Location Recommendation Using Content-Aware Collaborative Filtering

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Overview

Introduction

- Recommender systems – Netflix, YouTube, Amazon
- Location Recommendation
  - POI (Point Of Interest)
  - LBSN (Location Based Social Network)
  - Influences And Problems
- Content-aware collaborative filtering

Problem Statement

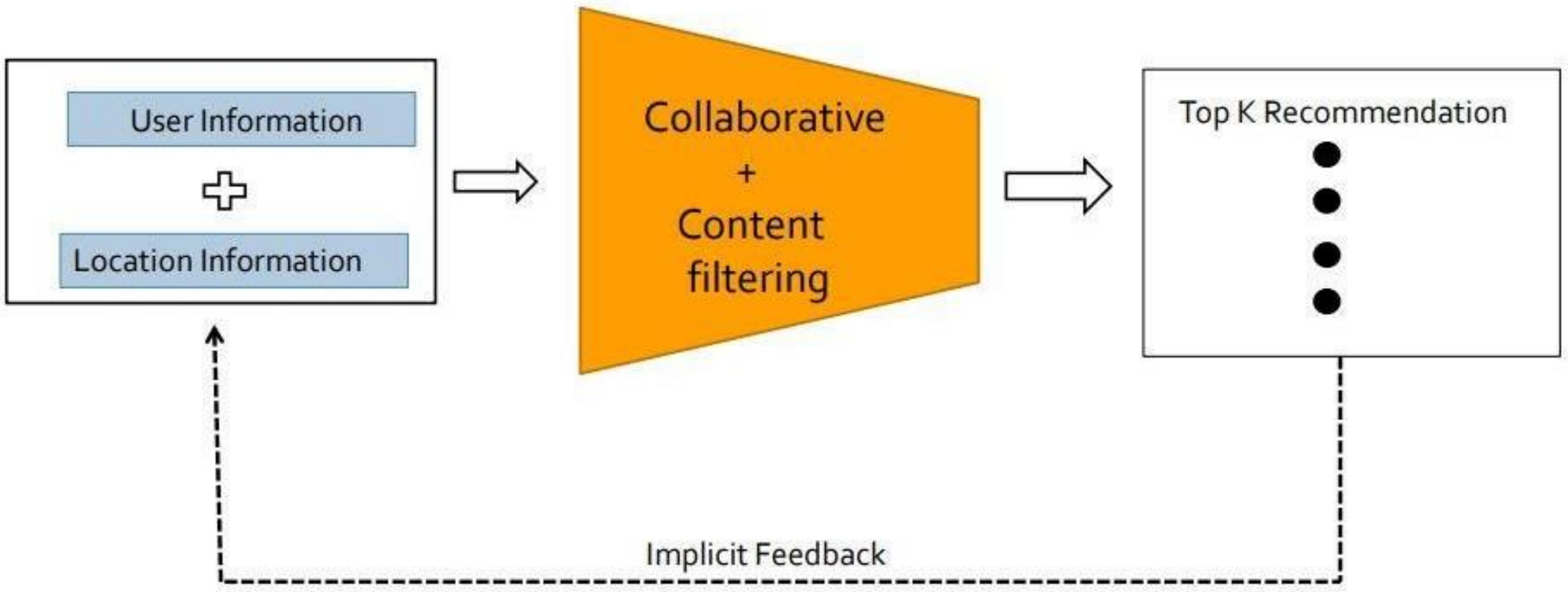
- Most Location Recommender are based on user-location rating and are generally not personalized.
  [Lack of personalization]

- Absence of explicit feedback(rating) in practical system.
  [Lack of feedback]

