Point of Interest Recommendation using Implicit Trust based on Combining Ratings and Check-ins of Smartphone Users

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ABSTRACT

This paper introduces a hybrid model called Implicit Trust based on Combining point-of-interest Ratings and user Check-ins (ITCRC) to address the cold-start challenges commonly associated with trust-based collaborative filtering methods. The model combines Point of Interest (POI) ratings and user check-ins to estimate implicit trust, facilitating location recommendations in a Location-Based Social Network (LBSN). In the Yelp dataset, the ITCRC model's trust and prediction matrices are calculated using Trust based on Ratings (TR), Trust derived from Check-ins (TC), and Trust based on the Hybridization of ratings and check-ins (TH), as well as three approaches derived by adapting O'Donovan's trust formula to the LBSN context. These six approaches are then compared using sparsity metrics and evaluation parameters such as RMSE, precision, and recall. The comparisons revealed that the TH approach significantly reduces the data sparsity of the prediction matrix by 36.08%, the TR and TC approaches improve the relevance of the recommendations (0.77% of precision and 0.99% of recall), and the OR, OC, and OH approaches improve the prediction accuracy by 0.2% in terms of RMSE.

Keywords-collaborative filtering; hybrid POI recommendation; implicit trust; sparsity; rating; check-in

I. INTRODUCTION

Recommender systems (RS) leverage users' past preferences to effectively anticipate their future interests and generate accurate predictions [1]. Among the various approaches to RS, Collaborative Filtering (CF) stands out for computing similarities and predicting future Points of Interest (POIs) based on user interactions [2-4]. Despite its popularity, CF faces significant challenges, including data sparsity, cold-start problems, and scalability issues [5]. To address these limitations, incorporating trust into POI recommendation systems has emerged as a promising solution [6]. Trust can be categorized as explicit, where it is directly stated by users [7-9], or implicit, where it is inferred from user behavior, such as ratings or browsing activity [10]. Implicit trust, inferred from interactions like ratings and check-ins, has shown considerable potential [11]. Location-Based Social Networks (LBSNs) play a key role in POI recommendation systems by capturing spatiotemporal data from users' shared experiences, including check-ins and ratings [12]. This rich dataset not only improves the understanding of user preferences, but also helps mitigate the challenges of data sparsity challenges in LBSNs [13]. Previous studies reveal that LBSNs using explicit trust often outperform systems relying on traditional similarity measures such as Pearson or Jaccard [14-16]. However, explicit trust is rarely expressed by users due to limited interest in expressing social relationships [17]. This highlights the importance of implicit trust as an alternative [18-20]. Researchers have explored various methods to infer implicit trust, such as leveraging friendships [21-22] or explicitly declared trust relationships [23]. Additionally, trust can be inferred between users who visit the same POI within a certain time frame [24]. Ekaterina et al. proposed that the relevance of user opinions diminishes over time, and introduced a trust model influenced by the publication date of opinions [25]. Similarly, Xu et al. developed a method to calculate trust between users by incorporating metrics like Jaccard mean square difference and average ratings [26]. Moreover, check-in and rating data in LBSNs are often subject to bias. Incorporating trust can improve recommendation accuracy by identifying and utilizing reliable relationships between users. In this regard, An et al. proposed a hybrid model that combines check-ins, ratings, and geolocation to improve POI recommendations [27]. However, the intricate relationships between users, POIs, and trust links require advanced methodologies to capture dynamic and contextual influences. Graph Neural Networks (GNNs) have been identified as a powerful tool for managing such complexities [28]. In addition, co-clustering algorithms can be used to group users and POIs based on their relational similarities, further optimizing trust networks [29]. Building upon these insights, this paper proposes a novel approach that integrates ratings and check-ins to effectively infer implicit trust between users. In doing so, it seeks to outperform existing methods, overcome the challenge of data sparsity, and improve the accuracy and relevance of POI recommendations.

II. PROPOSED APPROACH

This section outlines the formulas for calculating implicit trust between users based on their interactions with POIs, as well as the algorithms required to predict their future ratings using our recommendation model, Implicit Trust based on Combining point-of-interest Ratings and user Check-ins (ITCRC).

