Towards Generating Personalized Country Recommendation

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ABSTRACT

The rise in international migration over the past decades has given more audience to this crucial issue of human life. According to reports by *United Nations*, more than 243 million people live in a country that is not their place of birth. People decide to immigrate, based on a range of reasons, and choose the country of destination with the hope to begin a new life. However, such a risky decision may not necessarily lead to an improvement of life and in many cases could result in complete dissatisfaction of the emigrating person, and in the extreme cases, cause human catastrophe.

Recommender Systems (RSs) are tools that could mitigate this problem by supporting the people in their decision making process. RSs can interact with the people who are willing to immigrate and acquire certain information about their preferences on potential destinations. Accordingly, RSs can build predictive models based on the acquired data and offer suggestions on where could be a better match for the specific preferences and constraints of people.

This work is an attempt to build a RS that can be used in order to receive personalized recommendation of countries. The system is capable of eliciting preferences of users in the form of ratings, learning from the preferences, and intelligently generating a personalized ranking list of countries for every target user. We have conducted a user study in order to evaluate the quality of the recommendation, measured in terms of accuracy, diversity, novelty, satisfaction, and capability to understand the particular preferences of different users. The results were promising and indicated the potentials of the generating personalized recommendations in this less-explored domain.

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1 INTRODUCTION

World immigration accounts for more than 3.3 % of the population share. Foreign-born people in developed countries increased from 7 % to over 10% in recent years [11]. Today, "much of the developed world is now increasingly composed of nations of immigrants" [4].

Deciding to immigrate is indeed a challenging decision and it could be based on a range of reasons. Immigrants choose the country of destination with the hope to begin a new life. However, such a risky decision may not necessarily lead to a better life. This could be the case even for highly educated immigrants willing to find a better place to live. Improper decisions based on inaccurate data and misleading information could result in a complete dissatisfaction of the immigrating person, and in extreme cases, possibly result in human catastrophe.

The primary challenge for immigrating people is to accurately identify the best possible destination, matching their professional and personal preferences. The belief is that the new place will hopefully meet their expectations and result in a relative life satisfaction. There are a few number of (annually-published) ranking lists, presenting the best destinations to live in the world [35, 38]. However none of these lists offer a proper personalization mechanism that provides a ranking list of countries that match individual needs and constraints of an immigrating individual.

Recommender Systems (RSs) are decision support tools that can assist the users in making better decisions [31]. RSs can mitigate this challenge by making personalized recommendation of countries to immigrating people based on their particular preferences. These systems have been found successful in various application domains, including e-commerce [32, 37], entertainment [3, 6], tourism [5, 17], restoration [26, 28], health [18, 25], music [33, 34], art [10, 27] , education [21, 24], and even e-business [1, 8]. However, immigration domain substantially differs from all of these domains. The cost of irrelevant and incorrect recommendation in many of the noted domains could be negligible. Watching a wrong movie or listening to a boring song would not really cause a serious problem. However, immigrating to an unsuitable place, based on wrong information in social media or wrong suggestions could be extremely costly in any aspect (e.g., relocation cost or difficulty of learning a new language).

This work addresses this challenge by proposing a novel country RS. The system is capable of effectively eliciting the preferences of users, provided in terms of ratings, learn from these preferences and builds a recommendation models that can offer personalized suggestion of countries.

We have developed an evaluation methodology in order to assess the quality of recommendation made by our system. In a preliminary offline experiment, we have compared a range of common recommender algorithms in order to identify the top performing algorithms. Then, we have conducted a real user study where we requested users to compare the top algorithms in terms of different metrics. The results have shown that there is no best recommender algorithm. While a certain algorithm could offer higher accuracy of recommendation, however, other algorithms could recommend a more diverse and novel recommendations that can better suit a wider range of preferences.

We believe that our work is the first attempt to build a RS in this novel application domain, and to the knowledge of authors, no prior work addressed the challenge of recommendation of countries to people.

