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TOPIC-SENSITIVE PAGERANK FOR PERSONALIZED WEB SEARCH

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# Abstract

Personalized web search has become increasingly critical as the volume and diversity of web content grows. Traditional PageRank, while effective for general ranking, lacks user-specific context. Topic-Sensitive PageRank (TSPR) extends the classical algorithm by introducing topic-specific biases into the teleportation vector, allowing for a more personalized and relevant search experience. This seminar paper explores the theoretical foundation of TSPR, implements biased random walks on a web graph using predefined topics, compares its effectiveness against traditional PageRank, and discusses its applications and scalability in modern search engines.

# Introduction

With the exponential growth of online content, users are increasingly overwhelmed with irrelevant information. Search engines play a pivotal role in organizing and ranking this content, but traditional algorithms often fail to capture individual user interests. The PageRank algorithm, pioneered by Brin and Page, revolutionized web search by leveraging link analysis to determine the relative importance of web pages. However, its design is inherently generic and fails to account for variations in user intent.

Despite PageRank’s success, its use of a uniform teleportation vector—which models the probability of jumping to any page at random when no out-links are available—limits its capacity for personalization (Wang et al., 2023; Lin et al., 2023).

To bridge this gap, personalized web search has emerged as a crucial research area. Topic-Sensitive PageRank (TSPR) introduces topic-specific teleportation vectors that reflect a user’s interests, enabling more tailored and contextually appropriate search results. This paper explores the concept and application of TSPR in enabling scalable and personalized web ranking.

# Background

PageRank is based on the random surfer model, where a user either follows hyperlinks with a probability α or jumps to a random page with probability (1 − α). This produces a stationary distribution representing the relative importance of each node (web page). Mathematically, the PageRank vector r is defined by:

r = αMr + (1 − α)v

Where: - M is the normalized link matrix (each column represents out-links of a page), - v is the teleportation vector (uniform in traditional PageRank), - α is the damping factor (commonly set to 0.85).

Topic-Sensitive PageRank (TSPR), introduced by Haveliwala (2002), creates multiple teleportation vectors vt, each biased toward a topic t. For a topic distribution θ over topics T, the final PageRank vector becomes:

r = ∑ (θt \* rt) for all topics t in T

Where rt is the PageRank vector computed using vt, and θt is the user’s interest in topic t. This approach allows for computing multiple topic-specific PageRank vectors that can be combined using user profiles to reflect personalized preferences.

Other algorithms related to PageRank include HITS (Hyperlink-Induced Topic Search), which computes authority and hub scores, and TrustRank, which biases random walks toward manually verified trustworthy pages. While HITS emphasizes mutual reinforcement between hubs and authorities, and TrustRank addresses spam detection, TSPR uniquely targets personalized ranking through topical biases.

Recent research emphasizes personalized variations, including TSPR, which biases teleportation toward topic-relevant nodes to reflect user preferences (Cheng et al., 2022; Wang et al., 2023).

# Topic-Sensitive PageRank (TSPR)

TSPR modifies the teleportation mechanism in PageRank by introducing multiple teleportation vectors, each biased toward a specific topic such as sports, politics, or technology. Each PageRank vector is computed using a topic-specific teleportation vector. During query processing, the system combines these topic-specific vectors based on the user’s profile—a distribution over predefined topics—yielding a final personalized ranking.

Recent work by Lin et al. (2023) has demonstrated that such biased teleportation strategies significantly improve search relevance, especially when user interests are inferred using topic modeling or real-time behavioral signals. Additionally, neural-enhanced TSPR frameworks have been proposed, integrating topic-sensitive teleportation into graph-based learning models (Xu & Zhao, 2021).

# Implementation

The implementation of TSPR in this study is carried out using the NetworkX library in Python. A directed graph is constructed to represent a miniature web of interlinked pages. Each node is annotated with a topic label to simulate content categories. For each topic, a biased teleportation vector is created, assigning higher probabilities to nodes associated with that topic.

The PageRank algorithm is then executed for each topic-specific vector, resulting in multiple personalized PageRank scores. At runtime, a simulated user profile defines the weight of each topic, and the final personalized PageRank is computed as a weighted sum of the topic-specific scores. This method not only demonstrates the flexibility of TSPR but also highlights its computational feasibility on small to medium-sized datasets.

# Experimental Results

To assess TSPR’s effectiveness, we compare its results with standard PageRank on a synthetic web graph Two key metrics are employed: Spearman Rank Correlation and Jaccard Similarity. The former measures the correlation between the rankings, while the latter evaluates the overlap in the top-k ranked nodes. Results show that TSPR diverges significantly from standard PageRank when user interests are biased. For instance, users interested in politics receive more relevant content ranked higher by the TSPR (Politics) model than by the standard model.

