Development of a Visualization Agent for Spatial Sentiment Analysis Using Geo-Located Review Data of Urban Neighborhoods

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***Abstract*— Understanding emotional perceptions of urban environments is essential for human-centered urban analytics. This paper presents an Agentic AI for spatial sentiment analysis that interprets the "sense of place" in neighborhoods using user-generated reviews. Moving beyond lexical approaches, the system employs a generative language model and a sentiment classifier to extract nuanced emotional context. Integrated with digital mapping, the pipeline identifies locations, analyzes nearby review sentiment, and generates narrative summaries and sentiment heatmaps. Compared to previous tools, this method offers deeper interpretive insight and clearer visual feedback. Real-world case studies demonstrate its potential to scale and contextualize subjective experiences, advancing emotionally aware spatial analysis.**

Keywords*— *Geo-spatial sentiment modeling, Agentic language models, Urban semantic profiling, Natural language analytics, Location-based data mining

I. Introduction

Understanding emotional perceptions of urban environments is increasingly important in both urban studies and AI. Traditional methods like surveys and fieldwork provide depth but lack scalability and real-time insights [1], while earlier computational approaches—such as lexical sentiment analysis—often fail to capture emotional nuance due to their reliance on surface-level word polarity [2]. Recent advances in NLP and generative AI now enable more context-aware, scalable interpretations of user-generated content.

This paper introduces an Agentic AI system for spatial sentiment analysis that combines geo-tagged reviews, sentiment scoring, and large language models to describe the emotional character—or "sense of place"—of neighborhoods. The pipeline retrieves local reviews, computes metrics (e.g., sentiment score, popularity), and generates narrative summaries and sentiment heatmaps. By merging structured spatial data with unstructured text, the system reveals geographic patterns of public emotion, supporting applications in urban planning, tourism, and real estate [3].

II. Background

A. Emergence and Architecture of Autonomous Systems

Agentic AI represents a major shift from static, prompt-based systems to autonomous, context-aware agents capable of goal-driven behavior and real-time adaptation [4], [5]. Powered by foundation models, reinforcement learning, and long-horizon planning, these systems not only process inputs but also dynamically recalibrate their strategies in response to evolving environments [4], [6].

Rooted in Albert Bandura's psychological notion of human agency—intentionality, self-regulation, and autonomy [4]—agentic AI adopts a similar cognitive framework. Sapkota, Roumeliotis, and Karkee distinguish these systems from conventional agents by emphasizing their self-organizing goals and high-level reasoning [5].

At the architectural level, agentic AI integrates reinforcement learning for long-term strategy optimization, meta-learning for flexible adaptation, and persistent memory systems for maintaining continuity across tasks [4], [6]. What sets these agents apart is their orchestration capability—

deploying and coordinating multiple sub-agents across tasks like data parsing, geospatial analysis, and interface generation [5], [8], [9], [10]. Multimodal interfaces allow them to interact with diverse data sources and synthesize outputs with minimal human intervention.

B. Applications in Spatial and Urban Intelligence

Agentic AI is particularly useful in spatial analysis, where it fuses geographic, social, and economic data to produce real-time, adaptive insights. These systems autonomously adjust strategies based on streaming inputs—detecting regional disparities, tracking infrastructure failures, or modeling urban mobility trends. [11] One practical example involves combining geo-tagged user content with Natural Language Processing (NLP)-based sentiment classification to generate real-time emotion maps [12]. These visualizations support data-driven urban planning, public engagement, and policy design by presenting nuanced spatial narratives.

In architecture and design, agentic AI enables human-in-the-loop workflows where agents interpret sketches, site data, and design goals. Unlike traditional generative tools, these agents can evaluate emotional impact, adapt plans in context, and engage in iterative dialogue with designers [13], [14]. This results in a new form of intelligent co-authorship, supporting site-sensitive, participatory design and emotionally responsive environments. Table 1 summarizes these key agentic AI capabilities and their functional outcomes, highlighting their relevance to spatial and urban intelligence applications.

