Indonesian Journal of Electrical Engineering and Computer Science
Vol. 35, No. 1, July 2024, pp. 542∼550
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v35.i1.pp542-550

Extracting contextual insights from user reviews for recommender systems: a novel method

Rabie Madani, Abderrahmane Ez-Zahout, Fouzia Omary
Intelligent Processing and Security of Systems Team, Faculty of Sciences, Mohammed V University, Rabat, Morocco

Article Info

Article history:

Received Jan 26, 2024
Revised Mar 17, 2024
Accepted Mar 25, 2024

Keywords:

Context-aware recommender systems
Deep learning
Factorization machines
Named entity recognition
Recommender systems

ABSTRACT

Recommender systems (RS) primarily rely on user feedback as a core foundation for making recommendations. Traditional recommenders predominantly rely on historical data, which often presents challenges due to data scarcity issues. Despite containing a substantial wealth of valuable and comprehensive knowledge, user reviews remain largely overlooked by many existing recommender systems. Within these reviews, there lies an opportunity to extract valuable insights, including user preferences and contextual information, which could be seamlessly integrated into recommender systems to significantly enhance the accuracy of the recommendations they provide. This paper introduces an innovative approach to building context-aware RS, spanning from data extraction to ratings prediction. Our approach revolves around three essential components. The first component involves corpus creation, leveraging Dbpedia as a data source. The second component encompasses a tailored named entity recognition (NER) mechanism for the extraction of contextual data. This NER system harnesses the power of advanced models such as bidirectional encoder representations from transformers (BERT), bidirectional long short term memory (Bi-LSTM), and bidirectional conditional random field (Bi-CRF). The final component introduces a novel variation of factorization machines for the prediction of ratings called contextual factorization machines. Our experimental results showcase robust performance in both the contextual data extraction phase and the ratings prediction phase, surpassing the capabilities of existing state-of-the-art methods. These findings underscore the significant potential of our approach to elevate the quality of recommendations within the realm of context-aware recommender systems.

Corresponding Author:

Rabie Madani
Intelligent Processing and Security of Systems Team, Faculty of Sciences, Mohammed V University
Street of Michlifen, Rabat, Morocco
Email: rabie.madani@um5.ac.ma

1. INTRODUCTION

In various domains, recommender systems (RS) have gained paramount importance. They now play a critical role by suggesting products on e-commerce websites, proposing TV shows on streaming platforms, and even recommending connections on social networks. Functioning as a subset of information filtering systems, recommender systems leverage users' historical data to understand their behaviors. Subsequently, these systems provide recommendations that align with users' preferences [1]. Traditionally, RS focused on user-item interactions, often neglecting contextual elements such as mood, location, time, and weather, which significantly influence user preferences. To address this, context-aware recommender systems (CARS) [2] have emerged, integrating contextual cues to offer more precise and personalized recommendations. However, the primary challenge for CARS lies in collecting contextual information, which often involves sensitive personal data, leading to privacy concerns. User reviews, as a form of unstructured data, offer a wealth of valuable insights and serve as an effective solution to one of the core challenges faced by RS which is the scarcity of data. Recent studies have proposed innovative methods to enhance recommendations by leveraging user reviews, recognizing their potential to extract valuable insights without infringing on privacy. For instance, Zheng *et al.* [3] introduced the DeepCoNN model, which employs embedding methods and convolutional neural networks (CNNs) to extract user behaviors and item characteristics from reviews, utilizing factorization machines for predictions. Similarly, Catherine and Cohen [4] developed TransNets, using CNNs and an additional Transform layer to better capture contextual information within the recommendation process. McAuley and Leskovec [5] introduced a hidden factors and topics (HFT) method integrates user reviews with latent dirichlet allocation (LDA) to enrich recommendations with latent factors and topics, while Tan *et al.* [6] rating-boosted latent topics (RBLT) model learns user preferences by integrating comments and ratings, using replication to highlight topic importance and a latent factorization mchine for prediction, aiming for precision.

