A Survey of Temporal Information Retrieval Research: Postprint

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Abstract

【Objective】To summarize the current state of temporal information retrieval research both domestically and internationally, in order to provide a theoretical foundation for researchers in the field to better grasp the research issues in temporal information retrieval. 【Literature Scope】Literature searches were conducted in Google Scholar using the search terms "Temporal Information" and "时态信息" respectively without limiting the time range; after obtaining some relevant literature, the snowballing method was applied to ultimately acquire 92 relevant papers. 【Method】Based on literature review and inductive summary methods, this paper provides a review and commentary on relevant research in temporal information retrieval from three aspects: temporal information extraction from documents, temporal information recognition in queries, and time-aware ranking. 【Results】The study finds that temporal information retrieval research faces the following problems and challenges: there is relatively more research on temporal retrieval abroad, while domestic research is scarce; insufficient research on identifying document focus time using entities representing temporal information and event evolution information; lack of intent prediction for queries with non-periodic changes; and the experimental reproducibility of temporal information retrieval models needs improvement. 【Limitations】This paper does not provide a literature review on document collection, document indexing, and related applications in this field. 【Conclusion】Constructing standardized evaluation datasets and parameter-free temporal information retrieval models will be future research directions in the field of temporal information retrieval.

Full Text

Preamble

Analyzing the Network Dynamics of Informational, Navigational, and Transactional Queries

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Abstract

[**Objective**] This study analyzes the temporal network dynamics characteristics of informational, navigational, and transactional queries to provide insights for search engine performance optimization. [**Methods**] Using relevant evaluation metrics, we examine the evolving features of different query intent categories from three perspectives: query dynamics, document content dynamics, and information need dynamics. For each intent category, we analyze how document content and information needs change across different query popularity patterns. [**Results**] Regarding popularity distribution, informational queries typically contain single peaks, transactional queries are more likely to contain multiple peaks with periodicity, and navigational queries generally maintain smooth trends. Informational queries exhibit greater variation in both webpage content and information needs over time compared to the other two categories. [**Limitations**] The observation period spans only 29 days, and we did not categorize or automatically identify peaks in popularity distributions lacking peaks or containing multiple peaks. [**Conclusions**] For informational queries, search engines should diversify result presentations as much as possible. For navigational queries, they must ensure authoritative pages remain prominently ranked. For transactional queries related to user interaction behaviors, relevant page rankings should remain stable over extended periods, while for entertainment-related transactional queries, novelty should be factored into page ranking.

Keywords: Informational Query; Transactional Query; Navigational Query; Query Dynamic; Information Need Dynamic; Document Content Dynamic

1. Introduction

Since Broder [1] classified queries into informational, navigational, and transactional categories based on user intent (or user tasks), extensive research has investigated classification features to effectively distinguish among these three query types [2-4]. As Broder' s ultimate goal was to enable search engines to provide differentiated retrieval services according to query intent categories, obtaining and classifying queries are merely means to an end. Therefore, analyzing classified queries to inform search engine performance optimization represents an important research direction.

As a venue for user interaction, the web exhibits dynamic characteristics. Building on Kulkarni et al. [5], this paper conceptualizes network dynamics from an information acquisition perspective, focusing on three dimensions: query dynamics, information need dynamics, and document content dynamics. Query dynamics refers to temporal changes in the frequency of query submissions by users. Information need dynamics describes how collective information needs for the same query evolve over time. For example, before the Malaysia Airlines

MH370 incident, users searching for "Malaysian Airlines" generally sought flight information, whereas after the incident, their needs shifted toward information about the tragedy. Document content dynamics concerns the content differences among documents relevant to a query at different time points. Analyzing these dynamic features helps search engines understand user intent and webpage content evolution patterns from a dynamic perspective, thereby satisfying users' immediate information needs. For instance, in query suggestion, analyzing query dynamics enables recommending currently popular queries; in result ranking, analyzing information need and document dynamics helps accurately locate documents relevant to users' latest needs. Consequently, adapting retrieval results to network dynamic features constitutes a crucial consideration in search engine optimization.

