Social Information Retrieval using Linked Data and Deep Learning

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ABSTRACT

Online Social Networks (OSNs) are becoming increasingly important in business, government, and all areas of life. For-profit companies use them as rich sources of information and dynamic platforms to drive strategies in product design, innovation, relationship management, and marketing. However, analyzing and retrieving information from these platforms presents distinct challenges due to their inherent characteristics and dynamic nature. To address this, researchers have proposed various approaches for social information retrieval, ranging from term-based analysis to semantic-based methods. To overcome the limitations of existing techniques, the present study proposes a multilayer model that integrates graph analysis, semantic content, and deep learning. The general proposed approach is also presented. By combining learning-to-rank techniques with linked data, a robust framework for social information retrieval is constructed. This method enables a more nuanced understanding by leveraging both the rich contextual information provided by linked data and the structural characteristics of social networks. The proposed model is a flexible framework that can be easily extended to add or remove features and can be applied to various tasks. The experimental results confirm the effectiveness and efficiency of the proposed approach.

Keywords-online social network; social information retrieval; linked open data; entity linking; deep learning; learning to rank

I. INTRODUCTION

One of the main developments of the Web over the past decade has been the emergence of OSN platforms, such as Facebook, Twitter, and Instagram, with the latter being the most frequently used for influencer marketing. These platforms enable users to connect, share, and interact within online communities, generating vast amounts of data. As a result, an enormous volume of information is being produced at incredibly rapid rates, often making data quickly outdated [1]. Some of the most well-known applications of OSNs include viral marketing, decision-making processes, and brand advertising [2].

In this context, a key challenge is enabling users to find relevant information according to their interests and needs—an area commonly referred to as Social Information Retrieval (SIR) [3]. However, analyzing and retrieving information from these platforms presents unique challenges due to the short length and noisy nature of the content, which often includes slang, abbreviations, emojis, and mixed languages.

Early research did not take into account the social aspect of the Web. Traditional models treated web pages as static, homogenous collections of terms, relying on ranking algorithms (e.g., PageRank [4], HITS [5]) and text-based similarity measures between queries and documents (e.g., cosine similarity, Okapi BM25 [6]). Today, however, several projects aim to improve the SIR process by leveraging data from social networks [7]. Popular research areas include identifying influential users [8, 9], personalized recommendations [10], sentiment analysis [11], event detection, and real-time information retrieval [12].

Twitter is one of the most popular microblogging platforms, offering access to real-time data. This article proposes an approach for retrieving information from Twitter streams. The primary goal is to determine people's views about concepts, such as products, brands, and individuals. Microblogging retrieval systems face several challenges, as posts tend to lack context due to their short length and are often informal, noisy, and ambiguous. To address these issues, this study proposes a new framework: Multilayer Model for Social Information Retrieval based on Entity Linking and Learning to Rank (MSIR2L), which incorporates both semantic and social features. This paper presents the general proposed framework for social information retrieval, which combines deep learning methods with linked data. This approach enables a more nuanced understanding by leveraging both the rich contextual information found in linked data and the structural characteristics of social networks.

In order to properly situate this study's proposal, this section describes a few frameworks that have been presented in the literature. One of the first frameworks which used linked data for entity disambiguation was Linked Data Entity Linking Framework (LINDEN) [13], which combined linguistic analysis with semantic understanding from structured data sources, such as DBpedia. This allowed LINDEN to link items with high precision. However, it relied on vast amounts of interconnected data, which restricted its use in domains lacking such organized resources. The Learning-Based Named Entity Detection Framework (LINGE) [14] integrated machine learning techniques, such as Conditional Random Fields (CRF). Its effectiveness depended on the availability of large volumes of training data. Knowledge-Aware Entity Linking (KAURI) [15] significantly outperformed existing frameworks for tweet entity linking. It used a unified graph-based model that combined intra-tweet local information with inter-tweet user interest information, which proved highly effective in the novel setting of tweet entity linking. However, its reliance on external information limited its broader applicability. Yet Another Framework for Tweet Entity Linking (YAFTEL) [16] was specifically designed for linking entities in noisy, informal, and short texts. YAFTEL employed contextual and coherence-based measures to handle the ambiguities typical of social media content. It incorporated the degree of direct references between candidate entities into the traditional approach used by the KAURI system. Experiments showed that YAFTEL mapped entity mentions to Wikipedia entities more accurately than KAURI, particularly when candidate entities referenced each other mutually or unidirectionally. Nonetheless, YAFTEL was limited to tweet-based applications. Finally, Optimized Contextual Entity Linking (OPTIC) [17, 18] was based on contextual embeddings and utilized BERT for machine learning. OPTIC demonstrated significant improvements in linking accuracy, although its use of deep learning models made it computationally intensive. These frameworks illustrate the evolution from early linked data-based approaches to modern machine learning and context-aware models. Table I presents a comparison of the frameworks found in literature. The present work proposes a new framework: MSIR2L, a mixed entity linking method based on social and contextual features, integrated within a deep learning architecture.

