# Browsing Lost Unformed Recollections: A Benchmark for Tip-of-the-Tongue Search and Reasoning

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## Abstract

We introduce **B**ROWSING **L**OST **U**NFORMED **R**ECOLLECTIONS, a tip-of-the-tongue known-item search and reasoning benchmark for general AI assistants. BLUR introduces a set of 573 real-world validated questions that demand searching and reasoning across multi-modal and multilingual inputs, as well as proficient tool use, in order to excel on. Humans easily ace these questions (scoring on average 98%), while the best-performing system scores around 56%. To facilitate progress toward addressing this challenging and aspirational use case for general AI assistants, we release 350 questions through a public leaderboard, retain the answers to 250 of them, and have the rest as a private test set.

**Query**: I am trying to remember the title of a book I once read. It was published in 2017 and its cover had the image of a snowman looking over some mountains. It had something to do with the search for knowledge. I cannot remember the author of the book but he was a co-author of another book, Conversaciones para Triunfar. What is the title of the book I am looking for?

**File Input**: None

**Answer**: Hho the Snowman: The Great Journey

Figure 1: A sample **text-only** query and its corresponding answer from our BLUR dataset. An example that is multimodal *on input* is shown in Figure 4.

## 1 Introduction

Have you ever found it difficult to recall the name of something you can vividly describe? Like grasping at the memory of a movie whose title escapes you, even though its fragments remain vividly etched in your memory—the scene of a character gazing into the rain, murmuring something poignant about moments slipping away, or the way neon lights fracture through the downpour, casting the cityscape in wistful, melancholic hues. Unlike that of traditional search, *tip-of-the-tongue* (ToT) known-item retrieval queries (Arguello et al., 2021) (e.g. Figure 1) stand out for their varied information-seeking strategies, requirements of complex multi-hop reasoning, and frequent expressions of uncertainty. The continued growth of communities dedicated to resolving such ToT queries, like `r/TipOfMyTongue`, highlights this ongoing challenge and underscores an aspirational use case for improved solutions (Mun et al., 2024).

In this work, we introduce **B**ROWSING **L**OST **U**NFORMED **R**ECOLLECTIONS (**BLUR**), a multi-modal and multilingual benchmark for general AI assistants featuring 573 curated tip-of-the-tongue questions, validation chains, and corresponding answers. These queries represent real-world information needs, are easy to create and validate, and assess the capabilities of systems to reason under uncertainty. We hypothesize that, to excel on this benchmark, a general AI assistant will need to excel at multi-hop reasoning over multimodal information, scope potential uncertainty regions associated with questions, and be proficient in general tool use. For system designers, doing so will signify meaningful advancements in these capabilities (Wagstaff, 2012) as well as represent a major step towards addressing this challenging and aspirational real-world use case (Liu et al., 2024b). Human participants consistently score near-perfect results (98%) on these questions, while the best-performing system tested scores around 56%. Surprisingly, we find that the best agentic systems performed only marginally better than the base language models that power them, suggesting that large gaps remain in effective reasoning around tool use for this task. We open source a developer subset of 350 annotated questions from BLUR—while maintaining both public and private test sets—to avoid contamination and provide a fair and unbiased evaluation.

https://www.huggingface.co/datasets/PatronusAI/BLUR
[*]Work completed as a research fellow at Patronus AI.



*Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 8317–8331

## 2 Related Work

**Known-Item Retrieval.** In information retrieval, tip-of-the-tongue known item retrieval has emerged in recent years as a new challenge task for information retrieval systems. Using online community-based posts and answers from sources like Reddit (Bhargav et al., 2022), datasets for known item retrieval have mostly centered around movie (Arguello et al., 2021), music (Bhargav et al., 2023), and book (Lin et al., 2023) identification. Qualitative coding schemes and analyses of posts in these communities reveal that people mostly use such platforms for general entertainment or leisure information identification (Meier et al., 2021; Fröbe et al., 2023; Bogers et al., 2024). Using these datasets, recent work has explored leveraging LLMs to break down complex queries into their essential components through prompting (Lin et al., 2023), within content re-ranking (Borges et al., 2024), and in generating clarification questions (Chi et al., 2024). Furthermore, Kim et al. (2024) illustrate the potential for advancements in ToT identification to support patients with anomia, a difficulty in identifying the names of items.

Despite this wealth of online data, directly translating these sources into a task that both validly measures the ability of AI assistants to perform this task and evaluates underlying system capabilities remains a challenge. The first challenge lies in answer ambiguity. Multiple items may accurately match a user's query, as evidenced by the variety of responses typical posts receive. Measuring *correctness* becomes difficult with query underspecification, causing the number of *valid* answers to be unknown in a near-infinite set of possibilities (Arguello et al., 2021). The second challenge lies in the valid measurement of underlying system capabilities. Answers are often provided without explanations of their derivation, making it unclear which abilities a system must possess to perform well and obscures the skills ultimately being tested for a benchmark dataset (Liu et al., 2024b). The third challenge lies in data contamination. As most LLMs that power these systems are trained on publicly available internet data, contamination risks compromise the validity of evaluation results (Sainz et al., 2023). Here, we tackle these three challenges by ensuring questions have *unambiguous answers*, incorporate human reasoning chains for more robust *capability grounding*, and keep a private test set to *avoid data contamination.*