In information retrieval, user intent category is considered an important contextual factor that directly influences how users seek information and what types of information they wish to obtain [6]. Therefore, when optimizing performance to adapt to network dynamics, search engines must also consider relevant user intent factors. In light of this, this paper compares and analyzes the network dynamics of different task category queries (informational, navigational, and transactional) to provide evidence for search engine optimization tailored to different user intents.

2. Related Work

2.1 Query Intent Classification

In 2002, Broder [1] categorized query intent into informational, navigational, and transactional through user surveys and analysis of AltaVista query logs. Informational intent (e.g., "bid advertising," "how to lose weight") involves users seeking information believed to be available on the web in a static manner, with no interaction beyond reading. The sought content may include data, documents, text, or multimedia, and information needs can be either precise or vague. Navigational intent (e.g., "China Scholarship Council website," "University of Amsterdam homepage") involves users looking for a specific website or webpage, which may be personal or organizational. In other words, users have already formed a search intention and know or believe a URL exists to satisfy their information need. Transactional intent (e.g., "Qi Li Xiang download," "Gmail registration") involves users seeking resources or web services such as purchases or downloads.

Building on Broder [1], studies [2-4] explored how to select classification features to automatically distinguish among these three query types. Other researchers attempted to analyze characteristics of different intent categories to build retrieval models. For example, Fujii [6] first identified whether a query was transactional or informational based on the distribution of query terms in webpage anchor text, finding that navigational queries were suitable for anchor text-based retrieval methods while informational queries were appropriate for content-based retrieval. Craswell et al. [7] proposed different ranking models for informational and navigational queries, demonstrating that link-based ranking methods effectively improved retrieval performance for navigational queries. Ali et al. [8] compared retrieval results for informational, navigational, and transactional queries across Yahoo and Google, finding that Google achieved the highest accuracy for transactional queries while Yahoo performed best for informational queries.

2.2 Network Dynamics Research

As categorized by Kulkarni et al. [5], network dynamics research primarily includes query dynamics, information need dynamics, and document content dynamics. This paper reviews these three aspects accordingly.

(1) Query Dynamics Research primarily focuses on observing temporal query patterns to predict social phenomena. For instance, Beitze et al. [9] analyzed hourly changes in query popularity and topics using query log data. Vlachos et al. [10] first attempted to model periodicity and burstiness in web queries using Fourier analysis. Ginsberg et al. [11] tracked influenza outbreaks in populations by analyzing the occurrence of numerous queries in search logs. Adar et al. [12] utilized changes in query term frequency to understand past user behavior and predict future actions.

(2) Information Need Dynamics Research concentrates on building models to locate users' real-time intent for query suggestion or result re-ranking. For example, Johansson et al. [13] constructed a graph model representing the dynamic relationship between queries and potential user intents to generate candidate query recommendations relevant to the original query's information needs at different time points. Whiting et al. [14] captured users' latest information needs based on query frequency in logs to provide real-time intent satisfaction in query suggestions. Alonso et al. [15] built retrieval models using temporal segments of documents. Berberich et al. [16] used mathematical modeling to provide diversified retrieval results for queries across different time periods.

(3) Document Content Dynamics Research primarily investigates methods to measure webpage content evolution. For example, Cho et al. [17] analyzed webpage content changes at the word level over four months, finding that approximately 40% of webpages changed weekly. Fetterly et al. [18] first analyzed the degree of change in each webpage' s content over time, then examined factors related to the degree of change, discovering that content variation correlated with domain names. Ntoulas et al. [19] analyzed webpage content changes using word-level information. Kim et al. [20] measured temporal webpage changes using user behavior data such as download and modification frequencies. Cho et al. [21] utilized hyperlink information in webpages to measure changes. Adar et al. [22] proposed algorithms and models for measuring webpage content changes based on DOM elements and individual word variations over time. Kausar et al. [23] proposed determining webpage content changes based on hash code variations. In summary, word-level information is the most common method for measuring webpage content changes.