TABLE I. COMPARISON OF LITERATURE FRAMEWORKS

Framework	Foundations	Advantages	Limits
LINDEN	Linked data integration	High precision with semantics	Relies on comprehensive linked data
LINGE	General NER + EL	Adapts via ML	Needs large, high-quality training data
KAURI	Knowledge-based linking	Domain-specific adaptation	Requires external knowledge resources
YAFTEL	Tweet entity linking	Noisy/short text	Limited to tweets
OPTIC	Context-aware linking	Complex ambiguity	Computationally intensive
MSIR2L	Microblog retrieval/ tweet entity linking	Noisy/short text/document	Adds more features

II. PRELIMINARY AND DEFINITIONS

This work is related to the area of social information retrieval, specifically microblog post retrieval. A user is typically interested in reading a stream of microblog posts in real time. The main goal of real-time microblog post retrieval is to filter the stream of posts according to the user's interest profile (query) and determine their relevance score. Microblogging systems are commonly used for sharing short posts with online communities, resulting in a vast stream of content related to current topics, such as business, sports, politics, conferences, and natural disasters. Most early microblog information retrieval systems use term-based approaches, like TF-IDF and BM25 [6]. However, term-based techniques are highly sensitive to variations in terms of usage and often suffer from issues, like polysemy and synonymy.

For example, depending on the context, a single term, such as "Amazon", as shown in Figure 1, might refer to a rainforest, a river, a company, etc. To address this problem, semantic-based approaches [19] have been developed to interpret text based on its context. One method of introducing semantics into text is by linking named entity mentions detected in tweets (e.g., "Amazon") with their corresponding real-world entities in a knowledge base, such as DBpedia. This enables a more structured and machine-understandable representation of the data. This process of connecting tweets to a knowledge base is called entity linking [20].

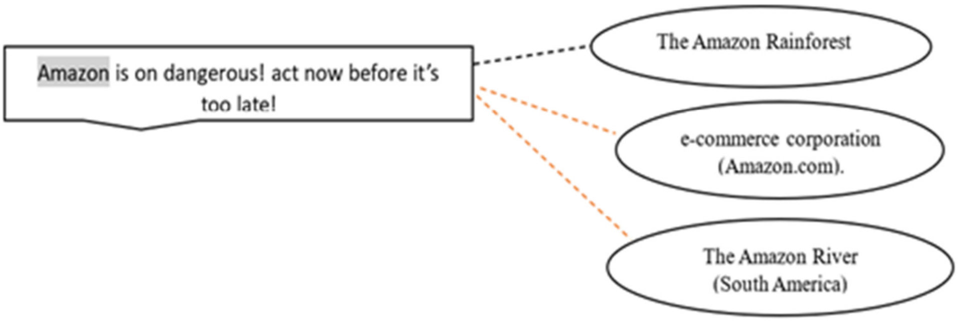

Fig. 1. Disambiguation entity example.

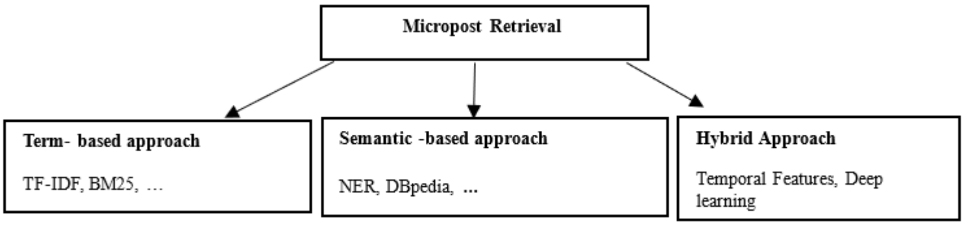

Fig. 2. Microblog information retrieval approaches.

Previous research has utilized hybrid approaches [21, 22], including social network analysis, to improve information access and investigate a real-time feature to address the problem of dynamicity in microblogging platforms, as depicted in Figure 2. This occurred because users care about the quality of information as much as about its fresh nature and the quality of the source. The proposed model is inspired by the hybrid approach and combines social features with entity linking using deep learning.