Zhang *et al.* [7] explicit factor models extract user sentiments and item features from reviews for interpretable recommendations, focusing on the rationale behind suggesting or not suggesting items. The previously mentioned studies have indeed leveraged reviews to enhance recommender systems but have often overlooked the potential benefits of incorporating contextual information, which could greatly enhance recommendation accuracy and personalization. In contrast, researchers like Aciar [8] have successfully integrated contextual information into recommendation tasks. He introduced a technique that employs classification and natural language processing (NLP) to identify relevant sentences in user comments, but it may not fully leverage the context for enhancing recommendations. Hariri *et al.* [9] proposed a system that utilizes user reviews for insights and combines these with historical ratings to improve the utility function prediction, focusing on contextual categorization through supervised topic modeling with LDA. Compos *et al.* [10] suggested extracting context from customer feedback using a taxonomy based on DBpedia, but their method mainly concentrates on context extraction rather than its application in recommendations. Madani and Ez-Zahout [11] developed a model using bidirectional encoder representations from transformers (BERT) for better contextual information extraction and integrated this into a matrix factorization technique for rating predictions, though the small corpora used for named entity recognition (NER) training might affect prediction quality. While these approaches innovate in extracting contextual information, they share common drawbacks. These include, a lack of comprehensive utilization of contextual information for direct recommendation enhancement, an ambiguity in the extraction process, a focus on the extraction of context rather than its practical application for improving the accuracy of predictions, and the possibility of compromised prediction quality due to the limited scale of training data. Addressing these challenges and the fundamental issue of collecting contextual data for CARS, we propose a comprehensive approach that introduces a novel model for contextual information extraction, alongside a tailored model designed to integrate this extracted data with the goal of enhancing prediction accuracy. Our innovative approach focuses on extracting context from unstructured sources like user reviews, integrating this information into the recommendation process without compromising user privacy. By creating a massive corpus from DBpedia [12] and training a NER model using BERT, bidirectional long short term memory (Bi-LSTM), and bidirectional conditional random field (Bi-CRF) techniques, we identify contextual elements efficiently. Additionally, our use of an innovative factorization machine algorithm incorporates this contextual data, significantly enhancing the accuracy and personalization of recommendations.

2. METHOD

This integration of context-aware techniques highlights a crucial evolution in RS, addressing both the challenges of privacy and the need for personalized recommendations. Our approach builds upon the foundations laid by existing studies, proposing a solution that leverages unstructured data to overcome the limitations of traditional RS. By examining the latest advancements in RS that utilize reviews and contextual information, we underscore the potential of our approach to refine and personalize the recommendation process, setting the stage for a discussion on the effectiveness of our model in the following sections. The rest of this article is organized as follows: second section provides an overview of recent studies in the field.

Third one introduces our model. Fourth one, discusses results. Finally, we provide a conclusion. This section elaborates on our proposed methodology in detail. Our method is designed with two primary goals in mind. Initially, it strives to extract contextual insights from user reviews. Subsequently, it aims to leverage this extracted data to forecast ratings. Our approach is depicted in Figure 1 and comprises of three distinct subprocesses: corpus building, context extraction, and rating prediction.

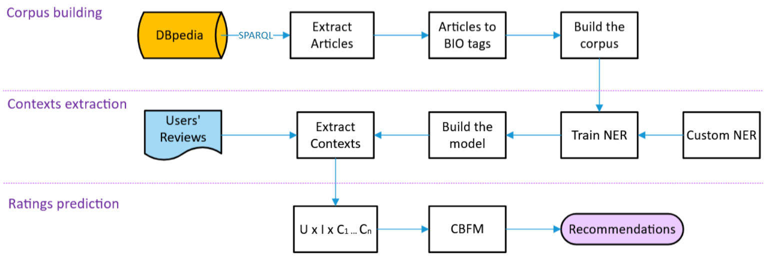


Figure 1. Main process steps

2.1. Corpus building

The corpus building step is pivotal in leveraging DBpedia to create a contextual corpus formatted with beginning, inside and outside (BIO) tags for custom NER. It starts with the precise definition of desired contexts, followed by the strategic extraction of relevant textual data through SPARQL queries aimed at fetching descriptions, labels, and abstracts embedding the contexts of interest. Post extraction, the textual content undergoes a thorough cleaning and normalization process, after which it is segmented into sentences. These sentences are then meticulously analyzed to identify and categorize contexts within them by applying the BIO tagging scheme. This structured approach ensures the assembly of a richly annotated dataset, which not only serves as a foundational resource for training machine learning models, particularly in NER tasks but also significantly enhances the capability to recognize and classify contexts within textual data. the initial phase revolves around defining and specifying the context.