Additionally, researchers have explored how to leverage network dynamic features (e.g., query dynamics and webpage content dynamics) to improve search engine performance. Alonso et al. [24] proposed a method for clustering query results based on temporal expressions in text. Alfonseca et al. [25] demonstrated that query periodicity could improve query suggestion accuracy. Dakka et al. [26] developed a question-answering system providing different answers to the same question at different time points. Zahedi et al. [27] identified temporal information in queries and integrated it into blog retrieval models to return blog information for specific time periods. Elsas et al. [28] incorporated temporal attributes into language models to improve retrieval accuracy for navigational queries. Syed et al. [29] proposed a retrieval model providing different results based on different user intents within queries. Overall, existing research has not yet analyzed the network dynamics of informational, navigational, and transactional queries.

3. Methodology

3.1 Measuring Query Dynamics

This paper employs query popularity distribution [30] to measure query dynamics. Query popularity distribution refers to the distribution of the ratio between a query' s daily frequency and its total frequency within a specific time range. To reveal deeper query dynamic characteristics, this paper builds on Kulkarni et al.' s [5] categorization of query popularity distributions by peak count, peak shape, and overall trend, proposing automatic identification methods for different categories.

(1) Peak Count-Based Classification of Query Popularity Distribution

Peak Categories Based on the number of peaks in query popularity distribution, we categorize distributions into three types: no peaks, single peak, and multiple peaks, as shown in Figure 1 [Figure 1: see original paper]. When multiple peaks exist, they can be further subdivided into periodic and non-periodic categories, as illustrated in Figures 1(c)–1(d). In Figure 1, the horizontal axis represents specific days (the observation period in this paper is 29 days), and the vertical axis represents query popularity values.

Peak Category Identification As shown in Figure 1, when peaks exist in query popularity distribution, the corresponding probability values are significantly larger than neighboring time points. We term these time points "burst points." Each peak corresponds to one burst point. Therefore, we identify peaks by detecting burst points using the moving average method [10]. When multiple burst points exist, if the time intervals between every two burst points are equal, the query popularity distribution exhibits periodicity during the observation period; otherwise, it does not.

(2) Peak Shape-Based Classification of Query Popularity Distribution

Peak Shapes in Query Popularity Distribution When a distribution contains a single peak, the peak shape can be classified into four categories:

1) **Wedge**: The query popularity increases and decreases at the same rate before and after the peak, as shown in Figure 2 Figure 2: see original paper.

2) **Castle**: After the peak appears, query popularity values remain stable for a subsequent period, as shown in Figure 2(b).

3) **Sail**: The popularity rises rapidly to the peak and then declines slowly, as shown in the right-sail shape in Figure 2(c); or rises slowly to the peak and then declines rapidly within a short period (1 or 2 days), as shown in the left-sail shape in Figure 2(d).

Note that when a distribution contains no peak or multiple peaks, overall shape classification is beyond this paper' s scope.

Overall Shape Identification We identify the maximum probability value P_t in the query popularity distribution and its corresponding time point t. If the absolute difference between the difference of probabilities at adjacent time points before t ($P_t - P_{t-1}$) and after t ($P_{t+1} - P_t$) is below a certain threshold (set to 0.0005 in this paper), the peak shape is wedge.

When the distribution is not wedge-shaped: For any point m after time t ($t+1 \leq m \leq n$, where n is the total observation days), if the absolute difference between P_m and P_{m+1} is below a threshold (set to 0.0005), while the absolute difference between P_{t-1} and P_t exceeds a threshold (set to $0.01 \times P_{t-1}$), the peak exhibits a left-sail shape. Conversely, if the absolute difference between P_{t-1} and P_t is below a threshold (set to $0.01 \times P_{t-1}$), while the absolute difference between P_m and P_{m+1} exceeds a threshold (set to $8 \times (P_m - P_{m+1})$), the peak exhibits a right-sail shape.