A. Calculation of Implicit Trust

O'Donovan and Smith define trust based on the reliability of a partner's profile in providing accurate recommendations in the past [30]. For example, a profile that has made numerous accurate recommendation predictions in the past may be considered more trustworthy than another profile that has consistently made poor predictions. This type of prediction can be calculated using (1) [31]:

$$PR_{a,i} = \overline{Rat_a} + \frac{\sum_{b=1}^{N}(Rat_{b,i} - \overline{Rat_b})sim(a,b)}{\sum_{b=1}^{N} sim(a,b)} \quad (1)$$

where $PR_{a,i}$ is the predicted rating for user a on item i, $\overline{Rat_a}$ is the average rating of user a for all items, $Rat_{b,i}$ is the actual rating of user b for item i, $sim(a,b)$ is the similarity between user a and user b, and N is the set of neighbors of user a.

However, to calculate the rating prediction for a user a on a given item i based solely on a user b considered as the recommender [30], (2) derived from (1) can be used [32]:

$$PR_{a,i}^{b} = \overline{Rat_a} + (Rat_{b,i} - \overline{Rat_b}) \quad (2)$$

where $PR_{a,i}^{b}$ is the predicted rating for user a on item i based on user b.

According to O'Donovan and Smith, the prediction of a rating for user a on item i based on a recommender b is considered "correct" only if the predicted rating $PR_{a,i}^{b}$ is close to the actual rating $Rat_{a,i}$ given by user a as indicated in (3).

$$Correct(i,b,a) \Leftrightarrow |PR_{a,i}^{b} - Rat_{a,i}| < \varepsilon \quad (3)$$

Consequently, $Correct(i,b,a)$ takes the value "1" if $|PR_{a,i}^{b} - Rat_{a,i}| < \varepsilon$, and the value "0" otherwise. O'Donovan and Smith then use (4) to define $RecSet(b)$ as the complete set of recommendations in which a recommender b was involved:

$$RecSet(b) = \{(PR_{1,1}^{b}, Rat_{1,1}), \ldots, (PR_{m,n}^{b}, Rat_{m,n})\} \quad (4)$$

where $PR_{j,k}^{b}$ represents the prediction of recommender b for the rating that user j (j ranges from 1 to m) will give to item k (k ranges from 1 to n). $Rat_{j,k}$ represents the actual rating of item k given by user j. From $RecSet(b)$, the subset of correct recommendations, denoted $CorrectSet(b)$, is calculated using (5) [30].

$$CorrectSet(b) = \{(PR_{j,k}^{b}, Rat_{j,k}) \epsilon RecSet(b): Correct(k, b, PR_{j,k}^{b})\} \quad (5)$$

Finally, the concept of trust at the profile level, denoted $Trust^{P}$ for recommender b, can be defined as the percentage of correct recommendations out of all the recommendations in which this recommender has participated, using (6) [30].

$$Trust^{P}(b) = \frac{card\{CorrectSet(b)\}}{card\{RecSet(b)\}} \quad (6)$$

Based on (6), a more refined item-level trust metric, denoted $Trust^{I}$, can be defined to measure only the percentage of correct recommendations for item i out of all the recommendations made by recommender b, as indicated in (7) [30].

$$Trust^{I}(b,i) = \frac{card\{(PR_{j,k}^{b}, Rat_{j,k}) \in CorrectSet(b) : k=i\}}{card\{(PR_{j,k}^{b}, Rat_{j,k}) \in RecSet(b) : k=i\}} \quad (7)$$

Equation (6) can be used to represent the reputation of a user, as it allows the calculation of the overall trust of a given user across all other users, based on their common ratings of all items [32-33]. On the other hand, (7) focuses on the reputation of a given user across all users, based on their common ratings for a specific item. In the same context, but inspired by the work of [34], the trust of a given user a in another user b (recommender) based on their common ratings for all items, can be defined using (8) [35]:

$$Trust^{U}(a \to b) = \frac{card\{(PR_{j,k}^{b}, Rat_{j,k}) \in CorrectSet(b) : j=a\}}{card\{(PR_{j,k}^{b}, Rat_{j,k}) \in RecSet(b) : j=a\}} \quad (8)$$

where $Trust^{U}(a \to b)$ is the trust of user a in recommender b, calculated as the percentage of correct recommendations that recommender b has participated in with user a, based on their common ratings for all items. Based on (8), the trust of user a in recommender b for a particular item i, denoted $Trust^{U}(a \to b, i)$, can be deduced as the percentage of correct recommendations that recommender b has participated in with user a, based solely on that item, as indicated in (9).