In existing literature, numerous propositions exist for modeling context, particularly within the realm of pervasive and ubiquitous computing. Table 1 summarizes the key modeling techniques for context. After a comprehensive review of previous research, it becomes clear that a prominent method for context modeling involves the use of taxonomy or ontology. Building upon insights derived from these models, our choice is to incorporate four fundamental dimensions of context: location, companion, weather, and time.

Table 1. key modeling techniques for context

Reference	Context categories
[13]	Location, time, fact, person.
[14]	Location, Time, Status, Goal, Role, Action.
[15]	Location, user, resource, network, service, device, activity.
[16]	Time, space, person, event, geo-spatial, agent, action, policy.
[10]	Time, social context, time, environmental context.
[11]	Time, location, companion, environmental.

Once the context dimensions are defined, the initial step involves extracting text content from DBpedia. It's worth noting that DBpedia extensively employs the simple knowledge organization system (SKOS) for data organization. By leveraging SKOS relations, it becomes feasible to traverse interconnected DBpedia categories hierarchically, encompassing both primary categories and their respective subcategories. This process entails the careful selection of relevant ”root” categories within DBpedia, such as 'dbc:Places' for denoting locations. We employ SPARQL, a query language designed for retrieving and manipulating data stored in RDF format. Table 2, show contexts and their associated categories.

The context extraction step is a crucial phase in our methodology for analyzing textual data, particularly after having built a comprehensive corpus from DBpedia. Following the corpus construction, this step delves into identifying and categorizing contexts within the text, leveraging the nuanced capabilities of a meticulously designed NER model. To capture contextual information, a dedicated NER model was developed.

The primary objective of employing NER is to identify entities within text and subsequently categorize these entities into pre-established classes. As depicted in Figure 2, this model is organized into three distinct layers: a word embedding one, a Bi-LSTM [17] one, and a Bi-CRF.

Table 2. Context categories and descriptions

Context category	Description
Time context	dbc: Time
Location context	dbc: Places
	dbc: Buildings and structures
	dbc: Educational institutions
	dbc: Transport by mode
Companion context	dbc: Interpersonal relationships
Weather context	dbc: Weather
	dbc: Meteorological phenomena

The initial layer is responsible for converting a sequence of words into word embeddings, utilizing the capabilities of BERT [18]. Unlike directional methods such as OpenAIGPT [19] and ELMo [20], BERT achieves pretraining by creating deep bidirectional embeddings from text, taking into account left and right contexts in every layer of its architecture. It outputs contextual embedding vectors for each word. These embeddings capture not only the meaning of the word but also its context within the sentence.

An issue with linear chain CRF [21] is their limited ability to capture label dependencies primarily in the forward direction. When faced with a complex entity like ”Mohammed V University,” these models may erroneously classify ”Mohammed” as a name, as they lack awareness of the ”University” token that comes later in the sequence. Indeed, in addressing the issue of linear chain CRFs being primarily forward-focused and potentially struggling with complex entities, using both Bi-LSTM and Bi-CRF layers can be an effective strategy.

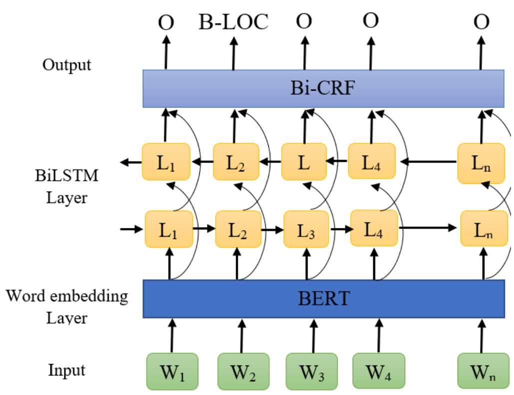


Figure 2. Custom NER architecture

After obtaining contextual word embeddings from BERT, the model includes a Bi-LSTM layer. Bi-LSTM is a type of recurrent neural network (RNN) that can capture sequential information from both directions (forward and backward) in a sequence. It’s commonly used for NER tasks to capture dependencies between words in a sentence. It consists of two LSTM networks. One LSTM processes the input sequence in a forward direction (from the beginning to the end), while the other LSTM processes the input sequence in a backward direction (from the end to the beginning). This bidirectional processing allows the model to capture contextual information for each token in the input sequence by considering both preceding and following tokens. The outputs of these two LSTMs are typically concatenated or combined in some way to create a richer contextual representation for each token.

