When the Music Stops: Tip-of-the-Tongue Retrieval for Music

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ABSTRACT

We present a study of Tip-of-the-tongue (ToT) retrieval for music, where a searcher is trying to find an existing music entity, but is unable to succeed as they cannot accurately recall important identifying information. ToT information needs are characterized by complexity, verbosity, uncertainty, and possible false memories. We make four contributions. (1) We collect a dataset—ToT_{Music} of 2,278 information needs and ground truth answers. (2) We introduce a schema for these information needs and show that they often involve multiple modalities encompassing several Music IR sub-tasks such as lyric search, audio-based search, audio fingerprinting, and text search. (3) We underscore the difficulty of this task by benchmarking a standard text retrieval approach on this dataset. (4) We investigate the efficacy of query reformulations generated by a large language model (LLM), and show that they are not as effective as simply employing the entire information need as a query-leaving several open questions for future research.

CCS CONCEPTS

• Information systems \rightarrow Music retrieval; Retrieval models and ranking; Document filtering; Multimedia and multimodal retrieval; Query reformulation; • Human-centered computing \rightarrow User studies.

KEYWORDS

Music Retrieval; Tip-of-the-Tongue Retrieval; Cross Modal Retrieval ACM Reference Format:

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1 INTRODUCTION

The *Tip-of-the-tongue* (*ToT*) retrieval task involves identifying a previously encountered item for which a searcher was unable to recall a reliable identifier. ToT information needs are characterized by verbosity, use of hedging language, and false memories, making retrieval challenging [1, 4]. As a consequence, searchers resort to communities like r/TipOfMyTongue and WatzatSong, where they can post descriptions of items that they know exist but cannot find,

*Work done during an internship at Spotify.



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SIGIR '23, July 23–27, 2023, Taipei, Taiwan © 2023 Copyright held by the owner/author(s). ACM ISBN 978-1-4503-9408-6/23/07. https://doi.org/10.1145/3539618.3592086 relying on other users for help. Recent research of ToT information needs explored how searchers pose these requests in specific domains like movies [1, 4], or games [24]. Music-ToT, however, is under-explored despite being frequent: it represents 18% of all posts made in a five-year period in the r/TipOfMyTongue community (cf. §3.1). Our work is motivated by the need to understand how such requests are expressed in the music domain.

We examined the r/TipOfMyTongue community, focusing on requests looking for musical entities like albums, artists or songs. We show that these requests often refer to multiple modalities (cf. §4) and thus encompass a broad set of retrieval tasks-audio fingerprinting, audio-as-a-query, lyric search, etc. In our work, we focus on song search. We create ToT_{Music}^{-1} : the dataset consists of 2,278 solved information needs pertaining to a song, each of which is linked to the corresponding correct answer in the publicly available Wasabi Corpus [7]. Using ToT_{Music} , we develop a schema for Music-ToT information needs to reveal what information is contained in them (cf. §3.2). In addition, we are interested in the extent to which standard text retrieval approaches are able to deal with ToT queries. To this end, we benchmark a subset of ToT_{Music} information needs² on the Wasabi corpus, as well as Spotify search. Across both settings, the low effectiveness—compared to non-ToT queries-of our evaluated retrieval methods underscores the necessity of novel methods to tackle this task. Lastly, we conduct a preliminary study on reformulating Music-ToT queries using GPT-3 [5]; we find that the task remains very challenging.

2 BACKGROUND

Tip-of-the-tongue (ToT) retrieval is related to known-item retrieval (KIR) or item-re-finding [31], however ToT queries are typically issued only once—not multiple times—and importantly, lack concrete identifiers, instead relying on verbose descriptions, frequently expressed uncertainty and possible false memories [1, 4, 16, 24]. Approaches for simulating such queries [3, 13, 26] may lack realistic phenomena like false memories [19, 20], necessitating the collection of real world data. Data on a large scale is available for only one domain, movies [4]; smaller scale datasets are available for games [24] and movies [1]. Hagen et al. [16] collect a corpus of general known-item queries, including music; however their focus was on general known-item queries and false-memories, and lacked retrieval experiments. Our focus is on the music domain, examining modalities employed by searchers and how they express Music-ToT queries. We build upon Arguello et al. [1] and Bhargav

 $^{^1}ToT_{Music}$ (along with annotations) will be made available here: https://github.com/spotify-research/tot

²Concretely, 1.2K *descriptive* information needs not containing hyperlinks – we aimed to exclude posts where important information is not encoded in the text of the post itself

et al. [4], with key differences in (1) the domain—music, (2) the corpus size—millions of items instead of thousands, and, (3) reformulation experiments utilizing an LLM. Music-ToT relates to several research areas in Music IR (MIR).