$$Trust^{U}(a \to b, i) = \frac{card\{(PR_{j,k}^{b}, Rat_{j,k}) \epsilon CorrectSet(b): j=a \& k=i\}}{card\{(PR_{j,k}^{b}, Rat_{j,k}) \epsilon RecSet(b): j=a \& k=i\}} \quad (9)$$

In the following, we have used (8) to deduce the implicit trust between users based on their ratings of POIs, which we will denote as $Trust\_R^U(a \rightarrow b)$. This type of trust is used to calculate the rating prediction using (10).

$$PR_{a,x} = \overline{Rat_a} + \frac{\sum_{b=1}^{N}(Rat_{b,x} - \overline{Rat_b}) * Trust\_R^U(a \rightarrow b)}{\sum_{b=1}^{N} Trust\_R^U(a \rightarrow b)} \quad (10)$$

In this article, we used the above (2) to derive the trust score of a given user based on the correct predictions of future POI ratings made by past users. The same principle is also used to calculate the trust levels of users based on their check-ins, as indicated in (11).

$$Ch_{a,i}^{b} = \overline{Ch_a} + \left(Ch_{b,i} - \overline{Ch_b}\right) \quad (11)$$

where $Ch_{a,i}^{b}$ is the predicted check-in of POI i for user a based on user b, $Ch_{b,i} \in \{0,1\}$ is the check-in of POI i by user b, $\overline{Ch_a}$ is the average check-ins of user a, and $\overline{Ch_b}$ is the average check-ins of user b. Equation (3) above can be applied in the case of check-ins to obtain (12).

$$Correct\_Ch(i, b, a) \Leftrightarrow \left|Ch_{a,i}^{b} - Ch_{a,i}\right| = 0 \quad (12)$$

Similarly, by replacing ratings with check-ins in (4) and (5) above, $RecSet\_Ch(b)$, which represents the complete set of recommendations, is given by (13), and $CorrectSet\_Ch(b)$, which indicates the subset of correct recommendations, is given by (14).

$$RecSet\_Ch(b) = \left\{\left(Ch_{1,1}^{b}, Ch_{1,1}\right), \ldots, \left(Ch_{m,n}^{b}, Ch_{m,n}\right)\right\} \quad (13)$$

where $Ch_{j,k}^{b}$ represents the prediction of recommender b for the check-in that user j (j ranges from 1 to m) will make at POI k (k ranges from 1 to n), and $Ch_{j,k}$ represents the actual check-in of POI k made by user j. Based on $RecSet\_Ch(b)$, the subset of correct recommendations, denoted $CorrectSet\_Ch(b)$, is calculated using (14).

$$CorrectSet_{Ch(b)} = \left\{\left(Ch_{j,k}^{b}, Ch_{j,k}\right) \epsilon\ RecSet\_Ch(b) : Correct\_Ch(k, b, Ch_{j,k}^{b})\right\} \quad (14)$$

Then, using check-ins, the trust of user a in user b can be deduced by applying (8) above, replacing ratings with check-ins to obtain (15).

$$Trust\_Ch^U(a \rightarrow b) = \frac{card\left\{\left(Ch_{j,k}^{b}, Ch_{j,k}\right) \in CorrectSet\_Ch(b) : j = a\right\}}{card\left\{\left(Ch_{j,k}^{b}, Ch_{j,k}\right) \in RecSet\_Ch(b) : j = a\right\}} \quad (15)$$

Finally, note that (16) below, derived from (10) above, can be used to calculate the POI rating predictions based on their trust derived from check-ins.

$$PR_{a,x} = \overline{Rat_a} + \frac{\sum_{b=1}^{N}(Rat_{b,x} - \overline{Rat_b}) * Trust\_Ch^U\ (a \rightarrow b)}{\sum_{b=1}^{N} Trust\_Ch^U\ (a \rightarrow b)} \quad (16)$$

where $Trust\_Ch^U(a \rightarrow b)$ is the trust based on check-ins.

