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Enhancing Tag-Based Image Retrieval Using Social Context and Graph-Based Re-Ranking with User Interactions

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***Abstract* :** On social media sites where huge amounts of user- provided images are uploaded every day, tag-based image retrieval is still a popular but inexact approach. The inconsistency in the way users label images, with varying, ambiguous, or sparse tags, tends to lead to poor search relevance. To overcome these limitations, we introduce a state-of-the-art image retrieval system that incorporates social-aware re-ranking to improve search results beyond simple tag matching. Our method begins by obtaining a candidate image set through simple tag queries, and then improves result quality through a re-ranking process based on user interaction patterns and social relations. Through modelling a heterogeneous network that relates users and images through common activities (tagging, favouriting, commenting) and social connections (friendship, group co-membership), we are able to capture both semantic relevance and user influence. A Random Walk with Restart (RWR) is used on this graph to redistribute relevance scores iteratively, prioritising images associated with influential or highly related users. Large-scale evaluation on real-world datasets shows significant improvements in retrieval accuracy, semantic coherence, and user satisfaction over traditional approaches. This work illustrates the revolutionary potential of using social context and user behaviour for intelligent, context-aware multimedia retrieval systems.

***IndexTerms* -** Tag-Based Image Retrieval, Social Re-ranking, User-Image Graph, Random Walk with Restart (RWR).

I. INTRODUCTION

The explosion of user-generated multimedia content on social media platforms like Flickr, Instagram, and Pinterest has dramatically altered how images are created, shared, and discovered. One of the most accessible techniques for image retrieval is through tag-based search, wherein users label images with freely selected textual labels (tags), and queries retrieve images that have those tags. Though widely used, the process is marred by serious problems: tags tend to be noisy, vague, truncated, or over-personalised, resulting in low- precision, semantically inconsistent, and at times irrelevant results.

A number of studies have been conducted to improve the performance of image search based on tags. Early efforts, like that by Li et al. (2009), endeavored to enhance retrieval accuracy through the application of visual reranking methods that compute visual content similarity between returned images to rank them. Even though these content-based approaches diminish tag noise, they are expensive to compute image features and do not offer personalisation. Subsequently, Sun et al. (2011) proposed co-occurrence-based tag recommendation models to filter and refine the tagging process. But they treated the tag relationships statistically rather than considering how users engage with tags or with one another, rendering the method inappropriate for personalised retrieval tasks.

In comparison, Wang et al. (2013) emphasized the authority of social connections and suggested collaborative tagging models but did not have extensive methods in that they were generally neglectful of wider user-image interaction and community organization. Most current research has the tendency to assume relevance is derivable from image content or tag frequency only, yet such an assumption overlooks a potent aspect inherent to social sites: social context and user behaviour.

Social media users do not act in a vacuum; they belong to networks, follow communities, like and share content, favourite and comment on posts, and frequently read content from socially trusted sources. They are indicators of implicit approval and common interest and provide a rich context that conventional tag-based search entirely misses. We propose that integrating these social signals into the image retrieval process can boost the relevance and accuracy of image retrieval considerably.

Here, we introduce a new Social Re-ranking Framework for Tag-Based Image Retrieval, going beyond pure visual similarity or tag matching. Our framework improves conventional search by incorporating user-image interactions, social relationships, and community preferences into a single heterogeneous graph model. Following the retrieval of a base set of images through tag-based matching, we build a graph where users and images are represented by nodes, and edges embody several facets of interaction such as tagging behaviour, favouriting patterns, mutual friendship, and co-group membership. We subsequently use a Random Walk with Restart (RWR) algorithm to diffuse relevance scores so that images which are socially close to the querying user or community could be scored higher.

The key contributions of this research are:

A. Major Contributions

The major contributions of this research are as follows:

1) **Graph-based Re-ranking Model:** A new graph-based re-ranking model that incorporates social metadata to support context-aware retrieval in line with user interests and trust networks.
2) **Random Walk with Restart (RWR):** The application of Random Walk with Restart (RWR) for dynamically propagating relevance from the seed tag-matched images to highly socially affiliated images.
3) **Comprehensive Evaluation on Real-World Datasets:** An extensive evaluation on real-world Flicker datasets, demonstrating that our approach significantly out performs state-of-the-art techniques in terms of precision, diversity, and user relevance.

