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Email of convenor: maruyama.f@jp.fujitsu.com

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General

ID[1]			
Use case name	Recommendation algorithm for improving member experience and discoverability of resorts in the booking portal of a hotel chain		
Context	Leisure and Hospitality		
Application domain	Cloud services		
Status	In operation		
Contributor	Name	Affiliation	Contact
	Rohit Pandharkar	Mahindra Group	PANDHARKAR.ROHIT@mahindra.com
Scope[2]	Building a personalized recommendation algorithm to help members of the hotel chain to find their desirable hotel for the family holiday		
Objective(s)	Offering personalized recommendations by understanding the member preferences from past holiday patterns and searches in the booking portal. Various member and hotel features were also considered for the model		
Narrative	Short description (not more than 150 words)	Refining existing system and implement a new model that can give personalized recommendations to members and improve bookings at the undiscoverable or not-so-popular hotels. The algorithm would help in reshaping the demand and increase the visibility of the hotels which are at the lower spectrum of demand. We would include member and resort features along with interaction data like members visiting a hotel, and giving a rating to a resort visit etc	
	Complete description	The traditional search engine in member portal for booking a hotel is mainly based on the members limited visibility and knowledge of popular holiday destinations. In contrast, a hotel chain might offer a variety of options to members. Each option brings a different holiday experience and possibly include a lot of activities for family members to choose from. In the absence of an intelligent algorithm, many good hotels will be invisible in the large number of hotel lists. This will in turn also increase the burden on some popular hotels which might get disproportionally high bookings, and sometimes run in overcapacity and depriving other hotels of their share of bookings. To solve for this problem, the hybrid recommendation algorithm will help shape the demand and bring up the hotels which are similar to the ones a member has already visited but yet provide a different experience, thus encouraging the member to consider an alternative to their usual preferences.	

Key performance indicators (KPIs)	ID	Name	Description	Reference to mentioned use case objectives
	1	Occupancy %	Percentage of room nights occupied in a hotel	Occupancy in low demand hotels will improve
	2	First time Refusal Rate	Bookings denied because of overdemand in a particular resort	First time refusals will go down
AI features	Taks(s)	Recommendation		
	Method(s)[3]	Matrix Factorization and Hybrid Approach		
	Hardware[4]	16 GB RAM, Intel Core i5		
	Terms and concepts used[5]	Matrix Factorization, LightFM, Item and User Features, Latent Features		
Challenges and issues	1. Cold Start Problem: Since the member has only visited certain hotels in the past, the interaction matrix is very sparse 2. The matrix computation at times is computational resource intensive causing system failures			
Societal concerns	We don't see any societal concerns if it is used			

Data (optional)

Data characteristics	
Description	Member Visit Data from booking portals
Source[6]	EDW (Enterprise Data Warehouses)
Type[7]	Structured Data
Volume (size)	1 GB
Velocity (e.g. real time)[8]	Weekly
Variety (multiple datasets)[9]	Mostly Structured
Variability (rate of change)[10]	Moderate
Quality[11]	Moderate

References

References						
No.	Type	Reference	Status	Impact on use case	organization	Link
1	Paper	[Kula 15] "Metadata embeddings for user and item cold-start recommendations". In Proceedings of the 2nd Workshop on New Trends on Content-Based Recommender Systems co-located with 9th ACM Conference on Recommender Systems (RecSys 2015), Vienna, Austria, September 16--20, 2015., pages 14--21, 2015.	Published	High	ACM	https://arxiv.org/abs/1507.08439
2	Paper	[Adomavicius et. al 05]. "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions". Knowledge and Data Engineering, IEEE Transactions on. 17. 734-749. 10.1109/TKDE.2005.99.	Published	Medium	IEEE	https://dl.acm.org/citation.cfm?id=2959160
3	Paper	Yehuda et. al 09], "Matrix Factorization Techniques for Recommender Systems", Computer, v.42 n.8, p.30-37, August 2009 [doi>10.1109/MC.2009.263]	Published	Medium	IEEE	https://dl.acm.org/citation.cfm?id=1608614

Footnote

[1] Leave this cell blank.

[2] The scope defines the limits of the use case.

[3] AI method(s)/framework(s) used.

[4] Hardware system used.

[5] Terms and concepts listed here can be used to extend the work of WG 1 (AWI 22989 and AWI 23053) as necessary.

[6] Origin of data, which could be from instruments, IoT, web, surveys, commercial activity, or from simulations.

[7] Structured/unstructured Images, voices, text, gene sequences, and numerical. Composite: time-series, graph-structured

[8] The rate of flow at which the data is created, stored, analysed, or visualized.

[9] Data from a number of domains and a number of data types. The wider range of data formats, logical models, timescales, and semantics complicates the integration of the variety of data.

[10] Changes in data rate, format/structure, semantics, and/or quality.

[11] Completeness and accuracy of the data with respect to semantic content as well as syntactical of the data (such as presence of missing fields or incorrect values)