A. *Entity Linking*

Recent developments in Wikipedia and the Linked Open Data (LOD) [23] have made it easier to automatically create machine understanding knowledge bases, such as YAGO [24] and DBpedia [25]. Using the collection of tweets to bridge these knowledge bases helps fill and enhance the current knowledge bases while also allowing for the exploitation and comprehension of the vast corpus of important personal data on the Web. Tweet entity linking is defined as the task to link the textual named entity mentions detected from tweets with their mapping entities existing in the Knowledge Graph (KG). A KG represents named entities (e.g. a person called "Jeff Bezos"), concepts (e.g. "Person"), or literal values (e.g., strings, integers, dates) as nodes, and links between nodes as directed edges.

- Definition 1: KG [26]: Formally, a KG is a graph KG (V, E), where V is a set of vertices and E is a set of edges. Each $v \in V$ represents a semantic thing, i.e., a named entity, a concept, or a literal value. Each $e \in E$ represents a property of a named entity or concept by linking the respective node to a named entity, concept, or literal value.
- Definition 2: Mention: A mention m is a sequence of words extracted from text and referring to some entities. A mention can refer to multiple entities.
- Definition 3: Tweet entity linking: Given the tweet collection T posted by some Twitter users and named entity mention set M, the goal is to identify the mapping entity e_i in the knowledge base for each entity mention $m_j \in M$. If the mapping entity of entity mention does not exist in the knowledge base, the user should return to NIL.

TABLE II. AN ILLUSTRATION OF THE TWEET ENTITY LINKING

Tweet	Candidate mapping entities
t1: "Amazon is breaking records this year in sales!"	Amazon.com; Amazon River, Amazon Rainforest, Amazon (mythology)
t2: "Conservation efforts for the Amazon are more important than ever."	Amazon Rainforest, Amazon River, Amazon.com, Greenpeace
t3: "Amazon warriors have always fascinated historians. #WonderWoman"	Amazon (mythology), Amazon Rainforest, Amazon (fictional team or group), Wonder Woman
t4: "The view from the Amazon is breathtaking—nature at its finest."	Amazon Rainforest, Amazon River, Amazon.com (e.g., metaphorical view of growth), National Geographic

In Table II, "Amazon" is the mention of Amazon.com, Amazon River, Amazon Rainforest, Amazon (mythology). To resolve such a multiple mapping between mentions and entities, entity linking is required.

B. *Deep Learning*

The information retrieval process can be enhanced by applying machine learning [22, 27]. Improved classification and ranking of relevant documents are made possible by the learning algorithms. Extracting information from such big data is difficult, though. To handle large data and automatically identify heterogeneous data, researchers started utilizing deep learning techniques. The primary deep learning methods are:

- Deep Neural Networks (DNN). It comprises of multiple hidden layers, with each layer having hundreds of nonlinear processing components. It takes large number of input features and extracts features automatically from various hierarchical stages by using neurons of different layers.
- Convolution Neural Networks (CNN). It consists of several convolutional layers and subsampling layers (reduces the feature map size). The feature maps are joined to get fully connected layers to get a final output.
- Recurrent Neural Networks (RNN). It takes sequential data as input and forms a directed cycle by allowing the connections among neurons in the same hidden layers. It may diminish the vanishing gradient problem by using Long Short-Term Memory (LSTM).
- Autoencoder. It has an encoder NN, which converts the information from the input layer to some hidden layers, and then feeds them to the decoder NN, which rebuilds its own inputs using lesser number of hidden layers. Hence, its basic purpose is dimensionality reduction.

III. PROPOSED APPROACH

This section describes the proposed framework, MSIR2L, as shown in Figure 3. MSIR2L is a generic framework that can easily be extended to add or remove features and can also be applied in different tasks, such as influencer detection and entity linking in long text.

A. *General Description of the Proposed Approach*

Retrieval in microblogs faces semantic problems. One effective way to solve these problems is to integrate a knowledge base. In fact, DBpedia is receiving more attention in recent years as one of the central datasets in the LOD. MSIR2L, as depicted in Figure 3. It integrates semantic, contextual, and social features with a learning-based ranking model to optimize entity linking accuracy, consisting of the following steps:

- Tweets are collected, pre-processed for tokenization, stop-word removal and entity mention extraction are performed, with features, like contextual keywords, hashtags, and social attributes.
- DBpedia, a popular knowledge base, utilizes semantic expansion techniques and feature engineering to enrich extracted features for learning- based ranking, expanding entity understanding and forming a structured representation.
- Tweet mention, where entities are matched using semantic features, and redirect pages to generate a candidate set, retaining only the relevant ones.