B. Proposed Algorithm

After describing how to calculate the trust between users, we can derive the values of the matrix TDMR (Trust Derivation Matrix based on Rating) and the matrix TDMC (Trust Derivation Matrix based on Check-in) from the matrices UPRM (User-POI Rating Matrix) and UPCM (User-POI Check-in Matrix). Then, we can use the TDMR and TDMC matrices to calculate the prediction matrices, denoted RPM1 (Rating Prediction Matrix) based on TDMR, and RPM2 (Rating Prediction Matrix) based on TDMC, respectively. These calculations are performed using Algorithm 1 and Algorithm 2 below.

```
Algorithm 1: TDMR and RPM1 Computation
   Input:  UPRM: User-POI Rating Matrix;
   Output: TDMR: Trust Derivation Matrix
   based on Rating;
           RPM1: Rating Prediction Matrix
   based on TDMR;
   Var: M2, M3, M4: User-User-POI Matrix of
   dimension m × m × n;
Begin
// Compute TDMR
For each user a and user b and POI i
   Step 1: Compute rating prediction
   M2(a,b,i) using (2)
   Step 2: Compute distance error M3(a,b,i)
   and binary success/fail score M4(a,b,i)
   using (3)
      If distance error < ε then
        Success (correct ← 1)
      Else
        Fail (correct ← 0)
      End if
   Step 3: The set of recommendations for
   user b using (4)
   Step 4: The set of correct
   recommendations for user b using (5)
   Step 5: Compute user-user trust
   TDMR(a,b) using (8)
End For
// Compute RPM1 using TDMR and (10)
For each user a and POI x
   Step 6: Compute Rating Prediction RPM1
   based on rating trust (TDMR)
End for
End

Algorithm 2: TDMC and RPM2 Computation
   Input:  UPCM: User-POI Check-in Matrix;
   Output: TDMC: Trust Derivation Matrix
   based on Check-in;
           RPM2: Trust Prediction Matrix
   based on TDMC;
   Var: M2, M3, M4: User-User-POI Matrix of
   dimension m × m × n;
Begin
// Compute TDMC
```

```
For each user a and user b and POI i
   Step 1: Compute check-in prediction
   M2(a,b,i) using (11)
   Step 2: Compute distance error M3(a,b,i)
   and binary success/fail score M4(a,b,i)
   using (12)
      If distance error = = 0 then
         Success (correct ← 1)
      Else
         Fail (correct ← 0)
      End If
   Step 3: The set of recommendations for
   user b using (13)
   Step 4: The set of correct
   recommendations for user b using (14)
   Step 5: Compute user-user trust
   TDMC(a,b) using (15)
End for
// Compute  RPM2 using TDMC and (16)
For each user a and POI x
   Step 6: Compute Rating Prediction RPM2
   based on check-in trust (TDMC)
End for
End
```

C. *Proposed Model*

This subsection describes the POI recommendation method of our model ITCRC, which integrates POI ratings and user check-ins from the Yelp dataset (as shown by arrows a.0 and b.0 in Figure 1) and is also based on Algorithms 1 and 2 described above. These two algorithms use the trust matrices TDMR and TDMC (arrows a.1 and b.1 in Figure 1) to calculate the matrices RPM1 and RPM2, which contain the POI rating predictions (arrows a.2 and b.2 in Figure 1). Then, the two trust matrices TDMR and TDMC obtained from Algorithms 1 and 2 can be combined using Algorithm 3 below (arrow c.1 in Figure 1) to form the matrix HTM (Hybrid Trust Matrix) of dimension $m \times m$, where m is the number of users. This matrix can be used to calculate the POI rating predictions (arrow c.2 in Figure 1) from the matrix RPM3 (Rating Prediction Matrix) based on HTM with dimensions $m \times n$, where m is the number of users and n is the number of POIs, using (17) and Algorithm 3.

