised models yield better performance (see Table 2). In summary, categorical NMF model and dimensional model show the better emotion identification performance as a whole.

1.1 Cohen's Kappa

The kappa score is used as the metric to evaluate the performance of each approach. Figure 4 graphically depicts the mean kappa scores and its standard errors obtained from the emotion classification. Comparisons between four approaches are shown and there are statistically significant differences in the kappa scores across all three datasets. MCB is excluded in the comparison because the mean kappa score of MCB is 0. Let \( MK_{\text{LSA}}, MK_{\text{PLSA}}, MK_{\text{NMF}}, \) and \( MK_{\text{DIM}} \) be the mean kappa scores of four methods. The highest score (\( MK_{\text{NMF}} = 0.382 \)) is achieved by the NMF when the dataset is SemEval. In fairy tales, the NMF method (\( MK_{\text{NMF}} = 0.652 \)) also displays better result than the others (\( MK_{\text{LSA}} = 0.506, MK_{\text{DIM}} = 0.304 \)). Note that the achieved results are somewhat different in case of ISEAR dataset in comparison with the aforementioned experiment which used precision, recall, and F-measure. The DIM (\( MK_{\text{DIM}} = 0.210 \)) clearly outperforms all methods like section 5.1. On the contrary, the kappa score of the PLSA approach (\( MK_{\text{PLSA}} \)) is quantitatively and significantly higher than the LSA (\( MK_{\text{LSA}} \)) and NMF (\( MK_{\text{NMF}} \)). Kappa score for the NMF-based methods is remarkably lower than the other three approaches. Nevertheless, we can observe that NMF-based categorical model and dimensional model got good grades on the whole.

1.2 Cohen's Kappa

The most frequent words used in ISEAR dataset for each emotion are shown in Table 4. NMF and Figure 1: Distribution of the ISEAR dataset in the 3-dimensional and 2-dimensional sentiment space. The blue ‘x’ denotes the location of one sentence corresponding to valence, arousal, and dominance.

Figure 2: Comparisons of Precision, Recall, and F-measure: (a) SemEval; (b) ISEAR; (c) Fairy tales.

| Data set | Prec. | Rec. | F1  | Prec. | Rec. | F1  | Prec. | Rec. | F1  |
|----------|-------|------|-----|-------|------|-----|-------|------|-----|
| MCB      | 0.077 | 0.250| 0.118 | 0.100 | 0.250| 0.143 | 0.102 | 0.250| 0.145|
| CLSA     | 0.363 | 0.348| 0.340 | 0.484 | 0.282| 0.228 | 0.662 | 0.640| 0.630|
| CPLSA    | 0.189 | 0.282| 0.219 | 0.260 | 0.317| 0.270 | 0.282 | 0.307| 0.280|
| CNMF     | 0.523 | 0.506| 0.505 | 0.461 | 0.258| 0.166 | 0.747 | 0.731| 0.733|
| DIM      | 0.446 | 0.422| 0.386 | 0.528 | 0.417| 0.372 | 0.530 | 0.404| 0.419|

Table 4: Overall average results

Figure 3: Comparisons of Mean Kappa: (a) SemEval; (b) ISEAR; (c) Fairy tales.
an acceptable level of agreement. On the basis of
this definition, the kappa score obtained by our
best classifier ($MK_{CNMF} = 0.652$) would be rea-
sonable. Most of the values are too low to say
that two raters (human judges and computer ap-
proaches) agreed upon the affective states. How-
ever, we have another reason with respect to this
metric in the experiment. We make use of the
kappa score as an unbiased metric of the reli-
ability for comparing four methods. In other
words, these measures are of importance in terms
of the relative magnitude. Hence, the kappa re-
results are meaningful and interpretable in spite of
low values. We can observe that the NMF-based
categorical model and the dimensional model
both experienced higher performance.

5.3 Frequently occurring words

The most frequent words used in fairy tales for
each emotion are listed in Table 5. We choose
this dataset since there are varying lexical items
and affective high agreement sentences, as men-
tioned in Section 5.1. Stemming is not used be-
cause it might hide important differences as be-
tween ‘loving’ and ‘loved’. CNMF and DIM
were selected for the comparison with the Gold
Standard because they were the two methods
with the better performance than the others. Gold
Standard is the annotated dataset by human raters
for the evaluation of algorithm performance. The
words most frequently used to describe anger
across all methods include: cried, great, tears,
king, thought, and eyes. Those used to describe
fear include: heart, cried, mother, thought, man,
and good. Joy contains happy, good, and cried
whereas sadness has only cried for three methods.

There is something unexpected for the word
frequencies. We can observe that the association
between frequently used words and emotion cat-
egories is unusual and even opposite. For in-
stance, a ‘joy’ is one of the most frequent words
referred to for sadness in the Gold Standard. In
CNMF and DIM, a ‘good’ is employed frequent-
ly with regard to fear. Moreover, some words
occur with the same frequency in more catego-
ries. For example, the word ‘cried’ is utilized to
express anger, fear, and joy in the Gold Standard,
CNMF, and DIM. In order to find a possible ex-
planation in the complexity of language used in
the emotional expression, some sentences ex-
tracted from fairy tales are listed below:

“The cook was frightened when he heard the or-
der, and said to Cat-skin, You must have let a
hair fall into the soup; if it be so, you will have a
good beating.” – which expresses fear

“When therefore she came to the castle gate she
saw him, and cried aloud for joy.” – which is the
expression for joy

“Gretel was not idle; she ran screaming to her
master, and cried: You have invited a fine guest!”
– which is the expression for angry-disgusted

From these examples, we can observe that in
these cases the affective meaning is not simply
propagated form the lexicon, but is the effect of
the linguistic structure at a higher level.

