An Interval Type-2 Fuzzy Logic System to Translate Between Emotion-Related Vocabularies

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Abstract

This paper describes a novel experiment that demonstrates the feasiblity of a fuzzy logic (FL) representation of emotion-related words used to translate between different emotional vocabularies. Type-2 fuzzy sets were encoded using input from web-based surveys that prompted users with emotional words and asked them to enter an interval using a double slider. The similarity of the encoded fuzzy sets was computed and it was shown that a reliable mapping can be made between a large vocabulary of emotional words and a smaller vocabulary of words naming seven emotion categories. Though the mapping results are comparable to Euclidian distance in the valence/activation/dominance space, the FL representation has several benefits that are discussed.

Index Terms: emotion, fuzzy logic, knowledge engineering.

1. Introduction

As a matter of practice, many emotion studies begin with an enumeration of emotion categories that will be the object of inquiry. For example, some common sets of emotions used include: { *negative*, *non-negative* }, { *angry*, *happy*, *sad*, *neutral* }, and { *angry*, *disgusted*, *fearful*, *happy*, *neutral*, *sad*, *surprised*}. While enumeration of categories may work in some domains, in many other cases imposing a categorization can cause over-simplification and lead to lack of interoperability with other systems of categorization. Categorizing emotion classes is especially exemplary of this problem due to the subjective nature of emotions. Also, this problem manifests itself in many practical issues of emotion research. It is difficult to generalize the results of experiments that use different emotional categories. Forced choice in human labeling tasks may bias results according to the categories presented. If an "other" choice is provided, it is not clear what to do with open-ended user input. It may be possible to have a precisely defined set of emotions in certain cases, such as extreme emotions associated with evolutionary behavior like fight-or-flight responses, but considering human language as the focal point in this argument, the subtlety of all emotions expressed by any person in any context warrants a more complete solution.

One popular way to circumvent the problems of a fixed set of emotions is the dimensional approach, which represents emotions in terms of coordinates in an emotional space. The two most common dimensions used are *valence*, representing an axis of pleasure/displeasure of the emotion, and *activation*, representing an axis of the energy or strength of the emotion [1]. Sometimes a third dimension is also used. In this study we use *dominance* as a third dimension, which represents the scale between aggressive and submissive. Another third dimension in the literature is *control*, which is a scale of how much conscious control a person has over a given emotion. Representing emotions in a dimensional space is an important insight which is used in this paper's research.

Common ways of using the dimensional approach fall short. Usually, an emotion's location in such a dimensional space is estimated using Likert scales or sliders. In both of these cases, users must pick a single point on a given scale. Any intra-user uncertainty is lost, though inter-subject uncertainty may be estimated from the ratings accumulated across users. Intra-user uncertainty may be estimated from repeated presentation of a given stimulus, but this can be infeasible when broad coverage is needed.

The approaches used in this paper, Interval Type-2 Fuzzy Logic and the Computing With Words paradigm, provide a solution to the problems raised above. The methodology we present uses double sliders to collect dimensional emotion ratings from subjects, as described in [2]. The span of the two sliders on a scale represents the region that the user wishes to select and is used to encode the user's lexical knowledge into an interval type-2 fuzzy set. A similarity metric for interval type-2 fuzzy sets [3] is used to map from one vocabulary to another, making it possible to compare different sets of emotion categorizations and deal with a wider range of user input, for example in the case when users choose "other" on a forced choice task and then provide open-ended input.

The motivation for undertaking this work comes from trying to deal with an open-ended set of emotionally descriptive words used as labels of the blog posts of the website livejournal.com. On this site, users can label their blog posts with a "mood" label. This makes the corpus a natural choice to study emotions in the blogs. However, users may enter any word, so there is a lot of noise in the labels and the set of labels has a "long tailed" Zipf distribution. Instead of discarding all the data except those labeled with a few basic emotional tags, we wanted to map a larger vocabulary, the words used in the blog labels, to a smaller, controlled vocabulary. Also, the survey, which collected data from internet users, could be seen as a way to extend the idea of social computing from the blogs and mood tags to a more uniform semantic representation.