Building upon the benefits of the Bi-LSTM, the Bi-CRF layer takes into account label dependencies in both directions. This means it considers not only the labels to the left of the current token but also the labels to the right. For complex entities or cases where label transitions are not strictly left-to-right, the Bi-CRF can help ensure more accurate and coherent labeling, even for distant parts of the entity.

2.2. Ratings prediction

The rating prediction step marks a critical juncture in our methodology, focusing on leveraging the insights gleaned from the context extraction phase to forecast user ratings with precision. This process hinges on the integration of contextual data a task made challenging by the prevalence of datasets characterized by a significant number of empty values. The introduction of contextual information, while enriching, compounds the complexity of the data scarcity issue, necessitating a judicious selection of algorithms capable of navigating these intricacies. Among the popular options, factorization machines (FMs) [22] represent a supervised learning algorithm suitable for both regression and classification tasks. Their popularity has surged, particularly in recommendation and prediction applications. FMs extend the conventional linear model, allowing them to capture intricate relationships between variables. FMs are designed to reduce the polynomial complexity that can arise in traditional methods for modeling feature interactions, such as polynomial regression. Instead of considering all possible feature combinations (which can grow exponentially with the number of features), FMs use a factorization trick to represent interactions efficiently. They are particularly effective in dealing with high-dimensional sparse datasets, which are common in recommendation systems, NLP, and many other domains. Their ability to capture interactions between sparse features makes them a popular choice in these applications. The equation of FMs is defined as (1).

$$y(x) = w_0 + \sum_{i=1}^{d} w_i x_i + \sum_{i=1}^{d} \sum_{j=i+1}^{d} < v_i, v_j > x_i x_j \tag{1}$$

w_0 R represents the bias term in the real numbers. $w \in R^d$ represents the weights associated with each feature vector in a d-dimensional space. VR^{dk} is the interaction matrix, with d rows and k columns. v_i, v_j denotes the feature interactions. Nonetheless, it's worth noting that FM's efficacy hinges on its compatibility with the collaborative filtering approach, typically suitable when dealing with data of limited dimensions. However, FM falls short in capturing the nuances of interaction strength within the data. Given these considerations, we decided to use a variant of FM, more adapted to work with high dimensional data called context-based factorization machines (CBFM) [23]. CBFM is designed to discern distinctions between various contexts during interactions by incorporating additional weights. The equation of this variant is define as (2).

$$y(x) = w_0 + \sum_{i=1}^{d} w_i x_i + \sum_{i=1}^{d} \sum_{j=i+1}^{d} < v_i w_{c(i)}, v_j w_{c(j)} > x_i x_j \tag{2}$$

where, wc(i) and wc(j) are weights used to differentiate the context of item i and item j.

3. RESULTS AND DISCUSSION

This section presents and analyzes the results derived from both the custom NER model and the deployed rating prediction model. For evaluating our model, we have opted to use the Amazon [24] and Yelp [25] datasets. The Amazon dataset is a rich collection of customer reviews, ratings, and product metadata, encompassing over 233.1 million reviews spanning the years from 1996 to 2018, covering 21 product categories. This dataset stands as one of the largest publicly available datasets for rating-related tasks. In contrast, the Yelp dataset is also freely accessible, housing at less 8.5 million reviews and featuring data on over 160,000 businesses.

3.1. Custom NER performance

To ensure that our model runs smoothly on a laptop equipped with a 6 GB GPU and 16 GB of RAM without exceeding the available GPU memory, we've made several configuration choices : we have set the mini-batch size to 32. This means that during each training iteration, our model processes 32 sequences at a time. This helps manage GPU memory usage efficiently. We have set a maximum sequence length of 512. Any input sequences longer than this threshold are either truncated or divided into smaller segments. Our model architecture consists of a single Bi-LSTM layer with a hidden size of 256. This architecture strikes a balance between computational complexity and the available hardware resources. The learning rate has been configured at 0.1. This hyperparameter determines the step size during the training process and is chosen based on the specific task and dataset requirements. It plays a crucial role in achieving effective model convergence.

