Detecting Novelty Seeking From Online Travel Reviews: A Deep Learning Approach

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Abstract. An important source of experience-related data for comprehending novelty seeking (NS), a natural personality feature that affects travel motivation and location selection, is online travel reviews. Due to the large number and disorganization of reviews, manually categorizing them is difficult. Therefore, our aim is to develop a deep learning model and classification system to overcome these challenges. We propose a framework that combines four dimensions related to the NS personality trait and use a DL model called BERT-BiGRU to automatically identify NS in TripAdvisor reviews using a dataset of 30,000 reviews. The classifier using the NS multi-dimensional scale and the BERT-BiGRU multi-dimensional scale accurately identified the NS personality trait. It achieved high accuracy and F1 scores. The BERT-BiGRU model outperformed other DL models in terms of accuracy. This study shows how computer methods can be used to automatically determine personality traits from travel reviews. It provides a comprehensive framework for categorizing personality traits in order to benefit marketing and recommendation systems in the travel industry.

Keywords: Tourism industry, BERT- BiGRU, novelty seeking, online travel reviews.

1 Introduction

The internet has become a vital component of our everyday life in this age of fast technological innovation, penetrating many industries, including the travel and tourist sector. The shift from analog to online platforms has had a profound impact on how people organize and enjoy their travels. This change has been largely shaped by the rise of online travel communities, as more and more travelers increasingly consult the internet for peer evaluations and destination information prior to booking [1].

Online tourism platforms serve as virtual forums where travelers share their perspectives, feelings, and thoughts about their experiences. The wealth of information

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generated by these user-generated reviews provides a valuable resource for understanding the emotional tendencies, praises, and criticisms associated with various elements of tourism services. Analyzing this data allows for the visualization of tourists' attitudes towards destinations, aiding prospective travelers in decision-making [2]. Furthermore, for tour operators, comprehending tourists' opinions enables the maximization of strengths and the mitigation of weaknesses, contributing to improved program customization and a competitive advantage [3].

Traditionally, personality traits, crucial drivers of individual behavior, were measured through self-reporting scales. However, the inherent subjectivity and potential for participants to align their responses with societal values posed limitations. The development of technology has introduced a new method for identifying personality traits, which involves analyzing online behavior data. This method transcends the static nature of traditional assessments, providing an automated means to identify and judge personality traits. By leveraging online behavior data, researchers can overcome the biases associated with self-reporting, presenting a novel avenue for understanding tourists' personality traits [6].

In this context, this paper explores the significance of online tourism platform reviews in uncovering tourists' emotional tendencies and evaluates the potential of personality trait recognition through online behavior data as a dynamic and objective alternative to traditional methods. This research not only addresses the current gaps in understanding tourist preferences and decision-making processes but also introduces innovative perspectives that can shape the future of personality trait acquisition in the field of tourism [5].

2 Literature Review

[12] in this they proposed EI-LSTM-CO system enhances lithium-ion battery SOC estimation using LSTM-RNN with extended input and constrained output, achieving improved accuracy and stability in various temperatures. Complex implementation may require advanced expertise, and real-time constraints could be challenging. Dependency on accurate slow time-varying information may limit applicability in certain dynamic scenarios. The system's effectiveness may be impacted by variations in battery chemistry and inconsistent slow time-varying information. Generalization to diverse battery types and extreme operating conditions may be challenging. Accurate mapping of nonlinear battery characteristics, adaptation to varying temperatures, and real-world integration pose challenges. Handling dynamic scenarios and ensuring robustness under diverse conditions require careful consideration. The EI-LSTM-CO system, incorporating extended input and constrained output in LSTM-RNN, demonstrates enhanced lithium-ion battery SOC estimation performance, addressing instability and fluctuations for improved accuracy and stability.

This study proposes a comprehensive framework [4] integrating tourists' personality traits (Big Five plus Honesty/Humility) and personal values to predict and understand travel motivation more effectively. Potential challenges include the subjectivity of self-reported data, cultural variations, and the complexity of correlating personality traits and personal values with diverse travel motivations, limiting universal applicability. The study relies on information given by the participants, which could lead to a potential bias in their answers. Generalization may be limited due to cultural differences, and the complexity of travel motivations might not be fully captured. Addressing cultural nuances in personality-travel motivation relationships, mitigating self-reporting biases, and adapting the model to diverse tourism contexts pose challenges in achieving a comprehensive understanding. Integrating personality traits and personal values enhances predicting travel motivation. Understanding the role of Honesty/Humility in this context contributes valuable insights, fostering a nuanced comprehension of tourists' motivations.