$$PR_{a,x} = \overline{Rat_a} + \frac{\sum_{b=1}^{N}(Rat_{b,x} - \overline{Rat_b}) * Trust\_H^U(a \to b)}{\sum_{b=1}^{N} Trust\_H^U(a \to b)} \quad (17)$$

where $PR_{a,x}$ is the predicted rating for user a on POI x, $\overline{Rat_a}$ is the average rating of user a for all POIs, $Rat_{b,x}$ is the actual rating given by user b to POI x, and $Trust\_H^U(a \to b)$ is the trust based on the combination of ratings and check-ins.

```
Algorithm 3: HTM and RPM3 Computation
   Input:   TDMR: Trust Derivation Matrix
   based on rating;
            TDMC: Trust Derivation Matrix
   based on check-in;
            UPRM: User-POI Rating Matrix;
   Output: HTM: Hybrid Trust Matrix;
            RPM3: Rating Prediction Matrix
based on HTM;
Begin
// Compute HTM
For each user a and user b and POI i
   If TDMR(a,b) exist and TDMC(a,b) exist
   then
```

$$HTM(a,b) = \frac{2 * TDMR(a,b) * TDMC(a,b)}{TDMR(a,b) + TDMC(a,b)}$$

```
   Else if TDMR(a,b) ! exist and TDMC(a,b)
   exist then
      HTM(a,b) = TDMC(a,b)
   Else if TDMR(a,b) exist and TDMC(a,b) !
   exist then
      HTM(a,b) = TDMR(a,b)
   Else
      HTM(a,b) = 0
   End if
End for
// Compute  RPM3 using HTM and (17)
For each user a and POI x
```

$$RPM3(a,x) = \overline{Rat_a} + \frac{\sum_{b=1}^{N}(Rat_{b,x} - \overline{Rat_b}) * HTM(a,b)}{\sum_{b=1}^{N} HTM(a,b)}$$

```
End for
End
```

Finally, these three rating prediction matrices, RPM1, RPM2, and RPM3, shown in Figure 1, can be compared with other approaches in the literature using evaluation metrics such as RMSE, precision, and recall thanks to the K parameter (arrows a.3, b.3, and c.3 in Figure 1).

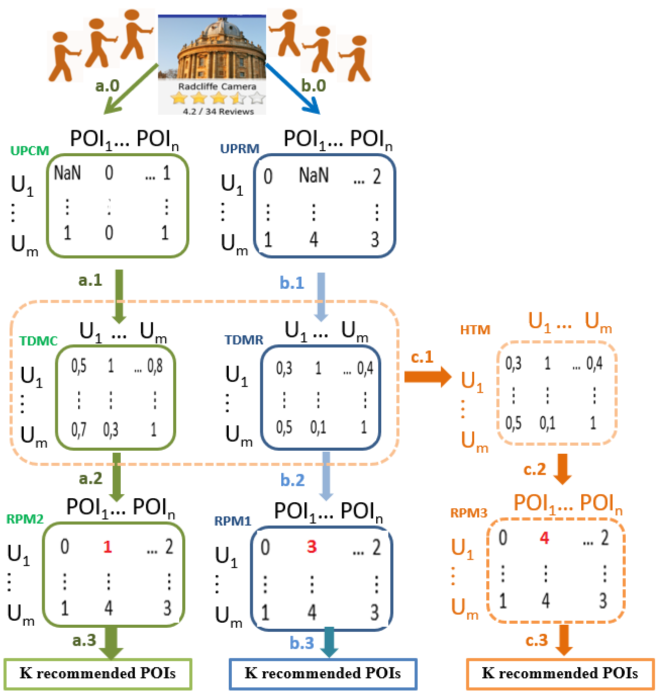

Fig. 1. Functional description of the ITCRC model.

III. RESULT AND DISCUSSION

A. Experimental setup

To evaluate the performance of the ITCRC model, we used the Yelp dataset [36] because it contains both POI ratings and user check-ins. We then divided this dataset into two parts, 80% for the model training set and 20% for the testing set. Next, we defined $\varepsilon = 0{,}9$ as the trust threshold. Finally, we adopted benchmark evaluation metrics such as RMSE, precision, and recall to assess the quality of the generated recommendations, as well as metrics to estimate data sparsity.

B. Comparison of ITCRC Model Variants

In this subsection, we compare the three variants of the ITCRC model: the approach based on Trust based on Ratings (TR), (2) the approach based on Trust derived from Check-ins (TC), and the approach based on Trust based on the Hybridization of ratings and check-ins. This comparison is made on the basis of the RMSE and F1 values, taking into account the evolution of the number of users, as shown in Figure 2 and Figure 3.