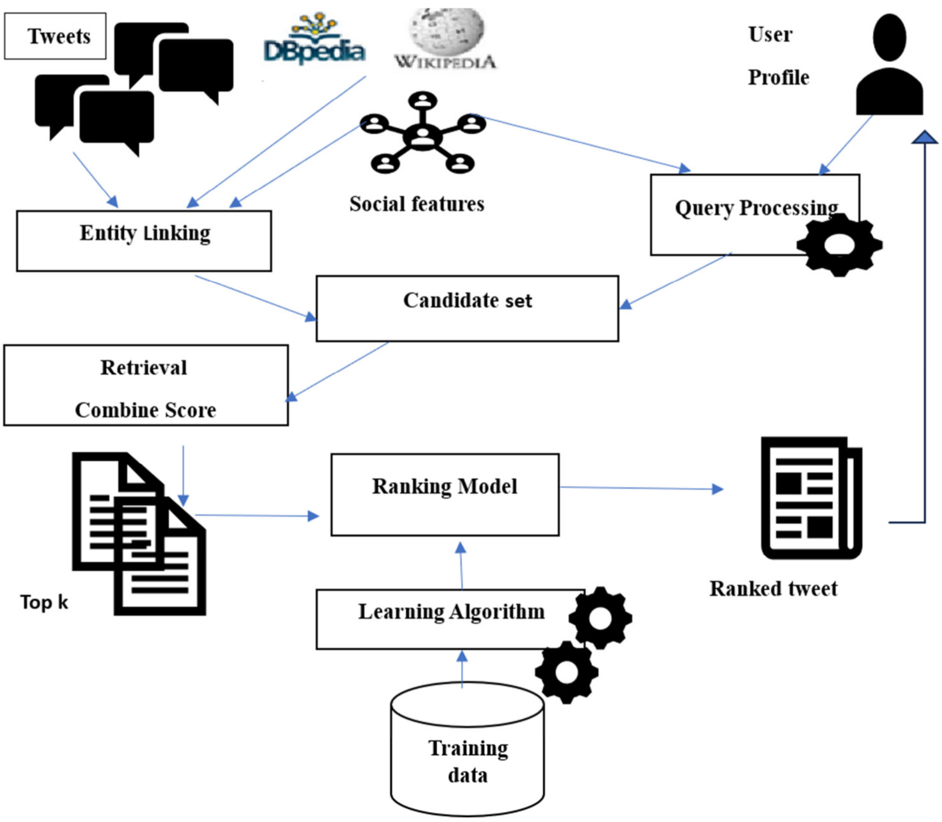

Fig. 3. Proposed framework MSIR2L.

B. Problem Statement and Algorithm

In this section, the goal of this paper is formally defined. Given the social media posts P = {p1, · · · ,pn }and an entity mention m in Pi posted by a user u, the goal is to determine the most liking real-world entity R from a candidate set E_m.

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Algorithm 1: Hybrid Retrieval

Input: Query Q, Tweets T, Knowledge Base
K, Weights (α, β, γ, δ, λ)
Output: Ranked list of microposts

Preprocess Query Q
Retrieve initial microposts T_Q
T_Q ← Micropost_Retrieval (Q, T)
// using TF-IDF
For each micropost t ∈ T_Q do
 // Initialize scores
Initialize Score_List
// Generate candidate entities
E in m_E← Candidate_ Generation (m, K)
Repeat For (each e in E do)
//Compute individual scores
Calculate_Social_Interest (u, e, U_e)
Compute_Popularity (e, E_m)
Compute_Recency (e, E_m, τ)
Compute_ContextualSim (m, e, T, K)
S(e) ← α * S_interest + β * S_popularity +
γ * S_recency + δ * S_context

