



INTELLIGENT TOURIST GUIDE

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Abstract : Traveler reviews are a source of information for tourists to know about tourist attractions. Unfortunately, many reviews are irrelevant and become noisy. Sentiment-based classification of reviews has shown promise; however, limited work exists on automatic aspect characterization, identifying implicit aspects, and co-dependency results in classification. This paper presents a confidence-based classification framework that identifies effective aspects and performs high-accuracy sentiment classification. The framework is implemented as a mobile application that helps tourists find the best restaurants or hotels. Experimental results show that reviews and opinions with accurately extracted aspects and opinion words outperform several existing sentiment-analysis methods. Findings reveal that moderate and purposeful use of social media enhances digital literacy, social awareness, and collaborative learning experiences. However, excessive use particularly for non-educational purposes has been linked to anxiety, depression, low self-esteem, reduced attention span, and academic underachievement.

Keywords: Business Analysis, Requirement Gathering, SQL Analysis, Functional Specification, Agile Methodology, Cross-Functional Collaboration, Tax Configuration, System Testing, Stakeholder Management, Process Optimization.

I. INTRODUCTION

The use of Big Data is rapidly expanding within tourism research (Fuchs et al., 2014). The four Vs volume, variety, velocity, and veracity play an important role in understanding consumer behaviour. Tourism, being a service-based industry heavily dependent on customer experience and feedback, has adapted significantly to technological advancements and new data sources.

Traditional survey-based feedback mechanisms have limitations such as cost, logistics, bias, and narrow scope (Veal, 2006; Dodds et al., 2015). The emergence of online user-generated content (UGC) and sentiment analysis provides new opportunities to evaluate tourist perceptions. Sentiment analysis aims to classify a review's polarity as positive, neutral, or negative (Feldman, 2013).

In tourism applications, sentiment analysis is still emerging despite its potential (Gao et al., 2015; Ribeiro et al., 2016). Online activities leave a digital footprint that can be mined using computational methods, contributing to a new research paradigm in tourism analytics.

Past research largely focused on business strategy, innovation, product development, and marketing. This study extends the exploration of online datasets to understand tourist satisfaction and experience more accurately.

II. REVIEW OF THE LITERATURE

1. **Sentiment Mining Techniques (Nandedkar & Patil, 2018; 2020)**
Nandedkar and Patil introduced advanced methods for sentiment mining such as the **Gradual Weight Updating technique** and **domain-independent opinion word extraction**. Their work focuses on polarity detection, cluster-based valence shifting, and improved feature–opinion co-extraction, forming a foundation for aspect-based sentiment analysis.
- 2.
3. **Role of Online Review Platforms (TripAdvisor, Expedia, VirtualTourist) – Alcoba et al., 2017**
Alcoba et al. emphasized the importance of user-generated content in tourism, noting that platforms like TripAdvisor (with 350M+ monthly visitors) significantly influence traveler perceptions. Online reviews provide rich datasets for understanding tourist behavior and service quality.
4. **Foundational Sentiment Analysis Approaches (Pang et al., 2002; Feldman, 2013)**
Early work by Pang et al. established sentiment analysis as a machine-learning classification task, while Feldman later defined it as a core component of computational linguistics. These works laid the groundwork for polarity classification (positive, negative, neutral) using supervised and unsupervised NLP techniques.
5. **Linguistic Resources and Multilingual Sentiment Analysis (Baccianella et al., 2010; Balahur & Turchi, 2014)**
Baccianella et al. developed **SentiWordNet 3.0**, a widely used lexical resource for scoring subjective terms. Balahur and Turchi further compared multilingual sentiment analysis techniques, demonstrating how supervised learning and machine translation improve cross-language opinion mining.
6. **Social Media Sentiment in Tourism Research (Barbagallo et al., 2012; Chmiel et al., 2011)**
Studies by Barbagallo et al. linked Twitter sentiment to traveler influence and behavioral trends, while Chmiel et al. showed how emotional polarity affects online engagement dynamics. These works highlight the growing role of social media analytics in tourism forecasting and decision-making.

III. OBJECTIVES OF THE STUDY

1. To identify and extract explicit and implicit aspects from tourism-related reviews using POS tagging, FLR scoring, and iterative bootstrapping techniques.
2. To develop an unsupervised sentiment classification model capable of analysing large volumes of online user-generated content without requiring labelled training data.
3. To evaluate the performance of the proposed aspect-based sentiment analysis approach using precision, recall, and accuracy metrics, and compare it with existing methods such as ARM and SPF.
4. To design and implement a prototype Intelligent Tourist Guide system that recommends hotels or restaurants based on automatically extracted aspects and sentiment polarity.
5. To analyse user behavior and digital adoption patterns through survey data, identifying challenges, awareness levels, and readiness toward AI-powered tools in the tourism and service domain.

