INFORMATION RETRIEVAL

TRAVALL

TRAVEL FOR ALL

21 APRIL 2024

GROUP NUMBER 48

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“The design is not just what it looks like and feels like. The design is how it works”

STEVE JOBS

PROBLEM STATEMENT

Travall is an all-accessible travel guide that leverages information retrieval to assist in personalized trip planning, itinerary creation, and travel destination suggestions.
The primary problem addressed in this project is the lack of an integrated platform that provides comprehensive accessibility information, personalized travel planning, and inclusive destination recommendations for everyone.

MOTIVATION

The concept of travel is inherently bound to the desire for exploration, understanding, and interaction with diverse cultures and environments. However, the accessibility of travel and tourism remains a significant challenge, particularly for individuals with special needs or disabilities. These travelers often encounter barriers that limit their full participation in travel experiences, from insufficient information on accessible facilities to a lack of personalized, adaptive services that cater to their specific requirements. Recognizing these challenges, the motivation behind the development of Travall, our all-accessible travel guide, stems from a deep commitment to inclusivity and the democratization of travel. Our goal is to transform the landscape of travel planning and destination discovery by ensuring that all individuals, regardless of physical limitations or special needs, can experience the world with confidence and ease. This initiative is not only a response to a clear market need but also a moral imperative to promote equality and accessibility in one of the most universally valued human activities—travel

LITERATURE REVIEW

CURRENT STATE OF THE ARTS

1

Awareness and Recognition: There is a growing awareness of the importance of inclusivity in travel, as highlighted by the efforts of organizations like the United Nations World Tourism Organization (UNWTO) in promoting accessible tourism.

2

Economic and Social Imperatives: Studies such as the one by Darcy and Dickson (2009) emphasize the economic and social imperatives of accessible tourism, recognizing the diverse needs of travelers with disabilities.

3

Awareness and Recognition: There is a growing awareness of the importance of inclusivity in travel, as highlighted by the efforts of organizations like the United Nations World Tourism Organization (UNWTO) in promoting accessible tourism.

4

Technological Advancements: The evolution of AI-driven recommendation systems in tourism, as discussed by Gretzel and Fesenmaier (2009), shows promise in enhancing travel planning through personalization.

5

Evaluation of Recommendation Systems: Studies like Zanker et al. (2019) evaluate existing recommendation systems in tourism, identifying limitations in adaptability and personalization.

6

Semantic Web-based Approaches: Semantic web-based approaches, as presented by Choudhury and Sahay (2014), offer potential for enhancing information retrieval in tourism.

7

Utilization of Big Data: While big data has been utilized in tourism research to improve services, as explored by Li and Wang (2020), there is limited exploration of its use in enhancing accessibility and personalization for travelers with special needs.

LIMITATIONS

1

Gap in Implementation: Despite guidelines being set by organizations like UNWTO, there is a significant gap in implementing accessible tourism globally, indicating varying levels of commitment and resources.

2

Lack of Comprehensive Solutions: There is still a lack of comprehensive, end-to-end travel solutions that cater to the diverse needs of travelers with disabilities.

3

Insufficient Integration of Accessibility Considerations: Existing recommendation systems often lack sophistication in integrating accessibility considerations, limiting their utility for travelers with special requirements.

4

Limitations in Adaptability and Personalization: Recommendation systems in tourism often lack adaptability and personalization, indicating a need for more dynamic and user-driven feedback mechanisms.

5

Lack of Comprehensive Accessibility Features: Semantic web-based approaches often lack comprehensive accessibility features, indicating a gap that could be addressed through integration with platforms like Travall.

6

Limited Exploration of Big Data in Accessibility and Personalization: Despite the potential of big data, there is limited exploration of its use in enhancing accessibility and personalization for travelers with special needs.

PROPOSED SOLUTION

Understanding Traveler Experiences

We initiate by delving into traveler reviews, sorting them by location to comprehend what makes each spot unique. This provides us with a solid grasp of what travelers enjoy and where areas for improvement lie.

Identifying Key Details

We propose pinpointing the most crucial words from these reviews using TF-IDF. This will help us capture the essence of each place and what sets it apart.

Deepen Insights with Sentence-BERT

Leveraging Sentence-BERT, we aim to dive deeper into these significant words, gaining a nuanced understanding of the overall sentiment expressed in the reviews. This will add depth and richness to our insights.

Enhance Accessibility

To ensure inclusivity, we propose fine-tuning a specialized model to focus on accessibility aspects like wheelchair access and visual aids. This will enable us to assign ratings to each destination, making it easier for travelers with specific needs to navigate their options.

Integrating Insights

We intend to merge the insights gained from TF-IDF and Sentence-BERT with the accessibility ratings. This holistic dataset will paint a comprehensive picture of each location, considering both its appeal and its practical accessibility.

Enriching Recommendations with RAG

To elevate our recommendations, we propose tapping into a model that fetches additional information from sources like Wikipedia. This will add context and depth to our suggestions, empowering travelers with valuable insights.

