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Personalized Mobile App Recommendation by Learning User's Interest from Social Media

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***Abstract:** In social media, user interests and knowledge are vital but often overlooked resources. There are a few ways to get a sense of what people are known for, such as Twitter lists and LinkedIn Skill Tags, but most people are untagged, so their interests and expertise are effectively hidden from applications like personalised recommendation and community detection and expert mining. We obtain personalised app recommendations by learning the interest's association between applications and tweets by introducing an unique generative model called IMCF+ to convert user interest from rich tweet information to sparse app usage. We analyse the performance of this technique predicts the top ten apps with an 82.5 percent success rate using only 10% training data. Furthermore, in the high sparsity situation and user cold-start scenario, this purpose technique outperforms the other six state-of-the-art algorithms by 4.7 percent and 10%, demonstrating the effectiveness of our technology. All of these findings show that our method can reliably extract user interests from tweets in order to aid in the solution of the personalised app recommendation problem.*
***Keywords:** Social Media, User Profile, deep learning, Privacy, matrix factorization,App recommendation.*

I. INTRODUCTION

Mobile applications (apps) have made Internet services extremely accessible and convenient. Today's Internet users prefer to use their mobile apps. App developers and network service providers will benefit from this. In order to provide higher-quality and tailored services, it is critical to understand how apps are used in various temporal and spatial settings.

While different agencies gather app usage data, there is raising concern about the privacy consequences of mining or sharing such statistics. Because of their particular interests and preferences, various users may use different collections of apps.We present a transfer learning model for the tailored app recommendation problem called Interest-aware Matrix Co-Factorization Plus in this research. This is a generative model that transfers user app usage and tweet knowledge to compensate for the lack of app usage data. We do ordinary language processing on user tweets and extract relevant terms to reflect the features that make up the user's social domain representation. We next employ matrix co-factorization to transfer the learnt interest into the app domain, allowing users' latent traits to be shared across domains. To guarantee that the statistical connection of app latent vector and word latent vector is consistent with their semantic correlation, we quantify the interest relevance of applications and words and factor it into our model. To summarise, this work makes three major contributions: We are the first to achieve personalised app assessment by transferring user tweet information from social media, which allows us to learn about user interests while compensating for the lack of app usage data. Second one, it discovers and learns the underlying latent or interest correlations between these domains, transferring the knowledge domain of textual content on social media into the domain of application usage. And last one, in the high sparsity scenario and the user cold-start problem; it surpasses the other state-of-the-art approaches by 4.7 percent and 10%, respectively, demonstrating its efficacy in tackling the challenge of individualised app recommendation.

II. LITERATURE REVIEW

Paper Citation	Advantages	Algorithm/ Techniques	Limitations	Summary
[1]	Users in a large metropolitan area's app usage patterns are examined in this study using a large-scale empirical measurement. It can help reduce the uniqueness of the data and the risk of privacy leakage.	Privacy-protection techniques.	There may be apps that use HTTPS protocols for all network requests, but these will not be included in our dataset, and our dataset does not cover apps that make no network requests at all, or apps that only use the WiFi network for network requests.	It is our hope that the findings of this study will help us develop more effective privacy protection systems for mobile users and more tailored internet experiences for them.

