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# S URVEY ON EMOTION CLASSIFICATION USING SEMANTIC WEB

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**Abstract**

**Interest in emotion classification has been growing steadily in the last years because of the increase in the number of applications and its usage in various fields. The emotion classification of text is an important research direction of text mining. This paper classifies the emotions using the semantic web with the help of ontology approach. Ontology is a formal representation of a set of concepts within a domain and relationship between those concepts. Each emotional concept is defined in terms of a range of values along the three-dimensional space of emotional dimensions using a language called OWL which is a formal language to encode Ontology. A POS tagger is used to split the sentences into words corresponding to their parts of speech. This paper provides the rankings for the affective words obtained from the POS tagging using ANEW word list in the form of three dimensions. The dimensions are compared with OWL file. Since, Ontology is being used, insertion of new instances of emotional concepts results in automatic classification under the corresponding branch of the hierarchy.**

**Key Words**

**Semantic web; Ontologies; ANEW; POS tagger; Emotion; OWL; Sentinet.**

## I.INTRODUCTION

The Semantic Web is being developed with the intention of providing a global framework for describing data, its properties and relationships in a standard fashion. Many developers and researchers on knowledge systems are taking the approach of using Semantic Web technologies in order to obtain more interoperability and reusability with existing software and to take advantage of the strong trend of development that these technologies are living nowadays.

An important challenge in addressing issues of affective computing is having an adequate

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representation of emotions. Existing approaches vary between identifying a set of basic categories with a name tag assigned to each one of them to designing a multi-dimensional space in terms of primitive elements or emotional dimensions such that any particular emotion can be defined in terms of a tuple of values along the different dimensions. For different purposes, one approach is better suited than the other.

In this context, the development of an ontology of emotional categories based on description logics, where each element is defined in terms of a range of values along the space of emotional dimensions, provides a simple and elegant solution. The ability to carry out automatic classification of concepts simplifies the addition of new concepts - possibly expressed only in terms of their values along the axes of emotional dimensions - without having to worry explicitly about where in the ontology they should be placed. The most common language to formalize Semantic Web ontologies is OWL (Ontology Web Language). Protege focuses on editing OWL ontologies. It is a powerful Java open source tool with a user-friendly interface to visualize ontologies.

This paper describes the classification of emotion using the ontology driven approach. By reasoning over the ontology, insertion of new instances of emotional concepts into the ontology results in their automatic classification under the corresponding branch of the hierarchy. The system can then trace the ascendants in the ontology of the corresponding value, until a more general emotion is classified.

The remaining of the paper is structured as follows. Section II is the literature survey. Section III gives summarization of emotion classification. Section IV is the proposed solution. Section V is the conclusion derived from this work.

## II.LITERATURE SURVEY

Matteo Baldoni et al., introduced ArsEmotica, an application software that aims at extracting a rich emotional semantics (i.e. not limited to a positive or a negative reception) of tagged resources. This approach exploits and combines multilingual lexicons (MultiWordNet), aff ective, and sentiment lexicons (WordNet-Aff ect, SentiWordNet) with an ontology of emotional categories (OntoEmotion). The first step of ArsEmotica checks if tags are “emotion denoting” words, directly referring to some concepts of an ontology of emotions. Then, check the tags with the sentinet and rank the prevalent emotions[1].

Ontology based information extraction (OBIE), that consists of identifying the key terms in the text and then relating them to concepts in the ontology. Ontology-Based Textual Emotion Detection depends on ontology extraction from the input sentence by using a triplet extraction algorithm by the OpenNLP parser, and then makes an ontology matching with the ontology base. If the extracted ontology doesn’t match any ontology from the ontology base, Keyword-based approach will be used. Learning based methods tries to detect emotions based on a previously trained classifier and rely on learning algorithms that automatically identify patterns in the data[2].