To evaluate the performance of our custom NER model, we utilized a set of three crucial metrics: precision, F1 score, and recall. In the context of NER, precision reflects how many of the identified named entities were correctly recognized, recall indicates how many of the actual named entities were successfully found, and the F1 score provides a balanced evaluation considering both precision and recall. These metrics help assess the NER model's ability to identify and classify named entities accurately in text data. In our evaluation, we compared our model against the RB-CARS model [16], which utilizes publicly available corpora like CoNLL-2003 and Groningen Meaning Bank (GMB) for training purposes. Table 3 showcases the comparative performance of our custom NER model against the RB-CARS model across different contextual categories. Despite the computational resource limitations that restricted training to just 15% of the collected data, our model demonstrates superior performance in all tested contexts. In the location context, the advantage of our model is relatively modest but notable. It achieves precision, recall, and F1 scores of 92.66%, 93.25%, and 93.12%, respectively, outperforming RB-CARS, which scores 91.47%, 87.23%, and 90.70%. This suggests a slightly better capability of our model to accurately identify and correctly classify location entities. The performance gap widens in the weather context, where your model significantly surpasses RB-CARS, achieving precision, recall, and F1 scores of 90.02%, 91.32%, and 91.50%, respectively, against RB-CARS' scores of 86.37%, 85.43%, and 85.90%. This marks a considerable improvement, suggesting that our model is better equipped at understanding and categorizing weather-related entities, which is a direct benefit from utilizing a corpus constructed from Dbpedia. The distinction is even more pronounced in the time context. Our model demonstrates superior precision 94.33%, recall 92.56%, and F1 scores 93.04% compared to RB-CARS, which lags with scores of 77.74%, 76.35%, and 77.04%, respectively. This significant leap in performance highlights our model enhanced capability in handling temporal information, likely benefiting from a more comprehensive and varied dataset that includes a wider array of temporal expressions.

The marginal improvements in the Location context contrast starkly with the significant advancements made in both the weather and time contexts. This discrepancy may point to RB-CARS' potential weakness in processing, due to an insufficient training corpus. Remarkably, our model's performance, achieved with a fraction of the available data, not only demonstrates its efficiency and effectiveness but also underscores the impact of building a corpus from knowledge databases over sheer volume of training data.

Table 3. Comparision between our custom NER and DB-CARS model

	RB-CARS			Proposed model		
Entity	Precision	Recall	F1 score	Precision	Recall	F1 score
Time	77.74%	76.35%	77.04%	94.33%	92.56%	93.04%
Location	91.47%	87.23%	90.70%	92.66%	93.25%	93.12%
Companion	91.59%	92.15%	91.34%	92.16%	94.15%	93.34%
Weather	86.37%	85.43%	85.90%	90.02%	91.32%	91.50%

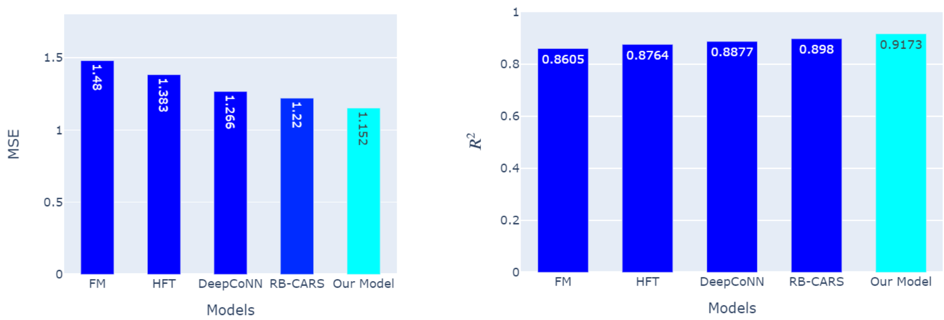
3.2. Rating prediction performance

We have constructed the CBFM model using the TensorFlow framework [26]. To evaluate its performance, we have divided the dataset into an 80% training set and a 20% test set. As we are addressing a regression problem, we fine-tune the model parameters by minimizing the loss function. Additionally, to mitigate overfitting, we incorporate an L2 regularization term into our model. Given that our data is sparse, we opt for a gradient-based optimizer, which is efficient for this scenario. We have set the number of iterations to 1,000 since the CBFM algorithm typically requires a longer time to converge.

To assess the effectiveness of our recommender system, we conducted a comparative analysis involving four models: FM [22], HFT [5], DeepCoNN [3], and RB-CARS [11]. We employ a dual-metric approach to assess our model's performance. The primary metric in our evaluation toolkit is the mean square error (MSE) complemented by R-squared (R^2) as the second key indicator.