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[2]	We identify a significant gap between the algorithms' empirical performance and the theoretical privacy bound.	De-anonymization methods. Privacy protection algorithms Attack Method.	When dealing with actual challenges, the designer of a de-anonymization approach should be aware of the consequences of mismatches.	In this paper, new algorithms developed to deal with these practical variables in both de-anonymization and location-privacy-preserving techniques have demonstrated promising performance, confirming our findings.
[3]	It is resistant to trajectory noise and simple to expand to external data such as PoI distribution.	Model: location encoder, trajectory encoder, and comparator network	We only evaluate simple external geographical context data, such as the PoI category, in datasets.	As part of this study, we used the power of deep learning to investigate the problem of linking user identities. We proposed an end-to-end deep learning system in order to connect disparate accounts of mobility data.
[4]	Author propose an attribute-based searchable encryption scheme by leveraging the ciphertext-policy attribute-based encryption technique	Detection Method, MLink Algorithm. supervised learning and un-supervised learning method	The only option to adapt these algorithms to the mobility trajectory data in our case is to build a "contact graph" to describe users' encounters with each other based on their mobility trajectories, however this ignores users' everyday mobility patterns, limiting the performance of linking user IDs.	Allows the data owner to perform a precise search authorization for the user of the information. An index keyword can only be searched for when the attributes of a data user match those of the data owner who encrypted it, and only then can the data user perform searches on that encrypted index keyword.
[5]	Because of this, a slew of new applications from operating systems, networks, app stores, profiling tools, and advertisers can now take advantage of the location-based app usage data.	Three state-of-the-art methods.	Our dataset is severely constrained because we have no way of knowing what state the application is in that is causing the network queries. It's impossible to tell the difference between apps that made a network request because the user requested it and background apps that do it on their own.	Using large-scale mobile data access records, we have developed the first system to predict location-level app usage from POI, and the system outperforms three current methods in terms of the accuracy of the top-N predictions and the total app usage distribution estimation.
[6]	To address this issue, a new unified model (TranSIV) combining social and item visibility with transfer learning has been proposed.	Using TranSIV as a recommendation algorithm. Five cutting-edge methods based on WMF, BPR, EXPOMF, SBPR, and SPF for making recommendations.	No, it's not compatible with natural visibility. It's limited to use with Recommendation systems must account for the fact that a user may not have had a chance to see an item if they didn't leave feedback; this is why visibility modelling is critical.	A PHR with fine-grained access control and efficient revocation is proposed by the authors in this paper. To achieve fine-grained access control when encrypting PHRs, patients can use an expressive access tree structure in conjunction with the ciphertext. Anonymous key issuing protocols can also be used by authors to ensure privacy.
[7]	The relationship between the co-authorship network and citation metrics is investigated. The PageRank and the h-index have a significant relationship.	social network analysis (SNA)	It is not explore the co-authorship network, such as evaluating the scientific impact of an individual or an institution.	In this research, we investigate author profiles on Google Scholar by crawling and analysing them. We collected 812.98K author profiles from Google Scholar using a distributed crawling strategy, which covers the vast majority (if not all) of publicly available author profiles.
[8]	The CVAE is able to significantly outperform the state-of-the-art recommendation methods with more robust performance.	Collaborative variational auto-encoder (CVAE).	CVAE is unable to learn a good representation from the content, thus it leads to degraded performance.	The collaborative variational auto-encoder is proposed in this research, which can jointly model the development of item content while extracting the implicit associations between things and users. It's a Bayesian probabilistic generative model that uses stochastic deep learning models and graphical models to connect collaborative and content information, resulting in reliable recommendation performance.
[9]	PTPMF had the highest accuracy across multiple metrics, suggesting that learning user-specific preferences for various types of relationships in social recommendation can help to enhance performance.	PTPMF method.	For example, it can only identify strong and weak ties at the same time, as well as learn a user's tie preference and other model parameters, so it can be difficult because of the lack of data in social networks.	For the purposes of social recommendation, we extend probabilistic matrix factorization to take into account individuals' individualised preferences for strong and weak ties. We then present a novel social recommendation model that takes into account individuals' individualised preferences for strong and weak ties.

[10]	It can learn high-quality user topical profiles and improves precision and mean average error by 10-15% when compared to a cross triadic factorization state-of-the-art baseline.	UTop Solver, UTop+ Solver algorithm,	No efficient	In this paper, we looked into how to make advantage of user-generated data across a wide range of footprints. In particular, we introduced UTop+, a generalised approach for learning high-quality user thematic profiles that combines numerous implicit and explicit footprints.

III.OPEN ISSUES

Lot of work has been done in this field because of its extensive usage and applications. In this section, some of the approaches which have been implemented to achieve the same purpose are mentioned. These works are majorly differentiated by the techniques for multi-keyword search and group sharing systems.

1) Not included in the dataset are apps that do not make any network requests, or apps that make most of their network requests via WiFi. A single network service provider is the source of all of our data.
2) Users' location privacy can be better protected by utilising spatio-temporal mismatches to enhance the usefulness of trajectory information.
3) In order to process the raw textual information contained in the check-in data, it is necessary to expand the embedding module.
4) Authors from a wide range of specialties are part of the global co-authorship network. Investigating this vast network necessitates a multidisciplinary approach.