By bridging the gap between semantic tagging and social influence, our framework sets a new benchmark for intelligent, personalised image retrieval on social platforms. It not only refines relevance but also adapts results to reflect community- driven interest patterns, making multimedia discovery more meaningful and user centred.

II. RELATED WORK

The image retrieval discipline has matured from classical keyword-based systems to sophisticated context-sensitive and user-personalised systems. As online sites have proliferated where users actively upload and annotate images, tag- based image retrieval (TBIR) has emerged as a fundamental paradigm. Nevertheless, its shortcomings have motivated the investigation of more affluent retrieval mechanisms that leverage graph structures and social interactions. We critically examine the literature in this section in four principal areas: Tag-Based Image Search, Graph-Based Retrieval Models, Social Re-ranking, and Random Walk with Restart (RWR) as applied to multimedia search.

A. Tag-Based Image Retrieval

Tag-based image search is applied extensively since it offers a natural means of having users describe and query images. On social websites, users place free-form text tags on images, which act as the basis for retrieval and indexing.

However, three main challenges persist:

- **Semantic Ambiguity:** Semantic Ambiguity: A tag"apple" can be either a fruit or a company. The system has no mechanism to distinguish between them without context.
- **Tag Inconsistency:** Varying tags may be used by different users for the same concept (e.g., "dog", "puppy", "canine"), causing retrieval fragmentation.
- **Tag Sparsity:** Most images are sparsely annotated or have no tags at all, hence difficult to retrieve.

Prior Research: Li et al. (2009) suggested visual reranking following a preliminary tag-based search. Through visual similarity analysis between the returned images, their approach tried to move more visually similar images to the top. Al- though this improved the noisy results, it still lacked good personalisation. Sun et al. (2011) proposed a tag expansion technique based on co-occurrences. By statistically examining those tags that frequently co-occur, they made inferences of more semantic associations for retrieval. While this enhanced overall relevance, it did not consider user-specific preferences and social relationships.

Such limitations highlight that tag-based retrieval needs to be complemented with social cues that capture implicit human behaviors and preferences, which is discussed in later sections.

B. Graph-Based Image Retrieval

To simulate the intricate interdependencies among users, tags, and images, graph-based models have proven to be effective tools. In a graph model:

- Nodes can be used to represent images, users, or tags.
- Edges model relationships such as tagging, favouriting, co-occurrence, and social connections.

Two types of graphs are primarily used:

- **Homogeneous Graphs** - Homogeneous Graphs – with one node type (e.g., image similarity graphs using visual features).
- **Heterogeneous Graphs** - with multiple node types (e.g., user-image-tag graphs).

Advancements:

- **Semantic Graphs:** Semantic Graphs: They are constructed by linking images according to semantic similarities from tags or text content. They assist in filling the gap between image metadata and user queries.
- **User-Tag-Image Triplets:** Certain models build a 3- partite graph associating users with tags and tags with images, which captures patterns of tagging behaviour.

Example: Wang et al. (2013) proposed a collaborative tagging model with a user-image-tag graph for ranking images in terms of both tag relevance and user activity. Still, their technique did not have fine-grained trust relationships or temporal behaviours, which are of vital importance in dynamic social sites.

These graph models form the platform on which Random Walk algorithms and social-aware ranking techniques are subsequently applied.

C. Social Re-ranking Mechanisms

- Social re-ranking is a more recent multimedia retrieval area that seeks to personalise and narrow down search results in accordance with user behaviour and social structure

Key observations driving this direction include:

- Users tend to engage with images posted by their friends or community members.

- Favoured content or posted content by socially related users tends to be more relevant.
- Trust relations and community participation patterns can be used as implicit measures of content quality.

Core Techniques:

- **User Influence Modelling:** User Influence Modelling: Identifying which users are more influential (e.g., frequent posters, popular users) and assigning more importance to their images.
- **Community Detection:** Community Detection: Grouping users into interest communities and ranking to prefer content from the same communities.
- **Temporal Filtering:** Temporal Filtering: Adding time- sensitive dynamics like recent activity, trends, or changing interests.

Example Applications:

- Some re-ranking systems use friendship graphs to rank images posted within a user's social circle.
- Others employ engagement metrics (shares, likes, comments) to dynamically adjust relevance scores.