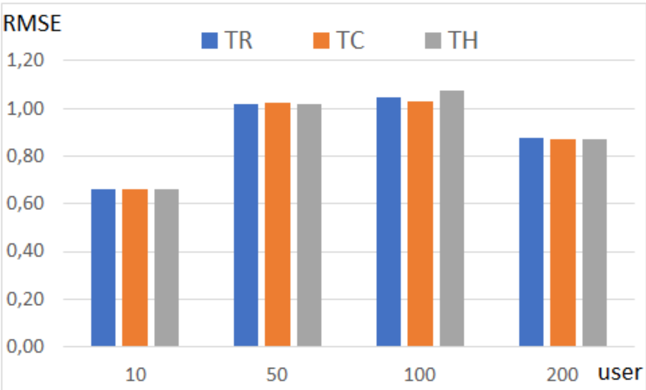

Fig. 2. Comparison of TR, TC, and TH approaches in terms of RMSE.

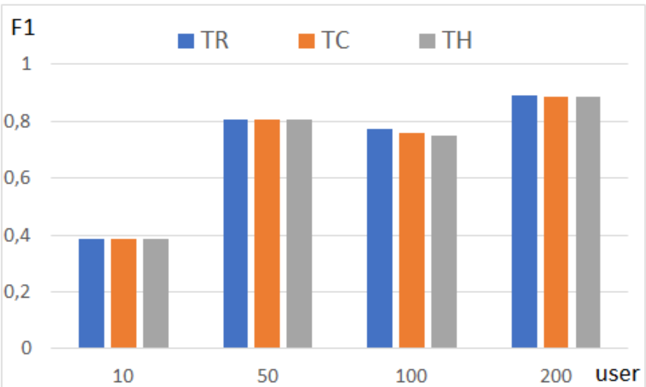

Fig. 3. Comparison of TR, TC, and TH approaches in terms of F1.

Furthermore, in Table I below, we observe that the TR approach outperforms the TC and TH approaches in terms of average RMSE, precision, and recall, denoted as AVG RMSE, AVG Precision, and AVG Recall, respectively.

TABLE I. COMPARISON OF TR, TC, AND TH APPROACHES USING AVG RMSE, AVG PRECISION, AND AVG RECALL.

Metric	TR	TC	TH
AVG RMSE	0,9440	0,9465	0,9484
AVG Precision	0,9154	0,9133	0,9119
AVG Recall	0,6537	0,6504	0,6497

C. The ITCRC Model and Sparsity

To address the sparsity problem that can occur in POI recommendations, we chose the Yelp dataset because it includes both user check-ins and ratings for visited POIs. Furthermore, we used the same density rate for the trust matrices in the TR, TC, and TH approaches to focus solely on the sparsity rate of the prediction matrices. For these reasons, we were able to show that the hybrid approach (TH) reduces the sparsity of the prediction matrices by 36.08% compared to the other approaches (TR and TC), as shown in Figure 4 and Table II.

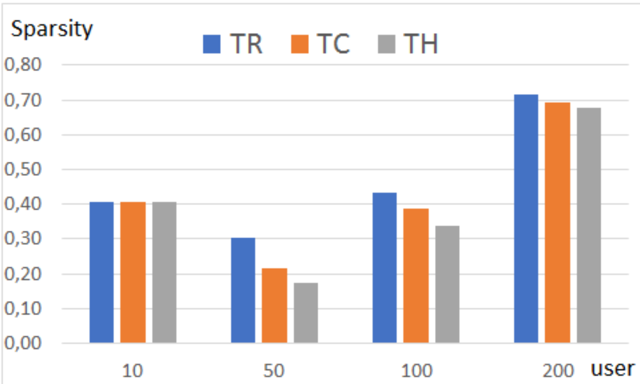

Fig. 4. Comparison of the sparsity of the prediction matrices for the TR, TC, and TH approaches as a function of the number of users.

TABLE II. COMPARISON OF THE DENSITY OF THE PREDICTION AND TRUST MATRICES FOR THE TR, TC, AND TH APPROACHES.