IV.CONCLUSION

We proved the capability of providing customised mobile app recommendations by transferring user tweet data from social media in this article. We tested our method's performance and discovered that our purpose method surpasses the other five state-of-the-art algorithms. App prediction is influenced by user and app attributes, according to the research. Our research is a step forward in transferring user data from social media to learn personal app preferences, paving the path for better-quality tailored mobile app recommendations and services for mobile consumers.

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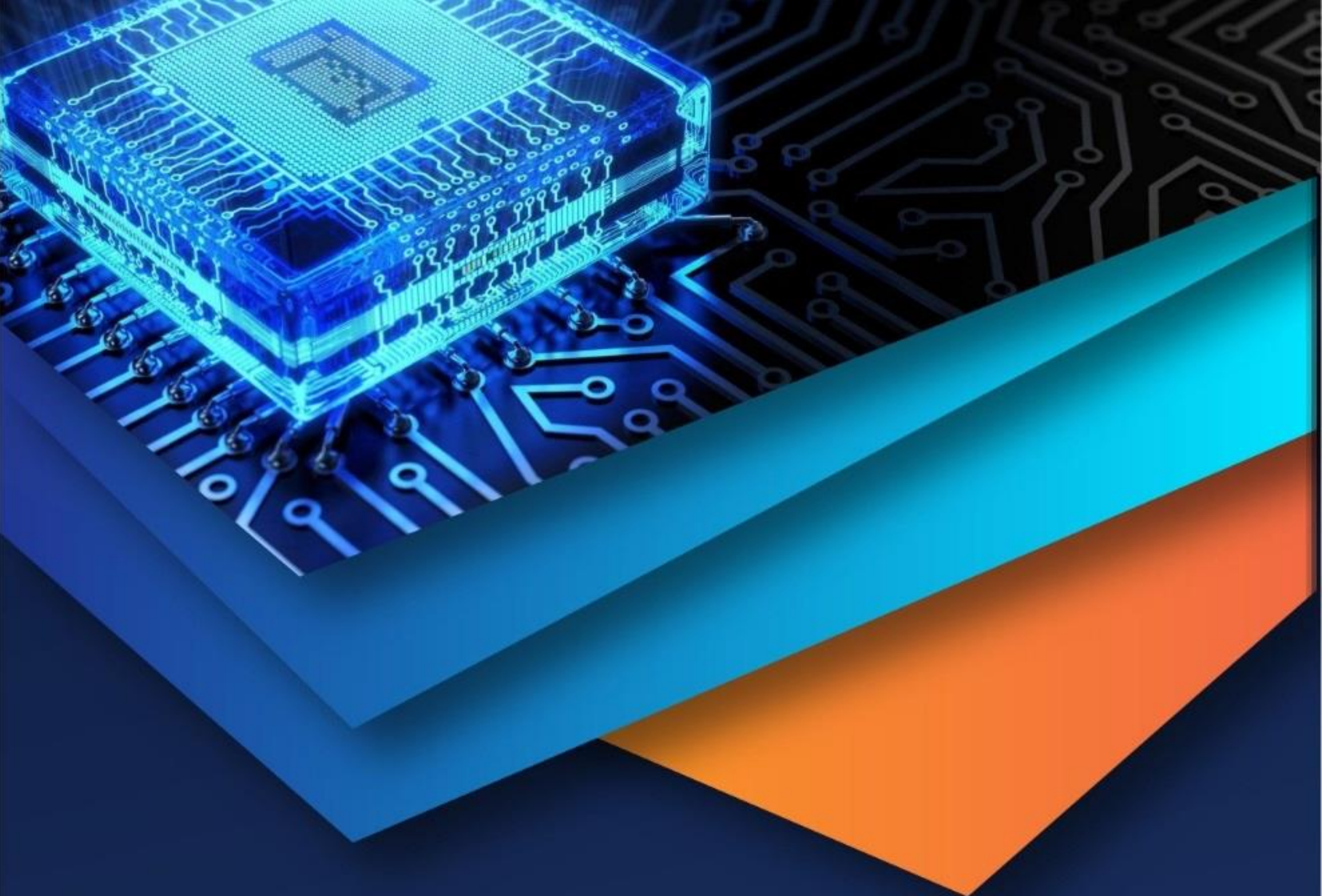

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