Lyric- and text-based retrieval involves retrieving a song using lyrics or text [11, 28]. Techniques to handle *misheard* lyrics are common [30, 35–37], including modeling speech sounds [22], which may be insufficient, since ToT queries can contain *descriptions* of lyrics, requiring semantic methods [32], or utilizing the audio itself [38]. Apart from lyrics, Music-ToT queries are frequently free-form natural language queries (cf. §4), requiring methods that can retrieve audio using text, as well as tags, genre or humangenerated descriptions [10, 12, 27, 29, 40].

Content-based audio retrieval [14] includes query-by-example (QBE) [21], where the audio is being queried as-is, e.g. audio fingerprinting [17]. Alternatively, users can *imitate* the wanted audio by vocalizing it, termed query-by-vocal-imitation (QBV) [25, 39], which includes query-by-humming (QBH) [15]. ToT queries frequently contain references to user created audio-clips as well as existing media like audio contained in videos (cf. §4).

Other modalities like videos may need to be handled as well, necessitating multi-modal or cross-modal (retrieving one modality using another) methods [33], e.g. retrieving audio using video [23, 34]. Approaches to solve Music-ToT have to account for multiple modalities and free-form natural language including noise, e.g., uncertainty [1] and/or false memories [1, 24].

3 METHODOLOGY

3.1 Data Collection

Gathering ToT_{All}. We gathered posts made across 2017-2021 in the r/TipOfMyTongue community, yielding 503,770 posts (after filtering out posts not marked Solved or Open), each containing two fields: title and description. We extracted text categories from the title, e.g. SONG from "[SONG] Slow dance song about the moon?". We manually identified a set of 11 overarching music-focused categories (e.g. Music Video, Band, Rap Music). We discarded the remaining non-music posts, resulting in ToT_{All}: 94,363 (60,870 solved and 33,493 unsolved) Music-ToT posts. These posts form a large proportion—18.73%—of the 503K posts we started out with.

Extracting ToT_{Music}. We extracted answers from Solved posts following Bhargav et al. [4], retaining Solved posts which have a URL as an answer. If the URL points to a track on Spotify, obtaining the answer was trivial. Otherwise, the title portion of the markdown inline URLs, formatted as [title](url) (with title often formatted as 'Artist-Song') was used as a query to the Spotify search API. Since the API returns multiple results, we created a classifier with 31 features based on the scores of the retriever, the edit distances between title and artist name, song title, etc. We used the classifier to predict if a title matches the track and artist, scoring 100% on precision on a held out set of 100 samples. Low-confidence candidates were filtered out. This left us with a set of 4,342 posts with Spotify tracks as answers. Lastly, we only retained those posts

where the ISRC⁴ of the answer track is also present in the Wasabi Corpus [7]: a total of 2,278 posts. We call this collection ToT_{Music} .

Gathering reformulations. We gathered reformulations for all posts in ToT_{Music} by prompting GPT-3 [5]⁵ with the respective post description and a word count limit: <description> Summarize the query above to <N> words, focusing on musical elements. We used $N = \{10, 25, 50\}$. We also employed a prompt without a specific word limit: <post description> Shorten the query above, focusing on musical elements.

3.2 Music-ToT Schema

Our annotation process involved three steps. We first developed and then refined a schema to describe Music-ToT information needs; in the final step, we annotated 100 samples from ToT_{Music} .

Developing the schema in 2 steps. A preliminary study conducted with one author (self-rated music expertise 7 out of 10) and two volunteers (music expertise 8/10 and 7/10 respectively) involved assigning one or more labels to 78 sentences from 25 randomly sampled posts from ToT_{Music} . We focused on developing new labels specific to Music-ToT, while also re-using labels from Arguello et al. [1]: specifically the Context labels, pertaining to the context an item was encountered in (Temporal Context, Physical Medium, Cross Media, Contextual Witness, Physical Location, Concurrent Events), and Other annotations (Previous Search, Social, Opinion, Emotion, Relative Comparison). The latter are generally applicable across ToT information needs. This preliminary study revealed 25 new music labels, in addition to 11 labels from prior work (6 \times Context and 5 \times Other). In the second step, the three authors (self-rated musical expertise 7, 6 and 5 respectively) of this paper labeled 110 sentences (20 posts from ToT_{Music}) to validate the schema. Based on our results and discussions, we combined a few finer-grained categories with low support into more general categories, e.g. specific musical elements like Rhythm / Repetition, Melody, Tempo, etc., were combined to Composition, resulting in 28 labels in total.