**Multi-Hop Reasoning and Retrieval.** Complex real-world tasks often demand more than single-step retrieval; they require sophisticated, multi-hop reasoning that aggregates information from multiple sources and modalities. ToT exemplifies this complexity, calling for iterative data gathering, reasoning, and comparative analysis (Arguello et al., 2021). While existing benchmarks highlight the importance of multi-step reasoning for tasks such as coding, data analysis, and open-ended question answering (Petroni et al., 2021; Jimenez et al., 2024; Hu et al., 2024), they do not fully capture how LLMs can dynamically plan and retrieve content from multimodal tools, including map or video platforms. Liu et al. (2024a), Yoran et al. (2024), and Deng et al. (2023) extend benchmarking by introducing operating system access, map navigation, and other utilities, thereby underscoring the significance of multimodal reasoning. However, these approaches rarely address ambiguous queries, misleading descriptions, or multi-domain exploration akin to real-world conditions. BLUR fills this gap by requiring complex, scenario-based reasoning and multilingual capabilities over a broad spectrum of multimodal tools.

**Evaluation.** Large language models are saturating measurements of their capabilities at an increasingly unprecedented rate (Kiela et al., 2023), spurring a surge of techniques aimed at pinpointing their vulnerabilities. Methods like adversarial and dynamic benchmarking rely on iterative, model-in-the-loop data collection to produce increasingly difficult tasks for existing models (Kiela et al., 2021; Wei et al., 2024). While these approaches successfully expose weaknesses, they often generate tasks that lack ecological validity (Bowman and Dahl, 2021; Phang et al., 2022; De Vries et al., 2020; Liu et al., 2024b) and do not reflect how models will be used in real-world scenarios (Liao and Xiao, 2023). Our field of evaluation must move beyond merely identifying shortcomings and instead broaden our evaluation strategies to address *genuine* cross-capability performance in *real-world contexts* (Bowman and Dahl, 2021).

Because human evaluation is expensive and hard to scale, many assessments resort to automated or simplified methods, including model-based judgments (Zheng et al., 2023) or string matching and multiple-choice questions for correctness checks. However, multiple-choice formats can obscure flawed reasoning, since a model may arrive at the correct answer without demonstrating a sound solution path (Mialon et al., 2024). Although substantial effort has gone into evaluating the specialized abilities of LLMs (Hendrycks et al., 2021; Rein et al., 2024), recent work has shifted attention to measuring general-purpose proficiency. Most of these efforts rely on closed systems or predefined API interactions (Patil et al., 2024; Li et al., 2023; Liu et al., 2024a), which may reward familiarity with specific APIs over broader, more transferrable competencies. To address these limitations, recent research—such as OpenAGI (Ge et al., 2024) and GAIA (Mialon et al., 2024), along with tasks like OSWorld (Xie et al., 2024) and systems like Claude 3.5 Sonnet's computer use (Anthropic, 2024)—advocates broader evaluations by foregoing strict API constraints and embracing more open real-world interactions. Similarly, Dynasaur (Nguyen et al., 2024) investigates the on-the-fly creation and execution of task-specific tools, employing code as a unifying representation. In BLUR, we focus on *human-driven tasks*, prioritize simplified automated evaluation, and center on aspirational general AI assistant capabilities.

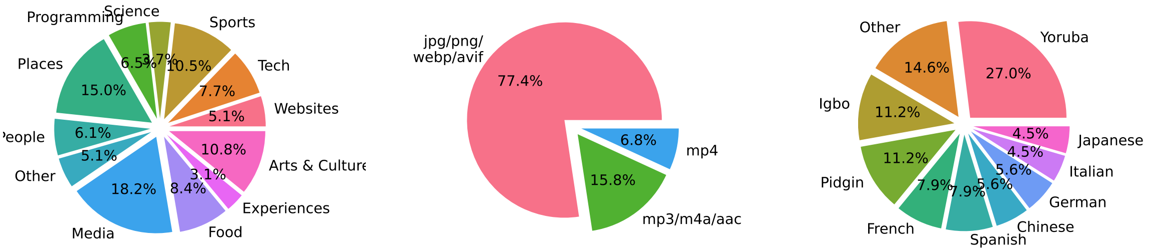
# 3 The BLUR Benchmark

BLUR is a benchmark designed to evaluate general AI assistants on a series of tip-of-the-tongue known-item retrieval tasks. It comprises 573 text-based questions covering a variety of topical domains, with 25% including additional input from a different modality (e.g., image, audio, or video) in the form of a file attachment. Although all prompt instructions are primarily in English, 30% of the queries are multilingual in the sense that they either directly feature descriptions written in other languages or reference items that are primarily available online in a different language other than English. Answers to these queries are validated to be unambiguously correct and formatted as concise strings for automatic verification either through a direct weak string match or with the help of an LLM-Judge. BLUR is easy to use, requiring only a zero-shot prompt with provided scaffolding against an AI assistant for answer elicitation. Success on BLUR demands strong multi-hop reasoning, effective tool use, and prompt uncertainty and ambiguity handling. Figure 2 illustrates the distribution of prompts across domains, file extensions, and languages. The following sections outline the design principles, question guidelines, dataset composition, and evaluation methodology. The set of guidelines given to annotators and annotator details are shown in Appendix Section A.