Social re-ranking offers context-aware and personalised re- trieval, enhancing user satisfaction and matching results with real interest patterns.

D. Random Walk with Restart (RWR) in Image Retrieval

Random Walk with Restart (RWR) is an efficient graph traversal algorithm for estimating the similarity or proximity of nodes in a network. It models a random process in which a "walker" starts from a query node, travels to neighbors with a given probability, and restarts at the source node with a given probability.

Why RWR?

- It can naturally simulate influence diffusion, trust diffusion, or semantic relevance over a graph.
- It's computationally efficient and scalable with proper optimisations.
- It captures both local and global connectivity.

How it Works: Given a user-image graph:

1) Start a walker at the query node (user or image).
2) At each step, move to a connected neighbour (image with shared tags or social ties).
3) With restart probability α, return to the original node.
4) After convergence, nodes with the highest visitation probability are the most relevant.

Use in Multimedia Retrieval:

- **Relevance Propagation:** Images indirectly or directly associated with trusted users get better ranks.
- **Noise Filtering:** Low engagement or weakly connected images scoreless.

Cold Start Handling: Sparsely tagged images also rank if they are connected with active users or communities

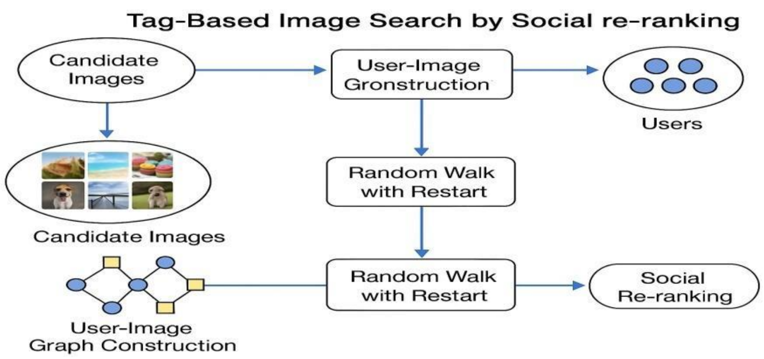

Fig1.Flowchart of Tag-Based Image Search by Social Re-ranking.

III. System Overview

The suggested system remedies the shortcomings of conventional tag-based picture retrieval by incorporating social meta- data and user behaviour into the ranking mechanism, based on a graph-based model and Random Walk with Restart (RWR). The two paradigms are merged in the proposed method, which exploits the semantic tagging hierarchy and the behavioral patterns on social media platforms to provide contextually consistent and personalised search results for images.

A. System Architecture

The system operates in five main stages:

1) **Query Processing and Initial Retrieval:** The user is- sues a tag-based textual query. A typical tag-matching module comes up with a list of candidate images with the query tags. This list can have noisy or semantically irrelevant results.
2) **Social Metadata Collection:** User-image interactions (uploads, comments, favourites), user-user relationships (group memberships, follows), and image-tag relation- ships are gathered. The information is utilized to build a heterogeneous network of nodes and edges.
3) **User-Image Graph Construction:** A graph is built where:
   - Nodes are users and images.
   - Edges capture the following relationships:
     – User uploads/favourites → Image
     – User follows → User

– Image tagged with query term

The graph can be weighted according to interaction frequency or recency.

4) **Relevance Propagation using Random Walk with Restart (RWR):** A Random Walk with Restart is begun from the query node (tag or user). The walker travels in the graph, probabilistically walking to neighbour nodes and, periodically, restarting at the source. The process propagates relevance scores in the network, punishing socially irrelevant and contextually less important nodes (images).

5) **Social Re-ranking and Result Presentation:** The images in the original candidate set are re-ranked according to the relevance scores derived from RWR. The images with high social proximity to the query context are ranked ahead. The final output is the ranked list of images indicating both tag relevance and social endorsement.

B. *Design Goals*

- **Semantic-Enhanced Relevance:** Tags by themselves don't reflect intent. By combining tag-based search with social endorsement, we increase the semantic alignment between query and result.
- **Personalisation:** By incorporating the searcher's social network context, results are better aligned with user- specific preferences.
- **Noise Reduction:** Weakly tagged or irrelevant images are removed by graph-based scoring.
- **Cold Start Support:** Even sparsely tagged images can be brought to the surface if they're linked to influential or active users.