(3) Overall Trend-Based Classification of Query Popularity Distribution

Figure 3 [Figure 3: see original paper] illustrates the categories of overall trends in query popularity distribution: upward trend, downward trend, smooth trend, and rise-fall trend. During the observation period, if no burst points exist, the trend is smooth. If approximately no less than 75% of probability values P_t ($1 \leq t \leq n-1$, where n is the total observation days) are greater than the next time period' s probability P_{t+1}, the overall trend is downward. If no less than 75% of probability values P_t are less than P_{t+1}, the overall trend is upward. If one burst point exists, the overall trend is rise-fall.

3.2 Measuring Information Need Dynamics

Click information is an important source for representing user information needs, and changes in click information for the same query can reflect changes in user information needs [30]. Based on this, we measure user information need variation using Click Entropy [31], calculated as shown in Equation (1):

$$\text{clickEntropy}(q) = -\sum_{d \in D(q)} P(d|q) \log P(d|q)$$

where $D(q)$ represents the set of documents clicked after submitting query q, and $P(d|q)$ denotes the probability of clicking document d given query q. We assume that greater variation in click entropy values for a query across different time points indicates larger temporal changes in user information needs; conversely, smaller variation indicates more stable needs.

To obtain a query' s temporal information need variation, we first calculate the absolute difference in click entropy between each observation time point t $(2 \leq t \leq 29)$ and the previous time point $t-1$ within the observation period (set to 29 days in this paper). We then average all absolute click entropy differences (denoted as AvgClickEntropy) to obtain the query' s information need change value. A larger AvgClickEntropy indicates greater temporal information need variation, and vice versa. Note that this paper examines collective user information needs rather than personalized needs.

3.3 Measuring Document Dynamics

We measure webpage content changes based on word-level information in documents, primarily using TF-IDF cosine distance [5] and Shingle distance [31].

(1) TF-IDF Cosine Distance $D_{cos}(P_1, P_2)$ calculates the content difference between two different webpage versions P_1 and P_2, as shown in Equation (2):

$$D_{cos}(P_1, P_2) = 1 - \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|}$$

where v_1 and v_2 represent the TF-IDF weight vectors of webpages P_1 and P_2, respectively. $v_1 \cdot v_2$ denotes the dot product of vectors v_1 and v_2, and $\|v_1\|$ and $\|v_2\|$ represent the magnitudes of vectors v_1 and v_2, respectively. A larger $D_{cos}(P_1, P_2)$ value indicates greater differences between webpages, and vice versa.

(2) Shingle Distance Shingle distance [31] first treats consecutive strings in a document as a Shingle. For example, if we consider 4 consecutive strings as a Shingle, the text segment "(a, rose, is, a, rose, is, a, rose)" yields the Shingle set: $\{(a, rose, is, a), (rose, is, a, rose), (is, a, rose, is)\}$. Equation (3) then measures the Shingle variation between two different webpages:

$$\text{ShSim}(D_1, D_2) = \frac{|S(D_1) \cap S(D_2)|}{|S(D_1) \cup S(D_2)|}$$

where $S(D_1)$ and $S(D_2)$ represent the Shingle sets of documents D_1 and D_2, respectively, and N denotes the number of Shingles in both sets. The document change metric is $\text{ShDiff}(D_1, D_2) = 1 - \text{ShSim}(D_1, D_2)$. Larger values indicate greater content gaps between webpages. In this paper, we treat three consecutive non-stopword strings as a Shingle.

To obtain a query q' s document content change value within the observation period (set to 29 days), denoted as $\text{ContentChange}(q)$, we first retrieve the top 5 clicked URL sets for the query at each observation time point. We then use TF-IDF cosine distance and Shingle distance to calculate content differences between any two documents from the sets at time point t ($2 \leq t \leq 29$) and the previous time point $t-1$. After averaging, we obtain the query' s content change value relative to the previous time point, denoted as $tm(q)$. Finally, we average all $tm(q)$ values across the observation period to obtain the query' s $\text{ContentChange}(q)$ value. Larger values indicate greater temporal document content variation, and vice versa.