This study introduces an integrative framework, rooted in self-determination theory, elucidating the impact of customer incivility on employee [5] service performance, emphasizing the moderating role of core-self evaluations. Subjectivity in interpreting incivility, potential biases in self-reported data, and the complexity of correlating employee intrinsic motivation with diverse core-self evaluations pose challenges to generalizability. Reliance on self-reported data introduces response bias. Cultural differences in interpreting incivility may affect results. Generalization might be limited to specific industries and contexts. Navigating cultural variations in interpreting customer incivility, addressing potential biases in self-reported data, and adapting the framework to different service industries pose challenges in achieving universal applicability. The proposed framework unveils the nuanced impact of customer incivility on employee service performance, with core-self evaluations moderating the mediated relationship via intrinsic motivation, offering insights for tailored interventions.

By combining text mining, association rule mining, and Bayesian network techniques, the system is able to successfully identify 78 risk factors related to coal mine safety. This allows for better understanding of how these factors interact with each other, aiding in pre-control management. Potential challenges include language-specific nuances affecting text analysis, the need for substantial data for accurate Bayesian network modeling, and potential biases in accident report text interpretation. Reliance on historical accident data may limit real-time applicability. Language barriers and variations in reporting styles could impact the accuracy of risk factor identification. Overcoming language-specific challenges in text mining, ensuring the scalability of the system to diverse coal mine contexts, and addressing potential biases in risk factor identification pose significant challenges. The proposed method, integrating text mining and Bayesian networks, offers a novel approach to identify and understand coal mine safety risk factors, emphasizing the crucial role of management and education.

The study suggests a new method for identifying topics in patient reviews by using dynamic mixed sampling and transfer learning. This involves using convolutional neural networks and self-trained Word2Vector to achieve better results. Potential cons include the need for extensive labeled data, possible biases in training corpora affecting Word2Vector, and sensitivity to variations in review styles and languages. Limited real-time adaptability due to reliance on pre-trained Word2Vector. Generalization may be challenged by diverse medical contexts and languages, and biases in patient reviews. Addressing the scarcity of labeled data, adapting to varied medical domains, and mitigating biases in patient reviews pose challenges. Ensuring language robustness and real-time adaptability are additional concerns. The CNN+ DMS + TL model, which combines dynamic mixed sampling and transfer learning, greatly improves the ability to identify topics in patient reviews. This method shows potential for automating and improving healthcare analytics.

3 Methodology

Our proposed study focuses on building a DL model and an extensive classification framework to detect the novelty seeking (NS) personality characteristic from online travel evaluations. Four dimensions—relaxation seeking, experience seeking, arousal seeking, and boredom alleviation—are included in this paradigm that has been synthesized from the body of literature. Utilizing a TripAdvisor dataset of 30,000 reviews, our methodology combines a DL model with a bidirectional gated recurrent unit (BiGRU) and bidirectional encoder representations from transformers (BERT) to automatically identify neural surface (NS) traits embedded in the reviews. We extend our investigation by comparing the performance of various DL architectures, including BERT-GRU, BERT-LSTM [11], BERT-CNN [12] , BiGRU, Word2Vec, Glove, LSTM, and LSTM + GRU. The accuracy of each algorithm is meticulously calculated to discern their respective strengths in capturing the nuanced expressions of novelty seeking within travel narratives. Furthermore, to enhance predictive accuracy and robustness, we explore ensemble methods. In this context, we employ a combination of predictions from multiple individual models. As an extension, we consider the potential improvement in performance by experimenting with alternative ensemble techniques, specifically evaluating the efficacy of LSTM and LSTM + GRU combinations, aiming to achieve the highest accuracy in discerning novelty seeking traits from online travel reviews.

This study utilizes DL techniques, specifically the combination of BERT and BiGRU, to develop a system architecture for detecting novelty seeking in online travel reviews. The input data consists of a dataset of 30,000 travel reviews obtained from TripAdvisor. The reviews are preprocessed and tokenized before being fed into the BERT-BiGRU model for automatic identification of Novelty Seeking traits.

