

**LEVERAGING EMOTIONS AND
SENTIMENTS IN TEXTUAL DATA FOR
CONTEXTUAL UNDERSTANDING IN
APPLICATION SPECIFIC NATURAL
LANGUAGE PROCESSING**

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**BHARTI SCHOOL OF TELECOMMUNICATION
TECHNOLOGY AND MANAGEMENT**

INDIAN INSTITUTE OF TECHNOLOGY DELHI

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by

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TECHNOLOGY AND MANAGEMENT**

submitted

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to the



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Dedicated to
My Teachers
Family
&
Friends

THESIS CERTIFICATE

This is to certify that the thesis titled **Leveraging Emotions and Sentiments in Textual Data for Contextual Understanding in Application Specific Natural Language Processing**, submitted by **Amit Oberoi**, to the Indian Institute of Technology, Delhi, for the award of the degree of **Doctor of Philosophy**, is a bonafide record of the research work done by him under my supervision. He has fulfilled the requirements for the submission of the thesis, which to the best of our knowledge has reached the required standard.

The material contained in the thesis has not been submitted in part or full to any other University or Institute for the award of any degree or diploma.

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Date: July 2024

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ABSTRACT

KEYWORDS: Natural Language Processing; Sentiment Analysis; Emotion Detection; Transformers; Emotional Mobility; Context in Text

In this research we present approaches for utilising emotions and sentiments for enhancing the context handling capability of Natural Language Processing algorithms. We base our work on the premise that emotions get reflected in the textual content generated by an individual. We leverage sentiment patterns and associated emotions within an utterance to predict helpfulness of Amazon reviews. We find that emotion-augmented embedding yields 1.85% better accuracy, 0.5% better precision, 6% better Recall and 3% better F1 Score than original BERT embedding. Our approach does not need resource intensive fine tuning of BERT, and can be generalised to an application specific use case.

In order to achieve better context, we need methods to enhance sentiment analysis. We therefore propose a stacked ensemble architecture and demonstrate that it outperforms existing state-of-the-art models by an accuracy score of 1% to 12% depending upon the dataset and configuration. Our approach requires minimal training and computing resource, and also does not require any pre-processing, and can be used in modified forms for many relevant use cases.

Exploring further, we have proposed enhancement of contextual awareness by discerning the degree of Emotional Mobility from textual content. We moot the term ‘Emotional Mobility’ which is characterised as an emphatic emotional expression, possibly triggered by an event, situation or an interaction and presents itself as a state involving rapidly changing sentiments. We propose a novel concept of treating the sentiment score as a waveform and examining it in frequency domain and thereafter using unsupervised learning for classifying set of sentences as per the corresponding degree of emotional mobility. We apply the proposed approach on dataset of speeches of US Presidents corroborating real world incidents from open source information. We have been able to demonstrate that this approach remains largely consistent across different sentiment analysis algorithms.

As an outcome of this research, we have proposed a new work item for International Telecommunication Union (ITU) Study Group-12 (SG-12) for assessing the emotional connect of a chatbot based application wherein we have proposed the concept of Quality of Emotional Experience (QoEE) as a part of Quality of Experience (QoE).

अमूर्त

प्रमुख शब्द: प्राकृतिक भाषा प्रसंस्करण; भावनाओं का विश्लेषण; भावना डी-टेक्शन; ट्रांसफार्मर; भावना-त्मक गतिशीलता; पाठ में प्रसंग

इस शोध में हम प्राकृतिक भाषा प्रसंस्करण एल्गोरिदम की संदर्भ प्रबंधन क्षमता को बढ़ाने के लिए भावनाओं और भावनाओं का उपयोग करने के लिए दृष्टिकोण प्रस्तुत करते हैं। हम अपना काम इस आधार पर करते हैं कि भावनाएं किसी व्यक्ति द्वारा उत्पन्न पाठ्य सामग्री में प्रतिबिंबित होती हैं। हम अमेज़न समीक्षाओं की उपयोगिता की भविष्यवाणी करने के लिए एक बयान के भीतर भावना पैटर्न और संबंधित भावनाओं का लाभ उठाते हैं। हमने पाया कि इमोशन संवर्धित एम्बेडिंग मूल BERT एम्बेडिंग की तुलना में 1.85% बेहतर सटीकता, 0.5% बेहतर परिशुद्धता, 6% बेहतर रिकॉल और 3% बेहतर F1 स्कोर प्रदान करती है। हमारे दृष्टिकोण को BERT की संसाधन गहन फ़ाइन ट्यूनिंग की आवश्यकता नहीं है, और इसे एप्लिकेशन विशिष्ट उपयोग के मामले में सामान्यीकृत किया जा सकता है।