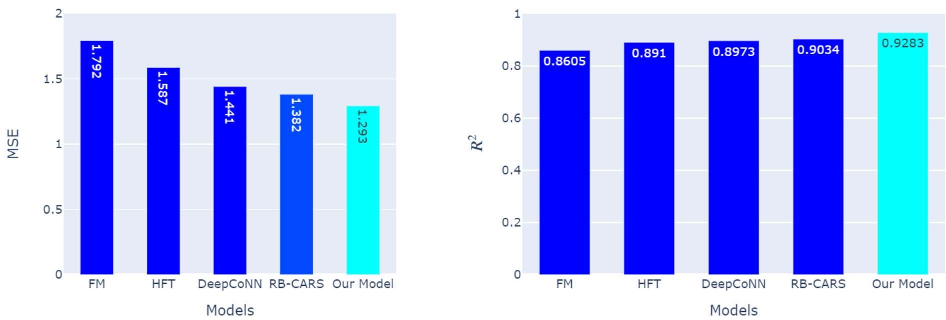
The data presented in Figure 3 for the Amazon dataset clearly illustrates the significant advancements in recommendation quality achieved through the implementation of the new model. As shown in Figure 3(a), our demonstrates a notable reduction an MSE achieving a score of 1.152. This is a lower MSE compared to the RB-CARS model, which is the next best with an MSE of 1.22. The figures also highlight that models lacking in contextual information integration, such as DeepCoNN and HFT, tend to exhibit higher MSE values.

This underscores the critical importance of incorporating contextual data to enhance the precision and quality of recommendations. Furthermore, Figure 3(b) illustrates the comparison of R-squared values reveals that the new model surpasses RB-CARS by 2% and DeepCoNN by 3%, indicating a more accurate representation of the dataset's variance and thereby, superior predictive performance. Extending the analysis to the Yelp dataset, Figure 4 confirm the findings from the Amazon dataset, further establishing the efficacy of the new model. In Figure 4(a), the model again registers the lowest MSE, this time with a value of 1.293, with DB-CARS trailing closely behind. Figure 4(b) exploration of R-squared values provides an easier interpretation of the data, where our model showcases an improvement of approximately 2.5% over the second-best performing model. Additionally, the FM model is pointed out for having the highest MSE among the models assessed, a direct consequence of not utilizing contextual data in its evaluation. This reinforces the notion that the integration of contextual information is pivotal for optimizing model performance in recommendation systems. These outcomes from the Yelp dataset experiment resonate with the observations from the Amazon dataset, solidifying the argument that contextual data significantly contributes to the enhanced performance of recommender systems, offering a clear edge in predictive accuracy and quality of recommendations.



(a) (b)

Figure 3. Results in terms of (a) the MSE and (b) the R^2 for Amazon dataset



(a) (b)

Figure 4. Results in terms of (a) the MSE and (b) the R^2 for Yelp dataset

3.3. Discussion

In addressing gaps within the domain of NER and rating prediction, our study not only leverages the vast datasets of Amazon and Yelp but also introduces a nuanced approach to model evaluation. Previous studies have seldom fully explored the integration of contextual data within these frameworks, an area our research aims to illuminate. Our custom NER model demonstrated an impressive ability to outperform existing models, such as RB-CARS, by achieving higher precision, recall, and F1 scores across various contexts, particularly in weather and time entities. For rating prediction, the CBFM model showcased a marked improvement in predictive accuracy over traditional models, evidenced by lower MSE scores and higher

R-squared values on both Amazon and Yelp datasets. The exceptional performance of our NER model, particularly in the weather and time contexts, underscores the model's refined capacity for processing and categorizing entities, benefitting significantly from a meticulously constructed corpus. In parallel, the CBFM model's success in rating prediction emphasizes the critical role of contextual data in enhancing recommendation systems' accuracy. These findings suggest a pivotal shift towards more contextually aware methodologies in the development of computational models. Our study, while comprehensive, acknowledges certain limitations. The constrained computational resources led to training on a subset of the available data, potentially limiting the models' learning capacity. Additionally, the focus on specific contexts and datasets might not fully capture the models' generalizability across varied scenarios. The evident success of integrating contextual data invites further exploration into expanding the models' training datasets and contexts. Future research could investigate the scalability of these models with increased computational power and explore their applicability across a broader spectrum of contexts. Additionally, refining the models to optimize their efficiency and adaptability to different datasets could further enhance their performance and utility. The significant advancements demonstrated by our custom NER and CBFM models not only address the identified gaps in the literature but also highlight the untapped potential of contextual data in improving model performance. These findings pave the way for future explorations into more sophisticated, context-aware computational models, offering promising directions for enhancing the accuracy and relevance of NER and rating prediction systems.

