Evaluation of Unsupervised Emotion Models
to Textual Affect Recognition

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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 estimate 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 sim(*I*, E_j), the categorical classification result, CCR, is more formally represented as follows:

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

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.

$$
A = U\sum V^T \approx U_k \sum_k V_k^T = A_k \tag{1}
$$

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 Anlaysis (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.

$$
P(d, w) = \sum_z P(z)P(w|z)P(d|z) \tag{2}
$$

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*.

$$
A \approx WH = \sum WH \tag{3}
$$

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.

$$
\min_{W,H} \|A - WH\|_F^2 , \qquad s.t. \ W, H \geq 0 \tag{4}
$$

where *W*, *H* ≥ 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 $\overline{w}$ in an affective space as:

$$\overline{w} = (valence, arousal, dominance)$$
$$= ANEW(w) \qquad (5)$$

The occurrences of these words in a text can be used, in a naïve way, to weight the sentence in this emotional plane. This is a naïve 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:

$$\overline{sentence} = \frac{\sum_{i=1}^{n} \overline{w}}{n} \qquad (6)$$

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:

$$\overline{emotion} = \frac{\sum_{i=1}^{k} \overline{w}}{k} \qquad (7)$$

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_c, F_c, J_c, and S_c be the centroids of four emotions. Then the centroids, which are calculated by the equation (7), are as follows: A_c = (2.55, 6.60, 5.05), F_c = (3.20, 5.92, 3.60), J_c = (7.40, 5.73, 6.20), and S_c = (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 $\overline{sentence}$ might be close to an $\overline{emotion}$ 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] For building the ISEAR, 1,096 participants who have different cultural backgrounds completed questionnaires about experiences and reactions for seven emotions including *anger*, *disgust*, *fear*, *joy*, *sadness*, *shame* and *guilt*.

The annotated sentences of the third dataset are culled from fairy tales (Alm 2009). Emotions are particularly significant elements in the literary genre of fairy tales. The label set with five emotion classes is as follows: *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

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

Table 3: Emotion identification results

dataset used in our experiment is shown in Table 1. In addition, sample sentences from the annotated corpus appear in Table 2.

Dataset	Sentences tagged with *Sadness/Sad*
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 toolkit (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.

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.[3] 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 performance results 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 MK_{CLSA}, MK_{CPLSA}, MK_{CNMF}, and MK_{DIM} be the mean kappa scores of four methods. The highest score ($MK_{CNMF} = 0.382$) is achieved by the CNMF when the dataset is SemEval. In fairy tales, the CNMF method ($MK_{CNMF} = 0.652$) also displays better result than the others ($MK_{CLSA} = 0.506$, $MK_{DIM} = 0.304$). On the contrary, the achieved results are significantly different in the case of the ISEAR dataset in comparison with the aforementioned datasets. The DIM ($MK_{DIM} = 0.210$) clearly outperforms all methods. The kappa score of the CPLSA approach ($MK_{CPLSA} = 0.099$) is quantitatively and significantly higher than the CLSA ($MK_{CLSA} = 0.031$) and CNMF ($MK_{CNMF} = 0.011$). 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

