SpotLite: A System for Personalized, Aspect-Based Restaurant Recommendation Near Tourist Destinations

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Abstract

Current restaurant discovery platforms are inefficient for tourists due to information overload and a lack of granular personalization. We propose SpotLite, a system that generates ranked recommendations based on fine-grained aspect extraction from user reviews. The system quantifies sentiment for each aspect, distinguishes between positive and negative keywords, and produces generative summaries using a T5 model. A preference-aware ranking function then tailors results to user-specified criteria. The evaluation framework is designed to quantitatively measure improvements in ranking relevance (NDCG) and task-oriented user efficiency against commercial baselines.

1 Problem Statement

Commercial platforms (e.g., Google Maps) exhibit three primary limitations for users with specific intents: 1) **Information Overload**, requiring manual review parsing to identify key attributes; 2) **Fragmented Keywords**, as semantically equivalent terms are not consolidated; and 3) **Limited Personalization**, with filters that lack support for multi-faceted queries.

SpotLite addresses these issues by ingesting a location URL and a structured preference set to output a ranked list of venues with summarized, aspect-level intelligence. The project's scope is confined to English-language reviews from the past year. The system's API schema is shown in Table 1.

2 Related Work

Our approach is built upon foundational NLP models. We leverage pre-trained transformers, specifically BERT-based architectures (Devlin et al., 2019), for deep language understanding.

- **Aspect-Based Sentiment Analysis**: We will implement aspect extraction and sentiment classification following established methodologies (Hu and Liu, 2004).
- **Keyword Extraction**: We will use the graph-based TextRank algorithm (Mihalcea and Tarau, 2004) to identify salient keywords, which is more robust than simple frequency models.
- **Semantic Clustering**: To group synonymous keywords, we will compute sentence embeddings using Sentence-BERT (Reimers and Gurevych, 2019).
- **Summarization**: We will employ a fine-tuned Text-to-Text Transfer Transformer (T5) model (Raffel et al., 2020) for abstractive summarization.

3 Hypothesis and Evaluation

Hypothesis: A system integrating aspect-based feature extraction and multi-criteria preference ranking will yield a statistically significant improvement in recommendation relevance and user efficiency over baseline systems.

We will conduct a two-tiered quantitative evaluation:

1. **Component-Level Validation**:
    - Aspect Classification: F1-score of $\geq$ 0.75 on an annotated dataset (N=200).
    - Keyword Clustering: Precision of $\geq$ 80% against a ground-truth synonym set.
2. **End-to-End System Evaluation**:

Input (JSON)

```
{
  "location_url": "https://share.google/...",
  "search_radius_meters": 800,
  "preferences": {
    "must_have": ["Japanese Cuisine"],
    "nice_to_have": ["quiet", "priced"],
    "exclude_keywords": ["queue", "noisy"]
  }
}
```

Output (JSON)

```
[
  {
    "rank": 1, "name": "The Tuna Sushi",
    "ai_summary": "...",
    "aspect_analysis": [
      {
        "aspect": "Taste", "score": 0.94,
        "positive_mentions": 85,
        "negative_mentions": 5,
      "positive_keywords": ["fresh fish", ...],
       "negative_keywords": ["rice was mushy"]
      },
      {
        "aspect": "Ambiance", "score": 0.87,
        "positive_mentions": 65,
        "negative_mentions": 10,
      "positive_keywords": ["quiet", "intimate"],
        "negative_keywords": ["a bit dark"]
      }
    ],
    "pros": ["High-quality ingredients", ...],
    "cons": ["Higher price point"]
  }
]
```

Table 1: System API Schema with detailed aspect analysis output.

- Ranking Relevance: Improve NDCG@10 by $\geq$ 15% over the Google Maps baseline.
- User Efficiency Study: A controlled experiment will measure **Task Completion Time** (Target: reduction of $\geq$ 50%) and **Correctness Rate** (Target: within 10% margin of control).

4 System Architecture

The processing pipeline is defined as: URL Ingestion $\rightarrow$ Data Preprocessing $\rightarrow$ NLP Feature Extraction $\rightarrow$ Preference-based Ranking $\rightarrow$ JSON Output.

1. **Data Preprocessing**: Filter non-English text via `langdetect`. Deduplicate using SimHash for near-duplicates and semantic embeddings for semantic matches.

2. **Aspect & Keyword Modules**: Classify sentences into an eight-aspect taxonomy. Extract keywords using TextRank. Cluster keywords using SBERT embeddings and K-Means.

3. **Sentiment Analysis & Quantification**: For each aspect, the system analyzes sentiment at the sentence level. It then aggregates these findings to count `positive_mentions` and `negative_mentions` over the last year. Keywords associated with each sentiment are collected into `positive_keywords` and `negative_keywords` lists. A normalized quantitative `score` (e.g., positive mention ratio) is then computed for each aspect.

4. **Summarization & Ranking**: A **t5-small** model generates a summary from the highest-scoring aspects. A weighted function computes the final rank based on rating, review count, distance, aspect scores, and user preferences.

5 Timeline & Deliverables

The project will be executed over four weeks, as detailed in Table 2.

Week	Milestone	Deliverables
W1	Data Ingestion	Cleaned Top-20 review dataset (JSON)
W2	NLP Modules I	Aspect/keyword annotated dataset
W3	NLP Modules II	Generated summaries & ranked outputs
W4	System Integration	Functional prototype & eval report

Table 2: Project Timeline and Deliverables.

References

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