4. CONCLUSION

In conclusion, This work heralds a significant leap forward in the development of recommender systems. By pioneering a model that proficiently extracts and integrates contextual data, we have not only addressed the challenge of obtaining such data but have also unlocked new dimensions of personalization and accuracy in recommendations. This advancement underscores the indispensable role of context in shaping user preferences and decisions, setting a new standard for personalized, context-aware recommender systems. Our research is structured around three key steps: corpus building, context extraction with custom NER and ratings prediction. The evaluation of our recommender system involves a comparative analysis with four other models, and the obtained results demonstrate the effectiveness of our model in delivering promising results. For future work, we have planned to further enhance our model in both of these critical steps. This includes improving the data extraction process by exploring advanced techniques and methodologies. Additionally, we aim to refine and optimize the techniques used for ratings prediction, ensuring better recommendation quality.

REFERENCES

[1] R. Madani, A. Ez-Zahout, and A. Idrissi, "An overview of recommender systems in the context of smart cities," in *2020 5th International Conference on Cloud Computing and Artificial Intelligence: Technologies and Applications (CloudTech)*, Nov. 2020, pp. 1–9, doi: 10.1109/CloudTech49835.2020.9365877.

[2] G. Adomavicius, B. Mobasher, F. Ricci, and A. Tuzhilin, "Context-aware recommender systems," *AI Magazine*, vol. 32, no. 3, pp. 67–80, Sep. 2011, doi: 10.1609/aimag.v32i3.2364.

[3] L. Zheng, V. Noroozi, and P. S. Yu, "Joint deep modeling of users and items using reviews for recommendation," *arXiv preprint arXiv.1701.04783*, p. 10, Jan. 2017, [Online]. Available: http://arxiv.org/abs/1701.04783.

[4] R. Catherine and W. Cohen, "TransNets: learning to transform for recommendation," in *RecSys 2017 - Proceedings of the 11th ACM Conference on Recommender Systems*, Aug. 2017, pp. 288–296, doi: 10.1145/3109859.3109878.

[5] J. McAuley and J. Leskovec, "Hidden factors and hidden topics," in *Proceedings of the 7th ACM conference on Recommender systems*, Oct. 2013, pp. 165–172, doi: 10.1145/2507157.2507163.

[6] Y. Tan, M. Zhang, Y. Liu, and S. Ma, "Rating-boosted latent topics: understanding users and items with ratings and reviews," *IJCAI International Joint Conference on Artificial Intelligence*, vol. 2016-January, pp. 2640–2646, 2016.

[7] Y. Zhang, G. Lai, M. Zhang, Y. Zhang, Y. Liu, and S. Ma, "Explicit factor models for explainable recommendation based on phrase-level sentiment analysis," in *Proceedings of the 37th international ACM SIGIR conference on Research & development in information retrieval*, Jul. 2014, pp. 83–92, doi: 10.1145/2600428.2609579.

[8] S. Aciar, "Mining context information from consumer's reviews," in *Proceedings of Workshop on Context-Aware Recommender System. ACM*, 2010, p. 5.

[9] N. Hariri, B. Mobasher, R. Burke, and Y. Zheng, "Context-aware recommendation based on review mining," *CEUR Workshop Proceedings*, vol. 756, pp. 30–36, 2011.

[10] P. G. Campos, N. Rodríguez-Artigot, and I. Cantador, "Extracting context data from user reviews for recommendation: a linked data approach," *CEUR Workshop Proceedings*, vol. 1892, pp. 14–18, 2017.

[11] R. Madani and A. Ez-Zahout, "A Review-based context-aware recommender systems: using custom NER and factorization machines," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 3, pp. 546–553, 2022, doi: 10.14569/IJACSA.2022.0130365.