## 3.1 Goals and Design Choices

To construct this dataset, we invited annotators to reflect on recent or current instances where they struggled to recall the name of something. Annotators were asked to describe everything they could recall about the item in question, framing it as a prompt they might use to seek help online or from a friend. Annotators were also given the option to upload a file in addition to providing a text input if they wished. We then tasked the writer with locating the item whose name they struggled to recall. Separately, a different annotator (the validator) was challenged to identify the item based solely on the original query provided by the writer. Both annotators were given access to a web browser and documented their search process step by step. If the validator's answer matched the writer's, the prompt was included in the final dataset. Otherwise, we presented the validator with the correct answer along with the writer's search steps and evaluated *posthoc agreement*—whether the validator acknowledged their error and could clearly articulate their mistake. If posthoc agreement was achieved, the prompt was included in the final dataset; otherwise, it was discarded. Prompts were finally minimally edited to standardize formatting and correct typos.

**Unambiguous Answers.** The majority of the effort in this two-stage dataset creation process—prompt writing followed by validation—focused on ensuring that the prompts were unambiguous, meaning they led to a single, correct answer (Rein et al., 2024; Mialon et al., 2024). In doing so, we deliberately avoided adversarial dataset construction, as it not only obscures the specific abilities benchmarks aim to measure (Bowman and Dahl, 2021), but also undermines ecological validity (De Vries et al., 2020). While the uniqueness of these items is sure to evolve over time—for example, a building might be replaced or new film releases might echo details in earlier films—we address potential *eventual ambiguities* by specifying the exact date the question was asked as part of the evaluation prompt scaffold (Figure 4). In addition, we periodically re-examine the *sources of truth* that validators relied upon to confirm their answers, ensuring that these details remain accessible and verifiable by systems.




(a) Prompt Domains (b) File Extensions (c) Non-English Languages

Figure 2: Distribution of prompts across **topical domains**, **file extensions** for prompts with attached files, and non-English-language-only prompt **languages**. Note that 75% of prompts are text-only without attached files, and 70% are exclusively in English.

**Multimodal and Multilingual.** While annotators were instructed to write their prompts in English, no language restrictions were placed on the details of the items remembered. Approximately 30% of our dataset is notably multilingual. This includes cases where descriptions are written in other languages or where the descriptions are in one language but the item itself belongs to a different language. Similarly, 25% of our dataset is multimodal *at input*, featuring prompts accompanied by file attachments rather than being exclusively text-based. This contrasts with Reddit-based ToT datasets in information retrieval (Meier et al., 2021), where attachments—though originally included in the posts by users—are typically removed or ignored during preprocessing. Files included sketches of the items recalled, similar images found online, video and audio files in which the item appeared in, and more. Note that, in addition to the explicit multimodal understanding required to process file inputs, a majority of queries in BLUR also require reasoning over multimodal sources of information encountered in web searches (images, videos, and more) despite being only text-based.

**Ease of Use.** Answers in the dataset are concise, consisting of a single string that can be evaluated for correctness using a weak string match with a LLM Judge (similar to Wei et al. (2024)). Prompts are designed for zero-shot answering and evaluation, structured within a question scaffold (Figure 4) that constrains the date the question was asked as well as the answer format. In practice, when faced with a ToT problem, user preferences may intuitively be split between favoring single-turn interactions or iterative engagement with a general AI assistant, correcting its mistakes over multiple conversation rounds to arrive at the correct answer.

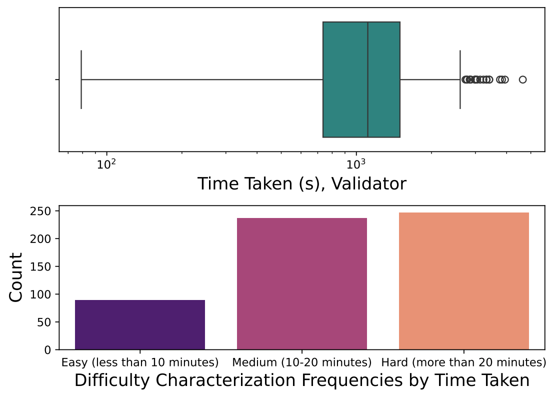



Figure 3: Distribution of **response times** taken by validators to answer questions (top) and the breakdown of **query difficulty** levels (bottom) as characterized by splits based on those times.

Here, we focus on the former usage scenario, curating questions depicting real information needs that *can* be resolved within a single turn.

**Hard to Game.** Data contamination and memorization pose significant challenges to accurately assessing a system's capabilities (Sainz et al., 2023). While it is not entirely impossible that similar questions or answers to some questions may exist in pretraining data by chance, the possibility of checking reasoning traces provides an additional mechanism to assess tool use and detect memorization behavior. Finally, we offer multiple leaderboard variations: one with a public validation set (including answers), another with a public test set (excluding answers), and a fully private test set (with both questions and answers withheld). These mitigations are designed to help ensure that improvements in system performance on this benchmark dataset reflect genuine advancements in system capabilities. Should memorization still occur despite these safeguards,

**Prompt Scaffold**: You are a general AI assistant assigned to help a user identify an entity they have forgotten. Below is the user's query, asked on December 15th 2024, consisting of a textual description possibly accompanied by an optional file attachment. Approach the task methodically, utilizing all available tools, and document each step you take in detail. Conclude your response with the following format: Final Answer: [Your final answer]. Your final answer should accurately provide the answer to the user's query as a short string.

**Query**: I visited a bank in Ibadan with a friend, but I can't recall its name or location. It was my first time in Ibadan, so my memory of the place is a bit vague. However, I remember taking a picture of an attractive building located opposite the bank. I'll attach the picture, can you help me identify the bank and its address?