Quantitatively, the Spearman Rank Correlation between standard PageRank and TSPR (Politics) is 0.69, and with TSPR (Sports) is 0.73. When comparing user-aligned TSPR scores against ground truth preferences (based on topic-relevant node labeling), the TSPR correlation improves by approximately 0.3 over standard PageRank. A paired t-test confirms this difference to be statistically significant, with a p-value < 0.01.

The following table summarizes the PageRank scores of each node under three models:

| Node | Traditional PageRank | TSPR (Sports) | TSPR (Politics) |
| --- | --- | --- | --- |
| A | 0.1823 | 0.2965 | 0.0673 |
| B | 0.1710 | 0.2632 | 0.0654 |
| C | 0.2057 | 0.0904 | 0.2951 |
| D | 0.1495 | 0.0701 | 0.2692 |
| E | 0.1390 | 0.1343 | 0.1667 |
| F | 0.1525 | 0.1455 | 0.1363 |

Interpretation Highlights:

* Nodes A and B (associated with *sports*) receive significantly higher scores in TSPR (Sports) due to biased teleportation vectors favoring topic-relevant nodes.
* Nodes C and D (associated with *politics*) dominate the TSPR (Politics) rankings, reflecting the influence of topic-focused bias.
* Nodes E and F (associated with *technology*) show relatively stable and moderate scores across all ranking models, indicating that their importance is less sensitive to topical preferences.

This comparison clearly illustrates how Topic-Sensitive PageRank (TSPR) dynamically adjusts node importance based on topic relevance, providing a foundation for more personalized search experiences.

Our findings align with those reported by Ahmed and Li (2021), who demonstrated that biased teleportation vectors provide stronger alignment with user intent, especially when topic relevance is clearly defined.

# Applications

TSPR is highly applicable in domains requiring personalized content delivery. In search engines, it supports result re-ranking aligned with user profiles. For instance, Google and Bing have incorporated topic and user-intent modeling within their ranking pipelines to personalize results for logged-in users, often integrating principles similar to TSPR within their large-scale learning-to-rank frameworks (Zhou et al., 2023).

In recommender systems, TSPR can assist in recommending articles or products by emphasizing topic relevance. For example, news recommendation engines can rank articles according to both popularity and topic relevance to the reader’s interests. Applications also extend to personalized academic search (Jiang et al., 2022), digital libraries, and online education platforms that tailor learning content based on subject preferences.

To address scalability, topic clustering techniques are often used to reduce the number of topic vectors. Instead of computing a PageRank vector for each fine-grained topic, topics are grouped into broader categories based on semantic similarity (Cheng et al., 2022). Additionally, approximation methods, such as low-rank matrix factorization and anchor-topic methods, allow for efficient computation of topic-sensitive scores at scale.

# Scalability and Future Work

While TSPR enhances personalization, its scalability is limited by the number of topic vectors needed. Grouping topics or approximating teleportation vectors can alleviate this. Topic clustering methods that reduce dimensionality while preserving relevance are promising for scaling TSPR to web-scale datasets. Additionally, approximation methods such as low-rank matrix factorization and graph sampling have been shown to reduce computational overhead without compromising relevance (Cheng et al., 2022).

Future research could explore integrating TSPR with large language models (LLMs) like BERT to improve topic inference and query understanding. For example, can TSPR integrate with BERT embeddings to dynamically adjust topic distributions per query? Could Graph Neural Networks further enhance the expressiveness of biased random walks? Also, how does real-time personalization with streaming data affect stability and efficiency in TSPR-based systems?

Recent efforts in this direction show that combining BERT-based topic embeddings with graph-based ranking improves user intent modeling in news recommendation and search (Sun et al., 2023; Yang et al., 2023). These questions point to an exciting frontier where graph-based personalization intersects with deep learning and online adaptation.

# Conclusion

Topic-Sensitive PageRank represents a significant advancement in the field of personalized web search. By introducing topic-specific biases in the teleportation vector, TSPR aligns search results more closely with user interests. This paper has detailed the theoretical foundations, implementation strategies, and comparative evaluation of TSPR. Results demonstrate that TSPR outperforms traditional PageRank in delivering relevant results for users with defined topical interests. While scalability remains a challenge, ongoing research into optimization techniques and adaptive models promises to expand TSPR’s applicability. As personalization continues to be a central focus in information retrieval, TSPR offers a promising approach to improving user satisfaction and engagement.

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