Besides analyzing the blog data, some possible applications of this research include: corpus annotation; information retrieval; translation and paraphrasing; social computing; emotion-aware applications where a small, fixed set of emotion labels is not practical; and fusion of different classifiers where each classifier might use a different set of classes, as in the case of multimodal analysis, where each modality is good at recognizing a certain subset of emotions. In spoken language processing, the speech itself can be thought of having different modalities, such as the acoustics and the symbolic string represented as text. Also, the fact that fuzzy logic is an extension of classical logic allows it to provide for semantic representations that can be used for language generation.

The main questions we try to answer in this paper are: Is the fuzzy logic approach both feasible and useful to represent emotions and model user emotional evaluation? Is the fuzzy logic approach better than a simpler representation where emotions are simply points in the emotional space? Did the survey provide a reliable form of gathering emotional intuitions from users? The answers to these questions will be defered until Section 4. First we will describe our experimental methodology in Section 2 and the results in Section 3. Finally, Section 5, summarizes the paper and proposes future work.

2. Methodology

The methodology section is divided into two parts. The first discusses the design of the survey, and the second describes the concepts of fuzzy logic that are relevant to the study.

2.1. Survey Design

The data used in this experiment was obtained through two online surveys of 32 subjects. Both surveys had a similar structure. First, the surveys gave the subject instructions. Then the surveys sequentially presented the subject with an emotional word, which we will refer to as the stimulus. Below the presented stimulus were sliders for each of the three emotional dimensions, valence, activation, and dominance. The sliders had two handles, which allowed the subjects to select ranges. The range of the sliders was 0-10, which was the maximum allowable range that a user could select. The minimum range allowed was 1, since the steps were integer values and the implementation imposed a constraint that the upper and lower endpoint could not be the same.

In the first experiment, each subject was presented with a series of stimuli that consisted of seven emotion category words (angry, disgusted, fearful, happy, neutral, sad, and surprised). For each subject, these seven stimuli were randomly presented three times over the course of the experiment. In the second experiment each subject was presented with a series of 22 emotion words selected randomly from a set of 40 words. These words were picked from the top 40 emotional mood labels used by the bloggers of LiveJournal (this blogging site lets users label each post with a mood label, which has been used as an annotated corpus for studying emotional text [4]). The surveys were web-based, with the slider functionality implemented using the Javascript library JQuery UI.

2.2. Interval Type-2 Fuzzy Logic and Computing With Words

This section will briefly explain the fuzzy logic topics relevant for understanding the paper and give detailed sources for the interested reader.

The first topic to explain is the typology of fuzzy sets. In traditional set theory (a.k.a, "crisp logic" or *Type-0*), a set A can be defined by an all-or-nothing boolean membership function μ that maps objects of the universe to $\{0,1\}$ depending on whether the object is in A:

$$\mu_A(x) = \begin{cases} 1, if\, x \in A \\ 0, if\, x \notin A \end{cases} \tag{1}$$

The initial insight of fuzzy logic was to generalize the notion of membership to a continuous range of $[0, 1]$, which is termed the *membership grade* to indicate its gradient nature. This is what is known as a *type-1 fuzzy set*. The traditional logic relations of union and disjunction are given new interpretations, such as maximum and minimum.

The newer notion of *type-2 fuzzy sets* is a bit more complex. The insight of this development is to account for uncertainty. In a type-1 fuzzy set, the membership grade for each point x in the universe is another point $\mu(x) \in [0, 1]$. In type-2 fuzzy sets, $\mu(x)$ is a distribution of the expected point in $[0, 1]$. However, estimating this distribution is difficult and working with full type-2 fuzzy sets is computationally intensive.

Interval type-2 fuzzy sets attempt to capture the uncertainty that full type-2 fuzzy sets model while still using the mathematics of type-1 fuzzy sets. Interval type-2 fuzzy sets were used in this paper because they offer the theoretical benefits of full type-2 fuzzy sets and they are practical to use. Instead of a distribution, an interval is used to model the uncertainty about the membership grade. This interval is represented as two type-1 fuzzy sets, an upper membership function and a lower membership function. When these coincide, the interval type-2 fuzzy set reduces to a type-1 fuzzy set [5, 6]. The region between these is known as the membership function's *footprint of uncertainty*. An example of this type of membership function can be seen in figure 1.