**File Input**:

**ChatGPT 4o**: from PIL import Image...

[Matplotlib Chart]

Searching Google Maps...

Based on the information provided and the image analysis, it appears that the bank you visited in Ibadan is the First Bank - Ibadan Ring Road Branch, located at 15 MKO Abiola Way, Oluyole, Ibadan 200212, Oyo, Nigeria. [Business List]

**Final Answer**: First Bank - Ibadan Ring Road Branch, 15 MKO Abiola Way, Oluyole, Ibadan 200212, Oyo, Nigeria

**Ground Truth**: Zenith Bank: 108, Lagos bye-pass Challenge, Ibadan.

**LLM Judge**: Weak String Match Result: FALSE

Figure 4: **Evaluation instance example** of a medium-difficulty query with a file input. The prompt scaffold is shown, along with the output provided by ChatGPT 4o and LLM Judge weak string match result. The step-by-step validation chain that a human validator took to answer this query is shown in Figure 5. Code execution in output is highlighted in gray, while web search is highlighted in orange; both are truncated for simplicity.

practitioners can easily create new questions by following the guidelines outlined in Appendix A.

### 3.2 Composition

Figure 2 illustrates the distribution of queries across topical domains, as categorized by the authors using a grounded coding scheme. It also highlights the file extensions associated with queries that include file inputs and the language capabilities identified by annotators as necessary to answer each query accurately.

**Query Domains and Capabilities.** Consistent with prior studies of posts in ToT information communities online (Fröbe et al., 2023), most prompts fall into the *Media* category, with queries about songs, movies, videos, shows, and books, among others. We characterize the capabilities required of general AI systems to perform perfectly on BLUR via grounded coding on the validation chains annotators recorded when answering queries. Below, we report the capabilities, as well as specify concrete examples of tools used by annotators. Note that tools may fall into more than one capability characterization.

- **Web Browsing**: Internet-based browsing and navigation. Examples include Google Search, Google Maps, and Wikipedia.
- **Multimodality**: Understanding visual and audio information. Examples include Youtube, Spotify, Bing images, Optical Character Recognition, Google Street View, Reverse Image Search, Google Lens, and Speech to Text.
- **Multilinguality**: Comprehension of textual information in languages other than English.

| BLUR Performance (↑) | | | | | | |
|---|---|---|---|---|---|---|
| Model / System | $Q_T$ | $Q_F$ | $H_E$ | $H_M$ | $H_H$ | Overall |
| Llama-3.1-405B | 0.34 | 0.17$^\circ$ | 0.35 | 0.32 | 0.25 | 0.30 |
| claude-3-5-sonnet-20241022 | 0.44 | 0.28$^\bullet$ | 0.42 | 0.42 | 0.36 | 0.40 |
| gpt-4o-2024-11-20 | 0.42 | 0.28$^\bullet$ | 0.39 | 0.43 | 0.35 | 0.38 |
| o1-2024-12-17 | 0.54 | 0.36$^\bullet$ | 0.56 | 0.52 | 0.44 | 0.49 |
| DeepSeek-R1 | 0.45 | 0.27$^\circ$ | 0.46 | 0.44 | 0.35 | 0.41 |
| Microsoft Copilot | 0.29 | 0.23$^\bullet$ | 0.29 | 0.32 | 0.22 | 0.27 |
| Mistral Le Chat | 0.40 | 0.27$^\bullet$ | 0.47 | 0.38 | 0.32 | 0.37 |
| Perplexity Pro Search | 0.31 | 0.15$^\bullet$ | 0.29 | 0.29 | 0.24 | 0.27 |
| ChatGPT-4o | 0.53 | 0.36 | 0.60 | 0.52 | 0.41 | 0.49 |
| HuggingFace Agents + Claude 3.5 Sonnet | 0.61 | 0.41$^\bullet$ | 0.60 | 0.56 | 0.54 | 0.56 |
| DynaSaur + GPT-4o | 0.58 | 0.27 | 0.61 | 0.52 | 0.44 | 0.50 |
| Operator | 0.57 | 0.46$^\bullet$ | 0.56 | 0.56 | 0.52 | 0.54 |
| Search Engine | 0.05 | 0.03$^\bullet$ | 0.08 | 0.05 | 0.02 | 0.04 |
| **Human** | **0.98** | **1.00** | 0.98 | 0.98 | 0.99 | **0.98** |

Table 1: **System and model performance** on the BLUR benchmark. $Q_T$ and $Q_F$ denote performance on text-only queries and queries with file inputs, respectively. System support for file inputs is indicated, where ○ signifies that the system does not support file uploads and ● denotes partial support of certain file type extensions; the absence of a circle denotes that all file type uploads are supported. $H_E$, $H_M$, and $H_H$ represent system performance on *easy*, *medium*, and *hard* query difficulty subsets, respectively.

Examples include Google Translate, Microsoft Translator, and webpage translation.

- **File Reading**: Understanding information present in files of various types. Examples include VLC, iTunes, and Photo Viewer.

**Difficulty.** The time validators took to answer these queries naturally serves as a proxy of their difficulty level for humans. Based on these times, we divided the dataset into three difficulty levels: *easy*, for questions resolved in under 10 minutes, *medium*, for those requiring 10 to 20 minutes, and *hard*, for those taking over 20 minutes to answer. Figure 3 illustrates the distribution of times taken by annotators to arrive at their answers, along with the number of queries in each difficulty category.