The architecture also includes an exploration of various DL models, such as BERT-GRU, BERT-LSTM, BERT-CNN, BiGRU, Word2Vec, Glove, LSTM, and LSTM + GRU, with their individual accuracies being calculated. To enhance predictive accuracy and robustness, an ensemble method is applied, combining predictions from multiple individual models. Additionally, the system allows for the investigation of alternative ensemble techniques, such as LSTM and LSTM + GRU combinations, aiming to optimize the system's ability to detect Novelty Seeking in online travel reviews.

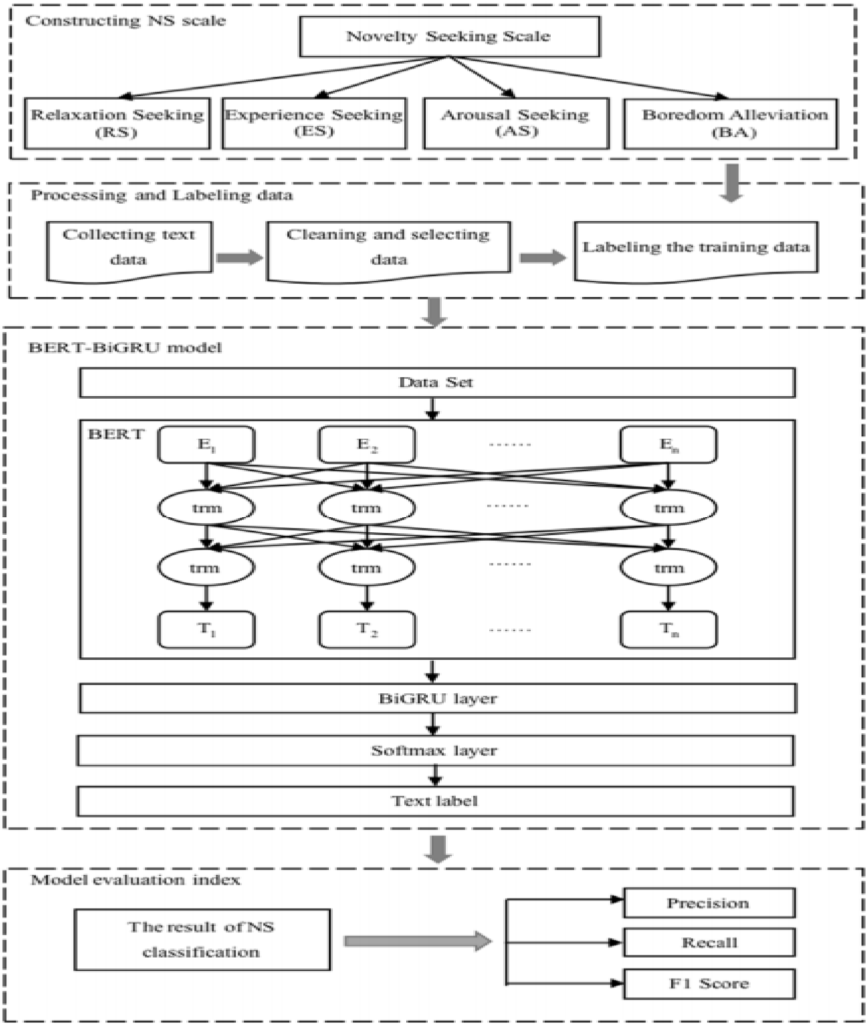

Fig 1 Proposed Architecture

Dataset: The dataset for our study is derived from TripAdvisor, a popular online platform for travel reviews. This dataset is curated to include 4,000 rows, each representing a unique travel review, and comprises three essential columns: 'content,' 'label,' and 'type.' The 'content' column encapsulates the textual content of the reviews, providing the narrative expressions of travelers regarding their experiences. The 'label' column is instrumental in categorizing the reviews based on the personality trait of novelty seeking. This column serves as the ground truth for the training and evaluation of our DL model, ensuring the accurate identification of novelty seeking tendencies within the reviews. Lastly, the 'type' column is designed to capture additional contextual information about the reviews, potentially influencing the expression of novelty seeking.

The meticulous collection of this dataset from TripAdvisor reflects the diversity of travel experiences, ensuring a comprehensive representation of user-generated content. The careful structuring of the dataset with these three key columns facilitates the effective training and validation of our proposed DL model, ultimately aiming to automate the identification of novelty seeking personality traits from the rich textual content found in online travel reviews.