[12] J. Lehmann *et al.*, "DBpedia - a large-scale, multilingual knowledge base extracted from Wikipedia," *Semantic Web*, vol. 6, no. 2, pp. 167–195, 2015.
[13] G. Castelli, A. Rosi, M. Mamei, and F. Zambonelli, "A simple model and infrastructure for context-aware browsing of the world," in *Fifth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom'07)*, 2007, pp. 229–238, doi: 10.1109/PERCOM.2007.4.
[14] J.-D. Kim, J. Son, and D.-K. Baik, "CA5W1HOnto: Ontological context-aware model based on 5W1H," *International Journal of Distributed Sensor Networks*, vol. 8, no. 3, p. 247346, Mar. 2012, doi: 10.1155/2012/247346.
[15] T. Chaari, D. Ejigu, F. Laforest, and V.-M. Scuturici, "A comprehensive approach to model and use context for adapting applications in pervasive environments," *Journal of Systems and Software*, vol. 80, no. 12, pp. 1973–1992, Dec. 2007, doi: 10.1016/j.jss.2007.03.010.
[16] H. Chen, T. Finin, and A. Joshi, "The SOUPA ontology for pervasive computing," in *Ontologies for Agents: Theory and Experiences*, Basel: Birkhäuser-Verlag, 2005, pp. 233–258.
[17] Z. Huang, W. Xu, and K. Yu, "Bidirectional LSTM-CRF models for sequence tagging," *arXiv:1508.01991*, p. 10, Aug. 2015, [Online]. Available: http://arxiv.org/abs/1508.01991.
[18] J. Devlin, M.-W. Chang, K. Lee, K. T. Google, and A. I. Language, "BERT: pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics*, 2018, no. Mlm, pp. 4171–4186.
[19] A. Radford, K. Narasimhan, T. Salimans, and I. Sutskever, "Improving language understanding by generative pre-training," *Homology, Homotopy and Applications*, vol. 9, no. 1, pp. 399–438, 2007.
[20] M. Peters *et al.*, "Deep contextualized word representations," in *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, 2018, pp. 2227–2237, doi: 10.18653/v1/N18-1202.
[21] J. D. Lafferty, A. McCallum, and F. C. N. Pereira, "Conditional random fields: probabilistic models for segmenting and labeling sequence data," in *ICML '01: Proceedings of the Eighteenth International Conference on Machine Learning*, 2001, pp. 282–289.
[22] S. Rendle, "Factorization machines," in *2010 IEEE International Conference on Data Mining*, Dec. 2010, pp. 995–1000, doi: 10.1109/ICDM.2010.127.
[23] R. Madani, A. Idrissi, and A. Ez-Zahout, "A new context-based factorization machines for context-aware recommender systems," *Studies in Computational Intelligence*, vol. 1102, pp. 15–23, 2023, doi: 10.1007/978-3-031-33309-5_2.
[24] J. McAuley, "Amazon product reviews," *cseweb.ucsd.edu*, 2023. https://jmcauley.ucsd.edu/data/amazon/. (accessed: Aug. 2, 2023).
[25] "Yelp open dataset," *Yelp*, 2004. https://www.yelp.com/dataset. (accessed: Aug. 2, 2023).
[26] M. Abadi *et al.*, "TensorFlow: A system for large-scale machine learning," *arXiv preprint arXiv.1605.08695*, p. 18, May 2016, [Online]. Available: http://arxiv.org/abs/1605.08695.

BIOGRAPHIES OF AUTHORS

Rabie Madani is currently a 5th year Ph.D. student at faculty of sciences, Mohammed V University. He has a master degree on computer sciences and big data, he is actually an administrator of the information system on the Institute of Arabization and also the Institute of Africain studies at Mohammed V University. He has launched he's research cursus with publishing this paper in collaboration with us at IJEECS journal. He can be contacted at email: rabie.madani@um5.ac.ma.

Abderrahmane Ez-Zahout is currently an assistant professor of computer science at Department of Computer Science/Faculty of Sciences at Mohammed V University. His researches are in fields of computer sciences, digital systems, big data and computer vision. Recently, He works on intelligent systems. He has served as invited reviewer for many journal. Besides, he is also involved in NGOs, student associations, and managing non-profit foundation. He can be contacted at email: abderrahmane.ezzahout@um5.ac.ma.

Fouzia Omary is the leader IPSS team research and currently a full professor of Computer Science at Department of Computer Science/ENS, Mohammed V University. She is a full time researcher at Mohammed V University and she is the chair of the international conference on cybersecurity and blockchain and also the leader of the national network of blockchain and cryptocurrency. She can be contacted at email: omary@fsr.ac.ma.