## 4 Evaluation

**Setting.** Answers to queries take the form of short strings. For consistency across evaluations, we provide a zero-shot prompt scaffold that is used to inform systems about the format of the answer output (shown in Figure 4) and the date that the question was asked. Given a returned answer and the correct ground truth answer, a weak string match is performed to check for correctness, which takes the form of a Llama 3.2-based LLM Judge within a scoring function, implemented alongside the leaderboard. The prompt for this judge is shown in Appendix Section B; human validation confirms the accuracy of this judge to be accurate on average 98% of the time. This figure was determined by (1) having independent human annotators assess whether, given a candidate answer, the true answer, and the query, the response was correct or incorrect, and (2) comparing the LLM judge's decisions against these human-annotated ground truth labels.

Using the prompt scaffold shown in Figure 4—unless systems have their own prompt scaffold to return a single, final answer—we evaluate ChatGPT-4o (OpenAI, 2024a), Perplexity Pro (Perplexity Team, 2024), Mistral Le Chat (Mistral AI Team, 2024), Microsoft Copilot,[1] HuggingFace Agents with Claude 3.5 Sonnet (HuggingFace, 2024),[2] DynaSaur with GPT-4o (Nguyen et al., 2024), and Operator (OpenAI, 2025), each with their default settings and sets of tools. We compare the performance of these systems against human validator performance, base LLM performance with Llama

[1]Accessed through https://copilot.microsoft.com/

[2]Specifically, the implementation that achieves the top attempt on the GAIA leaderboard as described in https://huggingface.co/blog/beating-gaia

1. I upload[ed] the picture on Google Lens to search.

2. I look[ed] through the results and click[ed] on this YouTube video.

3. I watch[ed] the video and compare[d] it to the uploaded image. I confirmed the location is Challenge Bus Terminal.

4. I searched for "Challenge Bus Terminal" on Google Maps.

5. I looked at the results and compared them with the uploaded image. I confirmed [that] they match.

6. I confirm[ed] through [Google] [S]treet [V]iew that there's a Zenith Bank opposite the terminal.

7. I [G]oogled "Zenith bank challenge Ibadan address[.]"

8. I looked through the results and clicked on this link.

9. I looked through the website and confirmed [that] the address is 108, Lagos bye-pass Challenge, Ibadan.

10. I confirm [that] the answer is Zenith Bank, 108, Lagos bye-pass Challenge, Ibadan.

Figure 5: Steps that a human validator took to answer the query shown in Figure 4. The time spent by the validator to arrive at the answer was fifteen minutes and forty-five seconds. Note that these traces reflect only the human steps taken to reach the correct answer, sometimes capturing trial, error, and iteration, where taken. Accordingly, these traces and the time validators required should only be seen as a *proxy* for the difficulty of the presented queries—*not* optimal solutions.

3.1 405B (Grattafiori et al., 2024), GPT-4o and o1 (OpenAI, 2024b), Claude 3.5 Sonnet (Anthropic, 2024), DeepSeek r1 (Guo et al., 2025), and web search, where we type the questions onto a webpage and assess if the correct answer may be obtained from the first page of displayed results. For robustness, due to inherent system stochasticity, we run each system on every question three times and report the average of the results. We assess our human baseline by measuring the rate at which validators reach the correct answer on their first attempt.

**Results.** As shown in Table 1, overall, peak system performance reaches approximately half of human performance, with consistent declines across higher difficulty tiers (Figure 3). Questions that take humans longer to solve are, on average, more often incorrectly answered by existing agent systems. Notably, systems with tool use enabled show only marginal (+7%) improvements over the strongest base models that lack tool use capabilities. Across the most frequent query domains (Figure 6), queries around *places* stand out as the hardest for existing systems and models to answer correctly, while queries about *sports* and *food* are comparatively easier. Together, these observations point to the following conclusions. One, *existing forms of parametric knowledge alone prove effective at answering real-world tip-of-the-tongue queries in* ***certain*** *domains:* Although the exact prompts for queries do not appear online in textual form, the underlying details of their queried items often do. With a reasoning chain for DeepSeek r1 shown in Appendix Section C, our findings demonstrate that the most successful models *can* assemble fragments of their learned parametric knowledge to reach correct answers for various query types that have this characteristic. Despite this, parametric knowledge alone is insufficient, particularly when dealing with scenarios that require information either distinct from web-based training data or more current than the model's training cutoff date. Two, *models fail to reason effectively about which tools to employ and how to employ them.* This behavior along with ineffective comprehension of information returned by tools in the context of given queries, results in performance that is only marginally better than if they used no tools at all. As observed in Appendix C, Operator misunderstands the initial search result for travel sites launched in 2000s and continues to pursue an incorrect result for Expedia. Overall, these results illustrate that though current models are effective at answering certain types of tip-of-the-tongue queries, they still greatly underperform—particularly in comparison to humans—when faced with the full breadth and complexity of this challenging real-world information need. In the following section, we note qualitative insights into system failures and examine key challenges.