बेहतर संदर्भ प्राप्त करने के लिए, हमें भावना विश्लेषण को बढ़ाने के तरीकों की आवश्यकता है। इसलिए हम एक स्टैकड एन्सेम्बल आर्किटेक्चर का प्रस्ताव करते हैं और प्रदर्शित करते हैं कि यह डेटासेट और कॉन्फ़िगरेशन के आधार पर 1% से 12% के सटीकता स्कोर द्वारा मौजूदा अत्याधुनिक मॉडल से बेहतर प्रदर्शन करता है। हमारे दृष्टिकोण के लिए न्यूनतम प्रशिक्षण और कंप्यूटिंग संसाधन की आवश्यकता होती है, और किसी पूर्व-प्रसंस्करण की भी आवश्यकता नहीं होती है, और कई प्रासंगिक उपयोग मामलों के लिए संशोधित रूपों में इसका उपयोग किया जा सकता है।

आगे की खोज करते हुए, हमने पाठ्य सामग्री से भावनात्मक गतिशीलता की डिग्री को समझकर प्रासंगिक जागरूकता बढ़ाने का प्रस्ताव दिया है। हम "भावनात्मक गतिशीलता" शब्द पर विवाद करते हैं, जिसे एक जोरदार भावनात्मक अभिव्यक्ति के रूप में जाना जाता है, जो संभवतः किसी घटना, स्थिति या बातचीत से उत्पन्न होती है और खुद को तेजी से बदलती भावनाओं से जुड़ी एक स्थिति के रूप में प्रस्तुत करती है। हम भावना स्कोर को एक तरंग रूप के रूप में मानने और आवृत्ति डोमेन में इसकी जांच करने और उसके बाद भावनात्मक गतिशीलता की संबंधित डिग्री के अनुसार वाक्यों के सेट को वर्गीकृत करने के लिए अप्रशिक्षित शिक्षण का उपयोग करने की एक नई अवधारणा का प्रस्ताव करते हैं। हम खुले स्रोत की जानकारी से वास्तविक दुनिया की घटनाओं की पुष्टि करने वाले अमेरिकी राष्ट्रपतियों के भाषणों के डेटासेट पर प्रस्तावित दृष्टिकोण लागू करते हैं। हम यह प्रदर्शित करने में सक्षम हैं कि यह दृष्टिकोण विभिन्न भावना विश्लेषण एल्गोरिदम में काफी हद तक सुसंगत है।

इस शोध के परिणामस्वरूप, हमने चैटबॉट आधारित एप्लिकेशन के भावनात्मक जुड़ाव का आकलन करने के लिए अंतर्राष्ट्रीय दूरसंचार संघ (आईटीयू) अध्ययन समूह -12 (एसजी-12) के लिए एक नया कार्य आइटम प्रस्तावित किया है जिसमें हमने गुणवत्ता की अवधारणा का प्रस्ताव दिया है। अनुभव की गुणवत्ता (क्यूओई) के एक भाग के रूप में भावनात्मक अनुभव (क्यूओईई)।

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ABBREVIATIONS

NLP	Natural Language Processing
BERT	Bidirectional Encoder Representation for Transformers
PCA	Principal Component Analysis
QoE	Quality of Experience
QoEE	Quality of Emotional Experience
NLTK	Natural Language Toolkit
RoBERTa	A Robustly Optimized BERT Pre-training Approach
VADER	Valence Aware Dictionary for Sentiment Reasoning
TF-IDF	Term Frequency- Inverse Document Frequency
GB	Gradient Boosting
LR	Logistic Regression
LSTM	Long Short Term Memory
GRU	Gated Recurrent Unit
HMI	Human Machine Interface
CNN	Convolutional Neural Networks
DNN	Deep Neural Networks
KNN	K Neural Network
FFT	Fast Fourier Transform
MLP	Multi Layer Perceptron
ROC	Receiver Operating Characteristic
EM	Emotional Mobility
SA	Sub-Approach
EEC	Emotion Extraction Capability
AE	Agreeableness and Empathy
AED	Adaptability and Emotional Drift
ETP	Emotional Trust and Privacy
GEEH	Graceful Emotional Error Handling
TDP	Tendencies for Dispositions and Personalisation
SEF	Self Learning and Feedback
TOEE	Transparency and Openness form Emotional Experience

NOTATION

Ψ	Sentiment Pattern vector / Stacked ensemble function / Spectrogram
e	Emotional Intensity vector
E	Set of emotions
f	Base sentiment analyzer model
ϕ	Meta-learner
x	Input utterance in the form of text
α	Threshold / Scaling factor
γ	Spectral subtraction value
β	Scaling factor for QoEE