DESIGN OF PERSONALIZED RECOMMENDER SYSTEM BASED ON HYBRID FILTERING AND FOG COMPUTING ARCHITECTURE

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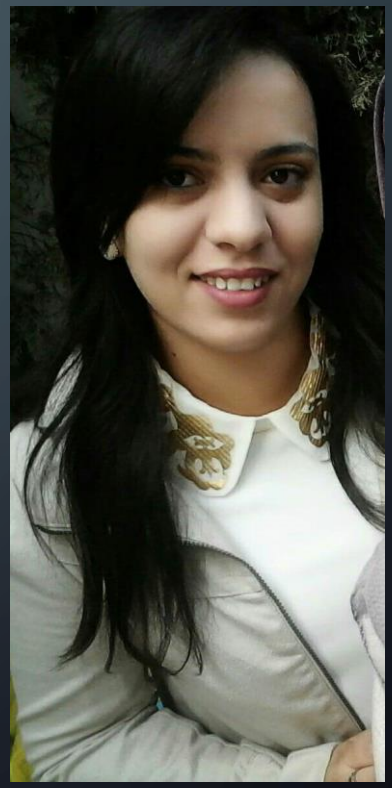
BIOGRAPHICAL SKETCH

Ms. Noura Abdaoui is currently a Phd Student at The University of Manouba, The National School of Computer Science (ENSI) in Tnunisia. She received her Master's degree in Multimedia and decision in 2017 from the Higher Institute of Multimedia Arts in Manouba University (ISAMM). Her research interests include interaction between smart devices in pervasive environment,ubiquitous computing, sensor technology and Location-Awareness. Recommender systems and Software Engineering for IoT.



OUTLINES OF THE TALK

- Introduction
- Integration of Fog Computing Architecture for the RS
- Experiments and Results
- Conclusion and Future work
- Question and Answer Session

INTRODUCTION

CONTEXT

- Ubiquitous computing can occur with any device, any time, any place and in any data format across the network technologies, such as RFID, Wi-Fi and Bluetooth.
- Apart of ubiquitous research deals with Location-Based Information Systems.
- Ubiquitous recommender systems facilitate users on location by providing them with personalized recommendations of items in the proximity via mobile devices.

MOTIVATION

- Various recommendations techniques have been developed to fulfill the needs of user in different scenarios: CF, CBF, hybrid filtering, ML…
- Personalization and recommendation are two important prerequisites that must be incorporated in the Iot environment.
- Both prerequisites are essential to produce a higher satisfaction level of ubiquitous recommender system which matches the preferences of the user.
- Most of Iot applications are connected to cloud computing with sensors and other devices which provide huge amount of data and require a high bandwidth for the network used.
- Real-time applications, 30 million clients are transferring data up to 25 000 records every second, which is not efficient for the cloud.
- With the growth of data quantity and the emergence of different kinds of dynamic end-user and access smart IoT devices, the information overload problem is becoming serious.

MOTIVATION

- Traditional ubiquitous recommender system failed to exploit dynamic and heterogeneous big data in delivering personalized recommendation.
- Scalability: Traditional algorithms in recommendation systems must respond to the user's needs immediately, regardless of the user's rating history and purchase situation, which requires high.
- Sparsity: the performance of the recommendation process may be degraded due to the cold start problems caused by data sparsity.
- Diversity: Unfortunately, some traditional algorithms may accidentally do the opposite because they always recommend popular and highly-rated items that some specific users love. Therefore, new hybrid methods need to be developed to improve the performance of the recommendation systems.

IMPROVEMENT FOR RELATED STUDIES

- Fog computing architecture: solve the ubiquitous recommendations issues related to Iot challenges.
- It is a multi-layer fog structure which aims to use the multi sources big data in order to propose personalized offers
- Fog computing: add an intermediate layer between mobile users and the cloud, where the new layer involves fog servers directly used near mobile users and IoT devices
- This solution: provide intelligent tools to target and recommend the personalized offers according to the mobile users' profile, and to track and analyze their feedbacks to improve the customers experiences and predict their demands.

INTEGRATION OF FOG COMPUTING ARCHITECTURE FOR THE RS

FOG ARCHITECTURE FOR IMPLEMENTING THE RECOMMENDER SYSTEM

- Things Layer: is the layer closest to the end mobile user and ubiquitous environment where data is generated.
- Fog Layer: contains a number of decentralized fog nodes in each given location. reduce the amount of data transmitted to the cloud layer and minimize the request response time for ubiquitous recommendations.
- Cloud data center Layer: is the top layer of the architecture consists of multiple high-performance servers, storage devices and network access to shared resources over the IoT network.