## 5 Discussion

**Where do systems fail?** A qualitative analysis of reasoning logs reveals several areas of failure in current systems capable of tool use. The first area lies in *contextual understanding*. Even with multimodal capabilities, systems can misinterpret or overlook critical details. For instance, in searching for a "grey-colored battery pack with a black top," Operator incorrectly identified a grey battery pack with *black buttons* as that item—an error that indi-

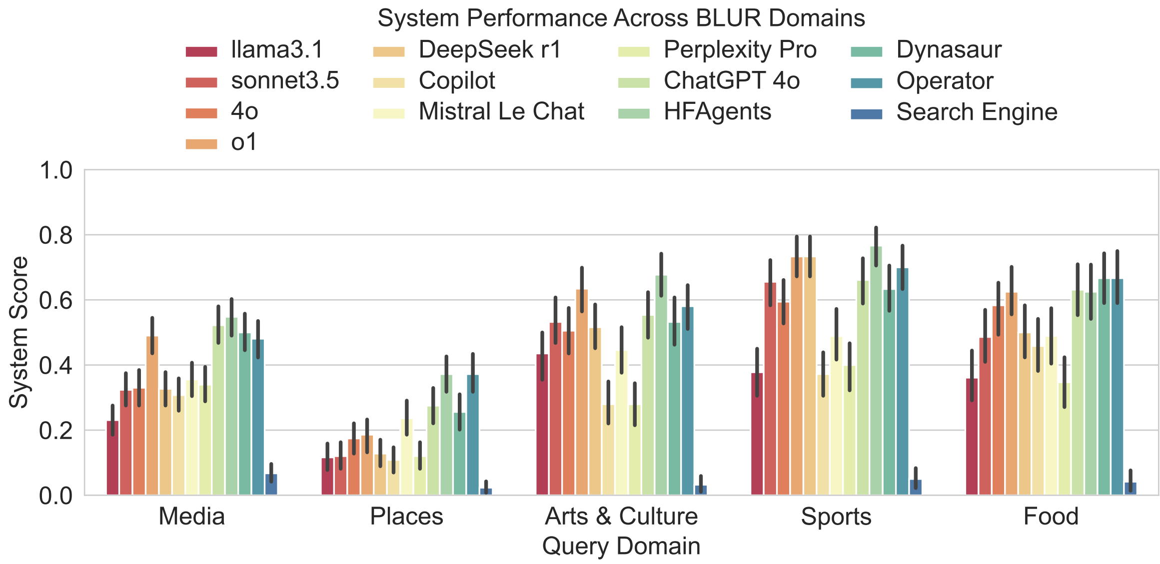



Figure 6: **System performance** as stratified across the five most frequent **domain categories**. 95% confidence intervals are shown. Queries about *places* are less likely to be captured by the typical parametric knowledge derived from internet text, which means they often require proficient tool usage and are consequently more challenging for current systems to answer accurately.

cates lingering gaps in contextual comprehension and can propagate to downstream answers. The second area lies in *orchestration*. Some systems prematurely terminate their search after finding an item that satisfies only part of the specified constraints. In contrast, systems like HuggingFace Agents iteratively verify whether additional constraints can be met before returning a final answer. Perplexity Pro, by comparison, performs a single retrieval-augmented generation step; if the correct answer does not appear in the retrieved documents, the system simply states it cannot answer the query. Their relative performance differences highlight the value of effective orchestration for query attempts and validation in succeeding at this task. The third area lies in dealing with *tool failures*. Tools can fail—on occasion, API rate limits or access restrictions (e.g., YouTube sometimes being inaccessible to Operator) can block a system from retrieving key information. Instead of seeking alternate sources, systems were often observed to become stuck in a loop of repeated attempts to access the same site, ultimately failing to retrieve the needed data. Finally, the fourth area lies in dealing with *long contexts*. Many queries require aggregating and verifying information from multiple sources, leading to lengthy action sequences. Over time, systems may lose track of the original query or become ensnared in an infinite loop of searches, preventing them from reaching a correct conclusion. These observations highlight existing areas of improvement for models to improve further at this challenging task.

**Is Tool Use *Really* Needed?** Although the best models without tool-use capabilities (i.e. o1) often succeeded by effectively leveraging their existing parametric knowledge to piece together the answers to queries, their failures in domains like *places* reveal the limits of relying solely on fixed pretraining knowledge. One alternative to further push the performance of these language-only models is to *augment pretraining data* even further with existing tools; i.e., through techniques like generating multiple textual descriptions for every building able to be found in Google Maps—so that more relevant information becomes integrated into and findable through textual parametric knowledge alone. However, this strategy would still fall short in queries about newer pieces of information, particularly those that arise *after* a model has been trained. In such cases, real-time tool use remains indispensable for accurate and up-to-date query responses.

**Application.** Achieving strong performance on this benchmark corresponds to benefits across several application domains in search, from information retrieval to product and people searches—tasks that can otherwise demand considerable manual effort. By reducing the labor involved, systems here stand to significantly improve user efficiency in these domains. Ostensibly, *search* remains one of the many capabilities desired by people in the broader concept of a "general AI assistant," which still remains loosely defined (Mialon et al., 2024) in current literature. This research constitutes an important step toward building AI systems and capabilities that address practical, real-world needs while also laying the groundwork for future enhancements in areas users *genuinely* care about in their daily lives.

## 6 Future Work

A key future challenge lies in *evaluating reasoning chains*, particularly when models arrive at the *wrong answer*. While correctness is relatively straightforward to confirm for successful outcomes, gauging how close a model was to the correct solution is a more nuanced question, especially apparent in tool-using reasoning agents (Prasad et al., 2023). Future research that develops methods to quantify the *distance* between a model's chain of thought and the correct reasoning process could provide more precise indicators for improving agent capabilities.

