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CUSTOMER EMOTIONS RECOGNITION USING FACIAL AND TEXTUAL REVIEW

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Abstract: Emotion analysis of posts is still challenging because of the limited contextual information that they normally contain. . This issue is resolved by constructing a separate space for emoticon as emotional space which is represented as feature matrix and projections of emotions and words is done here. this is based on semantic composition. Performance of emotion analysis is improved as proposed method is capable to capture more emotion sematic then other models which is done by projecting emoticons and words into emoticon space. This helps identify subjectivity, polarity and emotion in microblog environment. This paper in course gives insights for design of ECNN. Facial expressions give important clues about emotions. Sentimental analysis is other natural language processes for more task. Thus, many approaches have been put forth to classify human affective states.

In Facial expression analysis, features used are local spatial position or missing points or regions of face. In audio analysis, global statistics of acoustics is used as feature.

Keywords: *Emotion Recognition, Amazon Product Review, Text Mining, Natural Language Processing (NLP), Sentiment Analysis, Convolution Neural Network*

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I INTRODUCTION

The development of e-commerce platforms has given people a new way to generate and consume a great deal of information on the web. In the past, people used to get information from portal websites. A large number of websites provide a long list of topics varying from clothing to entertainment. These traditional online information sources are useful but less efficient because they often contain redundant information. However, since the arrival of online e-commerce platforms, people need not run to out for the basic need of regular stuff because of their fast and efficient features. As now a day's people are counting on online products therefore the importance of a review goes higher. For selecting a product, a customer must undergo thousands of reviews to know a product. And also a large number of shopping platforms such as Amazon, Paytm, Google+, and Facebook provide information for user's .Amazon is the most popular Shopping platform in the world. It is also the fastest growing marketplace and has a dominant position in the area of Cloud services and fastest growing business. More than 500 million registered users post 340 million Amazon Product Review messages every day, sharing their opinions and feelings about their daily shopping activities.

Compared with regular shopping platforms, Amazon Product Review messages are much shorter and with good explanation and photos. You are only allowed to post 140 Characters or less in one Amazon Product Review message. This feature makes Amazon Review easier for people to get the main point from the massive amount of information available online. Depending on the need of the users, Amazon users can follow whichever people and information source they prefer. With all of the advantages mentioned above, Amazon Product thus has become a powerful platform with many kinds of information from worldwide breaking news to purchasing products at home.

In the last few years, the information streams on Amazon Product Review have experienced an unbelievable increase in the popularity of this Marketplace. The users dispose a massive amount of information about different aspects.

All the information which comes to amazon about the product review is not useful to each and every user as they have different interest in product and preferences are also different, this creates the demand to have personalized service. Nowadays, more and more personalized services are provided to benefit the users. People need this personalized service to make their fast-paced lives more efficient. Every day, a large amount of information is published by users on the Amazon Site. These data relate to user's behavior and many research studies therefore focus on Amazon Review and this data collection. One of the research studies in the field of Amazon is user modeling. In order to provide a personalized service, researchers started to explore ranking and recommendations of web resources referenced from Amazon Product Review. A large amount of research focus on modeling users' interests based on users published data.

II REVIEW OF LITERATURE

A method to detect mood or emotion in any specific tweet is proposed in paper [1]. The authors classify the message under emotional category such as happy sad, angry under emoticons which are appeared. This approach is two steps based for classification, one of which is rule based approach while other in Machine learning Approach.Machine learning approach performance is better than rule based approach; the performance has been improved as we have removed the error data while training the model. The Authors logic is detection of emotion for non-hash tagged data and the labeled data creation for machine learning approach without manual creation.

Srinivasu Badugu, Matla Suhasini: This paper describes a Rule Based approach, which detects the emotion or mood of the tweet and classifies the Twitter message under appropriate emotional category. Earlier authors logic where only able to determine whether the specific sentiment is positive tweet or negative tweet with the proposal of new methods, the tweet is able to give deeper information about the tweet which can be used in various fields such criminology, psychology, Economics etc.

When a user is not specifically micro blogging about their personal emotive status, the message can reflect their mood.

Jasy Liew Suet Yan, Howard R. Turtle: The theory approach used to develop a corpus of 5,553 tweets manually annotated with 28 emotion categories was described first. From their preliminary experiments, they have identified two machine learning algorithms that perform well in this emotion classification task and demonstrated that it is feasible to train classifiers to detect 28 emotion categories without a huge drop in performance compared to coarser-grained classification schemes. A set of fine-grained emotion categories is where the application is done successfully after the examination of applying machine learning technique to perform well on grained emotion and sentiment classification. Due to the length limitation, language used to express emotions in tweets differs significantly from that found in longer documents (e.g. reviews, rating, and stories).