TABLE I. AGENTIC AI CAPABILITIES AND OUTCOMES

Agentic AI Capability	**Functional Outcome**
Autonomous Data Parsing & Integration	Automatically reads and integrates structured/unstructured data (e.g. CSV, APIs) into usable forms
Contextual Trend Analysis	Identifies region-specific trends and adapts goals to dynamic socioeconomic shifts
Geospatial Reasoning & Visualization	Produces real-time spatial visualizations such as sentiment heatmaps or risk maps
Dynamic Planning & Decision-Making	Adapts strategies based on environmental feedback, supporting goal-driven decisions
Multimodal Interaction & Tool Use	Synthesizes text, data, and spatial info into cohesive analytic outputs

C. Applications in Sentiment Analysis

BERT (Bidirectional Encoder Representations from Transformers) is a deep learning model developed by Google that processes text bidirectionally, thereby enabling it to capture context more effectively than earlier models [15]. This capability makes BERT especially powerful for sentiment analysis, where understanding subtleties such as sarcasm, negation, or contextual shifts is essential. In sentiment scoring, BERT is fine-tuned on labeled datasets: input text is tokenized and passed through the model to produce contextual embeddings, with a classification layer on top of the [CLS] token predicting sentiment categories such as positive, negative, or neutral [16].

Agentic AI—systems capable of autonomous, goal-directed behavior—can be integrated with BERT to interpret sentiment in real time and act on it [17]. In smart city applications, for example, agentic systems equipped with BERT can analyze geo-tagged user reviews to suggest context-aware improvements based on public sentiment. The synergy between BERT's advanced language understanding and agentic AI's autonomous responsiveness enables intelligent systems that not only interpret human emotions but also adaptively respond to them in meaningful and timely ways.

D. Challenges in Urban Spatial Sentiment Analysis

Extracting neighborhood-specific emotional insights from geo-located reviews presents several technical and interpretive challenges. A primary difficulty lies in parsing unstructured, vague user queries—such as "What is it like in Sinchon?"—and linking them to specific geographic regions. This process often struggles with linguistic ambiguity and the inconsistent representation of place names across platforms [18]. While tools like the Google Places API can retrieve structured data from informal queries, their efficacy is undermined when faced with slang, informal speech, or misspellings common in user-generated content. This mismatch frequently results in partial matches or the return of nearby but irrelevant venues lacking meaningful emotional data.

Another major hurdle was the loss of nuance in sentiment summaries. Even when sentiment scores were correctly computed for each venue, aggregated visual outputs often produced generic or undifferentiated heatmaps that failed to reflect the distinctive emotional character of a neighborhood. Base models also misclassified sarcasm, regional slang, or ambivalent reviews, leading to misleading sentiment readings [2]. To address these problems, we introduced system-level strategies, including prompt engineering, review filtering, and spatial parameter tuning. These refinements made it possible to generate more accurate, context-sensitive emotional maps that better reflect the unique character of each urban area.

III. DEVELOPMENT

A. Methodology for Spatial Sentiment Analysis

To address early interpretability issues, we refined the system pipeline across three areas: review filtering, sentiment computation, and spatial rendering. First, we implemented a Gemini-based query interpretation module that reformulates user queries into structured formats compatible with Google's searchText() and searchNearby() endpoints. This allowed us to retrieve place IDs, names, and geocoordinates for up to 1,000 relevant venues. Metadata collected included review counts and star ratings, enabling targeted retrieval of emotionally relevant places.

For sentiment analysis, we used the DistilBERT-base-uncased-finetuned-SST-2 model from Hugging Face, a compact version of BERT that preserves much of its performance while being faster and more lightweight [16]. To reduce noise, we filtered out reviews with confidence scores below 0.6—a threshold determined through validation on sample queries. Each valid review was scored using a weighted formula, with labels assigned as "Positive" or "Negative" depending on sentiment and scaled by the model's confidence. The following equation was used to calculate the sentiment score for each review:

$$\text{sentiment score} = \begin{cases} c, & \text{label} = \text{Positive} \\ -c, & \text{label} = \text{Negative} \end{cases}$$

Here, *c* represents the confidence score provided by the DistilBERT model during classification. This means the sentiment score could range from -1 (extremely negative) to 1 (extremely positive), with 0 indicating neutral sentiment. A separate popularity score was added to correct for the overrepresentation of sparsely reviewed venues for the spatial sentiment analysis of the desired location. We defined the equation used to measure relative popularity as:

$$\text{popularity score} = \overline{rating} \times \log(\text{total reviews} + 1)$$

This metric factored in both review count and average rating, helping to surface places with sustained public engagement and emotional impact.