V. Francisco et al., developed a system, together with its application as an interface between a text input marked up in terms of emotional dimensions and a set of rules for configuring an emotionally-enabled voice synthesizer. When text is given as input to the system, EmoTag marks up this text with the emotional dimensions (activation, evaluation and power). Each sentence of the marked up text is related to a point in the three-dimensional space of emotions. This point is the input to the ontology of emotions, which by means of the data type properties and the data Range restrictions, automatically classifies this point under a given emotional concept. Once the specific emotional concept to which the input point is related is identified, DLModel works recursively to obtain its ancestors until the one which corresponds to one of the five basic emotions (anger, happiness, sadness, fear and surprise) is located. Using the particular configuration of parameters for that particular basic emotion, the synthesizer reads out a loud the text with the emotion assigned by Emo Tag to the sentences[3].

Mohamed Haggag et al., proposed a new method for emotion detection from text which depends on ontology. This method is depending on ontology extraction from the input sentence by using a triplet extraction algorithm by the OpenNLP parser, then make an ontology matching with the ontology base that were created by similarity and word sense disambiguation. This ontology base consists of ontologies and the emotion label related to each one. The emotion label of the sentence with the highest score of matching is choosed. If the extracted ontology doesn't match any ontology from the ontology base ,the keyword-based approach is used[4].

Shiv Naresh Shivhare et al., described two main components such as Emotion Ontology, Emotion Detector. Protege, an ontology development tool is used to develop emotion ontology. Proposed ontology has class and subclass relationship format. Emotion classes at the primary level in emotion hierarchy are at the top of emotion ontology and emotion classes at the tertiary level are at the bottom of ontology. High weight age is assigned to the upper level emotion classes and low to the lower level emotion classes. Emotion of the textual data can be recognized with the help of the emotion detection algorithm. The algorithm calculates weight for particular emotion by adding weights assigned at each level of hierarchy and also calculates same for its counter emotion, then compares the both scores and greater one is taken as the detected emotion[5].

Ryoko Tokuhisa et al., used a classification method over the examples extracted from the web. The first step is to consider the quantity and accuracy of emotion-provoking examples to be collected and the second is to build EP corpus. Then, a two step approach is used. In the first step, i.e. sentiment polarity classification, only the positive and negative examples stored in the EP corpus are used and assume sentence to be neutral if the output of the classification model is near the decision boundary. and then classify only those judged positive or negative into 10 fine grained emotion classes. For fine-grained emotion classification, k-nearest-neighbor approach is used. The kNN model retrieves k-most similar examples from the all of the EP corpus[6].

Matteo Baldoni et al., discussed on the conversion from tags to the emotions. The proposed method checks whether a tag belongs to the ontology of emotions. Tags belonging to the ontology are immediately classified as "emotional". Tags that do not correspond to terms in the ontology are further analyzed by means of SentiWordNet, in order to distinguish objective tags, which do not bear an emotional meaning, from subjective and, therefore, affective tags. The latter will be the only ones presented to the user in order to get a feedback on which emotional concept they deliver. Based on data collected in the previous steps, the tool ranks the emotions associated by the users to the resource[7].

## III.SUMMARIZATION

Emotion can be expressed in many ways that can be seen such as facial expression and gestures, speech and by written text. Emotion Detection in text documents is essentially a content – based classification problem involving concepts from the domains of Natural Language Processing as well as Machine Learning. The emotion can be classified from the text through various ways. Ontology based information extraction (OBIE) identifies the key terms in the text and then relates them to concepts in the ontology. Several algorithms like emotion detector algorithm, k nearest neighbour approach and many machine learning algorithms are used to classify the emotions.

## IV.PROPOSED SYSTEM

The proposed system works with basic emotions which include fear, happy, sad and anger. This system overcomes the drawbacks of the existing system by using the Ontology based approach. Protege tool is used to create the emotion ontology. In Ontology, there is no need for separate classification algorithms like in several existing approaches, but it automatically classifies the emotions based on the hierarchy of emotion classes. Ontology can work with large amount of data through automatic annotations.