Maryam Hasan, Elke Rundensteiner, Emmanuel Agu: In this paper, authors propose a new approach to infer emotional states by classifying text messages of individuals. To model emotional states, they utilize the well-established Circumplex model that characterizes affective experience along two dimensions: valence and arousal. They have selected Amazon Product Review messages as input data set, In our methodology, Hashtags are used as labels which in course trains supervised classifiers, this detects multiple classes of emotions from tweeter databases. Several features for emotion analysis and detection does include detection of unigrams, punctuations, emoticons and negation remarks.

Casual Amazon Product Review language and noise: Tweets are casual, contain numerous punctuation and spelling errors and are limited to 140 characters of text.

Large numbers of potential features: The large number of features is available to categorize short text messages. Labeling for supervised learning: Text messages, in their raw form, do not have labels. However, in order to train a classifier, supervised learning methods require labeled data.

J. Bollen, H. Mao, and X.-J. Zeng: In this paper analyses electoral tweets for more subtly expressed information such as sentiment (positive or negative), the emotion (joy, sadness, anger, etc.), the purpose or intent behind the tweet (to point out a mistake, to support, to ridicule, etc.), and the style of the tweet (simple statement, sarcasm, hyperbole, etc.).There are two sections: on annotating text for sentiment, emotion, style, and categories such as purpose, and on automatic classifiers for detecting these categories.

S. M. Mohammad, X. Zhu, S. Kiritchenko, and J. Martin: In this paper explored an application of deep recurrent neural networks to the task of sentence-level opinion expression extraction. DSEs (direct subjective expressions) consist of explicit mentions of private states or speech events expressing private states; and ESEs (expressive subjective expressions) consist of expressions that indicate sentiment, emotion, etc., without explicitly conveying them. However, Mainly Time consumes and resource consuming for the system.

III PROPOSED METHODOLOGY

As the most popular e-commerce platform, Amazon review datasets has a vast amount of information available in the form of review shared by millions of users. Since this data stream is constantly growing, it is difficult to extract relevant information from users. More and more people want to benefit from these data and get a personalized service from Amazon Product Review. Extracting the semantic meaning of Amazon Product Review and modeling the interests of users allows people to enjoy a personalized service on Amazon Product Review. Meanwhile, research shows that people tend to express their emotions on Amazon. These emotional tweets usually clearly express the users preferences compared with other normal tweets. Therefore, the goal of this work is to design some emotion-based user modeling strategies which exploit these emotional data. This work introduces and analyzes the approaches for detecting emotion on Amazon Product Review. First it evaluates and compares the performance of proposed approaches of emotion detection. Then use these approaches of emotion detection to analyze Amazon Product Review sample dataset for the purpose of user modeling.

Face Detection

Given a picture, detecting the presence of a person's face may be a complex task thanks to the possible variations of the face. The various sizes, angles and poses human face may need within the image cause this variation. The emotions which are deducible from the face and different like conditions such as illumination and occlusions also affect facial appearances. The approaches of the past few decades in face detection are often classified into four: knowledge-based approach, feature invariant approach, template –based approach and appearance-based approach.

Facial Feature Extraction

Contracting the facial muscles produces changes in both the direction and magnitude of skin surface displacement, and within the appearance of permanent and transient countenance. Samples of permanent features are eyes, brow, and any furrows that become permanent with age. Transient features include facial lines and furrows that aren't present at rest. So as to research a sequence of images, we assume that the primary frame may be a neutral expression. After initializing the templates of the permanent features within the first frame, both geometric countenance and Gabor wavelets coefficients are automatically extracted the