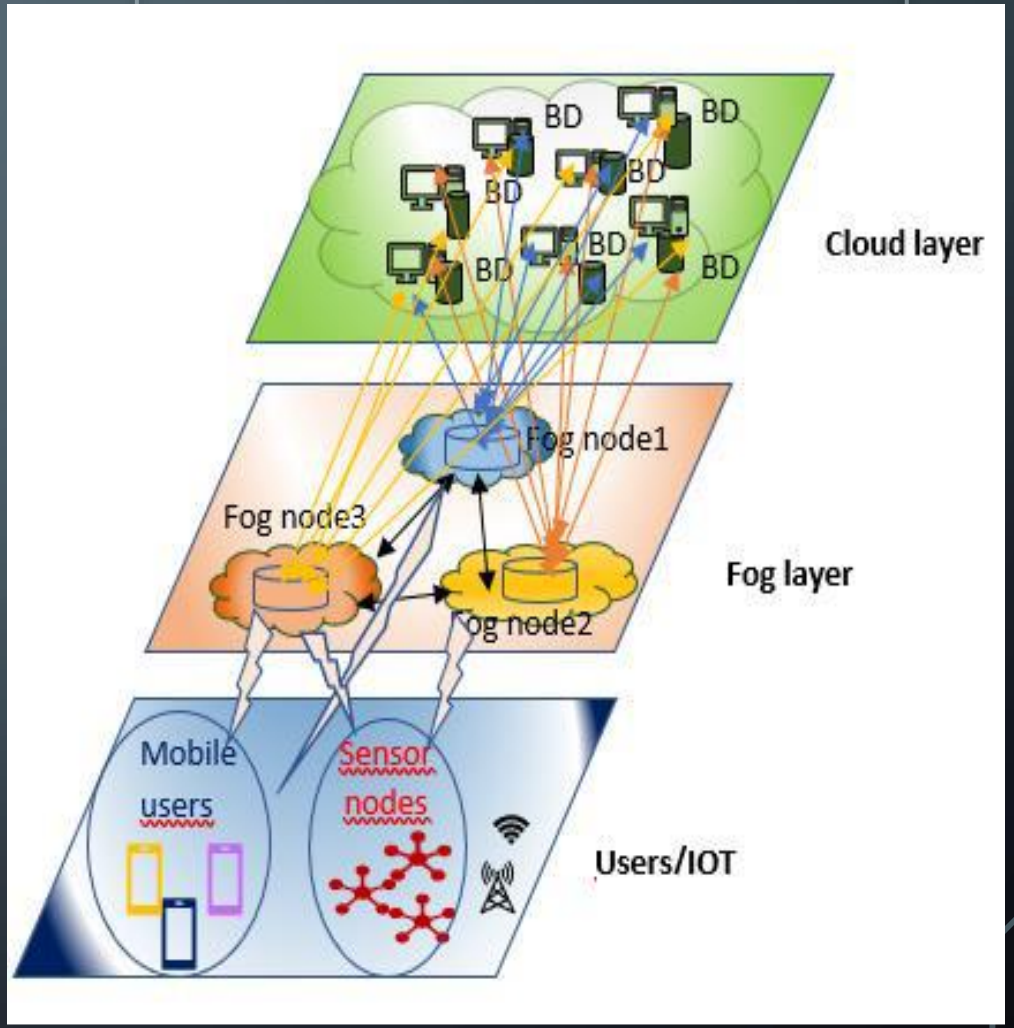


Figure: Fog architecture for implementing the RS

UBIQUITOUS FOG-BASED RS MODEL