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[3] Macro-averaging scores are defined as:
$$P_{\mathrm{m}} = \frac{1}{C}\sum_{i=1}^{C} p_i, R_{\mathrm{m}} = \frac{1}{C}\sum_{i=1}^{C} r_i, F_{\mathrm{m}} = \frac{1}{C}\sum_{i=1}^{C} f_i$$
where C is total number of categories, and p_i, r_i, and f_i stand for precision, recall, and F-measure, respectively, for each category i.
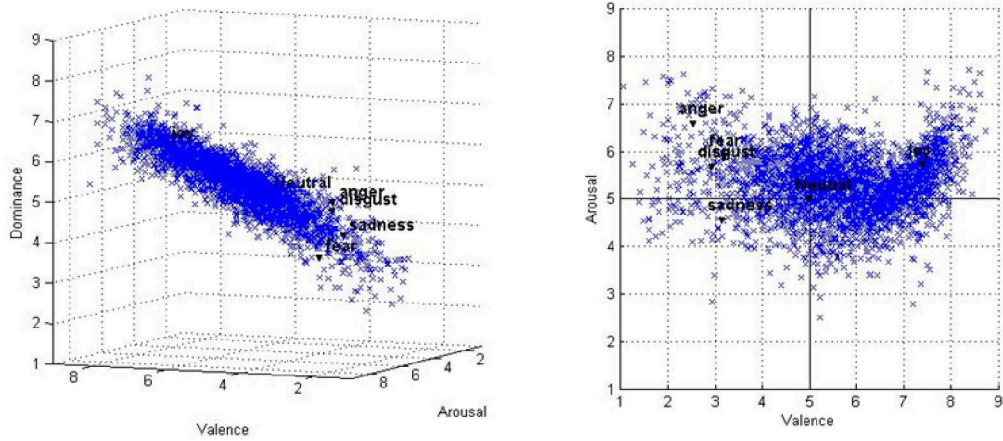
Figure 1: Distribution of the ISEAR dataset in the 3-dimensional and 2-dimensional sentiment space. The blue 'x' denotes the location of one sentence corresponding to valence, arousal, and dominance.
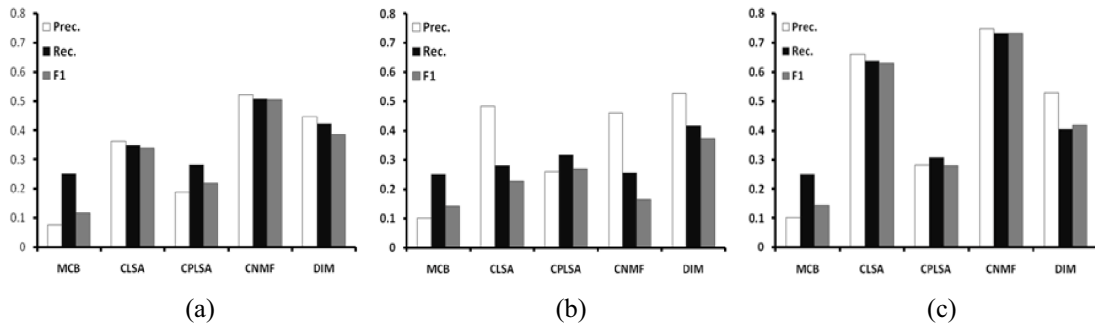

Figure 2: Comparisons of Precision, Recall, and F-measure: (a) SemEval; (b) ISEAR; (c) Fairy tales.

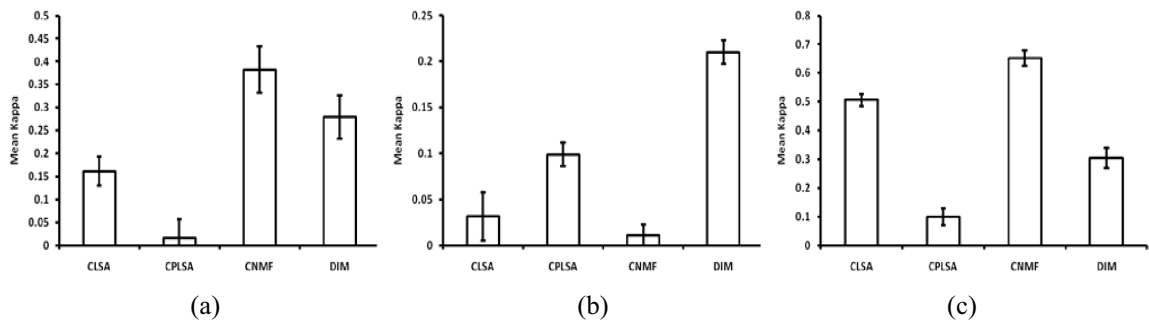| Data set	SemEval			ISEAR			Fairy tales		
	Prec.	Rec.	F1	Prec.	Rec.	F1	Prec.	Rec.	F1
MCB	0.077	0.250	0.118	0.100	0.250	0.143	0.102	0.250	0.145
CLSA	0.363	0.348	0.340	0.484	0.282	0.228	0.662	0.640	0.630
CPLSA	0.189	0.282	0.219	0.260	0.317	0.270	0.282	0.307	0.280
CNMF	**0.523**	**0.506**	**0.505**	0.461	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 reasonable. Most of the values are too low to say that two raters (human judges and computer approaches) agreed upon the affective states. However, 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 reliability for comparing four methods. In other words, these measures are of importance in terms of the relative magnitude. Hence, the kappa 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 mentioned in Section 5.1. Stemming is not used because it might hide important differences as between '*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 categories is unusual and even opposite. For instance, 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 frequently with regard to *fear*. Moreover, some words occur with the same frequency in more categories. 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 explanation in the complexity of language used in the emotional expression, some sentences extracted from fairy tales are listed below:

"The cook was frightened when he heard the order, 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 techniques, based on the categorical representation of emotions, and one based on the dimensional representation. 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.

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