// Rank entities and return the top one
If (S(e) > Max_Score then
R ← Entity_With_Highest_score
Return R
End
```

Each candidate entity is matched from a knowledge base K. The entity linking process involves calculating a combined score S(e) for each candidate entity based on four features:

1) Social Interest: Reflecting the user's engagement with the community discussing entity e.

2) Popularity: Measuring how frequently "e" is mentioned in the knowledge base.

3) Recentness: Evaluating the suitability of e based on recent tweets or events.

4) Contextual Similarity: To compute the contextual similarity between micro posts (tweets) and DBpedia entity descriptions, deep learning techniques are utilized. Specifically, an LSTM Autoencoder or Transformer-based embeddings (like BERT) can be used to extract dense vector representations of both the tweet text and the DBpedia entity descriptions. These embeddings are then compared using cosine similarity. The final score for each candidate is computed as:

$$S(e)=\alpha\cdot S\_interest(u,e)+\beta\cdot S\_popularity(e)+\gamma\cdot S\_recency(e)+\delta\cdot S\_context(m, e) \quad (1)$$

It should be noted that S_interest, S_popularity, S_recency are obtained from [16].

The originality in the present work is a combination of these four features. To learn the most significant features (word embeddings), this study employed the autoencoder neural network. An autoencoder neural network architecture is based on three main components to learn efficient representations: encoder, code and decoder. In this work, the Encoder-Decoder LSTM architecture was deployed.

IV. EXPERIMENTS AND RESULTS

This section details the experiments performed to evaluate MSIR2L. The obtained results are compared with those of state-of-the-art approaches. This paper presents the results of the comparison the proposed framework with KAURI, as the best EL Framework, and OPTIC, which also uses deep learning to annotate EL. However, it should me mentioned that further updates and experimentations are being developed.

The F1 score is utilized as the comparison metric, because it has been used as an evaluation metric for the disambiguation step of the EL task in several works. The present study employs the dataset microposts2016-Training from the NEEL challenge 2016 for training the neural network model. This dataset consists of microblog posts with 8665 instances of recognized mentions in their texts of which 6374 of DBpedia entities and 2291 of "NIL". All the programs were implemented in JAVA and all the experiments were conducted on a single machine server (eight 2.00GHz CPU cores, 10GB memory) with 64-bit Windows. For the training of the proposed model, the present work used the same configuration as in OPTIC. For disambiguation, a threshold of 0.7 was adopted for the probability of an entity candidate being the correct one.

TABLE III. RESULTS OF COMPARISON

Framework	OPTIC	KAURI	MSIR2L
F1 score	0.9541	0.8025	0.9782

MSIR2L and OPTIC performed better on the NEEL2016 dataset, since the training set of the proposed NN model is from that dataset. MSIR2L performed better than the current best framework KAURI.

The experimental results revealed that the proposed system achieved good results in terms of precision, recall, indicating its effectiveness in short queries, as displayed in Figure 4.

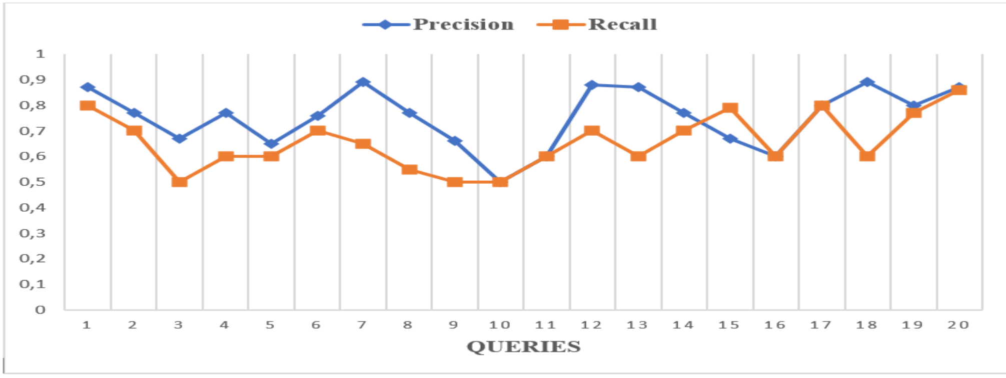

Fig. 4. Performance of the proposed system in terms of precision and recall using short queries.

V. CONCLUSION

This paper proposed an approach for micro post retrieval in microblogging platforms to improve retrieval effectiveness in Online Social Networks (OSNs). The problem of social information retrieval is addressed as a novel research area that bridges information retrieval and social network analysis to improve information access. The Multilayer Model for Social Information Retrieval based on Entity Linking and Learning to Rank (MSIR2L) framework was introduced. MSIR2L is a generic framework that can easily be extended to add or remove features and can also be applied in different tasks, such as influencer detection and entity linking in long text. The former was refined by incorporating improved semantic features and expanding the dataset for more comprehensive evaluations. Deep learning techniques were integrated for ranking, query expansion, and feature extraction. The experimental results demonstrate that MSIR2L significantly outperforms the state-of-the-art methods in terms of precision. Moreover, all features adopted by MSIR2L are quite effective for the microblogging information retrieval task. Compared to previous approaches, the proposed framework demonstrates superior performance, particularly in handling short documents and tweet retrieval. The introduced approach outperforms KAURI, a leading learning framework, in short texts and noise. More features are additionally used along with OPTIC to support diverse datasets. These results demonstrate the effectiveness of the proposed approach and its promise for further developments in entity linking, particularly in microblogging and short text application.

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