2 METHODOLOGY

2.1 Recommender Algorithms

The algorithms adopted for recommendation mainly focus on using a classical recommendation model called Collaborative Filtering (CF) [22]. Techniques based on CF exploit ratings provided by a network of users in order to predict the missing ratings of the items. The items with the highest predicted ratings are recommended to users. [13] briefly describes the approaches based on CF.

Neighbourhood-based this kind of algorithm such as k-nearest neighbors (KNN) computes rating prediction exploiting two sets of preference data: the ratings of the user for other items and the ratings of other like-minded users. The item's rating prediction is computed based on how the item was rated by the users similar to the target user. The rating $\hat{r}_{u,i}$ for the user u and the item i is predicted in the following way:

$$\hat{r}_{u,i} = \bar{r_u} + \frac{\sum_{u' \in N_{i(u)}} sim(u,u')(r_{u',i} - \bar{r_{u'}})}{\sum_{u' \in N_{i(u)}} |sim(u,u')|} \tag{1}$$

where $\bar{r}_u$ denotes the average ratings of user u, $sim(u,u')$ is a similarity measure between two users u and u', and $N_{i(u)}$ is a set of users similar to user u (neighbours) who rated item i. We computed the similarity based on Cosine metric.

Matrix Factorization techniques such as SVD learns for both users and items factor vectors of the same size. Those vectors are inferred from the user's rating. Each element of the factor vector, assigned to an item, reflects how well the item represents a particular latent aspect. User factor vectors measure the preference of the user for each factor. The task of the factorization is to split the matrix of ratings R into two matrices S and M:

$$R \approx SM^T \tag{2}$$

where S is $|U| \times F$ matrix, and M is $|I| \times F$ matrix. F represents the number of factors we wish to use. Then, predictions for the ratings are computed as follows [16]:

$$\hat{r}_{u,i} = \sum_{f=1..F} s_{uf} m_{if} \tag{3}$$

where s_{uf} denotes how much the user u likes the factor f and the value m_{if} denotes how strong the factor f is in the item i.

We adopted different types of neighbourhood-based recommenders, i.e., KNN Basic, KNN With Means, and KNN With Baseline. The former is a simple version while KNN With Means is an extended version that simply takes it into account the the mean ratings of each user. KNN with Baseline, on the other hand, takes into account the baseline rating. This is a factor that is estimated through a learning process. The number of neighbors for different versions of KNN algorithms is set to 40.

We also adopted two types of matrix factorization recommenders, i.e., SVD and SVD++ [23]. The later is an extension of SVD as it is capable of taking into account implicit ratings [14]. For both we set the number of factors to 100.

Co-Clustering is a different algorithm that groups similar users and similar videos clusters [19, 30]. The prediction of $\hat{r}_{ui}$ is computed by assigning the users and items to some clusters C_u, C_i and co-cluster C_{ui}:

$$\hat{r}_{ui} = \hat{C}_{ui} + (\mu_u - \hat{C}_u) + (\mu_i - \hat{C}_i)$$

where $\hat{C}_{ui}$ is the average rating of co-cluster C_{ui}, $\hat{C}_u$ is the average rating of u's cluster, and $\hat{C}_i$ is the average ratings of i's cluster, μ_u and μ_i represent the average rating for user u and item i, respectively. The clusters are assigned using a straightforward optimization method [19].

2.2 Implementation Details

We implemented a dynamic system, to provide recommendations in the real time to the active users and collect enough data for further analysis. We designed a system following a sample architecture shown in Figure 1.

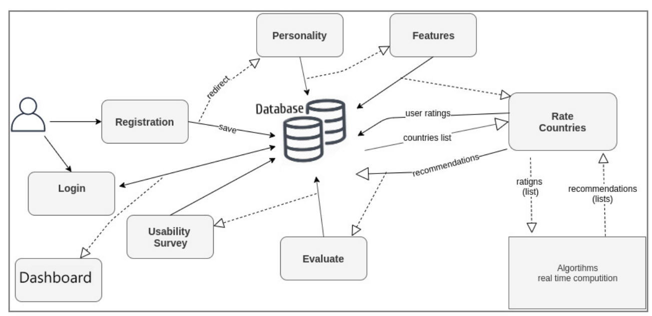

Figure 1: The System architecture.

