

Mining User Interests from Social Media

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ABSTRACT

Social media users readily share their preferences, life events, sentiment and opinions, and implicitly signal their thoughts, feelings, and psychological behavior. This makes social media a viable source of information to accurately and effectively mine users' interests with the hopes of enabling more effective user engagement, better quality delivery of appropriate services and higher user satisfaction. In this tutorial, we cover five important aspects related to the effective mining of user interests: (1) the foundations of social user interest modeling, such as information sources, various types of representation models and temporal features, (2) techniques that have been adopted or proposed for mining user interests, (3) different evaluation methodologies and benchmark datasets, (4) different applications that have been taking advantage of user interest mining from social media platforms, and (5) existing challenges, open research questions and exciting opportunities for further work.

CCS CONCEPTS

• **Information systems** → **Social networks**; **Information extraction**; • **Human-centered computing** → **User models**; **Social networks**.

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1 CONTEXT AND MOTIVATION

Mining user interests from user behavioral data is critical for applications such as online advertising. Based on user interests, service providers such as advertisers, can significantly reduce service delivery costs by offering the most relevant products (e.g., ads) to their customers. The challenge of accurately and efficiently identifying user interests has been the subject of increasing attention in the past several years. Early approaches were based on explicit input

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from individuals about their own interests. To avoid the extra burden of manually filling in and maintaining interest profiles, most methods in the past two decades have focused on the development of techniques that can automatically and unobtrusively determine users' interests based on user behavioral data from data sources such as browsing history, page visits, the links they click on, the searches they perform and the topics they interact with [3, 10].

With the emergence and growing popularity of social media such as blogging systems, wikis, social bookmarking, and microblogging services, many users are extensively engaged in at least some of these applications to express their feelings and views about a wide variety of social events/topics as they happen in real time by commenting, tagging, joining, sharing, liking, and publishing posts [6]. This has made social media an exciting and unique source of information about users' interests [16]. The development of techniques that can automatically detect such topics and model users' interests towards them from online social media would be highly important and have the potential to improve the quality of applications that work on a user modeling basis, such as filtering Twitter streams [13], news recommendation [1] and retweet prediction [9], among others.

2 TARGET AUDIENCE AND PREREQUISITES

The target audience for this tutorial are those who have familiarity with social media mining and basics of data mining techniques. Where appropriate the tutorial does not make any assumptions about the audience's knowledge on more advanced techniques such as link prediction, matrix factorization, deep matching, entity linking and knowledge-graph based reasoning, among others. As such, sufficient details are provided as appropriate so that the content are accessible and understandable to those who have a fundamental understanding of data mining principles. The tutorial only assumes familiarity with topics included in an undergraduate data mining course.

3 TUTORIAL OUTLINE

This tutorial presents a comprehensive survey of user interest mining from social media. In particular, this tutorial covers the following sections:

Background and Introduction to Theory of User Interest Mining. The tutorial begins with a session about basics of user interest mining from various social media such as information sources, representation units to represent each topic of interest

and user interest profile, temporal aspects and cross-system user interest modeling. This section also highlights on research questions to which user interest mining from social media would provide an answer for. Finally, we review topics that are covered in the tutorial followed by a disclaimer, i.e., what the tutorial is *not* about.

Techniques and Methods in User Interest Mining from Social Media. Depending on the desirable type of user interest profiles, i.e., explicit or implicit or future user interest profiles, previous work have adopted different approaches for addressing the problem. Within these three categories, we lay out the details and provide a comparative analysis of existing methods in terms of their representation power, flexibility, resource needs and scalability. Specifically, in this session, we elaborate on how previous studies have used different techniques such as collaborative filtering [2, 11], topic modeling [11, 20], link prediction [5, 20], graph-based methods [7, 19], Semantic Web technologies [8, 12, 21] and association rule mining [18] to construct a given type of interest profile for users (e.g. implicit interest profile).

Evaluation Methodologies, Benchmark Datasets and Applications of Interest Mining from Social Media. In this session, we first elaborate on different resources and two main approaches used in the literature to evaluate user interest profiles, namely intrinsic vs extrinsic evaluation techniques. Intrinsic evaluation helps to assess the quality of the constructed user interest profiles based on user studies [4, 12, 14] while extrinsic evaluations measure the quality of the user interest profiles by looking at its impact on the effectiveness of other applications such as news recommendation and retweet prediction [15, 19, 20]. Then, we describe the existing benchmark datasets and evaluation metrics [17]. Next, we introduce different applications that have been taking advantage of user interest modeling from social media platforms to improve their services.

Future Directions and Open Challenges. In this session, we present exciting open research questions in the state of the art for mining users' interests from social media. Accurate information extraction from social media poses unique challenges due to the special characteristics of them. Social posts are rather short, noisy and informal and they often do not provide sufficient contextual information for identifying their semantics. In other words, the semantics of the context of the communicated information within a post is often implicit. Moreover, as a large majority of social network users are free-riders and cold start users, the interests of such users is challenging and they cannot be directly identified from their explicit contributions to the online social network. This tutorial presents the open issues that are important but have not been well addressed in recent studies which can inspire future directions in this research field. We cover potential resources (e.g., Linked Open Data) and techniques (e.g. Learning-to-Rank, deep learning architectures and causal inference) that can be relevant for mining user interests.

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