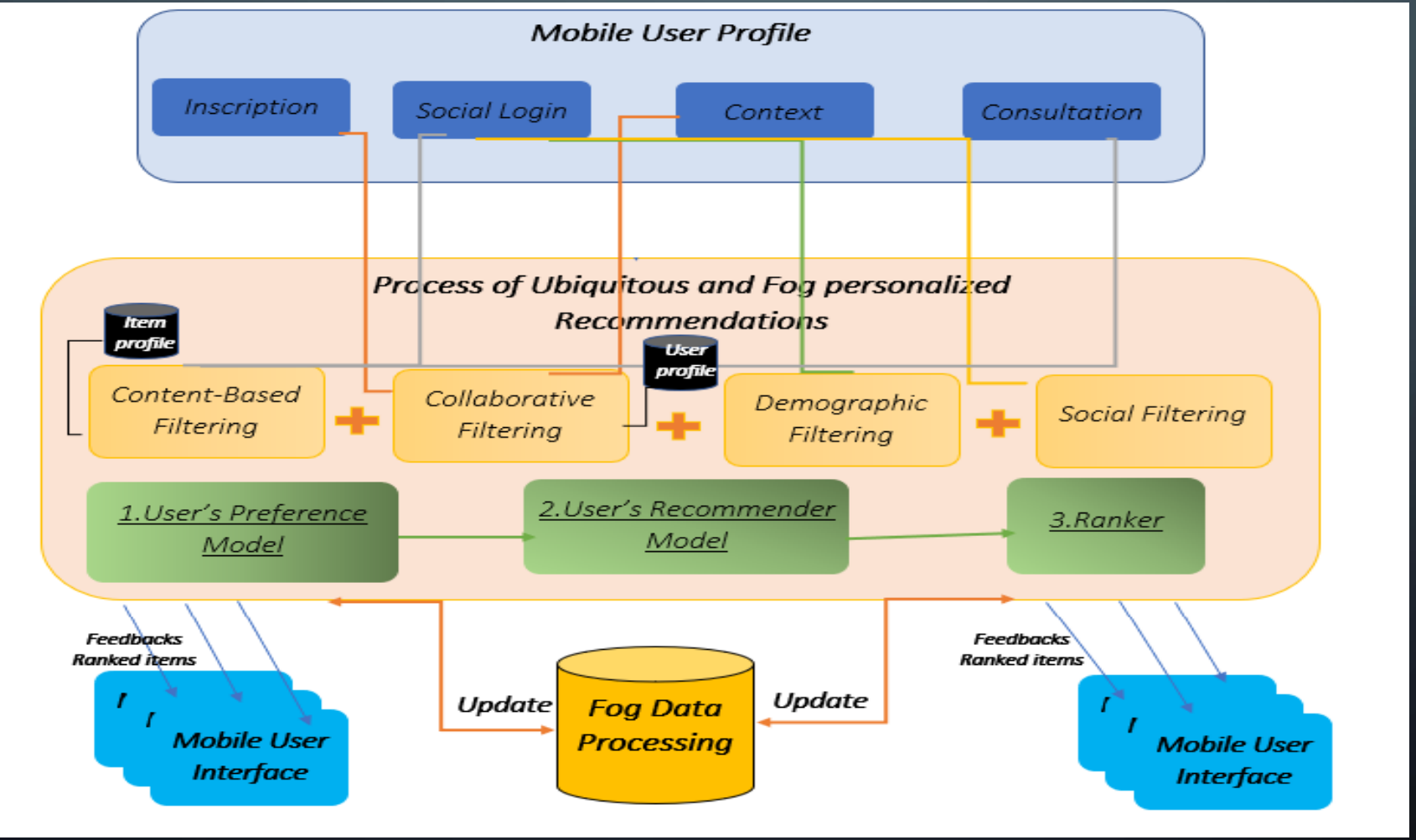


Figure: Personalized RS Architecture

EXPERIMENTS AND RESULTS

