Bridging Strange and Familiar: Design of Knowledge Expansion System via Daily Surroundings

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***Abstract*—Personalization technologies have made information increasingly tailored to individual interests, yet this very optimization risks narrowing the scope of what users encounter. Furthermore, even when users attempt to actively search for information, the scope of their discoveries is inherently limited by their interests. In this paper, we design a knowledge expansion system that leverages physical objects as triggers, guiding users toward domains beyond their existing interests. We also report an initial evaluation of its core bridging strategies as a preliminary step toward the full AR system, using two complementary approaches: *Making the Familiar Strange* and *Making the Strange Familiar*. The evaluation with 20 participants suggested potential for new perspective acquisition in everyday environments. The results also indicate limitations of static categorical profiling and suggest that effective bridging strategies differ depending on environmental familiarity.**

***Index Terms*—Serendipity, Recommendation Systems, Knowledge Expansion**

I. Introduction

Advances in information technology and recommendation systems have facilitated access to personalized information, enabling users to explore specific areas of interest deeply. However, excessive personalization causes systems to automatically filter out information beyond the user's current interests, leading to a phenomenon known as filter bubbles. To overcome this limitation, exploring unknown fields and fostering serendipity—the capacity to recognize and benefit from unexpected informational encounters—are effective methods; however, users face two primary barriers. The first is the limitation of active exploration: because exploratory behavior depends on the user's prior knowledge, exploring completely unknown domains is difficult. The second is the limitation of passive presentation: even when users are presented with random, unknown information, they often fail to perceive its value due to a lack of connection with their existing knowledge, leading them to dismiss it as noise. To bridge these cognitive gaps, information should be contextually grounded in the user's existing knowledge while simultaneously introducing novel elements. While similar approaches could potentially be realized in digital spaces, linking novel information to objects embedded in users' everyday physical environments may offer a distinct advantage for serendipitous discovery, since familiar surroundings provide a grounding context that could lower the cognitive barrier to engaging with unfamiliar content. Moreover, because user-initiated interaction is inherently biased toward existing interests, AR can complement user-initiated interaction by enabling the system to proactively present information about objects the user would otherwise overlook. In this paper, we present the design of a knowledge expansion system that uses physical objects as triggers to bridge users' interests toward domains beyond their existing interests. We also report an initial evaluation of its core bridging strategies as a preliminary step toward the full AR system.

The contributions of this paper are threefold: **(1)** A bridging framework that uses physical objects as triggers to connect information within and outside users' interest domains, comprising two complementary approaches: *Making the Familiar Strange* and *Making the Strange Familiar*. **(2)** Preliminary insights into the limitations of static categorical profiling for capturing user interests in physical environments. **(3)** An empirical indication that the effectiveness of bridging strategies varies depending on the familiarity of the environment.

II. Related Work

A. Filter Bubbles and the Limits of Information Discovery

Excessive information optimization creates filter bubbles, confining users to their existing interests. To counter this, serendipity-based recommendations have been proposed, utilizing large language models (LLM) [1], latent preference alignment [2], or dynamic receptivity assessment [3]; however, these approaches remain confined to digital behavioral histories; meanwhile, even active discovery is inherently limited by users' prior knowledge. Physical environments, unlike algorithmically filtered digital systems, contain diverse objects independent of personal preferences. Therefore, they can offer an opportunity for serendipitous discovery.

B. AR Information Presentation and Image Context in Physical Spaces

AR systems have evolved from task-oriented metadata retrieval through the integration of physical and digital entities [4]. Recent efforts have extended this to knowledge discovery, using smart glasses and vision language models (VLM) to surface contextually relevant information from physical environments [5]. However, these approaches primarily aim to deepen users' existing interests, potentially narrowing their