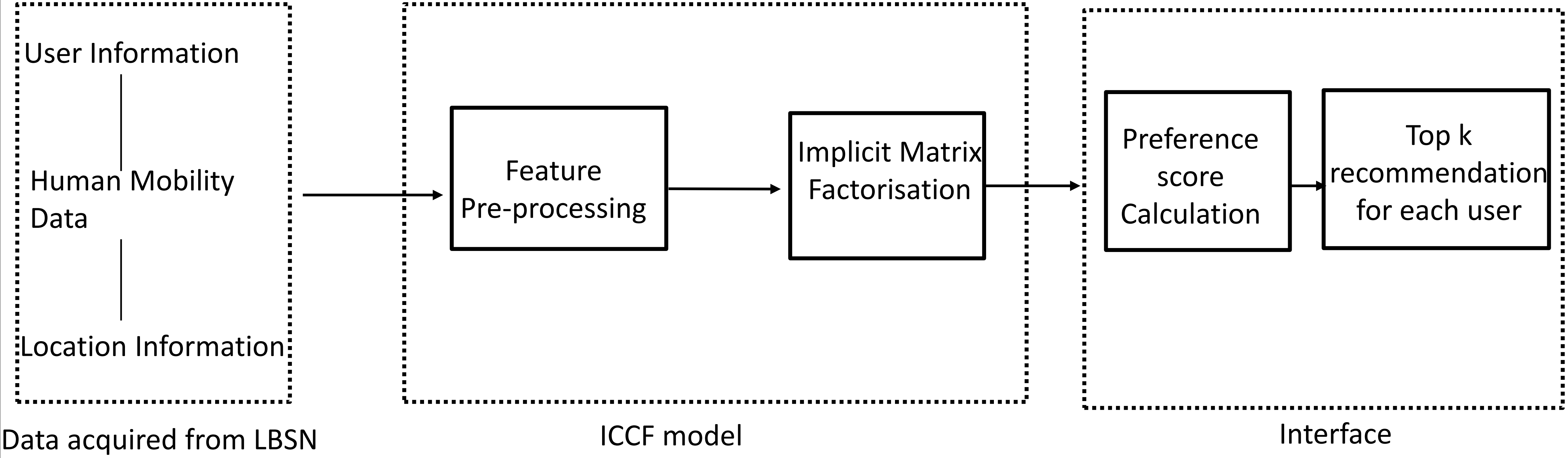
- Handling new users in C F based recommenders.
  [Cold Start problem]

S No.	Paper Description [Literature Survey]	Inferences
[1]	Scalable Implicit feedback based content aware collaborative filtering.	Trying to obtain user and location profile from social network information of each user to obtain user preferences.
[2]	CF based location-activity recommendation	General walk-in user centered recommendation. Does not address the Cold Start issue and lack of training and testing data.
[3]	Point-of-Interest Recommendation based on modeling the spatial clustering phenomenon	Handling sparsity of user POI matrix and exploiting clustering phenomena in human behaviour. Does not utilise social network information and useful for native POI recommendations only.
[4]	Collaborative Filtering for Implicit Feedback Datasets	Proposes treating the data as indication of positive and negative preference associated with vastly varying confidence levels. Does not address the cold start problem.
[5]	Personalized Ranking from Implicit Feedback using BPR	Generic optimization criterion for personalized ranking. Does not account for confidence level in ratings

Proposed Methodology



Overview Of ICCF Design



Overview of the Proposed Model

- Feature Pre-processing: Discretization, Standardization, Normalization
- Implicit Matrix Factorisation: Factorise into user-factor and item-factor matrices.
- Preference Score Calculation: Multiply the user-factor and item-factor matrices to obtain preference score (how much user prefers that location).
- Top k recommendation: Recommend k POI’s for each user based on preference score calculated.

Algorithms Evaluated

- LightFm
- Implicit
- MRec

Evaluation Measure

- hit : a count that get incremented only if the model is able to recommend a hidden location

- hit ratio : the ratio of number of hits to the total number of users

- one visit hide : for each user, one visit out of all the location visits the user has visited is hidden

- one item hide : for each user, one location out of all the unique locations the user visited is hidden

Performance Analysis

Effects of user and item feature matrices

- Significant increase in accuracy.
- They refine the preference score for user item pairs based in which recommendations are generated.
- Mrec seems to perform comparatively better because of the method it uses to compute and optimize the user factor and item factor matrices.
- Implicit performance is comparatively worse.

	Without user and item features	With user and item features
Implicit	3218 0.0949	----
LightFm	5577 0.1643	6782 0.2000
Mrec	8772 0.2581	9750 0.2896