The user interacts with the deployed system, after registration into the system by providing the basic information and filling up a short questionnaire. The questionnaire includes questions that identify the personality characteristics of the user. We collect the personality characteristics of the users for future studies (e.g., in [2, 15]). The users are also requested to enter a number of (1-3) key factors (features) that plays the most important role if making decision to which country to immigrate. The list of these features are provided in section 3.1 where we discuss the dataset.

Then, the user enters the preference elicitation phase where she is requested to choose the countries she has been or well-know and provide her ratings in the 5-point Likert scale (1-5).

When the preferences are received by the system, the top three recommender algorithms exploit these preferences in order to independently generate personalized recommendation of countries for the user. The recommendations are presented to the user in the form of three different lists, each generated by a different recommender algorithm. Each list consists of 5 recommended countries. The user is requested to proceed and complete a questionnaire, adopted to assess quality of the recommendations in terms of various metrics. We have adopted a validated questionnaire that can measure perceived quality of recommendation [12]. Perceived quality is the degree to which users assess recommendations positively and express their experience with the recommender system. Assessment of perceived recommendation quality could be implemented in terms of different metrics [12, 20, 29]:

- **Accuracy** (also called *Relevance*): how much the recommendations match the users' interests, preferences and tastes;
- **Diversity**: how much users perceive recommendations as different from each other, *e.g.* movies from different genres;
- **Perceived personalization 'Understands Me'**: the user's perception that the recommender understands their tastes and can effectively adapt to them;
- **User Satisfaction**: the global users' feeling of the experience with the recommender system.
- **Novelty**: the extent to which users receive new recommended movies;

The questionnaire consists of 14-question, as also used in [12]. The questions address different metrics, i.e., Accuracy (Q1,Q2), Diversity (Q3-Q5), Understand Me (Q6-Q8), Satisfaction (Q9,Q10) and Novelty (Q11-Q14):

- **Q1:** Which list has more selections that you find appealing?
- **Q2:** Which list has more obviously bad suggestions for you?
- **Q3:** Which list has more countries that are similar to each other?
- **Q4:** Which list has a more varied selection of countries?
- **Q5:** Which list has countries that match a wider variety of preferences?
- **Q6:** Which list better reflects your preferences in countries?
- **Q7:** Which list seems more personalized to your preferences?
- **Q8:** Which list represents more mainstream preferences instead of your own?
- **Q9:** Which list would better help you find countries to consider?
- **Q10:** Which list would you be more likely to recommend to your friends?
- **Q11**:Which list has more countries you did not expect?
- **Q12**:Which list has more countries that are familiar to you?
- **Q13**:Which list has more pleasantly surprising suggestions?
- **Q14**:Which list provides fewer new suggestions?

3 EXPERIMENTAL SETUP

In this section, we provide the details of the conducted experiments, aimed to investigate the effectiveness of our system.

3.1 Dataset

Initially, we have collected a small dataset of user preferences provided in the form of ratings for countries. We have shared a link and contacted people, through social networks (e.g., LinkedIn), and requested them to participate in a short survey where the participants were asked to enter the most important factors (i.e., features) that they consider if choosing a country for immigration. The participation was on the voluntary basis and participants were not paid. We have performed a literature review and choose twelve factors that are shown to be the most important for the immigration [9, 36, 39]. The factors are *Education quality, Political insecurity, Work opportunities, Health care, Income difference, Wars and dictatorship, Family member abroad, Cultural and linguistic similarities, Working atmosphere, Shorter distance, social conflict, and Crime rate* . Table 1 represents the list of the features that have been chosen by participants, ranked according to the frequency of choices.

Table 1: The ranking list of the most important features that participants chose.