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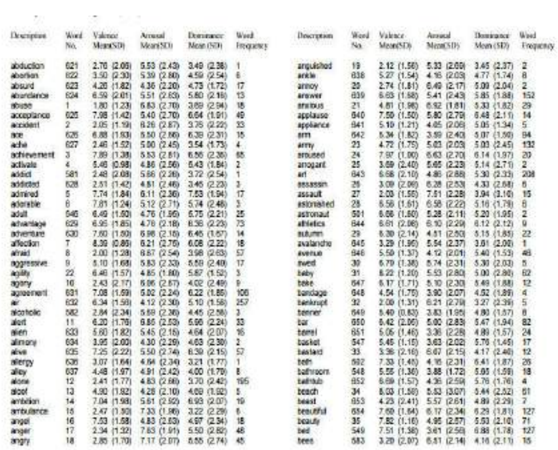
Fig.1.Architecture

The sentence to be analyzed is segmented with the help of POS Tagger. This approach minimizes the overhead involved while processing all the words in the sentence. POS tagger segments the sentence into appropriate parts of speech. The values for the emotions are specified in the form of three dimensions with the help of ANEW List. This file could then be loaded into a spreadsheet application with identifier strings in the first column and POS tag strings in the second. The adjective and the verb words are extracted and is compared with the ANEW list.

The Affective Norms of English words(ANEW) is being developed to provide a set of normative emotional ratings for a large number of words in the English language. The list has the various dimensions such as valence mean ,Arousal mean and dominance mean and word frequency. The affective words from the POS tagger are compared with the ANEW list and the dimensions for the affective words are compared and the higher dimension values are set for the input sentence. This tagged sentence is compared with the ontology.