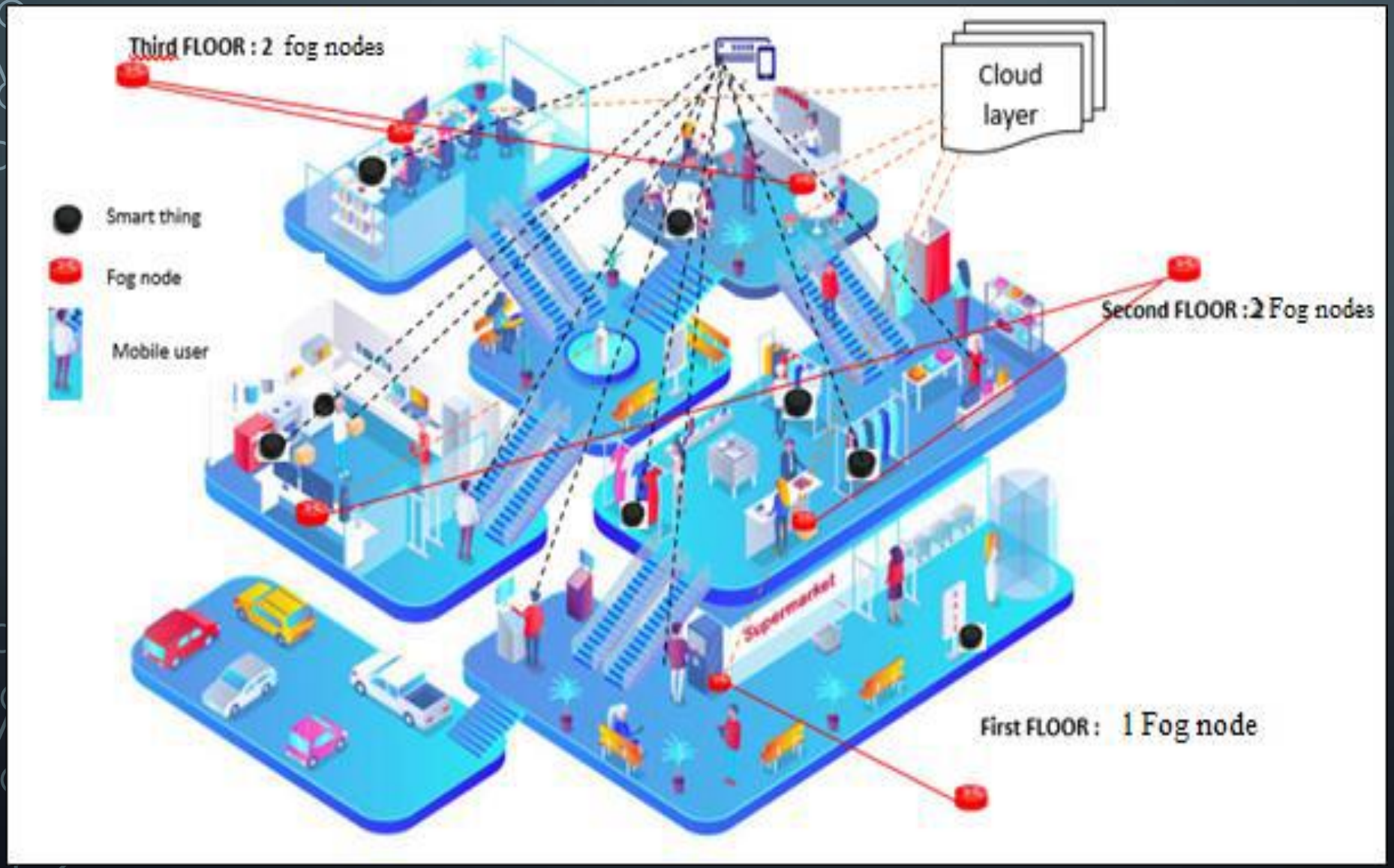


Figure: Integration of context-aware personalized RS in smart shopping with three floors