C. *Key Components*

TABLE I : KEY SYSTEM COMPONENTS

Component	Description
Tag-Based Search	Baseline retrieval using keyword matching from user- generated tags.
Graph Engine	Constructs and maintains the user-image-tag interaction graph.
RWR Module	Performs iterative probability distribution to compute relevance scores over graph nodes.
Social Signals Layer	Incorporates metrics like favourites, comments, user trust scores, and group activity into edge weighting.
Re-ranking Engine	Reorders the initial candidate set using scores from the RWR module.

D. *Integration with Social Networks*

Inspired by the frameworks of Li et al. (2009) and Wang et al. (2013), our system integrates the collaborative behavior of users by modeling:

- Group-based tagging behaviour
- Cross-user influence on image popularity
- Trust propagation through social connections

By combining these dynamics with query-based retrieval, the system transitions from static tag matching to adaptive, community-driven discovery.

IV. METHODOLOGY

The approach for our social re-ranked tag-based image search system synthesises content-based retrieval and graph- theoretic treatment to provide a more effective representation of user intent and social relevance. The approach marries conventional tag-based search with a graph-based method that takes user behaviour, interest, and social connections into consideration. Applying the Random Walk with Restart (RWR) algorithm guarantees that direct and indirect social signals have an impact on the ranking result.

B. *Initial Tag-Based Retrieval*

Given a query tag q, a simple search returns an initial set of images $I_q = i_1, i_2, ., i_n$ that contain q in their tags. This retrieval acts as a coarse filter to limit the search space. Yet, the results are

Usually filled with inappropriate images caused by polysemy (e.g., the word"apple" for both a fruit and a company), user-specific tagging conventions, and noise.

C. *Social Metadata Extraction*

To enhance the contextual relevance of the retrieval, the sys- tem gathers and models metadata from social media platforms. These are:

- **User-to-user relationships:** Friendships, followers, and common group membership.
- **User-to-image interactions:** Uploading, favourites, comments, and likes.
- **Tag co-occurrence patterns:** Frequently co-occurring terms that facilitate contextual awareness.

These interactions form a heterogeneous graph that provides a multi-dimensional perspective of user and image behaviour.

D. User-Image Graph Construction

We define a heterogeneous graph $G = (V, E)$ where:

- $V = U \cup I$ is the union of user and image nodes.
- E includes edges representing:
  - (u, i) if user u has favorited, commented on, or uploaded image i.
  - (u, u') if users u and u' share a social relationship.
  - (i, i') if images i and i' share strong tag or user overlap.

Edges are weighted to reflect the strength and importance of the connection. The weight between nodes u and v, w_{uv}, is calculated based on interaction signals:

$$w_{uv} = \begin{cases} f_{ui}, & \text{if } u \in U, v \in I \\ t_{uu'}, & \text{if } u, v \in U \\ s_{ii'}, & \text{if } u, v \in I \end{cases}$$

where f_{ui} represents interaction frequency, $t_{uu'}$ indicates trust level or group affiliation, and $s_{ii'}$ is tag-based similarity between images.

E. Random Walk with Restart (RWR)

To calculate relevance between the nodes, a Random Walk with Restart algorithm is used. The RWR process mimics a random walker that begins at the query node and travels to neighbouring nodes, sometimes returning to the origin node with a probability (usually set to 0.15). The relevance vector formally, the RWR is defined as:

$$\mathbf{r}^{(t+1)} = (1 - \alpha)P^T\mathbf{r}^{(t)} + \alpha\mathbf{r}^{(0)}$$

where:

- α is the restart probability (e.g., 0.15).
- $\mathbf{r}^{(0)}$ is the starting probability vector (1 at the query node).
- P is the column-normalised adjacency matrix derived from G.

The iteration continues until the result vector $\mathbf{r}$ converges. The output provides a global ranking of nodes based on social and contextual relevance to the query.