| Description | Word No. | Valence Mean(SD) | Arousal Mean(SD) | Dominance Mean (SD) | Word Frequency |
|---|---|---|---|---|---|
| abduction | 621 | 2.76 (2.06) | 5.53 (2.43) | 3.49 (2.38) | 1 |
| abortion | 622 | 3.50 (2.30) | 5.39 (2.80) | 4.59 (2.54) | 6 |
| absurd | 623 | 4.26 (1.82) | 4.36 (2.20) | 4.73 (1.72) | 17 |
| abundance | 624 | 6.59 (2.01) | 5.51 (2.63) | 5.80 (2.16) | 13 |
| abuse | 1 | 1.80 (1.23) | 6.83 (2.70) | 3.69 (2.94) | 18 |
| acceptance | 625 | 7.98 (1.42) | 5.40 (2.70) | 6.64 (1.91) | 49 |
| accident | 2 | 2.05 (1.19) | 6.26 (2.87) | 3.76 (2.22) | 33 |
| ace | 626 | 6.88 (1.93) | 5.50 (2.66) | 6.39 (2.31) | 15 |
| ache | 627 | 2.46 (1.52) | 5.00 (2.45) | 3.54 (1.73) | 4 |
| achievement | 3 | 7.89 (1.38) | 5.53 (2.81) | 6.56 (2.35) | 65 |
| activate | 4 | 5.46 (0.98) | 4.86 (2.56) | 5.43 (1.84) | 2 |
| addict | 581 | 2.48 (2.08) | 5.66 (2.26) | 3.72 (2.54) | 1 |
| addicted | 628 | 2.51 (1.42) | 4.81 (2.46) | 3.46 (2.23) | 3 |
| admired | 5 | 7.74 (1.84) | 6.11 (2.36) | 7.53 (1.94) | 17 |
| adorable | 6 | 7.81 (1.24) | 5.12 (2.71) | 5.74 (2.48) | 3 |
| adult | 646 | 6.49 (1.50) | 4.76 (1.95) | 5.75 (2.21) | 25 |
| advantage | 629 | 6.95 (1.85) | 4.76 (2.18) | 6.36 (2.23) | 73 |
| adventure | 630 | 7.60 (1.50) | 6.98 (2.15) | 6.46 (1.67) | 14 |
| affection | 7 | 8.39 (0.86) | 6.21 (2.75) | 6.08 (2.22) | 18 |
| afraid | 8 | 2.00 (1.28) | 6.67 (2.54) | 3.98 (2.63) | 57 |
| aggressive | 9 | 5.10 (1.68) | 5.83 (2.33) | 5.59 (2.40) | 17 |
| agility | 22 | 6.46 (1.57) | 4.85 (1.80) | 5.87 (1.52) | 3 |
| agony | 10 | 2.43 (2.17) | 6.06 (2.67) | 4.02 (2.49) | 9 |
| agreement | 631 | 7.08 (1.59) | 5.02 (2.24) | 6.22 (1.85) | 106 |
| air | 632 | 6.34 (1.56) | 4.12 (2.30) | 5.10 (1.56) | 257 |
| alcoholic | 582 | 2.84 (2.34) | 5.69 (2.36) | 4.45 (2.58) | 3 |
| alert | 11 | 6.20 (1.76) | 6.85 (2.53) | 5.95 (2.24) | 33 |
| alien | 633 | 5.60 (1.82) | 5.45 (2.15) | 4.64 (2.07) | 16 |
| alimony | 634 | 3.95 (2.00) | 4.30 (2.29) | 4.63 (2.39) | 2 |
| alive | 635 | 7.25 (2.22) | 5.50 (2.74) | 6.39 (2.15) | 57 |
| allergy | 636 | 3.07 (1.64) | 4.64 (2.34) | 3.21 (1.77) | 1 |
| alley | 637 | 4.48 (1.97) | 4.91 (2.42) | 4.00 (1.79) | 8 |
| alone | 12 | 2.41 (1.77) | 4.83 (2.66) | 3.70 (2.42) | 195 |
| aloof | 13 | 4.90 (1.92) | 4.28 (2.10) | 4.69 (1.92) | 5 |
| ambition | 14 | 7.04 (1.98) | 5.61 (2.92) | 6.93 (2.07) | 19 |
| ambulance | 15 | 2.47 (1.50) | 7.33 (1.96) | 3.22 (2.29) | 6 |
| angel | 16 | 7.53 (1.58) | 4.83 (2.63) | 4.97 (2.34) | 18 |
| anger | 17 | 2.34 (1.32) | 7.63 (1.91) | 5.50 (2.82) | 48 |
| angry | 18 | 2.85 (1.70) | 7.17 (2.07) | 5.55 (2.74) | 45 |
| anguished | 19 | 2.12 (1.56) | 5.33 (2.09) | 3.45 (2.37) | 2 |
| ankle | 638 | 5.27 (1.54) | 4.16 (2.03) | 4.77 (1.74) | 8 |
| annoy | 20 | 2.74 (1.81) | 6.49 (2.17) | 5.09 (2.04) | 2 |
| answer | 639 | 6.63 (1.68) | 5.41 (2.43) | 5.85 (1.88) | 152 |
| anxious | 21 | 4.81 (1.98) | 6.92 (1.81) | 5.33 (1.82) | 29 |
| applause | 640 | 7.50 (1.50) | 5.80 (2.79) | 6.48 (2.11) | 14 |
| appliance | 641 | 5.10 (1.21) | 4.05 (2.06) | 5.05 (1.34) | 5 |
| arm | 642 | 5.34 (1.82) | 3.59 (2.40) | 5.07 (1.59) | 94 |
| army | 23 | 4.72 (1.75) | 5.03 (2.03) | 5.03 (2.45) | 132 |
| aroused | 24 | 7.97 (1.00) | 6.63 (2.70) | 6.14 (1.97) | 20 |
| arrogant | 25 | 3.69 (2.40) | 5.65 (2.23) | 5.14 (2.71) | 2 |
| art | 643 | 6.68 (2.10) | 4.86 (2.88) | 5.30 (2.33) | 208 |
| assassin | 26 | 3.09 (2.09) | 6.28 (2.53) | 4.33 (2.68) | 6 |
| assault | 27 | 2.03 (1.55) | 7.51 (2.28) | 3.94 (3.10) | 15 |
| astonished | 28 | 6.56 (1.61) | 6.58 (2.22) | 5.16 (1.79) | 6 |
| astronaut | 501 | 6.66 (1.60) | 5.28 (2.11) | 5.20 (1.95) | 2 |
| athletics | 644 | 6.61 (2.08) | 6.10 (2.29) | 6.12 (2.12) | 9 |
| autumn | 29 | 6.30 (2.14) | 4.51 (2.50) | 5.15 (1.85) | 22 |
| avalanche | 645 | 3.29 (1.95) | 5.54 (2.37) | 3.61 (2.00) | 1 |
| avenue | 646 | 5.50 (1.37) | 4.12 (2.01) | 5.40 (1.53) | 46 |
| awed | 30 | 6.70 (1.38) | 5.74 (2.31) | 5.30 (2.03) | 5 |
| baby | 31 | 8.22 (1.20) | 5.53 (2.80) | 5.00 (2.80) | 62 |
| bake | 647 | 6.17 (1.71) | 5.10 (2.30) | 5.49 (1.88) | 12 |
| bandage | 648 | 4.54 (1.75) | 3.90 (2.07) | 4.52 (1.89) | 4 |
| bankrupt | 32 | 2.00 (1.31) | 6.21 (2.79) | 3.27 (2.39) | 5 |
| banner | 649 | 5.40 (0.83) | 3.83 (1.95) | 4.80 (1.57) | 8 |
| bar | 650 | 6.42 (2.05) | 5.00 (2.83) | 5.47 (1.94) | 82 |
| barrel | 651 | 5.05 (1.46) | 3.36 (2.28) | 4.89 (1.57) | 24 |
| basket | 547 | 5.45 (1.15) | 3.63 (2.02) | 5.76 (1.45) | 17 |
| bastard | 33 | 3.36 (2.16) | 6.07 (2.15) | 4.17 (2.40) | 12 |
| bath | 592 | 7.33 (1.45) | 4.16 (2.31) | 6.41 (1.87) | 26 |
| bathroom | 548 | 5.55 (1.36) | 3.88 (1.72) | 5.65 (1.58) | 18 |
| bathtub | 652 | 6.69 (1.57) | 4.36 (2.59) | 5.76 (1.76) | 4 |
| beach | 34 | 8.03 (1.59) | 5.53 (3.07) | 5.44 (2.52) | 61 |
| beast | 653 | 4.23 (2.41) | 5.57 (2.61) | 4.89 (2.29) | 7 |
| beautiful | 654 | 7.60 (1.64) | 6.17 (2.34) | 6.29 (1.81) | 127 |
| beauty | 35 | 7.82 (1.16) | 4.95 (2.57) | 5.53 (2.10) | 71 |
| bed | 549 | 7.51 (1.38) | 3.61 (2.56) | 6.88 (1.78) | 127 |
| bees | 583 | 3.20 (2.07) | 6.51 (2.14) | 4.16 (2.11) | 15 |