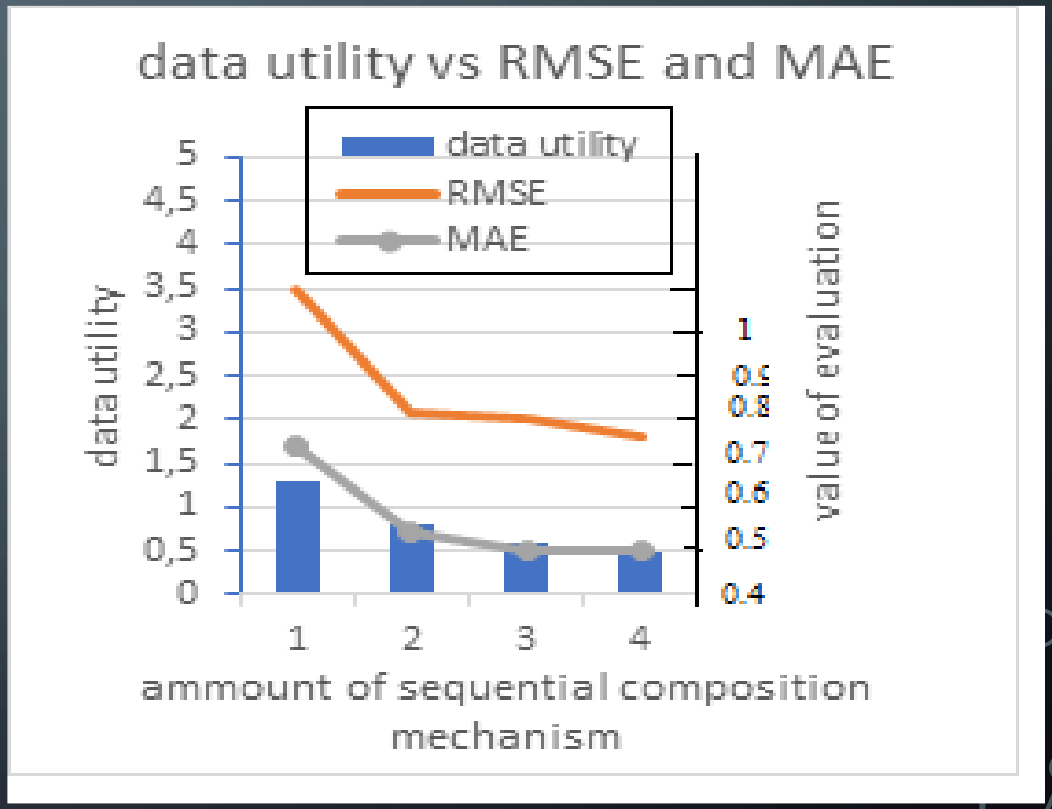
DATASET

- Dataset containing ID address, destination IP address, connected fog server IP address, and the localization of the mobile user.
- Each ID address as a user, because it is a unique identifier of his Mobile in our fog environment.
- item refers to Idsensor connected to a product or a web site visited by a person.
- Three floors with Static nodes such as beacons attached to different products and fog nodes in the different floors. Also, we use mobile nodes such as mobile phone.
- Each mobile user is identified by his mobile's API. Mobile user sensor is detected by mobile devices which contact the fog node with the proximity information.
- Fog-based hybrid recommender system on each fog server and an Alibaba cloud server. The mobile user can access to the Internet and use smart devices by connecting to the corresponding fog server.
- We collect 200 records of different users' interaction with different items in the mall. All data are obtained from the deployed five simulated fog servers. Due to the small amount of data set, we use all the data and split data into 80% for training purpose, 20% as test data set.

EVALUATION DATA UTILITY VS RMSE AND MAE

- We set up a decay factor for the weight parameter wj to observe its impact to the prediction accuracy and data utility,
- wj is fixed as 0.7, n varies from 1 to 4. This value also been mapped to the amount of privacy levels, thus there are 4 privacy levels from ϵ [0, β] based on location
- Three measurements show the similar trend. The value of data utility decrease from 1.3 to 0.5. The RMSE and MAE value both decreased. RMSE decreased from 3.5 to 0. 77. MAE decreased from 1.7 to 0. 5. If wj is higher, both MAE and RMSE results are better. If n is higher, both evaluation results are better as well; however, the trend becomes weaker.