Annotating. Lastly, in step 3, two authors employed the final schema to annotate 536 sentences corresponding to 100 posts. The resulting labels, their frequency, category, inter-rater agreement (Cohen's κ [2, 9]) along with their description and an example, are presented in Table 1.

4 DATA ANALYSIS

We now first discuss Table 1, followed by a brief discussion about the modalities present in the whole collection, ToT_{AII} .

Annotation results. Among the music-focused annotations, *Genre* and *Composition*, a description of musical elements and how they fit together, are the two most frequent labels. This is followed by *Music Video Description*, and either direct quotes (*Lyric Quote*) or a description of the lyrics (*Story/Lyric Description*) further highlighting the different information needs that need to be addressed i.e., lyric search, text search and multi-modal search. However, a simple

 $^{^3}$ Random Forest classifier, parameters selected with grid search on $\{10,\,20,\,30,\,40,\,50\}$ estimators, max depth $\{2,\,3,\,4\}$ and min/max scaled features.

⁴The international standard recording code (ISRC) is a standardized code for uniquely identifying recordings.

⁵Model: text-davinci-003, with temperature 0.7

 $^{^6}$ Based on manual inspection, we discarded N=5 (too few words for a cohesive query, leading to crucial information being left out) and N=100 (model hallucinations).

Table 1: Annotation Schema: Label, frequency of occurrence in 100 submissions / 536 sentences (F), annotator agreement (κ) and description of label, along with an example for each label.

	Label	F	κ	Description	Example
	Composition	87	0.74	Describes (part of) the composition of a piece of music including rhythm, melody, tempo, pitch, chords, notes, and keys; or how they are composed into a cohesive piece of music.	playing the same major-key pattern over each chord in a fairly simple repeating loop.
MUSIC ANNOTATIONS	Genre	77	0.92	References a genre.	It sounded like a <i>reggae/ska</i> type beat
	Music Video Description	75	0.89	Describes a music video associated with a song.	However, once the music starts, the store is lit up and the tone shifts completely as everything in that store has a pastel colour scheme.
	Lyric Quote	65	0.89	Directly quotes lyrics that the user overheard, not including sounds / vocalizations	it wasn't until he said something about the "just somebody that I used to know" song that I
	Story/Lyric Description	60	0.71	Describes either the story conveyed by the lyrics, or the gist of the lyrics instead of directly quoting it.	The song is a woman singing to/about a man that she was in love with and died, I think he was in the military and got killed and she had a baby at home?
	Artist Description	54	0.92	Describes the artist.	He was maybe a tad overweight, shaggy hair, maybe curly.
	Time Period / Recency	49	0.89	References the time period the user thought the music was produced.	Late 90s-early 2000s hip hop song that sounds similar to clip
Ę	Instrument	30	0.86	Mentions instruments that were overheard.	The guy performing was at a keyboard/piano
A.	Vocals	28	0.69	Describes the voice or vocal type.	High pitched but kind of floaty female vocals, a bit
IUSIC	Name	23	0.81	Describes a song/artist/album name, what it resembles/contains, or what the searcher remembers of it.	the name of the song was brief, one nordic word.
2	Popularity	18	0.83	Describes the popularity of the music, artist, album or music video.	I'm surprised I can't find it since I can remember many specific lyrics, I guess it's $\textit{more obscure}$
	Recording	15	0.80	A description or reference to user-created content	I did a vocaroo of the tune, sorry about my voice and any pos- sible background guinea pig noises: URL
	Language / Region	14	0.92	Either mentions the language of the piece of music and/or references a particular region like state, country, etc.	A $\ensuremath{\textit{Japanese}}$ song that I don't remember any words to or how the tune goes at all,
	Album Cover	5	1.00	Describes the album cover.	On the cover there was also a cyan teal line going along the bottom with white text in it.
	Song Quality / Type	4	0.00	Describes the type of music (original/cover, live/recorded) or the production quality (professional, amateur, etc.)	Live Cover of All Along the Watchtower where
	Uncertainty	162	0.79	Conveys uncertainty about information described.	I don't know what genre the song was, it was fairly calming and I feel like it couldve been on tiktok but I don't really know.
	Social	54	0.77	Communicates a social nicety.	Any help appreciated!
	Opinion	43	0.44	Conveys an opinion or judgment about some aspect of the music.	I don't remember the lyrics or title, only that it was a kind of angsty teen "I want to set the world on fire"
SNO	Temporal Context	36	0.87	Describes when the music was heard, either in absolute terms or relative terms.	I heard like in a billion videos 6 years ago.
CONTEXT et al. ANNOTATIONS	Listening Medium	26	0.75	References the medium associated with the item. (e.g., radio, streaming service, etc)	I heard it on the <i>radio</i> a couple of times in
	Embedded Music	26	0.58	References or describes extant media (e.g., Youtube / Twitch URL), including timestamps.	I do have a video with the song (this video at around minute 4:21: URL)
	Other Cross Media	26	0.19	Describes exposure to the piece of music through different media, excluding other Cross Modal labels	I'm pretty sure was performed on one of the <i>early seasons</i> of Glee or maybe Smash.
	Previous Search	25	0.67	Describes a previous attempt to find the item, including negative results (i.e., it is not song X).	I've tried humming it into shazam and other sites, looking up the two generic lyrics I remember, even doing those rhythm tapping things and nada
	Relative Comparison	25	0.77	Describes a characteristic of the music in relative (vs. absolute) terms, by explicitly comparing it with another song / artist / album.	The melody I remember resembles the beginning of the song "Run to the hills" by Metallica
	Emotion	25	0.05	Conveys or describes how a piece of music made the viewer feel	Even talking about it makes me tear up.
	Concurrent Events	18	0.09	Describes events relevant to the time period when music was en- countered, but excluding descriptions of the music itself.	when I was driving down the country but for the life of me can't remember the name.
	Physical Location	9	0.61	Describes physical location where music was encountered.	record a 9 second portion of this song at a Marriott hotel bar in downtown Chicago
	Contextual Witness	9	0.49	Describes other people involved in the listening experience.	A few years back, a friend of mine showed me an