Pre-processing Dataset:Feature selection is an essential step in the process of fine-tuning the dataset to extract relevant information for model training in the context of the research that aims to detect novelty seeking from online travel reviews. The preprocessing steps encompass a comprehensive approach to enhance the quality of textual data. Firstly, the removal of URLs and special characters helps eliminate noise, ensuring that the subsequent analysis focuses on relevant content. Punctuation removal further streamlines the text, while the exclusion of stop words contributes to a more refined representation of the review content. Normalization of the data ensures consistency in textual patterns, aiding in subsequent analyses.

The next steps involve tokenization and lemmatization, breaking down the reviews into individual words and reducing them to their base forms. Following this, a lexicon-based approach is employed for vectorizing the text, transforming the reviews into numerical representations for ML model compatibility.

For feature extraction, three distinct techniques are implemented. The Counter Vectorizer captures the frequency of words, creating a feature matrix that quantifies the importance of each term in the reviews. Keras processing involves additional neural network-based feature extraction, leveraging the DL capabilities of the framework. BERT (Bidirectional Encoder Representations from Transformers) [11] is employed as a state-of-the-art feature extraction technique, capturing contextualized word representations and enhancing the model's ability to understand intricate nuances in the text.

In summary, these feature selection and extraction techniques collectively contribute to the creation of a robust dataset, empowering the subsequent DL model to discern novelty seeking traits in online travel reviews effectively.

Training & Testing:The training and testing phase of the project involves splitting the preprocessed dataset into two subsets: one for training the DL model and another for evaluating its performance. The dataset is randomly divided into training and testing sets, typically with a commonly used split ratio such as 80-20 or 70-30.

During training, the BERT-BiGRU architecture is utilized by the DL model to process the training set. The algorithm optimizes its capacity to detect novelty seeking behaviors in online travel evaluations by learning the underlying patterns and correlations within the data and modifying its weights and parameters accordingly. The training process involves multiple iterations (epochs), refining the model's understanding through backpropagation and gradient descent.

The model is evaluated on the designated testing set after the training phase to see how well it generalizes to new data. The testing set provides a trustworthy gauge of the model's capacity to generalize and generate precise predictions on fresh, unobserved reviews since it includes cases that the machine has not seen during training. Performance measures are computed to evaluate the model's efficacy in identifying novelty seeking personality characteristics, including accuracy, precision, recall, and F1 score. This rigorous training and testing process guarantees the robustness and dependability of the model in practical circumstances, enabling the implementation of a well verified system for automatic novelty seeking identification from online travel evaluations.

Algorithms used:

BERT – GRU: The (BERT - GRU) algorithm combines Bidirectional Encoder Representations from Transformers (BERT) and Gated Recurrent Unit (GRU) architectures for natural language processing. It leverages BERT's contextual embeddings and GRU's sequential modeling to capture both global and local contextual information, enhancing performance in tasks like sentiment analysis or text classification.

BERT – LSTM: The (BERT - LSTM) algorithm integrates Bidirectional Encoder Representations from Transformers (BERT) with Long Short-Term Memory (LSTM) for natural language processing. By combining BERT's contextual embeddings and LSTM's sequential modeling, the algorithm effectively captures intricate contextual information, making it suitable for tasks like sentiment analysis and text classification.[11]

BERT – CNN: The (BERT - CNN) algorithm combines Bidirectional Encoder Representations from Transformers (BERT) with Convolutional Neural Network (CNN) architectures for natural language processing. By integrating BERT's contextual embeddings with CNN's ability to capture local patterns, the model efficiently extracts both global and local contextual information, enhancing performance in tasks such as text classification and sentiment analysis.[12]

BiGRU (- Word2vec – glove): The BiGRU (- Word2Vec - GloVe) algorithm utilizes Bidirectional Gated Recurrent Unit (BiGRU) for sequential modeling. It integrates pre-trained Word2Vec and GloVe embeddings to capture semantic relationships in text. This hybrid approach combines the strengths of recurrent networks and word embeddings for effective natural language processing tasks, like sentiment analysis.

LSTM: LSTM is a widely used RNN architecture in DL that excels at recognizing long-term dependencies. It is particularly well-suited for sequence prediction tasks due to its ability to handle complete data sequences. Unlike traditional neural networks, LSTM can effectively identify and predict patterns in sequential data, including time series, text, and voice.

LSTM + GRU: The LSTM (Long Short-Term Memory) + GRU (Gated Recurrent Unit) algorithm is a hybrid recurrent neural network model. Combining the memory-preserving properties of LSTM with the computational efficiency of GRU, it excels in sequential data tasks. This model is adept at capturing long-term dependencies and is widely used in natural language processing and time-series analysis.