Metric	TR	TC	TH
AVG Sparsity trust matrix	0,388	0,388	0,388
AVG Sparsity prediction matrix	0,361	0,304	0,265

D. Comparison of the Variants of the O'Donovan model

In this subsection, we compare the different variants of the model based on O'Donovan's formula for calculating trust. This model includes three types of approaches. The first approach, referred to as OR (O'Donovan trust based on Rating), relies on ratings to compute the matrix that represents the trust value of each user (profile trust) [30] whereas the second approach, referred to as OC (O'Donovan trust based on Check-in) is an adaptation of the OR approach for the check-in context, as outlined in Algorithm 4 below.

```
Algorithm 4: O’Donovan Trust Computation
Input:  UPCM: User-POI Check-in Matrix;
Output: TProfile: Trust Profile matrix
based on check-in;
```

```
        RPM4: Rating Prediction Matrix
based on TProfile;
Var: M2, M3, M4: User-user-POI matrix of
dimension m × m × n;
Begin
// Compute TProfile
For each user a and user b and POI i
   Step 1: Compute check-in prediction
   M2(a,b,i) using (11)
   Step 2: Compute distance error M3(a,b,i)
   and binary success/fail score M4(a,b,i)
   using (12)
   If distance error = = 0 then
      Success (correct ← 1)
   Else
      Fail (correct ← 0)
   End if
   Step 3: The set of recommendations for
   user b using (13)
   Step 4: The set of correct
   recommendations for user b using (14)
   Step 5: Compute profile trust
   TProfile(b) using (6) adapted for check-
   in
End for
// Compute RPM4 using TProfile and (16)
For each user a and POI x
   Step 6: Compute rating prediction RPM4
   based on TProfile
End for
End
```

The third approach, referred to as OH (O'Donovan trust based on the Hybridization of rating and check-in), is a hybrid approach that combines the OR the OC approaches. To compare these three approaches, we analyzed their RMSE, precision, and recall values based on the variation in the number of users, as shown in Figure 5.

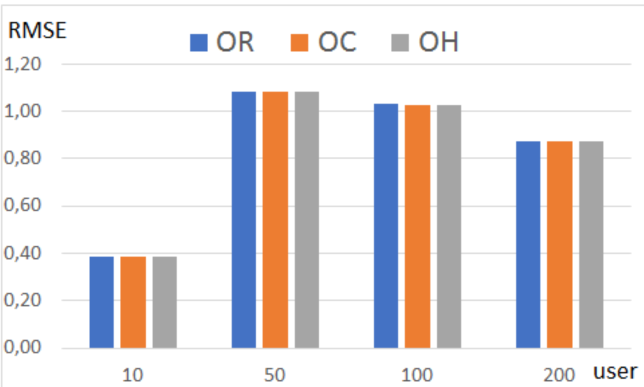

Fig. 5. Comparison of the OR, OC, and OH approaches using RMSE.

From Table III and Figure 5, we observe that the classic O'Donovan approach based on ratings (OR), adapted to the context of LBSNs, outperforms the other approaches, OC and OH, in terms of RMSE.

TABLE III. COMPARISON OF OR, OC, AND OH APPROACHES USING AVG RMSE, AVG PRECISION, AND AVG RECALL

Metric	OR	OC	OH
AVG RMSE	0,9420	0,9428	0,9423
AVG Precision	0,9083	0,9083	0,9083
AVG Recall	0,6391	0,6391	0,6391

E. Comparison Between the ITCRC Model and O'Donovan Model

In this subsection, we compare the different variants of our ITCRC model with those of O'Donovan's model using the same dataset (Yelp), as shown in Figure 6 and Table IV.

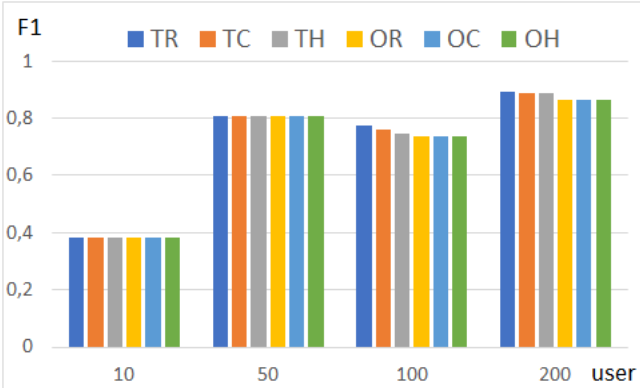

Fig. 6. Comparison of the TR, TC, TH, OR, OC, and OH approaches using F1.