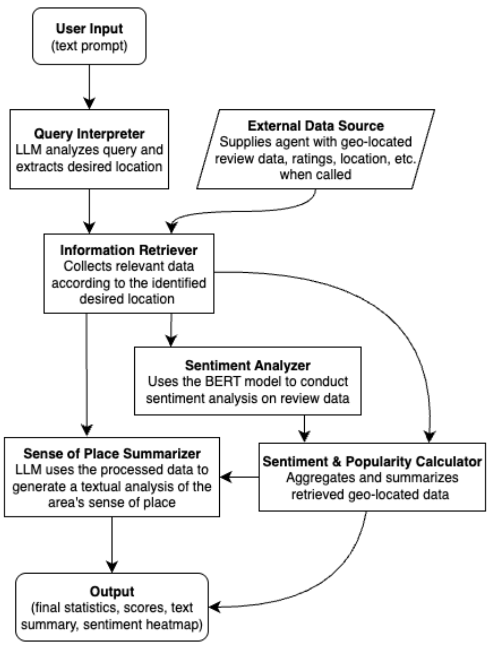


Fig. 1. Agentic Data Processing Methodology

B. *Visualization and Model Adaptation*

The spatial visualization component was optimized using Deck.gl's HeatmapLayer, where early maps suffered from over-clustering or lack of granularity. We resolved this by empirically tuning key parameters. The radiusPixels value was set to 40 for neighborhood-level resolution, while aggregation was set to 'SUM' to reflect cumulative sentiment intensity. The intensity parameter remained at 1 to ensure visual scaling consistency, and a threshold of 0.03 was applied to exclude weak signals. These calibrated parameters allowed the heatmaps to surface meaningful emotional contrasts across city neighborhoods without overwhelming users with visual clutter.

In parallel, we applied prompt engineering to refine the prompting strategy for the language model used to summarize neighborhood sentiment. To improve this, prompts were restructured to explicitly reference relevant statistics, place names, and a consistent descriptive tone. This, combined with sentiment filtering and improved spatial rendering, enabled us to extract more interpretable and reproducible emotional patterns from urban review data—without retraining the sentiment model itself. The result is a scalable system that links unstructured queries to meaningful, location-specific emotional insights.

IV. Evaluation and Results

A. *Case Study of Sinchon, Seoul*

To assess the system's practical utility, we conducted a case study of Sinchon, a lively student-focused neighborhood in western Seoul [19]. Using the Google Places API, the agent collected 826 user reviews from venues within 1.5 km of the center of Sinchon. After filtering out low-confidence sentiment predictions (below 0.6) using the DistilBERT model, we aggregated sentiment scores by venue.

Sinchon-dong showed an average sentiment score of 0.47, indicating a moderately positive tone. Examining the agent's output for Sinchon in Fig. 3 reveals sentiment hotspots around Yonsei-ro and Hyundai Department Store U-PLEX, highlighting areas described as vibrant and socially energetic. In contrast, side streets showed neutral sentiment or sparse data. Notably, venues with similar star ratings (e.g., 3.9 vs. 4.0) often had differing sentiment densities, underscoring the added nuance captured by textual analysis over numeric ratings.