4 Experimental Results

Accuracy: The effectiveness of a test in distinguishing between sickness and good health determines its accuracy. We should compute the percentage of true positive and true negative in each analyzed instance in order to assess the accuracy of a test. In terms of math, this is expressed as:

$$Accuracy = \frac{(True\ positives + True\ Negatives)}{Total\ no\ of\ Test\ samples} \quad (1)$$

Precision: Precision measures the percentage of correctly categorized samples or instances among the positive samples. Consequently, the following is the formula to determine the precision:

$$Precision = \frac{(True\ positives)}{True\ Positivies + False\ positives} \quad (2)$$

Recall: Recall in ML measures how well a model can identify all relevant instances of a specific class. It indicates the model's ability to accurately capture examples of that class. This is calculated by dividing the correctly predicted positive observations by the total number of actual positives.

$$Recall = \frac{(True\,positives)}{True\ Positivies + False\ Negatives}\,(3)$$

F1-Score: The F1 score is a statistical measure used in ML to evaluate the accuracy of a model. It combines both the model's accuracy and recall ratings. The accuracy measure calculates the number of correct predictions made by the model across the entire dataset.

$$F1\ Score = 2X\frac{(Precision * Recall)}{(Precision + Recall)}\,(4)$$

Table 1. Performance Evaluation Table

ML Model	Accuracy	Precision	Recall	F1 score
Existing BERT-LSTM Model	0.994	0.994	0.994	0.994
Propose BERT-BI-GRU Model	0.995	0.995	0.995	0.995
Extension BERT-CNN-BI-GRU Model	0.975	0.975	0.975	0.975
Existing BERT-LSTM Model	0.994	0.994	0.994	0.994

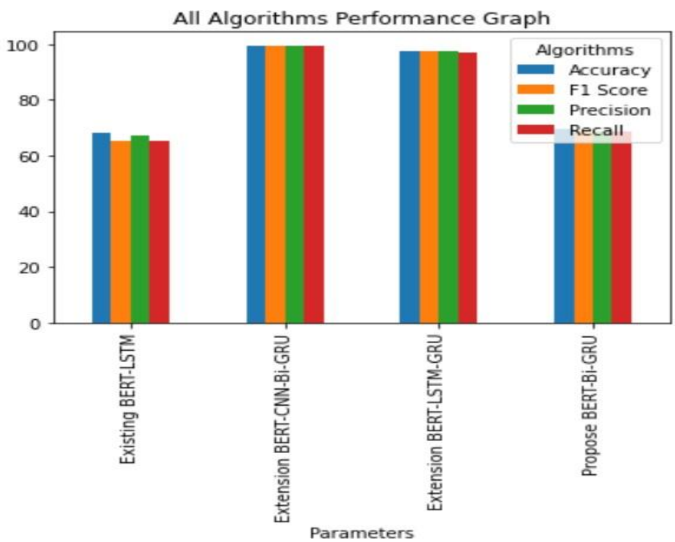

Fig 2. Performance Comparison Graph

The method shown in this study showed the capacity to properly detect in provided travel reviews and obtained an accuracy of 99% for enhanced ensemble approaches BERT and LSTM + GRU in detecting novelty seeking. This performance represents a substantial advancement compared to the existing methods.

5 Conclusion and Future Work

We show how DL may be applied to automatically assess large volumes of internet travel reviews using a theory-based categorization of neurotypical personality features. We demonstrate how sophisticated computational methods may be used to efficiently and automatically identify personality characteristics. The idea encompasses several aspects with a high level of abstraction, yet the NS dimensions are subjective. Depending on the number of dimensions of the scale, multi-category recognition can be carried out in addition to the straightforward two-category method for novelty recognition. Further research could involve improving the tourist destination recommendation system by considering the NS personality, which includes grouping users based on their NS traits, improving the understanding of user preferences, and implementing targeted marketing strategies.

The future scope of this project involves exploring advanced ensemble techniques to further enhance the model's predictive accuracy. Additionally, incorporating user feedback and continuous learning mechanisms can improve the model's adaptability to evolving linguistic patterns. Integration with real-time data sources and expanding the dataset's diversity will contribute to a more comprehensive understanding of novelty seeking in varied travel contexts, ensuring the model's applicability across a broader spectrum of online travel reviews.

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