Fig.2.ANEW List

For supporting the semantic necessity of emotional systems, an ontology of emotional categories called OntoEmotions is developed which acts as a useful resource for the management of emotional content. By using this ontology one can identify relations between different levels of specification of related emotions when the emotional content is represented as emotional categories. This paper deals with emotional categories (i.e. emotion-denoting words such as happiness, sadness and fear) as first class citizens of ontology. In particular, the basic emotions as sadness, happiness, fear and anger are used. The ontology is written in OWL using Protégé tool. Emotional categories are structured in a taxonomy that covers from basic emotions to the most specific emotional categories. In addition, the ontology relates each of the emotional categories to the three emotional dimensions by means of data ranges.

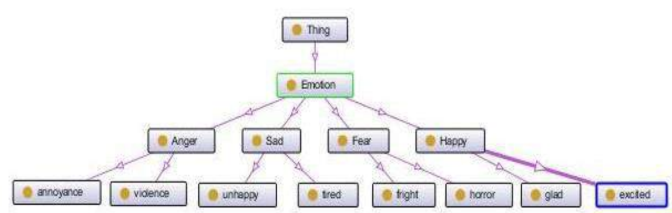



Fig.3.Partial view of ontology

Once a hierarchy of emotions and relations between the emotion-denoting words is established, their language and the concepts are represented, a link is made to the emotional concepts in the ontology with the three main emotional dimensions. Numeric data can be represented in OWL using datatype properties. To achieve this, three datatype properties are used : has Evaluation, has Activation, has Power.

## V.CONCLUSION

An emotional ontology based on description of the dimensions has been implemented using semantic web technologies. Each emotional concept is defined in terms of a range of values along the three-dimensional space of emotional dimensions, that allows the system to make inferences. The ontology described in this paper has demonstrated as part of a complex process of converting unmarked input text to emotion. There are limitations in the system. The common words are only specified in the ontology. It will not cover all the affective words. OWL using Protégé is used. Still Wordnet can also be integrated with the ontology to support the unspecified words. This proposed solution uses automatic annotation features, analyze semantic relationships and gives quantitative output.

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