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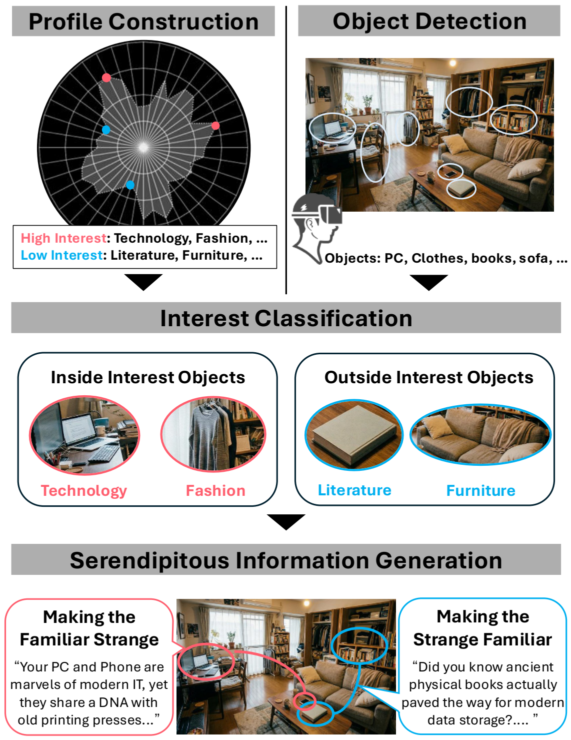

Fig. 1. System Overview. The pipeline covers profile construction, object detection, interest classification, and information generation.

focus to familiar domains [6]. Consequently, bridging users from familiar objects toward domains outside their current interests remains unaddressed in physical spaces.

C. Cognitive Models Supporting Knowledge Expansion

As a theory for guiding users into unfamiliar domains, defamiliarization—the intentional presentation of the familiar everyday as the unfamiliar—is considered crucial [7]. As Data/Frame Theory demonstrates, when the surprise of defamiliarization causes existing cognitive frameworks to break down, humans transition to a process of sensemaking [8]. This behavior is explained by information foraging theory, which models the trade-off between benefits and costs [9]. Taken together, these theories suggest that fostering knowledge expansion in everyday spaces calls for defamiliarization to disrupt automated cognition, while leveraging existing knowledge as a bridge to manage the cognitive costs of exploration.

III. System Design

Serendipitous discovery in physical environments requires both accurate modeling of user interests and context-aware information generation. To address these challenges, we present the design of a system that uses physical objects as triggers for knowledge expansion.

A. System Overview

As illustrated in Fig. 1, this system semantically extends spatial environments by integrating visual environmental information with user interest profiles. First, the user's interest profile is constructed through Profile Construction prior to system use. Next, Object Detection is performed to identify objects within the user's field of view, while VLM extracts detailed visual context explaining the object's presence in that specific setting. The system then performs Interest Classification by calculating the linguistic similarity between the extracted object information and the user's profile, determining whether the observed object falls inside or outside the user's existing areas of interest. Finally, based on this classification, Serendipitous Information Generation produces contextual bridges to guide the user toward domains beyond their existing interests.

B. User Interest Profiling

To ensure this architecture functions effectively in physical environments, we propose an interactive profiling system. Standard categorical metrics suffer from severe granularity issues, failing to capture subtle differences in user preferences. Conversely, relying solely on free-text descriptions is limited by users' ability to articulate their preferences. Therefore, the proposed system combines a semantic vector space with progressive elicitation. The system dynamically presents specific trigger items, including both potentially interesting and uninteresting concepts. By having users rate their degree of interest, the system applies positive and negative weights to shift their profile vector.

C. Contextual Bridging Approaches

Based on the user's interest profile and whether the target object falls inside or outside those interests, the system generates contextual bridges rather than merely displaying facts. Specifically, it employs the following two approaches:

- Making the Familiar Strange (F→S): For objects within the user's interests, this approach introduces topics from lower-interest domains, expanding toward perspectives outside current interests.
- Making the Strange Familiar (S→F): For objects outside the user's interests, high-interest topics serve as a bridge to link unfamiliar objects to familiar knowledge, evoking curiosity toward new domains.

D. Adaptive Information Generation

To ensure users naturally accept the generated contexts, we propose a dynamic control system. Because our approach intentionally bridges high-interest and low-interest elements, a simple binary evaluation of interest is insufficient. Heavily detailing a low-interest theme, for instance, may lead to user rejection. Therefore, the proposed system is designed to dynamically adjust the granularity of the generated narrative based on specific interest levels. When introducing an uninteresting theme, the system keeps the information coarse-grained and accessible. Conversely, when using a user's strong interest as a familiar trigger to explain an unknown object, the system can utilize fine-grained details to bridge the semantic gap. This dynamic adjustment aims to ensure that unexpected connections remain logical and comprehensible to the user.