6 Conclusion

We compared the performances of three tech-
niques, based on the categorical representation of
emotions, and one based on the dimensional rep-
resentation. This paper has highlighted that the
NMF-based categorical classification performs

| Model     | Emotion | Top 10 words                                      |
|-----------|---------|--------------------------------------------------|
| Gold Standard | Anger   | king, thought, eyes, great, cried, looked, joy, mother, wife, tears |
|           | Fear    | great, cried, good, happy, thought, man, heart, poor, child, mother |
|           | Joy     | thought, mother, good, cried, man, day, wept, beautiful, back, happy |
|           | Sadness | cried, fell, father, mother, back, joy, dead, danced, wife, tears |
| CNMF      | Anger   | great, cried, eyes, mother, poor, joy, king, heart, thought, tears |
|           | Fear    | cried, king, happy, good, man, heart, thought, father, boy, mother |
|           | Joy     | mother, thought, cried, king, day, great, home, joy, good, child |
|           | Sadness | thought, cried, good, great, looked, mother, man, time, king, heart |
| DIM       | Anger   | eyes, fell, heart, tears, cried, good, stood, great, king, thought |
|           | Fear    | king, cried, heart, mother, good, thought, looked, man, child, time |
|           | Joy     | eyes, man, children, danced, cried, good, time, happy, great, wedding |
|           | Sadness | cried, thought, great, king, good, happy, sat, home, joy, found |

Table 5: Most frequent 10 words from fairy tales
the best among categorical approaches to classification. When comparing categorical against dimensional classification, the categorical NMF model and the dimensional model have better performances. Nevertheless, we cannot generalize inferences on which of these techniques is the best performer because results vary among datasets. As a future work, we aim at performing a further investigation on this connection in order to identify more effective strategies applicable to a generic dataset. Furthermore, we aim at exploring improvements in the methodology, employed in this work, and based on the combination of emotional modeling and empirical methods.

Acknowledgments

This research is partially sponsored by a Norman I. Price Scholarship from the University of Sydney.

References

C. O. Alm (2009). Affect in Text and Speech, VDM Verlag Dr. Müller.
S. Aman and S. Szpakowicz (2007). Identifying expressions of emotion in text. Text, Speech and Dialogue.
M. M. Bradley and P. J. Lang (1999). Affective norms for English words (ANEW): Instruction manual and affective ratings. University of Florida: The Center for Research in Psychophysiology.
J. Cohen (1960). A coefficient of agreement for nominal scales. Educational and psychological measurement 20(1): 37-46.
S. D’Mello, A. Graesser, and R. W. Picard (2007). Toward an affect-sensitive AutoTutor. IEEE Intelligent Systems 22(4): 53-61.
S. D’Mello, S. Craig, A. Witherspoon, B. McDaniel, and A. Graesser (2008). Automatic detection of learner’s affect from conversational cues. User Modeling and User-Adapted Interaction 18(1): 45-80.
P. Ekman (1992). An argument for basic emotions. Cognitive & Emotion 6(3): 169-200.
J. L. Fleiss and J. Cohen (1973). The equivalence of weighted kappa and the intraclass correlation. Educational and psychological measurement 33: 613-619.
H. He and E. A. Garcia (2009). Learning from Imbalanced Data. IEEE Transactions on Knowledge and Data Engineering 21(9): 1263.
T. Hofmann (2001). Unsupervised learning by probabilistic latent semantic analysis. Machine Learning 42(1): 177-196.
B. Kort, R. Reilly, and R. W. Picard (2001). An affective model of interplay between emotions and learning: Reengineering educational pedagogy—building a learning companion. IEEE International Conference on Advanced Learning Technologies, 2001. Proceedings.
T. K. Landauer, P. W. Foltz, and D. Laham (1998). An introduction to latent semantic analysis. Discourse processes, Citeseer. 25: 259-284.
P. J. Lang (1980). Behavioral treatment and biobehavioral assessment: Computer applications. Technology in mental health care delivery systems: 119-137.
D. D. Lee and H. S. Seung (1999). Learning the parts of objects by non-negative matrix factorization. Nature 401(6755): 788-791.
P. Penumatsa, M. Ventura, A.C. Graesser, M. Louverse, X. Hu, Z. Cai, and D.R. Franceschetti (2006). The Right Threshold Value: What Is the Right Threshold of Cosine Measure When Using Latent Semantic Analysis for Evaluating Student Answers? International Journal on Artificial Intelligence Tools, World Scientific Publishing.
J. A. Russell (2003). Core affect and the psychological construction of emotion. Psychological review 110(1): 145-172.
K. R. Scherer and H. G. Wallbott (1994). Evidence for universality and cultural variation of differential emotion response patterning. Journal of Personality and Social Psychology 66: 310-328.
C. Strapparava and R. Mihalcea (2007). Semeval-2007 task 14: Affective text. Proceedings of the 4th International Workshop on Semantic Evaluations, Association for Computational Linguistics.
C. Strapparava and R. Mihalcea (2008). Learning to identify emotions in text. SAC ’08: Proceedings of the 2008 ACM symposium on Applied computing, Fortaleza, Ceara, Brazil, ACM.
C. Strapparava and A. Valitutti (2004). WordNet-Affect: an affective extension of WordNet. Proceedings of LREC.
R. B. Yates and B. R. Neto (1999). Modern information retrieval. ACM P.
Zeimpekis D. and E. Gallopoulos (2005). TMG: A MATLAB toolbox for generating term-document matrices from text collections. Grouping multidimensional data: Recent advances in clustering: 187-210.