4. Experimental Dataset

We used the Sogou Labs query log dataset from June 2008 (June 1–June 29) as our experimental dataset. The data format is shown in Table 1 .

Table 1 Sample Format of Sogou Query Log Data

User Access Time	User ID	Query	Clicked URL Rank in Results	Clicked URL
00:00:03	[Free Name Generation]	1	http://huaxia.wangzhan8.com/	
00:00:03	[Blonde European Girl]	1	http://a.se2222.com/Html/OPIC/index.html	
00:00:03	[google]	1	http://www.google.com/	

Due to resource constraints, we could not analyze every query in the log. We first applied Poisson sampling [31] to extract 3,000 queries from the Sogou dataset, satisfying two conditions: (1) each query appeared at least 2,000 times in the logs, and (2) each day contained at least 5 distinct clicked URLs.

Three annotators manually labeled the intent category (informational, navigational, or transactional) for these 3,000 queries. Recognizing that a query may belong to multiple categories (e.g., "MP3"could be informational—learning about MP3; navigational—reaching an MP3 site; or transactional—downloading MP3 files), we asked annotators to identify the most likely category in most cases. When intent was ambiguous, the three annotators discussed and decided collectively. Manual annotation yielded 305 navigational queries, 752 transactional queries, and 1,943 informational queries. We then randomly sampled 100 queries from each category for experimental analysis.

To investigate temporal changes in webpages relevant to queries, we selected the top 5 URLs by click frequency for each query daily, crawled their content using a web crawler, and performed main content extraction and word segmentation.

5. Results

5.1 Query Dynamics Analysis

We statistically analyzed query dynamics for the selected informational, navigational, and transactional queries in the Sogou dataset, obtaining the distribution ratios of each intent category across different query popularity patterns, as shown in Table 2 .

Table 2 Ratio of Informational, Navigational, and Transactional Queries Across Query Popularity Distributions

Popularity Distribution	Informational	Navigational	Transactional
No Peak	32%	90%	36%
Single Peak	68%	10%	36%
Multiple Peaks	0%	0%	28%

Regarding peak count in popularity distributions, most navigational queries (90%) contain no peaks, indicating stable user demand for navigational topics. We observed that peakless navigational queries mostly (76%) relate to public institutions, while peaked navigational queries mostly (71%) involve company names. Over half (68%) of informational queries contain peaks, mostly (81%) related to news events, while peakless informational queries typically concern concepts (e.g., "search engine principles"). Transactional queries show 64% with peaks, mostly related to TV programs. When multiple peaks exist, both informational and transactional queries are more likely to be non-periodic. Comparative data shows informational queries are more likely to contain a single peak, while transactional queries are more likely to contain multiple peaks with periodicity.

For single-peak shapes, informational (38%) and navigational queries (8%) are more likely to exhibit right-sail shapes, suggesting user interest in these categories tends to emerge rapidly and gradually decline afterward. Transactional queries are more likely (28%) to show wedge shapes, indicating that interest in transactional topics emerges and disappears at similar speeds.

Regarding overall trends, informational and transactional queries are more likely (45%) to show rise-fall patterns, indicating user interest in informational queries is more volatile within specific timeframes. Navigational queries are more likely (68%) to show smooth trends, suggesting more stable information needs. We observed that smooth-trend navigational queries mostly relate to organizations (e.g., "Peking University"), while upward and rise-fall navigational queries mostly involve company names or celebrity homepages (e.g., "Andy Lau blog"). Transactional queries also tend to show upward trends, indicating growing user attention to transactional topics over time. Notably, smooth-trend transactional queries mostly relate to user interaction behaviors (e.g., "Yahoo mail registration"), while upward and rise-fall transactional queries mostly involve entertainment activities such as game downloads or TV program viewing. Comparative results demonstrate that navigational queries have the highest probability of maintaining smooth trends, informational queries are most likely to show rise-fall patterns, and transactional queries are most likely to exhibit upward trends.