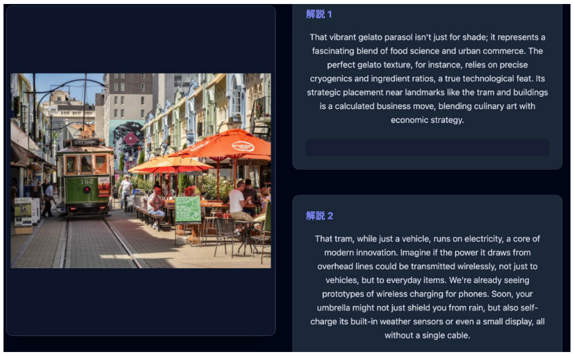

Fig. 2. Evaluation System Overview. Static images replaced live AR input in this preliminary evaluation.

IV. Evaluation of Core Approaches

In this section, as an initial step toward the full system, we evaluate the core information generation approaches to verify two core aspects: (1) whether the contextual bridging approaches: F→S and S→F, function effectively with real-world environmental content, and (2) how accurately the current categorical profile maps to users' actual interest in real-world objects.

A. Experimental Setup

*1) **Participants and Stimuli.**:* We conducted a within-subject experiment with 20 participants (aged 20–60, majority graduate and undergraduate students in their 20s) using five static images rather than a live AR environment. The five images ranged from least to most familiar: a wildlife safari, an overseas street, a Japanese street, an indoor room, and a scene from the participant's own daily life. Before the experiment, participants rated their interest in 40 categories of the IAB Content Taxonomy [10] using a 7-point Likert scale to construct their initial interest profiles.

*2) **System Implementation.**:* The system utilized Gemini 2.5 Flash for VLM-based scene context extraction and LLM-based explanation generation, with prompts incorporating the detected object label, scene context, and user interest profile. Object labels and IAB category descriptions were embedded via a sentence-transformer model (L2-normalized), and the interest score for each object was computed as:

$$\text{Score} = \cos(\mathbf{v}_{c^*}, \mathbf{v}_{\text{obj}}) \times w_{c^*} \quad (1)$$

where $c^* = \text{argmax}_c \cos(\mathbf{v}_{\text{obj}}, \mathbf{v}_c)$ is the most similar IAB category, $\mathbf{v}_{\text{obj}}$ is the object label embedding, and $w_{c^*} \in [0, 1]$ is the normalized user interest weight for c^*. Objects scoring above 0.5 were assigned to F→S, others to S→F.

*3) **Comparison Methods.**:* We compared the two proposed approaches against the following comparison methods:

- Baseline: A simple description of the object's context
- Comparative Method: Based on AiGet [5], generating information optimized for utility, novelty, and relevance within existing interests as a state-of-the-art reference for knowledge discovery.

Each method employed a prompt tailored to its respective information generation strategy.

*4) **Measures.**:* For each object detected in the presented images, participants provided a binary manual rating (Interested or Not Interested) to evaluate the accuracy of the system's interest assessment. For each presentation, participants evaluated the "acquisition of new perspectives" as a primary indicator of knowledge expansion, using a 7-point Likert scale (1. Not at all to 7. Very much), specifically responding to: "Did the explanation provide new discoveries or unexpected perspectives on things you weren't previously interested in?" Fig.2 shows the system overview for this evaluation.

B. Results

Two main trends were observed in the experiment. The first concerns the relationship between interest expansion and everyday familiarity, and the second concerns the accuracy of interest profile determination.

1) Relationship between the expansion of interest and everyday familiarity: Both proposed methods scored higher than the baseline, suggesting that object-triggered information presentation in physical spaces has potential to facilitate new perspective acquisition. F→S scored consistently lower than the Comparative Method, yet remained relatively stable across all conditions, in contrast to the familiarity-dependent decline observed in Comparative Method scores. A notable trend was also observed in relation to environmental familiarity. In familiar everyday environments, S→F scored higher on average than the Comparative Method, suggesting potential for new perspectives on typically overlooked objects. In contrast, in unfamiliar environments, scores for the Comparative Method were higher on average than those of S→F (See Fig.3).
2) Accuracy of profile determination: Although a weak positive correlation was observed between the system's interest assessment and participants' subjective evaluations, the two did not perfectly align (See Fig.4).