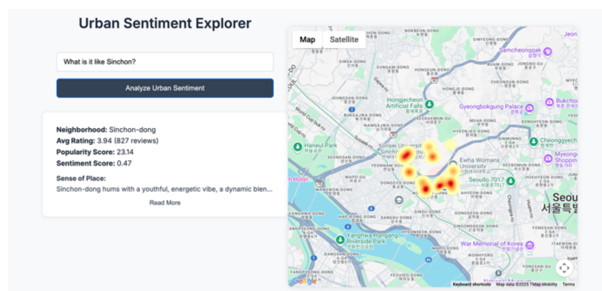


Fig. 2. Spatial Sentiment Agent User Interface (UI) Output for Sinchon

The language model-generated summary accurately captured the area's lived experience. It described Sinchon as " a vibrant blend of academic pursuits and trendy urban life," emphasizing the influence of Yonsei and Ewha universities, the presence of trendy cafés and global franchises, and a sense of constant activity. Moderately positive sentiment was interpreted as a reflection of overall contentment, though occasional mentions of crowding and busy foot traffic tempered the tone. The summary reinforced observations from the heatmap and structured metrics, tying spatial and emotional dimensions into a cohesive narrative. An excerpt from the output for Sinchon's sense of place goes as follows, highlighting the agent's ability to utilize the information it received from the API call to understand the area's sense of place and visualize it through the sentiment map:

"Sinchon-dong pulses with youthful energy, a vibrant blend of academic pursuits and trendy urban life. The presence of Yonsei and Ewha Women's University infuses the area with a studious, yet stylish atmosphere, reflected in the modern storefronts and student-friendly eateries. While the average

rating of 3.9 and a positive sentiment of 0.47 suggest generally pleasing experiences, the high review count (827) and popularity score (23.14) tell a tale of a bustling hub, constantly in motion ... Sinchon offers a dynamic mix of tradition and innovation ... The presence of trendy accommodations and hostels reflects a visitor-friendly environment. The numerous and well-visited establishments ... all contribute to a lively, accessible, and student-centric vibe."

B. Comparative Analysis: Sinchon-dong vs. Seongsu-dong

To demonstrate the system's ability to differentiate neighborhoods with distinct identities, a second analysis was performed on Seongsu-dong, an emerging neighborhood known for creative studios and post-industrial redevelopment [20]. Approximately 817 reviews were processed using the same sentiment classification pipeline. The resulting sentiment map on Table III for Seongsu-dong displayed more dispersed and less intense hotspots, with sentiment clustering around repurposed warehouses, cafés, and boutique venues. The average sentiment score was slightly lower than Sinchon's, and user language in reviews leaned toward aesthetic appreciation and spatial openness rather than social vibrancy.

TABLE II. GEO-LOCATED REVIEW DATA

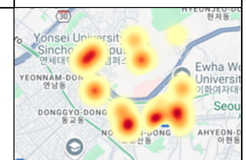
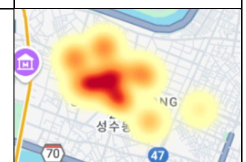
	Results			
Prompt (What is it like in ... ?)	***Identified area***	***Total reviews***	***Average rating***	***Popularity score***
Sinchon	Sinchon-dong	827	3.94	23.14
Seongsu	Seongsu-dong 2(i)-ga	817	4.33	22.99

The summary generated for Seongsu-dong characterized it as "artistic, slower-paced, and rooted in transformation," highlighting its shift from factory zone to creative enclave. Compared to Sinchon's compact and youth-driven energy, Seongsu-dong presented a more introspective and spacious mood. This comparison confirmed the system's ability to detect and articulate emotional distinctions between neighborhoods with different spatial configurations and cultural identities. The integration of sentiment maps and summaries enabled a side-by-side understanding of how two popular districts offer contrasting experiences, despite their comparable popularity. An excerpt from the output for Seongsu's sense of place goes as follows:

"Seongsu-dong 2(i)-ga pulses with a vibrant, revitalized energy. Its high average rating (4.3) and impressive review count (817) suggest a place where experiences consistently resonate. The popularity score (22.99) speaks to its emergence as a "hot spot," while the moderately positive sentiment (0.42) hints at a sophisticated, design-conscious atmosphere ... The neighborhood is a haven for the trendy and aesthetically-minded ... This blend of grit and glamour gives Seongsu a uniquely creative and cool edge ... It's a neighborhood where heritage meets innovation, where art, fashion, and food converge in a dynamic and stylish setting."