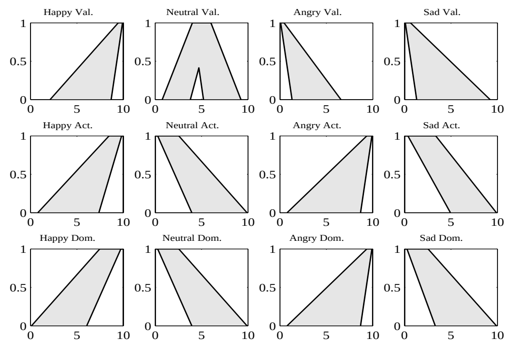

Figure 1: *Example membership functions (MF's) for happy, neutral, angry, and sad. All the membership functions shown here,except the valence for neutral, are shoulder MF's that model the edges of the domain of μ. The region between the upper and lower MF's, the footprint of uncertainty, is shaded.*

Computing With Words (CWW) is another topic to be explained. "CWW is a methodology in which the objects of computation are words and propositions drawn from a natural language" [7]. The approach used here uses data collected from the surveys (Section 2.1) to encode an interval type-2 fuzzy set on each emotion dimension, using a methodology described in [8, 2]. Then an input vocabulary is mapped to an output vocabulary using a similarity metric defined on interval type-2 fuzzy sets, which combines the notions of proximity and shape similarity [3]. For some w_x in the input vocabulary W_x, the computing with words approach maps it to some word w_y in the output vocabulary that maximizes the similarity S between w_x and w_y:

$$w_y = \underset{w_y \in W_y}{\operatorname{argmax}}\, S(w_x, w_y) \tag{2}$$

One novel aspect of the research presented here is that the fuzzy sets that represent words are actually three separate fuzzy sets, one for each emotion dimension. Therefore, to make a single similarity matrix, we considered both sum and product to combine the separate similarity matrices of each dimension.

To map between one vocabulary, the emotion category words, and another, the blog mood labels, all that is necessary is a similarity matrix where the rows represent input words and the columns, the output. Given an input word, the output is found from the maximum value along its row. The column corresponding to this maximum gives the output word.

3. Results

Below, we display the results of calculating a similarity matrix between each emotion-related word, displayed using *multidimensional scaling* (MDS). The result of combining the similarities of the valence, activation, and dominance dimensions was slightly different using sum versus product in that the sum combination produced a more spread out distribution of the words, while the product combination produced a distribution with tighter clusters, as seen in Figure 2. One can notice that in the target vocabulary, "happy" and "surprised" are very close, as are "angry" and "disgusted". Since mapping between vocabularies is done using similarities, this implies that these pairs could be confusable.

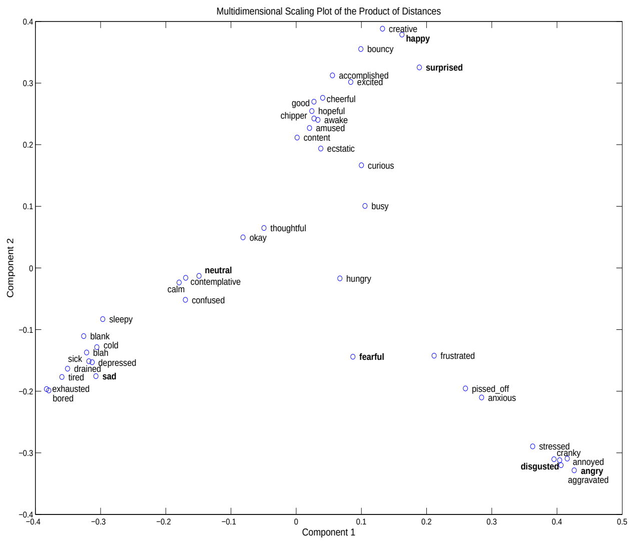

Figure 2: *Multidimensional Scaling (2-D) representation of the emotional words' similarity. When viewing electronic versions of this paper, please use the zoom function of the PDF viewer.*

To check the mapping induced by the similarity matrices, below we show the similarity matrix (Table 1) for the product combination of the similarity matrices of the valence, activation, and dominance dimensions. The location of the maximum of each row is bolded to show the translation from the larger vocabulary (rows) to the smaller vocabulary (columns).