extraction of *Genre* and metadata such as *Time Period/Recency, Instrument*, etc., may not be useful without considering the most frequent label, *Uncertainty*. Search systems therefore would have to handle these elements, as well as consider potential false memories. Furthermore, annotations like *Social, Opinion* are also fairly common occurrences in our data, which may have limited utility for retrieval [1], motivating reformulations (cf. §3.1). Searchers also express their queries in terms of other music entities in a *Relative Comparison*, and describe *Previous Search* attempts, explicitly ruling out certain candidates. References to other modalities like user created clips (*Recording*) or existing media (*Embedded Music*) also

pose a challenge. We now explore this challenge with a brief study of references to external content in the entire collection, ToT_{All} .

Cross-modal references Music-ToT, like other ToT domains, contains cross-modal and media references [1], where a searcher refers to external content. We here show that Music-ToT posts in particular contain such references frequently. To this end, we gathered frequent websites that appear in ToT_{All} . One author manually labeled these as one of: (1) *User Created*: a clip uploaded by a user, e.g., Vocaroo, Clyp.it, Google Drive, Dropbox, Instaudio, musiclab, Onlinesequencer, Streamable, Speakpipe. (2) *Extant Media*: a clip

unlikely to be uploaded by a user, e.g. an existing clip, corresponding to content/social media websites like Spotify, Twitch, Tiktok, or YouTube. (3) *Other URL*: Not belonging to the previous two categories. We find that *Extant Media* forms a larger proportion of queries (19K, 20.9%) compared to *User Created* queries (14K, 15.3%), with a small number of posts containing references to both types (1.1%). Therefore, Music-ToT information needs are inherently multimodal. We characterize the remaining 57.7% of queries as *descriptive* queries, which include references to lyrics, or story descriptions (cf. §3.2). In summary, Music-ToT information needs are characterized by uncertainty and multi-modality, requiring methods like text-based audio retrieval, content based audio retrieval/fingerprinting and multi- or cross-modal retrieval.