Overall, the system produced consistent, interpretable outputs across different neighborhoods. In Sinchon, the heatmap highlighted emotional hotspots, and the sentiment score of 0.47 matched its energetic, student-friendly atmosphere. In contrast, Seongsu-dong showed a calmer tone, demonstrating the model's ability to adapt to different cultural and spatial contexts.

TABLE III. AGENTIC SENTIMENT ANALYSIS

	Results		
Place	***Avg. Sentiment***	***Defining Keywords***	***Sentiment Map***
Sinchon-dong, Seoul	0.47	Youthful Lively Collegiate	
Seongsu-dong 2(i)-ga, Seoul	0.42	Trendy Industrial Artistic	

C. Observations on Output Quality and Interpretability

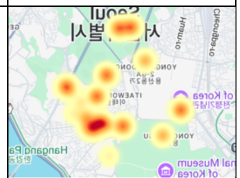
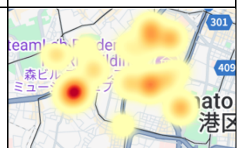
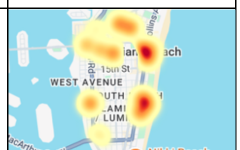
The system consistently produced interpretable outputs across diverse neighborhoods, demonstrating its robust ability to adapt to varying cultural and spatial contexts. This adaptability was evident in how the heatmaps and the summarized sense of place accurately reflected the distinct atmospheres of different urban areas, such as Sinchon's energetic vibe versus Seongsu-dong's calmer tone. This flexibility supports broader applications, including agentic spatial sentiment analysis on both the national and global scales. For example, Tables 3 and 4 compare Itaewon in Seoul, South Beach in Miami, and Roppongi in Tokyo, spaces all known for vibrant nightlife and foreign influence [21], [22], [23]. The agent effectively captured both their shared traits and distinct local identities.

TABLE IV. GLOBAL REVIEW DATA

	Results			
Prompt (What is it like in ... ?)	***Identified area***	***Total reviews***	***Average rating***	***Popularity score***
Itaewon	Itaewon-dong	5937	4.35	31.60
Roppongi	Roppongi	11679	4.16	34.45
South Beach	South Beach	5590	4.30	35.31

Rather than relying solely on numerical review scores, the system contextualized emotional feedback through both visualization and language generation. The synergy between quantified sentiment scores, visual heatmaps, and narrative descriptions offered a well-rounded understanding of urban sentiment, making the outputs accessible to a range of users—from city planners to tourists and local businesses. This confirmed the system's strength in extracting meaningful patterns from unstructured review data and translating them into spatially grounded, emotionally resonant insights.

TABLE V. GLOBAL AGENTIC SENTIMENT ANALYSIS

	Results		
Place	***Avg. Sentiment***	***Defining Keywords***	***Spatial Sentiment Map***
Itaewon-dong, Seoul	0.62	Cosmopolitan Diverse Dynamic	
Roppongi, Tokyo	0.57	Cosmopolitan Elevated Artistic	
South Beach, Miami	0.55	Glamorous Energetic Touristy	

V. CONCLUSION

This research presents a practical system for spatial sentiment analysis that uses geolocation data, sentiment classification, and large language model summarization to interpret public opinion across urban neighborhoods. By analyzing user-generated reviews, the system transforms raw data into visual and textual representations—such as sentiment heatmaps and narrative summaries—that reveal how emotions are distributed across space. These outputs provide a more intuitive understanding of public sentiment than star ratings or basic metrics.

Rather than offering a comprehensive view of urban emotion, this study introduces a structured method for comparing localized perceptions between neighborhoods. Its ability to highlight emotional hotspots, summarize public mood, and reflect neighborhood identity has potential applications in urban planning, tourism, and community engagement. The framework also opens many opportunities for future improvements, including the integration of multimodal data, tracking changes over time, and supporting multiple languages—making it a flexible and scalable tool for exploring the emotional dimensions of urban life.

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