C. Discussion

The evaluation results highlighted both the potential and the challenges of supporting knowledge expansion in real-world environments. The following subsections discuss the implications of these findings in relation to the system requirements identified in the system design.

1) Spatial familiarity and knowledge discovery: The results suggest that when viewing scenes of familiar everyday spaces, users likely focus on their existing interests while ignoring other items, pointing to the potential of S→F in providing new perspectives on typically overlooked objects. Conversely, when viewing unfamiliar scenes, users appear to prefer explanations directly linked to their existing interests to quickly orient themselves. For familiar everyday scenes, therefore, S→F may be more effective in re-contextualizing mundane objects through defamiliarization, as users may already possess sufficient knowledge about surrounding objects.

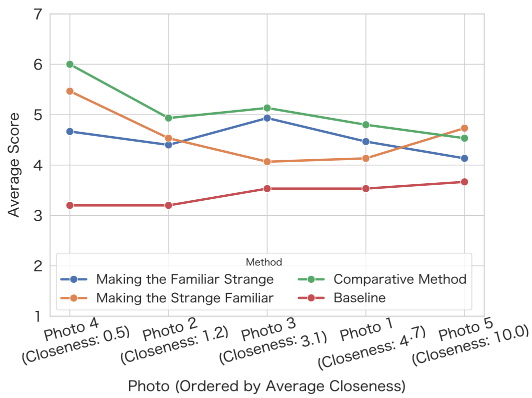

Fig. 3. New Perspective Acquisition by Method and Environment Familiarity. Scores (7-point Likert) averaged per photo, from least to most familiar.

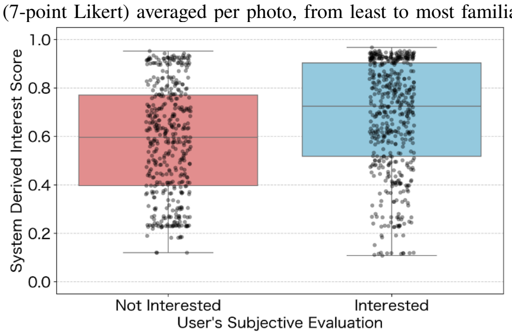

Fig. 4. Correlation between Interest Score and User Response. System score vs. manual user rating ($r = 0.215$, $p < 0.001$, $N = 950$).

F→S, which bridges from familiar objects toward entirely unknown domains, showed more consistent but lower scores overall, suggesting larger semantic gaps may require stronger scaffolding. These findings also suggest that effective bridging may require dynamic adjustment of information granularity to accommodate varying levels of environmental familiarity.

2) Limitations of categorical granularity: The mismatch between the system's interest scores and actual user responses likely occurred because we simply applied broad web content categories to physical objects. While the results indicated some tendency toward interest classification, the static categorical approach based on the IAB taxonomy indicated limitations in accurately capturing users' fine-grained preferences in physical environments. These findings suggest that to accurately capture fine-grained interests in the real world, a personalized, interactive profile structure as we described in the system design may be necessary.

3) Information Acceptance Limits and Dynamic Control: While the system design aims to provide new perspectives, the results revealed practical limits to information acceptance. In some cases, forced or unnatural explanations appeared to reduce acceptance scores. This suggests that large semantic gaps in generated information may lead to user rejection. To maintain comprehensible connections, the system should dynamically control information granularity based on specific user interest levels.

V. Conclusion and Future Work

In this paper, we presented the design of a knowledge expansion system that uses physical objects as triggers to bridge users' interests toward domains beyond their existing interests, and reported an initial evaluation of its core bridging strategies as a preliminary step toward the full AR system. The two complementary approaches, *Making the Familiar Strange* and *Making the Strange Familiar*, showed potential for new perspective acquisition in scenarios simulating everyday environments. The evaluation also provided preliminary insights into the limitations of static categorical profiling, and suggested that effective bridging strategies differ depending on environmental familiarity. Future work will focus on implementing the interactive profile structure and dynamic granularity control, with the ultimate goal of realizing the full AR-based system through long-term studies in real-world environments using wearable devices such as smart glasses.

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