5.2 Information Need Dynamics Analysis

Based on the selected query log dataset, we calculated AvgClickEntropy values for informational, navigational, and transactional queries during the observation period, with results shown in Table 3 .

Table 3 AvgClickEntropy Values for Informational, Navigational, and Transactional Queries

Query Category	AvgClickEntropy
Informational	0.42
Navigational	0.20
Transactional	0.35

The data shows that informational queries exhibit greater temporal information need variation than the other two categories. To examine differences in AvgClickEntropy values across intent categories, we conducted independent samples t-tests, with results shown in Table 4 .

Table 4 Differences in Information Need Changes Among Informational, Navigational, and Transactional Queries

Comparison	t-statistic	Significance
Informational vs. Navigational	32.64*	$p < 0.05$
Navigational vs. Transactional	21.21*	$p < 0.05$
Informational vs. Transactional	2.45*	$p < 0.05$

The results reveal significant differences between informational queries and the other two categories (informational vs. navigational: t = 32.64, $p < 0.05$; informational vs. transactional: t = 21.21, $p < 0.05$).

5.3 Document Content Dynamics Analysis

Using the collected result sets for sample queries, we calculated average ContentChange(q) values for different query categories using TF-IDF and Shingle metrics, with final results shown in Table 5 .

Table 5 Average ContentChange(q) Values for Informational, Navigational, and Transactional Queries

Query Category	TF-IDF Average	ShDiff Average
Informational	0.49	0.38
Navigational	0.15	0.12
Transactional	0.32	0.25

The data indicates that informational queries show larger temporal webpage content changes compared to transactional and navigational queries, while navigational queries exhibit the smallest content variation. To examine differences in TF-IDF and ShDiff averages across intent categories, we conducted independent samples t-tests, with results shown in Table 6 .

Table 6 Differences in Temporal Webpage Content Changes Among Informational, Navigational, and Transactional Queries

Comparison	TF-IDF Average	ShDiff Average
Informational vs. Navigational	23.10*	13.40*
Navigational vs. Transactional	0.25*	0.44*
Informational vs. Transactional	2.45*	5.23*

Significant differences exist between informational queries and other categories (informational vs. navigational TF-IDF: t = 23.10, $p < 0.05$; informational vs. transactional TF-IDF: t = 2.45, $p < 0.05$; informational vs. navigational ShDiff: t = 13.40, $p < 0.05$; informational vs. transactional ShDiff: t = 5.23, $p < 0.05$).

5.4 Analysis of Information Need and Document Dynamics with Query Dynamics

Compared to other network dynamic features, query popularity characteristics are more easily observable. Therefore, we explore how information need dynamics and document dynamics manifest across different query popularity patterns for each query category, aiming to infer implicit features from more observable ones.

(1) Information Need Dynamics Analysis To examine information need changes across different query dynamics for each category, we calculated AvgClickEntropy values for different intent categories under various query dynamic features, with results shown in Table 7 .

Table 7 Average AvgClickEntropy Values for Informational, Navigational, and Transactional Queries Across Different Query Dynamics

Query Dynamic Feature	Informational	Navigational	Transactional
Single Peak	0.38	0.18	0.32
Multiple Peaks	0.45	0.22	0.36
Periodic	0.40	0.20	0.34
Non-periodic	0.42	0.21	0.35
Wedge Shape	0.41	0.19	0.33
Castle Shape	0.39	0.20	0.37
Sail Shape	0.40	0.20	0.34
Smooth Trend	0.35	0.16	0.28
Upward Trend	0.44	0.23	0.36
Rise-Fall Trend	0.46	0.24	0.38

The data shows that queries with multiple peaks exhibit higher AvgClickEntropy values than single-peak queries, indicating that multi-peak queries contain greater temporal information need variation. When different intent categories share the same peak type, informational queries show larger information need changes than the other two categories. Regardless of periodicity, informational queries demonstrate greater information need variation than other categories.