A. Architecture

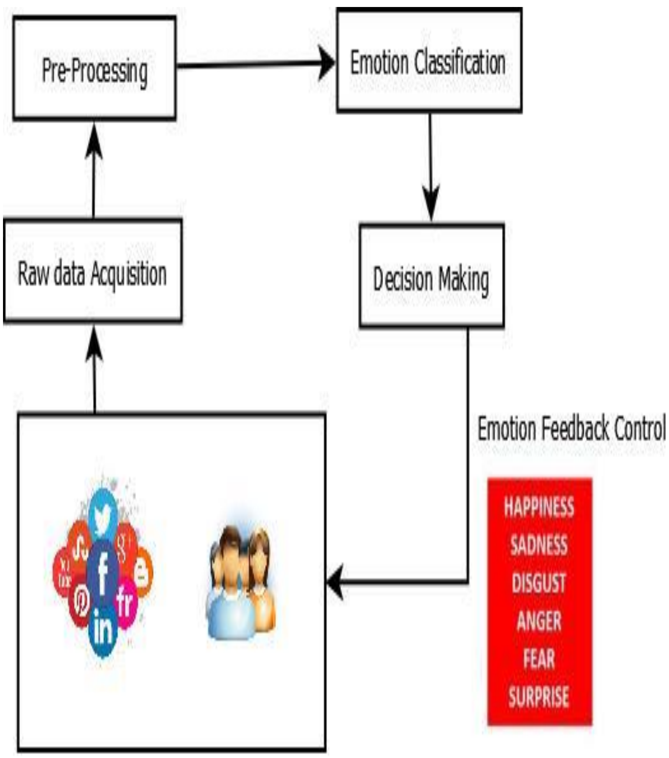

Figure 1. Proposed System Architecture

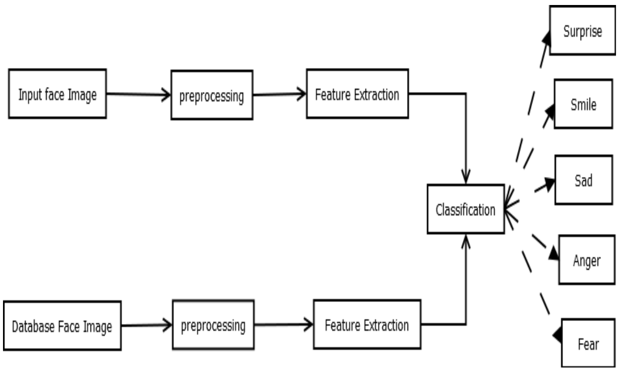

Figure 2. Image processing System Architecture

B. Algorithms

1. Support Vector Machine:

In data analytics or decision sciences most of the time I come across the situations where I need to classify our data based on a certain dependent variable. To support the solution for this need there are multiple techniques which can be applied; Logistic Regression, Random Forest Algorithm, Bayesian Algorithm are a few to name. SVM is a machine learning technique to separate data which tries to maximize the gap between the categories.

Algorithm for classification of emotion.

Input: D Dataset, Semantic of Tokens, Tweets;

Output: Classification of Application

Step1: for each tweet tweet id in D do

Step2: Get on-demand features and stored on vector x for tweet id

Step3: x.add (Get Features (tweet id));

Step4: end for

Step5: for each tweet in x vector do

Step6: Fetch first feature and stored in b, and other features in w

Step7: h w, b (x) = g (z) here, z = (w T x + b) Step8: if (z≤0)

Step9: assign g(z) = 1;

Step10: else g(z) = -1;

Step11: end if

2. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is comprised of one or more convolutional layers (often with a subsampling step) and then followed by one or more fully connected layers as in a standard multilayer neural network. The architecture of a CNN is designed to take advantage of the 2D structure of an input image (or other 2D input such as a speech signal). This is achieved with local connections and tied weights followed by some form of pooling which results in translation in variant features. Another benefit of CNNs is that they are easier to train and have many fewer parameters than fully connected networks with the same number of hidden units.

Input: User Amazon Product Review Tweets or post.

Output: Extraction of topic.

C.Mathematical Model

Let S is the whole system consists:

S= {I, P, O}

I= {I0, I1, I2, I3, I4, I5}

I0= Amazon Product Review dataset of user post

I1= Amazon Product Review bag-of-words

I2= support of tweet

I3= confidence of tweet

I4= tweets of user

I5= MODEL

P= {P0, P1, P2, P3, P4, P5}

P0= read posts

P1= stop word removal

P2= tokenization

P3= train the model

P4= classification of tweets

P5= update the MODEL

O= {O0,O1,O2,O3}

O0= token array

O1= bag of words array

O2= trained model

O3= classification of MODEL

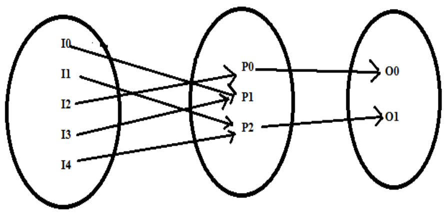

Figure 3. : Venn Diagram

IV RESULTS AND DISCUSSION

Results for work are shown in Table 1. This shows the performance of the emotion recognition systems based on facial expressions, for each of the five facial blocks such as Forehead, Eyebrow, Low Eye, Right Cheek, Left Cheek, and the combined facial expression classifier. The results show that the cheek areas give valuable information for emotion classification. It also shows that the eyebrows, which have been widely used in facial expression recognition, give the poorest performance. Results reveals that the combined facial expression classifier has an accuracy of 85%, which is higher than most of the 5 facial blocks classifiers. Notice that this database was recorded from a single actress, so clearly more experiments should be conducted to evaluate these results with other subjects.