A second future challenge in evaluation lies in *efficiency*—namely, the time required for a model to arrive at the correct answer, which is also of practical importance to end users. Evaluating efficiency becomes especially complex when the results from tool use are stochastic. Future research could focus on reliably measuring this aspect, perhaps by tracking token usage or other metrics that gauge the time and computational cost of each reasoning step. This would enable more informed comparisons of models' performance in real-world scenarios, in addition to base comparisons of answer correctness.

Finally, a third challenge lies in *multi-turn* evaluation. For queries that *cannot* be answered in a single round, an exciting open question remains on how to best facilitate and evaluate answer-seeking strategies across multiple conversation rounds. It surmises that users may desire and benefit from collaborating with an assistant to navigate through incomplete information, refine their questions, and progressively build toward the correct answer—unlike traditional search which generally relies on well-defined queries—suggesting related ideas along the way that might help trigger recognition.

## 7 Conclusion

We presented BROWSING LOST UNFORMED RECOLLECTIONS (BLUR), a demanding 573-question tip-of-the-tongue known-item search and reasoning benchmark that is both multilingual and multimodal on input for general AI assistants. Evaluations show that current LLMs, LLM-based agents, and general AI systems still fall well short of human-level performance on this task. We hope that our release will foster more human-centered research and drive improvements in a search challenge that resonates across multiple domains.

## Limitations

**Answer Longevity.** As the internet is constantly changing, the sources used to answer these questions may not always remain accessible—webpages can be taken down or become unavailable. To address this, we recorded the "sources of truth" (i.e., the websites visited) that annotators relied on when creating validation chains for each question. As part of this data release, we periodically check that these, or alternate sources, remain available. If any links stop working, we shall remove the affected questions to maintain valid evaluations. Even in the event of widespread unavailability, it remains straightforward to create a new dataset measuring the same capabilities by following our established annotation procedures.

**System Stochasticity.** This benchmark primarily focuses on evaluating *capability*, without a need to specify or restrict to any sets of tools in requirement. However, as the underlying tools—often outside the control of individual system designers—in these systems can change and evolve, system capabilities may shift over time as well. For example, we originally sought to benchmark MagneticOne (Fourney et al., 2024)—an agentic system powered by the AutoGen framework—but it lost its OCR capabilities during testing after the OpenAI API stopped processing OCR requests.[3] These issues highlight the difficulty in system evaluation, especially when certain and necessary system components fall outside the direct control of the system's designers.

**Models Measured.** Our ability to benchmark certain models—such as OpenAI's Deep Research—was constrained by stringent rate limits. While

[3]https://github.com/microsoft/autogen/issues/4482

we were able to circumvent some limitations (for example, the absence of API access) by manually submitting queries through the interface, as we did with OpenAI's Operator, additional rate restrictions on other models rendered comprehensive benchmarking impractical.

**Human Performance.** The "human performance" reported here applies exclusively to the subset of tip-of-the-tongue questions that survived our rigorous post-hoc agreement validation pipeline—not to tip-of-the-tongue tasks writ large. In practice, any question whose writer and validator disagreed (for instance, due to initial question ambiguity and/or underspecification) was discarded and thus contributes no data to this measure. Consequently, this figure reflects only those items in the final dataset and should not be construed as indicative of general human ability on tip-of-the-tongue problems.

## Ethical Considerations

Following data collection, we reviewed all data items manually and ensured that no Personally Identifiable Information (PII) was present in the data. Annotators were paid for their time at a rate of $20 an hour.

## Acknowledgments

We thank Chris McConnell, Annie Franco, Thomas Sciacolm, Selvan Sunitha Ravi, Devanshu Bansal, Matthew Toles, Douwe Kiela, Stephen Roller, Victor Sanh, Aochong Li, and Anubhav Jangra for helpful conversations during the completion of this paper, and the anonymous reviewers for their helpful suggestions.

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# A Annotation Details

**Annotators.** A total of 12 annotators participated in the data collection process. Age-wise, 10 (83%) annotators were within the 26–35 age range, and 2 (17%) were within the 18–25 age range. 7 (58%) identify as women, 5 (42%) identify as men. 11 (92%) hold a Bachelor's degree, and 1 (8%) holds a Master's degree.

**Query Creation Guidelines.** Have you ever been caught at a loss for words? Where you know something exists—and can describe it—but don't know the exact or key phrase to search for on Google? We want to augment the dataset of the provided questions below. We're looking for creativity in this process, not for only variations of what we already have. Try to be as diverse as you can in the examples you come up with!

When creating examples, it's helpful to recall a time in the past when you tried to remember the name of something—and knew how it looked, how it felt, how it sounded, etc.—but just couldn't recall its name. What did it feel like when you were trying to recall what it was called?

The following list is provided for inspiration of potential domains to choose from when creating your dataset. They are by no means exhaustive—do feel free (in fact, it's very encouraged!) to come up with examples that fall outside of these domains and descriptions. By no means do they need to be famous or well-known. In fact, it's usually the obscure ones that are hard to remember!

- Places—i.e. buildings, places you've been to, and more.

- People
- Science—i.e. academic papers.
- Arts & Culture—i.e. artwork, artisan crafts, books and novels, etc.
- Entertainment & Media—i.e. music, TV shows, movie characters, commercials, animations, etc.
- Technology & Tools—i.e. apps, old gadgets, etc.
- Experiences—i.e. rituals, local adventures, etc.
- Programming—i.e. specific github repos
- Websites
- Others—feel free (& it's encouraged!) to come up with your own!