Regarding peak shapes, when peaks are wedge-shaped, informational queries show greater information need changes than transactional queries. When peaks are castle-shaped, transactional queries exhibit greater changes than informational queries. When peaks are sail-shaped, all three categories show similar information need variation. For overall trends, queries with smooth distributions show relatively small information need changes, while those with upward or downward trends show larger changes. Across all trend types, informational queries demonstrate greater information need variation than other categories.

(2) Document Content Dynamics Analysis To examine webpage content changes across different query dynamic features, we calculated average ContentChange(q) values for each intent category under various query dynamic characteristics, with results shown in Table 8 .

Table 8 Webpage Content Changes for Informational, Navigational, and Transactional Queries Across Query Popularity Features

Query Popularity Category	TF-IDF	ShDiff
	Info	Nav
Single Peak	0.52	0.14
Multiple Peaks	0.58	0.16
Periodic	0.48	0.15
Non-periodic	0.55	0.17
Wedge Shape	0.56	0.18
Castle Shape	0.45	0.14
Sail Shape	0.47	0.15
Smooth Trend	0.50	0.13
Upward Trend	0.54	0.16
Rise-Fall Trend	0.49	0.15

The results show that during the observation period, more peaks in query popularity distribution correlate with larger webpage content changes for the query. When different intent categories share the same peak type, informational queries exhibit greater webpage content changes than other categories. Regarding periodicity, periodic queries show smaller webpage content changes than non-periodic queries. When query popularity distributions are periodic, informational queries demonstrate greater webpage content changes than transactional queries. Periodic transactional queries typically relate to current popular TV programs or sports events, while periodic informational queries mostly relate to celebrities.

For peak shapes, wedge-shaped peaks correspond to larger webpage content changes than sail or castle shapes. For the same peak shape, transactional queries show greater webpage content changes than other categories. Regarding overall trends, rise-fall trend queries show smaller webpage content changes, while smooth and downward trend queries show larger changes. This occurs because rise-fall and upward trend queries contain different query facets, and users are interested in different facets at different times, resulting in content differences in relevant documents across time points. Additionally, for the same overall trend, navigational queries show smaller webpage content changes than other categories, indicating that users prefer search engines to return consistent content for navigational queries across time periods.

6. Recommendations for Search Engine Performance Optimization

Based on the experimental results, we propose the following recommendations for search engine optimization:

(1) For Informational Queries Search engines should continuously capture potential user intents within queries and diversify result presentations as much as possible, returning information relevant to different query facets to meet diverse user needs. Additionally, for informational queries with peaked popularity, candidate queries can be prioritized for recommendation within 3–5 days after peak emergence.

(2) For Navigational Queries User information needs are explicit, so search engines must ensure authoritative pages remain prominently ranked. Since user information needs for navigational queries are relatively fixed, search engines can maintain consistent webpage content for such queries and leverage long-term information (e.g., past user behavior) to optimize results.

(3) For Transactional Queries For transactional queries related to user interaction behaviors, user needs and webpage content change minimally, so relevant page rankings should remain stable over long periods. For entertainment-related transactional queries, users may be periodically interested in the latest events, so search engines should crawl fresh webpages periodically, integrate them into results, and consider webpage novelty in ranking.

7. Conclusion

This paper analyzed the network dynamics of informational, navigational, and transactional queries from three perspectives: query dynamics, information need dynamics, and document content dynamics. We further examined how information need dynamics and document content dynamics vary with query dynamics across different intent categories. Finally, we provided recommendations for search engine performance optimization.

Nevertheless, this study has several limitations to address in future work: examining network dynamic characteristics over longer time periods, automatically categorizing and identifying peaks in popularity distributions lacking peaks or containing multiple peaks, and comprehensively considering document structure and word changes to identify document content variations.

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Note: Figure translations are in progress. See original paper for figures.