TABLE IV. COMPARISON OF THE TR, TC, AND TH APPROACHES WITH THE OR, OC, AND OH APPROACHES USING AVG RMSE, AVG PRECISION, AND AVG RECALL

Metrics	TR	TC	TH	OR	OC	OH
AVG RMSE	0,944	0,946	0,948	0,9420	0,9428	0,9423
AVG Precision	0,915	0,913	0,911	0,9083	0,9083	0,9083
AVG Recall	0,653	0,650	0,649	0,6391	0,6391	0,6391

In Table IV, we demonstrate that the OR, OC, and OH approaches, derived by adapting O'Donovan's formula to the context of LBSNs, outperform the TR, TC, and TH approaches of our ITCRC model by 0.2% in terms of RMSE. However, the latter approaches outperform all approaches of O'Donovan's model by 0.77% in terms of Precision and 0.99% in terms of Recall.

F. Summary of Results and Discussion

A comparative analysis of the three variants of the ITCRC model was conducted using the Yelp dataset and the metrics of sparsity, RMSE, Precision, and Recall to recommend POIs based on trust derived from ratings, check-ins, or a combination of both. Although the three approaches, TR, TC, and TH, exhibit similar levels of density for trust matrices, the prediction matrices in the hybrid approach (TH) are less sparse, which makes it a more effective choice for fragmented datasets. The OR, OC, and OH approaches, inspired by the adaptation of O'Donovan's formula to the context of LBSNs, outperform the TR, TC, and TH approaches of the ITCRC model. This means that the OR, OC, and OH approaches are more accurate in predicting users' actual ratings. Furthermore, the TR, TC, and TH approaches of the ITCRC model surpass the OR, OC, and OH approaches in terms of Precision and Recall. This shows that the ITCRC model is more effective in identifying relevant POIs and reducing false positives. Finally, these results indicate that the choice of model and approach depends on the main objective: prediction accuracy (O'Donovan) or recommendation quality (ITCRC).

IV. CONCLUSION

The Implicit Trust based on Combining point-of-interest Ratings and user Check-ins (ITCRC) model, leveraging its Trust based on the Hybridization of ratings and check-ins (TH) approach, has proven to be highly effective in addressing data sparsity issues in Location-Based Social Networks (LBSNs). By significantly reducing the sparsity of prediction matrices, the ITCRC model improves the quality of recommendations, enabling the identification of relevant Points of Interest (POIs) while reducing false positives. This strength is particularly beneficial in scenarios with limited data coverage, making the model a powerful tool for improving recommendation systems in real-world settings where data is often incomplete or fragmented. On the other hand, the O'Donovan trust based on Rating (OR), the O'Donovan trust based on Check-in (OC), and the O'Donovan trust based on the Hybridization of rating and check-in (OH) approaches, which are adaptations of O'Donovan's formula tailored to LBSNs, have demonstrated superior accuracy in predicting POI visits by minimizing the RMSE parameter. These approaches are particularly effective when the goal is to provide users with precise ratings. The comparison between the ITCRC model and the O'Donovan-inspired methods underscores that the choice of approach depends on the specific priorities of the application: the ITCRC model excels at improving recommendation quality in sparse datasets, while the O'Donovan-inspired methods are better suited for delivering providing explicit predictions.

Despite these advancements, several challenges remain. A key limitation of the ITCRC model is its computational complexity, which may hinder scalability when applied to large-scale LBSNs with rapidly growing user and POI data. Future research should investigate optimization techniques or parallel processing frameworks to improve the model's scalability and computational efficiency. In addition, the reliance on user check-ins and ratings for implicit trust inference may introduce biases, especially in datasets with uneven user participation. Further studies could explore the integration of alternative data sources, such as social media interactions or geospatial data, to reduce these biases and strengthen the robustness of trust inference.

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