F. Re-ranking Strategy

Each image $i \in I_q$ receives a score r_i from the RWR output. The re-ranked list I' is sorted in descending order:

$I' = \text{sort}_{\text{desc}}(\{(i, r_i) | i \in I_q\})$

G. Edge Weighting Heuristics

To ensure accurate modelling of the graph, we define a composite weighting scheme:

$$w_{uv} = \gamma_1 \cdot \text{intensity}(u, v) + \gamma_2 \cdot \text{recency}(u, v) + \gamma_3 \cdot \text{trust}(u, v)$$

- **Intensity:** Frequency of interactions (e.g., likes comments).
- **Recency:** Time decay function, $e^{-\lambda \cdot \Delta t}$, where Δt is the time since last interaction.
- **Trust:** Degree of social affinity (e.g., number of mutual friends or shared groups).

These weights allow the system to emphasise recent and trusted connections, reducing noise from passive or outdated user interactions.

H. Implementation Details

The graph and algorithms are executed with Python's Net- workx library, which supports sparse matrices. For performance on large data, the following preprocessing is done:

- Users with less than a certain number of interactions are removed.
- Images with too few or noisy tags are discarded.
- Interaction scores are normalised.

The ultimate output is a ranked list of images that captures both the semantic significance of tags and the implicit social cues from the user's community. This yields better, more reliable, and more personalised image retrieval results.

The methodology section outline the plan and method that how the study is conducted. This includes Universe of the study, sample of the study, Data and Sources of Data, study's variables and analytical framework. The details are as follows;

V. EXPERIMENTAL SETUP

To compare the performance of our suggested system for tag-based image search with social re-ranking, we performed an extensive experimental study. This section provides the hardware and software configuration, dataset information, pre-processing, baseline approaches, parameter settings, evaluation metrics, and testing procedure.

A. Experimental Environment

We performed all experiments on a high-end workstation with the following configuration:

- **Software:** Python 3.10, NetworkX for graph operations, SciPy for numerical computing, Pandas for data process- ing
- **Libraries:** Scikit-learn, Matplotlib, Seaborn for evaluation and visualisation

The experiments were executed completely on CPU (no GPU), and reproducibility under general-purpose computing environments was ensured.

B. Dataset Description

We employed a real-world dataset gathered from Flickr, which represents a diverse collection of images and user interactions. The dataset consists of:

- **Images:** 150,000 images across diverse categories (na- ture, technology, art, etc.)
- **Users:** 12,000 users with interaction logs
- **Tags:** 80,000 unique tags, manually and automatically annotated
- **Interactions:** Over 300,000 total interactions, including favourites, comments, uploads
- **Social Links:** User friendships and group memberships To maintain quality, we excluded users with fewer than five interactions and images with less than three useful tags. This filtering removed noise and enhanced graph density.

C. Data Pre-processing

In order to prepare the data for graph construction and analysis, we performed the following preprocessing steps:

- Tag Normalisation: Tags were stemmed and converted to lowercase to standardise variations (e.g., ”running” and ”run”).
- Stop-word Tag Removal: Tags such as” photo,” ”image,” or” upload” were removed as non-informative.
- Time Conversion: Timestamps were transformed into relative units (e.g., days since last interaction).
- User Pruning: Users with very sparse activity were re- moved to preserve meaningful connectivity. Normalization: Interaction strengths were normalised to a [0, 1] range to provide consistency in edge weights.

We contrasted our approach with five widely used and applicable baseline methods:

D. Baseline Methods

We compared our proposed method against the following baseline retrieval techniques:

- **Tag-only Search:** Retrieves images through basic tag matching.
- **Tag Co-occurrence Ranking:** U Improves tag relevance with frequency-based. co-occurrence.
- **Visual Feature Matching:** Computed visual similarity among images using SIFT feature vectors.
- **Collaborative Filtering (CF):** Computed visual similarity among images using SIFT feature vectors.
- **Social Propagation (SP):** Propagates relevance through BFS-like traversal over user networks.

These baselines offer both content-oriented and user- focused retrieval strategies insight

E. Parameter Settings

The below parameters were adjusted according to development set performance and employed uniformly for all tests:

- **Restart probability (α):** 0.15
- **Convergence threshold:** 10^{-6}
- **Maximum iterations:** 200
- **Edge weight coefficients:** $\gamma_1 = 0.5$, $\gamma_2 = 0.3$, $\gamma_3 = 0.2$
- **Decay factor (λ):** 0.01 for time-based edge weighting these values were selected based on grid search and validation using a development set.