The combined facial expression classifier can be seen as a feature level integration approach in which the features of the 5 blocks are fused before classification. These classifiers can be also integrated at decision-level. Table 1 shows the performance of the system when the facial block classifiers are fused by the use of different criteria. In general, the results are very similar. All these decision-level rules give slightly worse performance than the combined facial expression classifier.

Area	**Overall**	**Anger**	**Sad**	**Happy**	**Neutral**
Forehead	0.73	0.82	0.66	1.00	0.46
Eyebrow	0.68	0.55	0.67	1.00	0.49
Low Eye	0.81	0.82	0.78	1.00	0.65
Right Cheek	0.85	0.87	0.76	1.00	0.79
Left Cheek	0.80	0.84	0.67	1.00	0.67
Combined Classifier	0.85	0.79	0.81	1.00	0.81

Table 1: Performance of the facial expression classifiers

V CONCLUSION

In this work, we investigate the effect of semantic classification on NLP tasks. We analyze the reason of why these emotion and sentiment analysis can improve the model accuracy. Although emotional words have good emotional semantic discrimination in word vector space, the sentiments have better discrimination than the emotional words in emotional semantic space. In this paper, we propose an Emotion Recognition on Amazon Product Review using Python based new Emotion-Semantic Enhanced Convolutional Neural Network (ECNN) Model that construct the emotional space by using the vectors corresponding to the sentiments. The ECNN model is more capable of capturing emotional semantics than other models. Future scope of the system is to recognize the emotion based on uploaded multimedia (i.e. images) by user.

REFERENCES

[1] Niko Colneric and Janez Demsar, "Emotion Recognition on Amazon Product Review: Comparative Study and Training a Unison Model", IEEE TRANSACTIONS ON AFFECTIVE COMPUTING, FEBRUARY 2018.

[2] A. Radford, R. Jozefowicz, and I. Sutskever, "Learning to Generate Reviews and Discovering Sentiment", 2017.

[3] B. Nejat, G. Carenini, and R. Ng, "Exploring Joint Neural Model for Sentence Level Discourse Parsing and Sentiment Analysis",Proc .of the SIGDIAL2017.

[4] N. Nodarakis, S. Sioutas, A. Tsakalidis, and G. Tzimas, "Using Hadoop for Large Scale Analysis on Amazon Product Review: A Technical Report", arXiv preprint arXiv:1602.01248, 2016.

[5] Y. Zhang and B. C. Wallace, "A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification", ArXiv preprint arXiv:1510.03820v4, 2016.

[6] J. Guo, W. Che, H. Wang, and T. Liu, "A Universal Framework for Inductive Transfer Parsing across Multi-typed Treebanks", Proc. of the 26th Int. Conf. on Computational Linguistics (COLING-16), pp. 1222, 2016.

[7] S. M. Mohammad and S. Kiritchenko, "Using Hashtags to Capture Fine Emotion Categories from Tweets", Computational Intelligence, vol. 31, no. 2, pp. 301326, 2015.

[8] B. Plank and D. Hovy, "Personality Traits on Amazon Product Review or How to Get 1,500 Personality Tests in a Week", in Proc. of the 6th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, 2015.

[9] D. Bamman and N. A. Smith, "Contextualized Sarcasm Detection on Amazon Product Review", in Proc. of the 9th Int. AAAI Conf. on Web and Social Media. Citeseer, 2015.

[10] X. Liu, J. Gao, X. He, L. Deng, K. Duh, and Y. Y. Wang, "Representation Learning Using Multi-Task Deep Neural Networks for Semantic Classification and Information Retrieval", Proc.of the Conf. of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 921, 2015.

[11] F. Feng, X. Wang, and R. Li, "Cross-modal Retrieval with Correspondence Autoencoder", Proc. Of the 22nd ACM Int.Conf.on Multimedia,pp.716,2014.

[12] Zhaolong Li, "Analyzing Emotion on Amazon Product Review for User Modeling", Master's Thesis, October 2013.

[13].Gimpel,N.Schneider,B.OConnor,D.Das,D.Mills,J. Eisenstein,M.Heilman, D. Yogatama, J. Flanigan, and N. A. Smith, "Part-of-Speech Tagging for Amazon Product Review: Annotation, Features, and Experiments," in Proc. of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, vol. 2, no. 2. ACL, 2011, pp. 4247.

[14] I. T. Jolliffe, "Principal Component Analysis", in Springer Series in Statistics, 2002.

[15] R. B. Bradford, "An Empirical Study of Required Dimensionality for Large scale Latent Semantic Indexing Applications", Proc .of the 17th ACM Conf.,p. 153, 2008.Cengiz Karakoyunlu, " Toward a Unified Object Storage Foundation for Scalable Storage Systems "