Tailoring Recommendations

When users input their preferences, we plan to tailor their choices to match our dataset. By aligning their interests with our insights, we can recommend destinations that cater to their tastes and accessibility requirements.

Prioritizing Accessibility

Our recommendations will go beyond mere matching; we also plan to prioritize accessibility factors like wheelchair access and visual aids. This will ensure that everyone, irrespective of their needs, can access suitable travel options.

Delivering Personalized Experiences

Through our personalized approach, we propose combining user preferences, destination characteristics, and accessibility ratings. This will ensure that each traveler receives recommendations tailored to their unique interests and requirements.

NOVELTY

NOVELTY

- **Integration of Accessibility Features:** Travall embeds detailed accessibility information directly into the travel recommendation process, covering wheelchair-friendly facilities, sensory-sensitive accommodations, and options suitable for various conditions. This ensures all travelers find accessible and enjoyable options.

- **Personalized Travel Recommendations:** Travall processes reviews and user input using advanced algorithms to offer tailored travel suggestions. It matches individual preferences and accessibility requirements, offering a deeper level of customization.

- **Crowdsourced Reviews and Real-Time Data:** Leveraging crowdsourcing, Travall gathers and updates information about destinations, accommodations, and activities, ensuring up-to-date and reflective recommendations. Real-time data adaptation allows refinement based on user feedback.

- **Benefits to Diverse User Groups:**
  - Travelers with Special Needs: Gain access to tailored recommendations considering unique needs.
  - Individuals with Mobility Issues: Find destinations accommodating mobility aids.
  - General Travel Enthusiasts: Enjoy personalized experiences based on preferences.
  - Tourism Industry Stakeholders: Enhance service offerings and cater to diverse clientele.

METHODOLOGY

Data Collection and Preprocessing

- The project starts with compiling a review dataset, including city and place columns, and concatenating reviews into single text blocks per place. This dataset serves as the foundation for understanding travelers' sentiments and experiences at various destinations.

Feature Extraction Using TF-IDF:

- A TF-IDF analysis is conducted on the concatenated texts to identify the top 100 most relevant words. This method helps highlight key themes and important descriptors within the reviews, critical for feature analysis and subsequent steps.

Embedding Generation with Sentence-BERT:

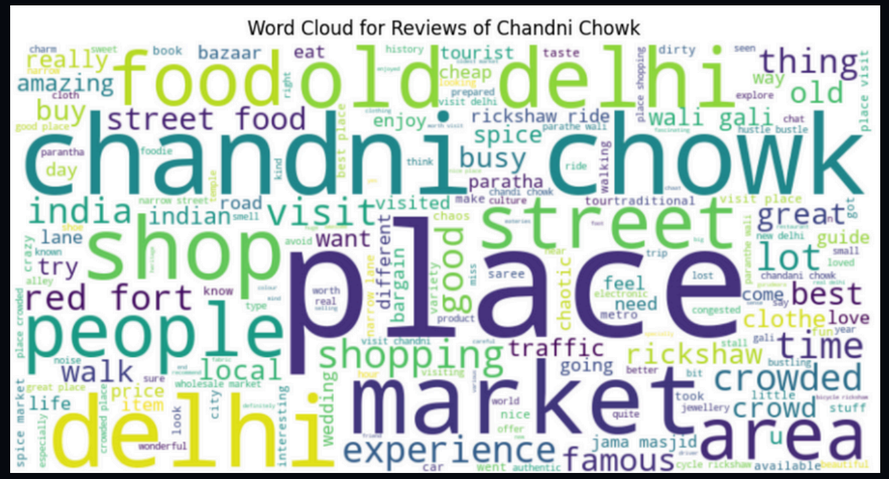
- Significant words extracted via TF-IDF are used to generate embeddings using Sentence-BERT, capturing semantic nuances for deeper analytical capability in later processes.

Fine-Tuning BERT for Accessibility Ratings

- A separate dataset is prepared, and a BERT model (BertQuestionAnswerLM) is fine-tuned on descriptions of travel destinations to derive accessibility ratings, focusing particularly on wheelchair access and visual accessibility. This tailored model allows extraction of detailed accessibility information critical for inclusivity.

Combining Datasets

- Sentence-BERT embeddings and outputs from the fine-tuned BertQuestionAnswerLM are merged into a comprehensive dataset. This combination provides semantic understanding, relevance matching from the embeddings, and integrates essential accessibility ratings, enabling a more nuanced and tailored recommendation process.



Implementation of Model 2: Retrieval-Augmented Generation (RAG)

- In addition to primary models, a Retrieval-Augmented Generation (RAG) model is implemented on web-scraped data from Wikipedia. This model dynamically retrieves and generates content relevant to the user's natural language queries, providing a rich layer of supplemental information.

User Query Processing and Recommendation Generation

- User queries are preprocessed and transformed into embeddings using Sentence-BERT, ensuring semantic alignment with the data in the system. These embeddings are then used to perform similarity assessments with destination embeddings.