The majority of these mappings from the words on the rows to those on the columns seem to be intuitively correct, though there are several exceptions. The most glaring exception is that "fearful" is not in the range of the mapping from large vocabulary to small vocabulary. Cases where one would expect to have a mapping to "fearful" (e.g., "anxious", "stressed") do show elevated similarity to "fearful" but "angry" or "disgusted" are higher. The observation that most of the values in the "fearful" column are lower than the other columns, we normalized each

Table 1: Similarity matrix where row labels are the input vocabulary and column labels are the output vocabulary codebook. The each row's maximum value has been marked in bold.

	Angry	Disgusted	Fearful	Happy	Neutral	Sad	Surprised
Amused	0.004	0.003	0.005	**0.060**	0.004	0.005	0.053
Tired	0.006	0.003	0.034	0.001	0.038	**0.196**	0.001
Cheerful	0.003	0.003	0.003	**0.109**	0.001	0.002	0.088
Bored	0.015	0.012	0.075	0.004	0.064	**0.335**	0.004
Accomplished	0.015	0.013	0.008	**0.151**	0.006	0.008	0.139
Sleepy	0.007	0.005	0.018	0.009	**0.172**	0.128	0.010
Content	0.005	0.004	0.007	**0.044**	0.015	0.012	0.040
Excited	0.015	0.017	0.006	**0.255**	0.002	0.002	0.213
Contemplative	0.006	0.004	0.012	0.006	**0.161**	0.075	0.007
Blah	0.014	0.010	0.049	0.005	0.166	**0.359**	0.007
Awake	0.020	0.017	0.016	0.061	0.015	0.014	**0.068**
Calm	0.003	0.002	0.011	0.007	**0.137**	0.069	0.008
Bouncy	0.009	0.012	0.002	**0.361**	0.000	0.001	0.311
Chipper	0.002	0.002	0.001	**0.066**	0.002	0.003	0.059
Annoyed	**0.393**	0.380	0.080	0.041	0.002	0.023	0.076
Confused	0.026	0.020	0.064	0.014	0.046	**0.170**	0.017
Busy	0.068	0.079	0.049	0.111	0.013	0.012	**0.116**
Sick	0.008	0.004	0.032	0.001	0.023	**0.204**	0.001
Anxious	**0.207**	0.181	0.091	0.028	0.003	0.025	0.038
Exhausted	0.015	0.011	0.048	0.003	0.046	**0.298**	0.004
Depressed	0.008	0.005	0.050	0.001	0.015	**0.218**	0.001
Curious	0.038	0.042	0.014	**0.203**	0.011	0.006	0.176
Drained	0.009	0.007	0.039	0.002	0.061	**0.280**	0.003
Aggravated	0.578	**0.618**	0.114	0.047	0.002	0.020	0.087
Ecstatic	0.000	0.000	0.000	0.108	0.000	0.000	**0.117**
Blank	0.006	0.004	0.017	0.005	0.133	**0.137**	0.006
Okay	0.016	0.013	0.035	0.017	**0.076**	0.057	0.020
Hungry	**0.084**	0.082	0.029	0.045	0.013	0.034	0.052
Hopeful	0.009	0.007	0.007	0.047	0.010	0.009	**0.050**
Cold	0.005	0.003	0.026	0.001	0.047	**0.123**	0.002
Creative	0.027	0.037	0.007	**0.524**	0.001	0.002	0.462
pissed_off	**0.383**	0.363	0.052	0.016	0.000	0.008	0.035
Good	0.004	0.003	0.004	**0.067**	0.005	0.006	0.060
Thoughtful	0.005	0.003	0.004	0.011	**0.079**	0.029	0.012
Frustrated	0.186	**0.233**	0.068	0.022	0.001	0.012	0.030
Cranky	0.325	**0.351**	0.099	0.045	0.002	0.022	0.060
Stressed	0.288	**0.304**	0.158	0.044	0.003	0.026	0.053

column by its maximum value. Doing this does in fact produce the intuitive mapping of "anxious" and "stressed" to "fearful", but also changed other values.

To better quantify the intuitive goodness of the mapping from one vocabulary to another, we undertook a small evaluation where four human subjects were given the larger set of words as stimuli and asked to choose the words from the small set that best describe each stimulus. We found that at least one of the subject's choices matched the predicted mapping except in 5 cases (i.e., performance of approx. 84%): "confused", "busy", "anxious", "hungry", and "hopeful". Filtering out clearly non-emotional words may have improved the results here, but our aim was to use a possibly noisy large vocabulary, since the data came from the web.