No restrictions are placed on the language of the information present in the query you have, but please make sure that the instructions of the query are in English. If you find it hard to describe, in natural language, a piece of information that you remember about the entity in question, feel free to include it as part of a file upload! Please structure your prompt in how you might seek help online or from a friend.

When you've finished creating your prompt, please go ahead and spend some time trying to find the item in question! When doing so, please record the steps you took to try to find the answer to the query (even if they were wrong!). Once you've found the item, record it down in the form of a short string. Some general guidelines:

- Make sure the answer to your question is unambiguous.
- Make sure your question can be answered in a reasonable amount of time by a human annotator.
- Make sure the answer to your question is at most a few words.
- Make sure the answer to your question does not exist on the internet in plain text.

*Here, one of the example questions shown to annotators is provided; others are left out for privacy reasons.*

> *Example Question 1.* I remember this song. It's in Chinese. The start of this song is like the piano opening of the song I've attached, though I'm pretty sure the start of the song I'm thinking of was not in piano. It's by someone pretty famous, and I remember going to their concert and hearing this song, I think, sometime around 2008-2012, in Beijing, China. A lyric I remember from the song is like "我不想再写" and "满天的风雪" something. The concert was pretty pink, and everyone had pink lightsticks. It was like a sea of pink. There was something about broken butterflies in the song. I think the song's theme was about breaking up or love. What is the name of the song I'm thinking of? **File Input:** MP3 file to Yuri On Ice.

**Query Validation Guidelines.** Please identify the entity mentioned in the following query. You may consult any files or programs you wish, and you are especially encouraged to use a web browser for assistance. Note that this query was originally asked by a user on December 15, 2024.

Your response should be a concise string. Once you have formulated your answer, record it and then click Confirm. Afterward, compare your answer to the indicated answer. If the two do not match, please provide a brief explanation—either affirming why your answer is correct or explaining any mistake you may have found in your reasoning.

Finally, state whether you believe the query is unambiguous, specifically addressing whether the indicated answer is the only valid option you discovered during your process of arriving at a solution.

## B Prompts

**LLM judge.** You are a judge. You will be provided with three pieces of information:

- **Question**: A question asked by the user.
- **Ground Truth Answer**: The correct, specific answer to that question.
- **User-Provided Answer**: A potentially correct or incorrect attempt at answering the question.

Your task is to determine if the User-Provided Answer unambiguously corresponds to the same information/entity described by the Ground Truth Answer, in the context of the Question.

- If the User-Provided Answer clearly and uniquely identifies the same information as the Ground Truth Answer (even if phrased differently or missing non-essential details), then it should be considered **correct**.

- If it is ambiguous, incomplete, or could refer to multiple different answers, then it must be considered **incorrect**.

Please output your reasoning, alongside one of the following: "Correct" if the User-Provided Answer unambiguously matches the Ground Truth Answer, and "Incorrect" otherwise.

## C Reasoning Traces

Due to the lack of transparency in reasoning traces in o1, here, we use DeepSeek r1 to show examples of varying behavior in reasoning traces in cases without tool use. In the first instance below, the model is capable of recalling the correct book a character is in when directly prompted with a vague description of the story, highlighting how non-tool-use models can be effective at piecing together pieces of information already contained in parametric knowledge.

> Okay, let's try to figure out the name of the main female character the user is talking about. The novel is about a couple who have to go through dating and marriage again because the woman loses her memory after a car accident less than a year into their marriage. It's based on a true story and focuses on themes of love, commitment, and the impact of memory loss.
>
> **First, I remember there's a novel called "The Vow" which is based on a true story.** The real-life couple is Kim and Krickitt Carpenter, who experienced a similar situation where Krickitt had amnesia after a car accident and couldn't remember her marriage...

When the entity may not be in parametric knowledge, below, DeepSeek r1 appears to make an educated guess.

> ...Since the user's query is from December 2024, this might be the upcoming content they saw a preview of. If Season 8 was releasing episodes around that time (webpages 1 and 2 have episodes 4 and 5 in December 2024 and January 2025), **maybe the character Oluwabunmi was introduced in Season 8.**...

For systems with tool-use capabilities, here, ChatGPT 4o with Deep Research misreads the text in an image "Kapital Kitchen" as "Krispy Chicken," which orchestrates a series of wrong searches. A cropped version of the image centering on the mistake is shown for display purposes.

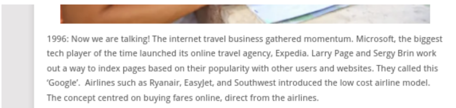

> Thanks for sharing the image! I see the restaurant in the photo, which is "Krispy Chicken."...
>
> ...Identifying Lounge Near Krispy Chicken...
>
> ...I'm mapping out a lounge near Krispy Chicken...

In a prompt that specifies a travel site "launched in the early 2000s," Operator begins and continues its search for early 2000s travel sites that fit its description. Despite this queried constraint, it narrows in on Expedia, which was launched in 1996—even when it continuously encounters said information during its search.

> Searching for flight and hotel tracker
>
> ...
>
> Scrolling for early 2000s website info
>
> ...
>
> Refining search for early 2000s travel sites
>
> ...
>
> Scrolling for early 2000s travel sites

...

Researching Expedia's design and features




Exploring Web Design Museum for insights


Identifying Expedia as user's reference

**Final Answer: Expedia, launched in 1996.**