Cosine Similarity and Accessibility Filtering:

- The system calculates cosine similarity between user query embeddings and destination embeddings to identify potential matches. These matches are then filtered and ranked according to their accessibility scores based on user-specific requirements such as wheelchair access or visual aids.

Ranking and Final Recommendation:

- Final recommendations are ranked based on a combination of cosine similarity and the accessibility scores, ensuring that the most relevant and accessible options are presented to the user. This ensures that recommendations are not only personalized to the user's preferences but are also practical and usable for individuals with specific accessibility needs.

EVALUATION

Accuracy of the model is: 66.8 %

	precision	recall	f1-score	support
Chandni Chowk	0.43	1.00	0.60	29
Connaught Place	0.00	0.00	0.00	38
Delhi Airport Metro Express	1.00	1.00	1.00	40
Friday Mosque (Jama Masjid)	0.28	1.00	0.44	37
Gurudwara Bangla Sahib	0.00	0.00	0.00	35
Hauz Khas Village	1.00	1.00	1.00	32
Humayun's Tomb	1.00	1.00	1.00	31
ISKCON Temple Delhi	0.00	0.00	0.00	32
India Gate	1.00	1.00	1.00	30
Lodhi Garden	1.00	1.00	1.00	31
Lotus Temple	0.00	0.00	0.00	24
Qutub Minar	1.00	1.00	1.00	37
Rashtrapati Bhavan	1.00	1.00	1.00	31
Red Fort (Lal Quila)	0.00	0.00	0.00	37
Swaminarayan Akshardham	0.53	1.00	0.69	36
accuracy			0.67	500
macro avg	0.55	0.67	0.58	500
weighted avg	0.55	0.67	0.58	500

	precision	recall	f1-score	support
Chandni Chowk	0.00	0.00	0.00	29
Connaught Place	0.57	1.00	0.72	38
Delhi Airport Metro Express	1.00	1.00	1.00	40
Friday Mosque (Jama Masjid)	1.00	1.00	1.00	37
Gurudwara Bangla Sahib	1.00	1.00	1.00	35
Hauz Khas Village	1.00	1.00	1.00	32
Humayun's Tomb	0.00	0.00	0.00	31
ISKCON Temple Delhi	1.00	1.00	1.00	32
India Gate	1.00	1.00	1.00	30
Lodhi Garden	1.00	1.00	1.00	31
Lotus Temple	0.00	0.00	0.00	24
Qutub Minar	0.30	1.00	0.46	37
Rashtrapati Bhavan	0.00	0.00	0.00	31
Red Fort (Lal Quila)	1.00	1.00	1.00	37
Swaminarayan Akshardham	1.00	1.00	1.00	36
accuracy			0.77	500
macro avg	0.66	0.73	0.68	500
weighted avg	0.69	0.77	0.71	500

	precision	recall	f1-score	support
Chandni Chowk	1.00	1.00	1.00	29
Connaught Place	1.00	1.00	1.00	38
Delhi Airport Metro Express	1.00	1.00	1.00	40
Friday Mosque (Jama Masjid)	1.00	1.00	1.00	37
Gurudwara Bangla Sahib	1.00	1.00	1.00	35
Hauz Khas Village	1.00	1.00	1.00	32
Humayun's Tomb	0.46	1.00	0.63	31
ISKCON Temple Delhi	1.00	1.00	1.00	32
India Gate	1.00	1.00	1.00	30
Lodhi Garden	1.00	1.00	1.00	31
Lotus Temple	1.00	1.00	1.00	24
Qutub Minar	0.00	0.00	0.00	37
Rashtrapati Bhavan	1.00	1.00	1.00	31
Red Fort (Lal Quila)	1.00	1.00	1.00	37
Swaminarayan Akshardham	1.00	1.00	1.00	36
accuracy			0.93	500
macro avg	0.90	0.93	0.91	500
weighted avg	0.89	0.93	0.90	500

Model	Accuracy
Baseline (TF-IDF)	66.8%
BERT Embeddings	77%
Final Model (TF-IDF + Sentence Transformer)	93%

RESULTS

- Developed a comprehensive methodology integrating advanced NLP techniques and machine learning algorithms.
- Successfully collected and processed diverse travel data, enabling personalized and accessible travel recommendations.
- Achieved semantic understanding and relevance matching through TF-IDF and Sentence-BERT embeddings.
- Fine-tuned BERT model for detailed accessibility ratings, enhancing inclusivity.
- Implemented Retrieval-Augmented Generation (RAG) model for enriched recommendation generation.
- Generated personalized recommendations based on user queries, ensuring relevance and accessibility.
- Ranked and presented recommendations based on a combination of similarity and accessibility scores.
- Resulted in a highly accessible and personalized travel planning tool, catering to the needs of diverse travelers.

CONLUSION

Through systematic evaluation and experimentation, we have demonstrated the effectiveness of our travel recommendation system. By leveraging advanced techniques such as fine-tuned embeddings and model finetuning, we have significantly improved recommendation accuracy and user experience. Our approach also ensures the consideration of accessibility aspects, making our system more inclusive and informative for all users.

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THANK YOU