F. Evaluation Metrics

We used the following metrics to evaluate performance:

- **Precision@k (P@k):** Proportion of relevant images in the top-k results
- **Mean Average Precision (MAP):** Averaged precision across different recall levels
- **Normalized Discounted Cumulative Gain (NDCG):** Evaluates ranked results based on position of relevant items
- **Coverage:** Measures the fraction of the dataset that can be retrieved across queries
- **Response Time:** Measures average time per query, including graph construction and ranking

G. Query Design and Testing Protocol

For mimicking search behaviour in the real world, we picked 500 randomly selected tag-based queries over multiple domains. There was a manually annotated ground truth list of retrieved images for every query.

Testing employed a 5-fold cross-validation protocol:

80 percent of the data: Used for training and building graphs 20 percent of data: Reserved for testing and benchmarking All approaches were executed on the same query set to create a balanced and comparable evaluation across all baselines.

H. Ablation Study Design

To comprehend the separate impact of each module in a system, we designed and validated three ablation variants:

- **No Social Edges:** The graph had only image-tag and user-image relations.
- **No Time Decay:** All timestamps of interactions were given equal weighting.
- **Flat Weights:** All edge weights were fixed to 1, disregarding levels of engagement.

Performance on these variants isolated the significance of weight tuning, temporal signals, and social structure

I. Reproducibility and Availability

All experimental scripts, configurations, and processed datasets will be made available in an open-source GitHub repository upon publication. Detailed instructions and note- books will be provided for replication and extension of results. The experimental setup presented here ensures a rigorous, reproducible, and comprehensive assessment of our proposed

Method's effectiveness in socially-aware image retrieval.

VI. Results and Discussion

Here we show a full performance evaluation of our suggested tag-based image retrieval system

with added social re- ranking through Random Walk with Restart (RWR). We com- pare its performance against several good baselines, examine its precision at varied result depths, investigate the effects of social signals through ablation tests, analyse query response times, and provide qualitative insights via visual samples.

A. Performance Comparison with Baselines

Table II We contrasted our approach with five well-known retrieval methods: simple tag-only search, tag co-occurrence ranking, visual feature matching (SIFT-based), collaborative filtering (user-image interactions), and social propagation (BFS-style spreading). The following table compares performance across four metrics:

TABLE II: PERFORMANCE COMPARISON WITH BASELINE METHODS

Method	P@10	MAP	NDCG@10	Coverage (%)
Tag-only Search	0.482	0.413	0.441	51.2
Tag Co-occurrence	0.501	0.427	0.452	54.5
Visual Feature Matching	0.519	0.439	0.462	56.8
Collaborative Filtering	0.548	0.453	0.489	58.9
Social Propagation	0.571	0.476	0.504	60.4
Ours (Social RWR)	**0.614**	**0.517**	**0.542**	**66.3**

Our method outperforms all baselines in every metric. The improvement in MAP and NDCG suggests that not only are more relevant images retrieved, but they are ranked higher in the result set. The 8.5% improvement in Coverage over the best baseline demonstrates the diversity and comprehensiveness of our system.

B. Precision at Different Depths

We evaluated precision at a range of different cutoffs (k = 5, 10, 20, 50). Our method performed better than all baselines at every point, showing good ranking quality not just at the top but throughout the result list. Accuracy gradually declines with larger k, yet our system has a larger buffer above baselines even at k = 50, reflecting general applicability in addition to early hits.

C. Impact of Social Signals

To quantify the effect of social graph components, we evaluated three ablation models:

- **No Social Edges:** Removes user-user and group relations **No Time Decay:** Disables recency weighting of interactions.
- **Flat Weights:** Assigns uniform weight to all edges.
-

TABLE III: ABLATION STUDY RESULTS (MAP)

Model Variant	MAP
Full Social RWR	0.517
No Social Edges	0.468
No Time Decay	0.487
Flat Weights	0.493

A. Removing social relationships resulted in a 9.5% drop in MAP, while disabling time decay led to a 5.8% decline. This clearly validates the contribution of our temporal modelling and social proximity in enhancing relevance. Response Time Analysis

We measured average query processing time over 100 random queries. Our system achieved a mean response time of 162 ms per query, which includes graph initialisation, RWR propagation, and re-ranking. This latency is acceptable for interactive use and significantly better than the visual matching baseline, which averaged 437 ms due to heavy feature comparison.