5 BENCHMARKS

5.1 Experimental Setup

Corpora. We run experiments on two corpora. The first is the Wasabi 2.0 Corpus [6, 7]. It consists of 2M commercial songs from 77K artists and 200K albums. Crucially, (1) songs have the ISRC linked, enabling linking to data in Spotify; (2) it is an open dataset, consisting of rich information that includes lyrics, extensive metadata, and music snippets. We index the $Song\ Name$, $Artist\ Name$ and $Lyrics^7$ of all songs using Elasticsearch (BM25 with default parameters). The second corpus corresponds to the Spotify US catalog, consisting of hundreds of millions of tracks. The Spotify search system [18] utilizes multiple retrieval stages (including lexical- and semantic search) and incorporates historic log data for retrieval purposes.

Queries. We conducted experiments on the 1,256 posts (849 train, 191 validation, and 216 test) from ToT_{Music} that contain no URLs in the post title or post text; we make this choice as in the most extreme case, the entire post may contain just a URL, requiring audio-based search while we focus on text-based methods. From each post, we create different *queries* and label them as follows: (1) Title: using the post title only; (2) Text: post text; (3) Title+Text: title & text concatenated; and finally, (4) Keywords: extracting up to ten keywords from the post text⁸ with Yake [8]; (5) Reform_N: reformulations with $N = \{10, 25, 50, \infty\}$.

Evaluation. We report Recall@K, equivalent to Success@K (i.e., one correct answer) for $K = \{10, 100, 1000\}$ on Wasabi. All reported results are on the test set. For *Spotify* search we describe the observed trends (due to the proprietary nature of the system).

5.2 Results

Table 2 provides an overview of our Wasabi results.

Post parts as query. The low success across queries and K underscores the difficulty of the task. On Wasabi, Title queries are more effective than Text queries—increased verbosity leads to retrieval failure. However, the text may indeed contain data useful in retrieval, with comparable or higher effectiveness scores for Title+Text over Title at $K = \{100, 1000\}$, motivating keyword extraction: crucial details might be present in the text, but including the entire

Table 2: Overview of retrieval experiments on Wasabi, using Elasticsearch (BM25).

Query	S@10	S@100	S@1000
Title	0.0370	0.0833	0.1389
Keywords	0.0231	0.0463	0.0787
Text	0.0139	0.0648	0.0926
Title+Text	0.0324	0.0833	0.1713
Reform ₁₀	0.0139	0.0509	0.1204
$Reform_{25}$	0.0278	0.0602	0.1389
Reform ₅₀	0.0185	0.0741	0.1389
$Reform_\infty$	0.0139	0.0741	0.1574

need as a query might harm effectiveness. Our keyword selection method though fails to outperform other queries except for Text on S@10.

On *Spotify* search we observe a different trend: Title+Text is the most effective query followed by Title.

LLM reformulations as query. Examining Table 2, reformulations have limited success compared to Title queries. Reform₂₅ and Reform₅₀ perform as well as Title on S@1000, with Reform_∞ outperforming it. While Keywords beat all but Reform₂₅ on S@10, it is outperformed by reformulations on S@100 and S@1000. On *Spotify* search, we find that reformulations fare worse than Title queries for S@10, but see limited success on S@100, with Reform₂₅ and Reform₅₀ achieving higher effectiveness. Most importantly, there is no ideal N on either index, with varying success across metrics. We thus conclude that in our study, reformulations generated using state-of-the-art LLMs have only mixed success.

6 CONCLUSIONS

We explored Tip-of-the-Tongue retrieval for music. Of the 94K posts corresponding to Music-ToT information needs from an online community for ToT requests, we linked 2,278 posts to the corresponding answers in the Wasabi corpus, resulting in ToT_{Music} , thus enabling further research for this challenging task.

We iteratively developed and refined a Music-ToT schema that contains 28 fine-grained labels as shown in Table 1. Labeling 100 posts using this schema, we showed that users express uncertainty frequently, and almost as often refer to other modalities. We benchmarked a subset of 1.2K descriptive queries from ToT_{Music} , and highlight the difficulty of the task. Future work should leverage cross- and multi-modal retrieval as well as better approaches for reformulations.

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 $^{^7\}mathrm{We}$ also experimented with other fields like Album Title, but saw no improvement in retrieval effectiveness.

⁸Keywords were deduplicated with threshold = 0.2 and algorithm = seqm.

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