Effects of user and item feature matrices

Performance Analysis

Effects related to visit hide and item hide

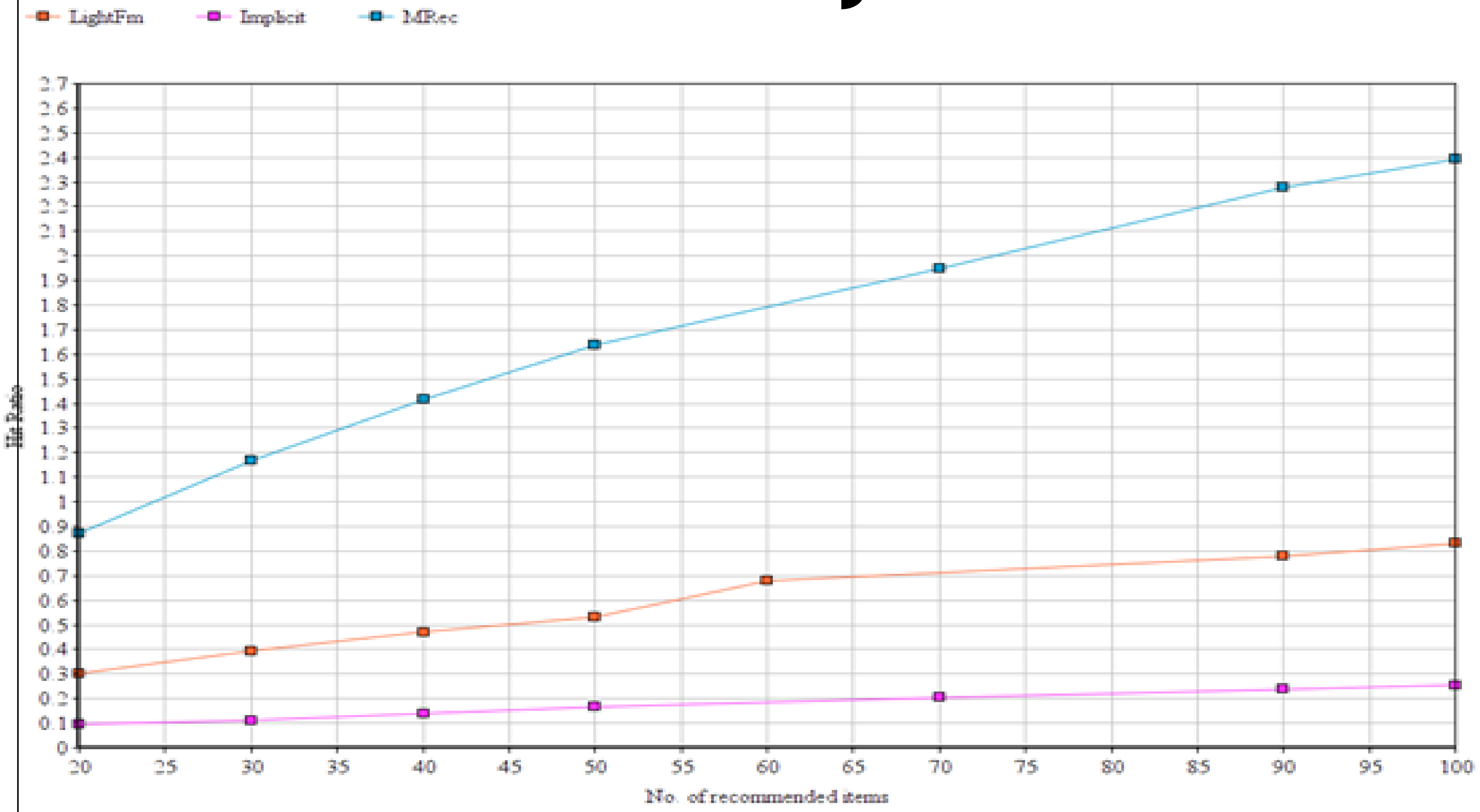
- Mrec seems to perform comparatively better

- Implicit performance is comparatively worse

	One visit hide@10	One item hide@10
Implicit	3218 0.0949	295 0.0063
LightFm	5577 0.1643	1147 0.024
Mrec	8772 0.2581	7451 0.2581

Effects related to visit hide and item hide

Performance Analysis



Accuracy when number of predicted items is increased

Conclusion

- A content-aware collaborative filtering from implicit feedback dataset framework called ICCF was used to perform comparative study of some state-of-the-art recommender algorithms in providing top k recommendation to each user based on mobility history.
- User features are used to refine mobility similarity between users and also handle the cold start case and thereby provide recommendation to new users and existing users.
- For further work, the evaluation measure needs to be extended so that it can evaluate cold start case as well. This may include incorporating live A/B testing of recommendation to get immediate feedback from users and also being able to quantify the novelty and popularity of location.

References

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[2] V. Zheng, B. Cao, Y. Zheng, X. Xie, and Q. Yang, 2010,"Collaborative filtering meets mobile recommendation: A user-centred approach”, Proceedings of AAAI’10.

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[5] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, Lars Schmidt-Thieme, 2016 “BPR: Bayesian personalized ranking from implicit feedback”, Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence, pp. 452-461.