IV. RESEARCH METHODOLOGY

1. Data Collection

Relevant information was obtained from client requirement documents, stakeholder discussions, and clarification calls. These inputs provided a clear understanding of tax rules, business logic, and operational expectations.

2. Requirement Analysis

The collected data was reviewed, interpreted, and broken down into functional components. Ambiguities or unclear scenarios were identified and resolved through follow-up discussions with stakeholders and subject matter experts.

3. Data and System Evaluation

SQL queries, Excel analysis, and transaction flow checks were used to examine client data and system behaviour. This step helped identify configuration gaps, mismatches, and areas requiring correction or improvement.

4. Validation and Documentation

Findings, clarifications, and finalized requirements were documented thoroughly. These records supported accurate implementation, testing, and communication with product, engineering, and QA teams.

III Proposed System

An online survey of 70 participants was taken via google forms with their consent and anonymous responses.

Questionnaire-

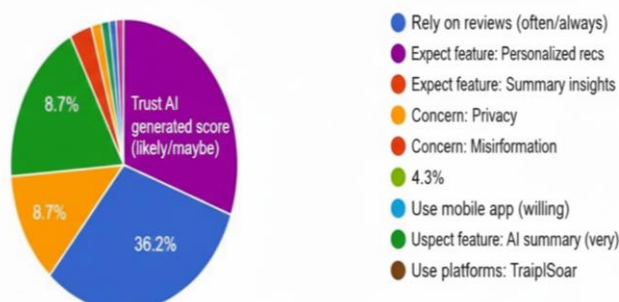
1. How often do you rely on online reviews before selecting a hotel, restaurant, or tourist spot?
2. Which online platforms do you frequently use to read travel-related reviews?
3. Which aspects do you consider most important when evaluating a hotel or restaurant? (e.g., cleanliness, food quality, service)
4. Have you ever encountered fake, misleading, or exaggerated reviews while planning a trip?
5. How useful would an AI-based tool be in summarizing large volumes of reviews into simple insights?
6. Would you trust an AI-generated sentiment score when choosing a hotel or restaurant?
7. Which features would you expect in an Intelligent Tourist Guide application?
8. How comfortable are you with AI analyzing your travel preferences to generate personalized recommendations?
9. What concerns do you have regarding AI-driven travel recommendation systems?
10. Would you be willing to use a mobile application that evaluates reviews and recommends the best tourist options using sentiment analysis?

IX. DATA ANALYSIS AND INTERPRETATION

Graph 1:

Online Survey: AI-powered Tourist Guide

70 participants



Job Function/Department	Percentage	Count (Approximate)
Student	37.7%	26
IT	36.2%	25
Siuance	8.7%	6
Marketing	8.7%	6
Others (HR, Bpo, Music Studio, B. Com)	8.7%	6
Total	100%	69

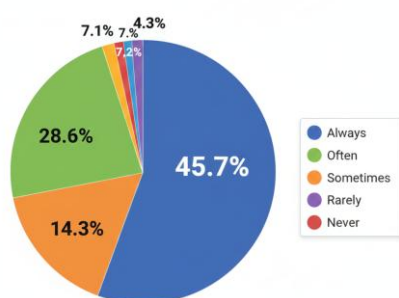
Interpretation

The respondent pool is heavily concentrated in the **Student** 37.7% and **IT** 36.2% categories, which collectively account for over 73% of the total responses. The remaining survey participants are distributed across various smaller functions, with **Siuance** and **Marketing** representing the next largest distinct groups, each at 8.7%.

Graph 2:

How often do you rely on online reviews before selecting a hotel, restaurant, or tourist spot?

70 responses



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Interpretation

The core interpretation is that the survey sample is heavily skewed toward **Students** 37.7% and **IT professionals** 36.2%, forming nearly **three-quarters 73.9%** of the respondents. This dominant concentration means the study's insights are primarily drawn from academic and technical perspectives, while other sectors like Marketing are minor contributors.

Conclusion and Future Scope

The research successfully proposed an unsupervised, domain- and language-independent model for aspect-based sentiment analysis that accurately detects both explicit and implicit aspects from online tourist reviews. By avoiding the need for costly and time-consuming labeled training data, the model provides an effective solution for classifying traveler opinions to improve the decision-making process for tourists.

Future efforts will focus on enhancing the Intelligent Tourist Guide system by:

1. **Scalability and Performance:** Improving the **ability to scale** and accelerating the **overall response time** to enhance the user experience.
2. **Fraudulent Review Detection:** Working on methods to detect **fraudulent reviews** posted by miscreants to malign the image of hotels and restaurants.
3. **Advanced Linguistic Analysis:** Examining and incorporating additional sequences, such as **emoticons**, as restrictions or features within the model to further refine sentiment classification.

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