FIGURE: DATA UTILITY VS RMSE AND MAE

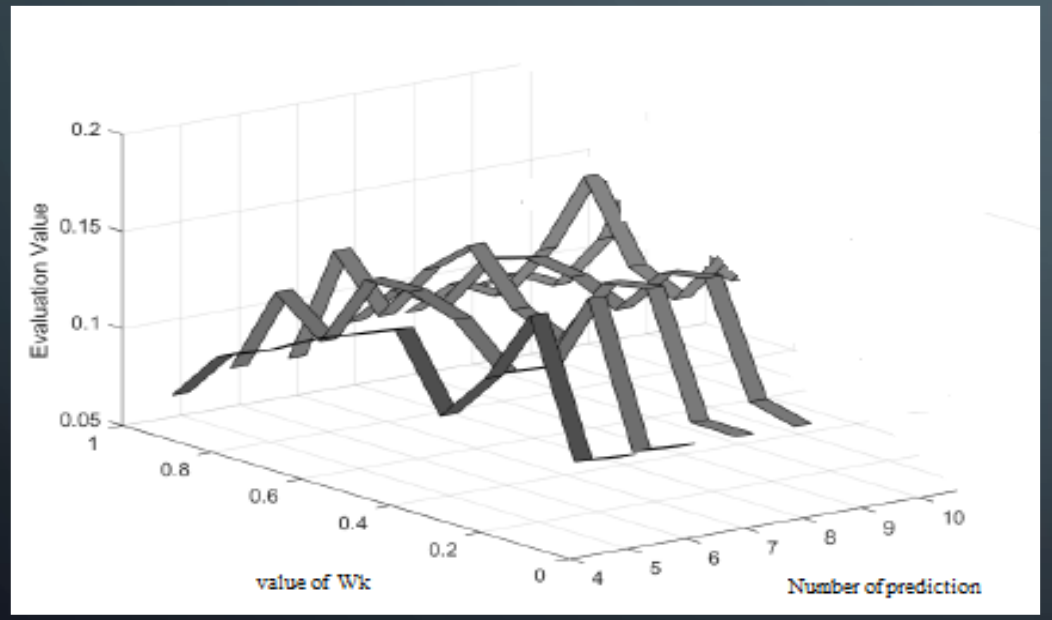


$RMSE = \sqrt{\sum(TEST-RSL)^2 / |TEST|}$

$MAE = \sum |TEST-RSL| / TEST$

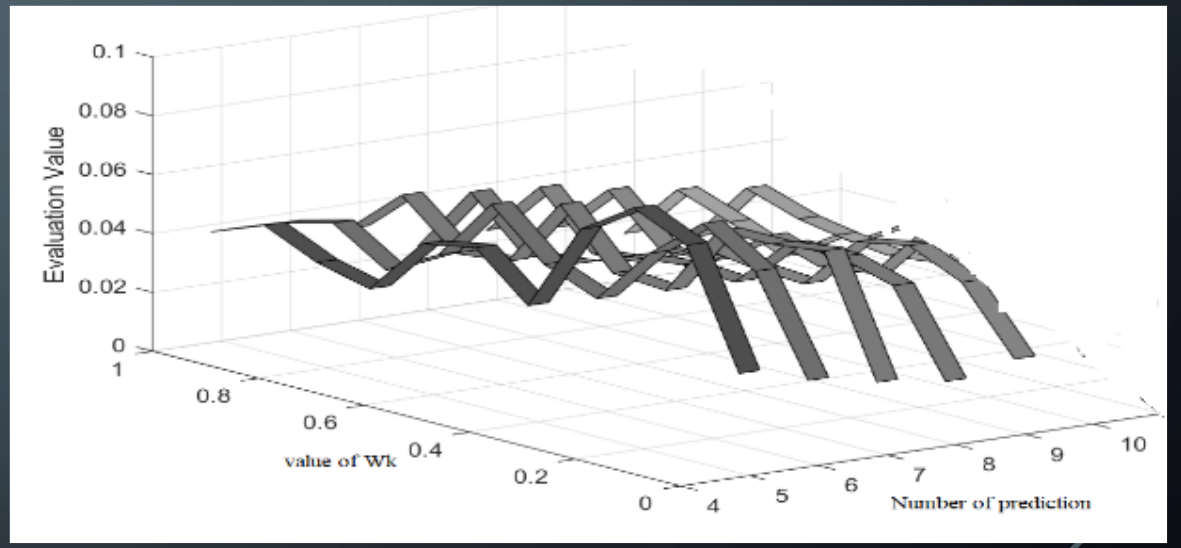
EVALUATION VALUES OF PRECISION AND RECALL

FIGURE: EVALUATION VALUE OF RECALL



Recall=Nc/Nr_rec

FIGURE: EVALUATION VALUE OF PRECISION



Precision=Nc/Nr

RECALL

- We vary the weight value wk from 0 to 1 with the step size of 0,2 to observe the impact of result accuracy. We also modify the number of prediction items from 4 to 10 to observe the impact of result accuracy.
- The height of each point on a given band is the evaluation value of recall. The length between two points on a given band represents the difference between two results. Various bands represent different numbers of predictions, corresponding to items recommended to a fog server. A higher value of the prediction number means requiring more storage space on a fog server.
- More items are predicted, the higher the recall value.

PRECISION

- We also observe that the more items are predicted, the lower the precision value; if wk is 0.3, we obtain most accurate result on each band.
- If wk is 0,3, we obtain the best evaluation results for both precision and recall. The prediction number does not impact the trend pattern of the evaluation value. However, the more items are predicted, the worse are the predicted results, and the higher the recall.

CONCLUSION AND FUTURE WORK

- The system helps fog servers to choose the most frequently requested content to purchase in order to save bandwidth, storage resources and used network resources, also provides much more accurate recommendation results for certain items based on fog server location
- The model of personalized recommendation resolves the cold start problem and the huge number of data which referred to Big data.
- The proposed system of recommendation improves the user's experience in the smart shopping center where we have used lot devices.
- In future research, we intend to extend our proposal to areas with deep learning algorithms and reinforcement learning which can be used to improve the current research and overcome limitations.

QUESTION AND ANSWER SESSION

Thank you!

Any question is warmly welcome…