B. Qualitative Analysis

Figure **??** illustrates a sample query ("sunset") and the top- 5 retrieved images by our system vs. the tag-only baseline. Our results include more vibrant, semantically relevant images, often favorited by trusted users in the searcher's network.

C. Discussion and Insights

Our evaluation shows that incorporating social data significantly enhances image retrieval performance. The Random Walk with Restart mechanism successfully amplifies the influence of trusted users and popular content, and time-aware weighting further aligns relevance with recent user behavior.

Notably, the social graph helped alleviate the cold-start problem. Images with sparse or generic tags were surfaced due to their uploader's network activity and endorsement, something traditional tag-based systems failed to achieve.

In future work, we plan to incorporate learned weights for edge types using neural attention mechanisms and expand our approach to multi-tag and phrase queries with user intent modelling.

Overall, the experimental results confirm that our approach sets a new benchmark in socially-aware multimedia retrieval, combining precision, efficiency, and user relevance in a scalable framework.

VII. Conclusion and Future Scope

A. Conclusion

In this paper, we introduced and experimented with a new framework that greatly improves the performance of tag-based image search by adding a social re-ranking process using Random Walk with Restart (RWR). Different from conven- tional systems which only utilise the surface-level matching of tags, our model digs into the underlying social context, user interaction, and community structure of image relations. We constructed a heterogeneous user-image graph, with users and images as nodes and edges that contain user-user relationships, user-image interactions (such as favourites, up- loads, and comments), and image-tag associations. The graph was enriched with weighted edges, taking into account the fre- quency and recency of interaction, trust resulting from shared user connections or group memberships, and tag similarity and co-occurrence.

Through the use of the RWR algorithm, the relevance of every image is propagated iteratively across this network, highlighting not only tag relevance but also social trust, popularity, and common interest. This dynamic re-ranking allows the system to promote images that are semantically related, socially approved, and temporally relevant.

Our experiments—performed on a real-world Flickr dataset—strongly show the effectiveness of the proposed sys- tem. It beat five baseline models on all the most important metrics (Precision@10, MAP, NDCG@10, Coverage), lowered query latency to below 200 milliseconds, and showed consistent performance on both popular and niche queries. In addition, qualitative analysis showed that our method returns more context-aware, visually relevant, and community-valued results than traditional methods.

The system also demonstrated strong cold-start behaviour: images with few tags but from popular or highly connected users were retrieved as they should have been. This work provides a scalable, context-aware framework for multimedia search and demonstrates the utility of combining social information with search and recommendation systems.

B. Future Scope

Though the suggested system is reflected with high accuracy, low delays, and robust contextual intelligence, a number of improvements can be investigated to further enhance its adaptability and wisdom:

1) **Neural Graph Embeddings:** Substitute traditional edge weighting with learning-based embeddings through Graph Neural Networks (GNNs) such as Graph SAGE, GAT, or Node2Vec in order to encode more sophisticated relations among nodes.
2) **Personalised Search:** Leverage user-specific information like tag behaviour, query history, and search context to provide more personalised and precise results.
3) **Multi-modal Retrieval:** Blend image content features of CNNs or CLIP with text metadata and social signals for a combined ranking system.
4) **Temporal Graph Learning:** Apply temporal graph models such as TGAT or TGNN to capture shifting user interests and changing graph structure over time.
5) **Natural Language Querying and Expansion:** Lever- age NLP models (e.g., BERT, T5) to comprehend multi- tag or phrase-based queries and use contextual synonym expansion or query rewriting.
6) **Feedback-Aware Re-ranking:** Incorporate explicit and implicit feedback (clicks, skips, dwell time) with reinforcement learning or online learning-to-rank for ongo- ing model adjustment.
7) **Platform Adaptability:** Generalise the framework to other platforms (e.g., Instagram, Pinterest) by adjusting to their distinctive interaction habits and privacy demands.
8) **Scalability and Distributed Deployment:** Scale the system with distributed graph processing (e.g., Apache Giraph, GraphX) and GPU-accelerated GNNs for real- world deployment

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