To see if the fuzzy logic approach performed better than a simpler approach, we converted the survey interval end-points to single points by taking the midpoint and then averaging across all users. With the points in the 3-D emotional space, we determined that the Euclidean similarity relations were essentially the same as those determined by the fuzzy logic similarity measures (which combined both shape and proximity).

4. Discussion

To return to the questions posed in the introduction, we can say that the approach presented here is feasible and provides a suitable closeness to human intuitions. However, this approach gave similar results to a simpler approach of just representing emotion words as points in a Euclidean space. One justification of the approach presented here is that fuzzy logic offers theoretical benefits such as allowing logical operations, which could be useful in many ways. For example, some of the mappings from the input vocabulary pick an output from two close candidates. If another value is close to the maximum, it may make sense to choose both words, if the application permits. By combining some set of basic emotions, like those in the small vocabulary, it may be possible to make a better mapping from a larger vocabulary. One insight into combination of emotions comes from looking at the direction of the mapping. When mapping from a large vocabulary to a smaller one, the specificity of the larger vocabulary seems to warrant a disjunction ("and") of the more general words of the small vocabulary, making the combined terms more specific. On the other hand, going the other way, from a large vocabulary to a small one seems to warrant union ("or") to generalize from the specific words of the large vocabulary to the smaller vocabulary (this is assuming that a larger vocabulary implies more specific words).

Besides providing a better mapping, using a combination of emotions may be advantageous in multimodal applications where, as noted in the introduction, different modalities are better at recognizing and expressing different emotions. One example of fuzzy logic applied to emotions is the *fuzzy logical model of perception* (FLMP). [9] gives an example where FLMP can be applied to mulimodal emotion recognition. Another example of fuzzy logic in emotion recognition is [10, 11], which used fuzzy logic rules to map acoustic features to a dimensional representation in valence, activation, and dominance. This example also shows how it could be possible to incorporate emotion recognition into the research presented in this paper. For example, the mapping from acoustic features to the emotional space could be further mapped to an appropriate output vocabulary.

Another issue to note is that although the approach we presented was designed to handle a larger set of emotional descriptive words, the set of words used is closed. However, if an unknown word can be assigned valence, activation, and dominance values, it will be possible to use a truly open set of words for emotional labels. One way of doing this would be to prompt a user with a slider-type survey, as described above, when unknown words are encountered. However, this may not be feasible in all applications. One more general approach would be to estimate an unknown word's fuzzy membership function from mined text statistics.

In the results we saw that no emotions in the larger vocabulary map to fearful. Upon examination of the interval endpoints from the surveys it was apparent that many users were confused about the dominance value for this emotion. Theoretically, anger and fear are both alike in valence and activation, but differ in dominance. For other emotion pairs, dominance tends to be correlated with activation. This could indicate need for more instructions for the surveys or perhaps dropping the dominance scale, except in cases where it is distinctive.

Another result to mention is that the pair "happy" and "surprised" and the pair "angry" and "disgusted" were located very close to each other, which made them potentially confusable. To make a better mapping from one vocabulary to another, one should choose a subset of the target vocabulary, or codebook, that better covers the emotional space. One of the benefits of the fuzzy logic approach is that the plots of the membership functions are a good way of visually choosing such a spanning sub-vocabulary. The rationale for choosing a sub-vocabulary is that it will result in a smaller set of "if-then" rules in a computing with words fuzzy logic system. Also, for some human labeling tasks, using the smaller vocabulary to label input might result in less confusion between these labels.

Another aspect of our approach that should be discussed is the fact that we merged the distances of the fuzzy sets of each emotional dimension in a rudimentary way. We tried both normalized sum and product. These operations preserve the distance metric, but other possibilities exist, such as a weighted integration of the distances in each dimension.

5. Conclusions

This paper presented a methodology for encoding human knowledge of the meaning of emotional words into interval type-2 fuzzy sets over a three-dimensional emotional space of valence, activation, and dominance. The computing with words approach was used to map between different emotional vocabularies. While this fuzzy logic approach did not offer performance increases over a simpler approach, it did no worse. This approach offers theoretical benefits, such as an extension of logical operations that would make it possible to combine emotions.

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