Selected Features	Replies
Work Opportunities	161 (72%)
Education Quality	105 (46%)
Working Atmosphere	100 (44%)
Health Care	97 (43%)
Income difference	84 (37%)
Political Insecurity	59 (26%)
Crime Rate	58 (26%)
Social Conflict	49 (22%)
Cultural & Linguistic Similarities	47 (21%)
Wars & Dictatorship	37 (16%)
Family Member Abroad	20 (8%)
Shorter Distance	15 (6%)

The participants were also requested to rate a number of countries that might be familiar to them. The rating would indicate how a country may match the overall expectation of the participant, according to the particular factors participants have chosen. The list of countries have been obtained from yearly migration report of 2018, by the International Organization for Migration (IOM), reported to be the top destination countries for international migrants. During the 13 days of data collection process, we received 3400 ratings from 136 participants. We used this rating dataset and performed a preliminary experiment where we have cross-validated a set of recommender algorithms and selected the top performing algorithms.

We integrated these algorithms in our recommender system where the users can register, provide their particular preferences, and receive lists of recommendation and evaluate them through a questionnaire. The design of the experiment was a within-subjects study. We have contacted the previous participants as well as new ones (through social networks) and requested them to complete the whole process of using our system.

At the end, a total of 281 participants have registered to the system, while only 189 participants provided their preferences and completed the final evaluation questionnaire (i.e., 67 % of all). By average, participants provided 7 ratings (minimum 5 ratings and maximum 41 ratings) resulting in a dataset of 1284 ratings. The participants were from a wide range of countries, namely, USA, Spain, Canada, Germany, Hungary, Netherlands, Italy, Belgium,

Table 2: Offline evaluation: comparison of different recommender algorithms.

Recommender	RMSE	MAE
SVD	**21.71**	**16.06**
SVD++	58.21	51.06
Non-negative MF	48.65	41.43
Slope One	23.47	18.62
KNN basic	21.97	16.88
KNN with Mean	21.59	16.49
KNN Baseline	**21.58**	**16.47**
Co-cluster	**21.39**	**16.63**
Baseline Only	23.50	19.21
Random Predictor	37.93	30.91

Australia, France, India, Morocco, Egypt, Kuwait, UAE, Pakistan, India, Turkey, Iran, Afghanistan, Brazil, Mexico, Qatar, Sweden, Ireland, Norway, Ukraine, Russia, Singapore, Syria, Czech Republic, Indonesia, Japan, Sri Lanka, Austria, Nigeria, Dominica, Tunisia, Korea, Croatia, Switzerland, Lithuania, Chile, Malta, Romania, Guiana, Palestine, New Zealand, Slovenia, Slovakia, Saudi Arabia, Panama, Jordan, Armenia, and Portugal. Around 71% of participants were male, 27 % were female and 2 % refused to disclose. The age of the participants varied very much: 5% were 18 years old, 42% were 18-24, 39% were 25-35 years old, 9% were 35-45 years old, 4% were 45-55 years old and 1% were over 55 years old.

4 RESULTS

Offline Evaluation. After collecting an initial rating dataset provided by a number of participants, to their familiar countries, we have performed a preliminary offline evaluation to identify the top algorithms. Such algorithms could better fit our particular task at hand. We have performed a 5-fold cross-validation where the dataset is split into five non-overlapping subsets, where in each iteration of the experiment, one fold is used for test set and the remaining folds as train set. The performance of the recommender algorithms are measured in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) both measuring accuracy of rating prediction [34].

The results are presented in Table 2. As it can be seen, the best-performing algorithm is Singular Value Decomposition (SVD) achieving MAE value of (16.06) and RMSE value of (21.71). The next best algorithms are K-Nearest Neighbor With Baseline and Co-clustering, with MAE values of 16.47 and 16.63, as well as RMSE values of 21.58 and 21.39, respectively. An unexpected result has been observed for SVD++ that has achieved a surprisingly inferior result. This could be due to the characteristics of our dataset of explicit ratings and not implicit ratings (e.g., clicks). SVD++ is an algorithm that fits better when using implicit ratings.

Online Evaluation. We have identified three top recommender algorithms (i.e., SVD, KNN With Baseline, and Co-Clustering) and integrated them into our system. Accordingly, the users can register, provide their preferences, and receive three lists of recommendation, each generated by one of these algorithms. At the end, the system requests users to compare the quality of recommendation lists in terms of different metrics.

Table 3 presents the results that we have obtained in online evaluation process. As it can be seen, in terms of accuracy, understanding users and user satisfaction, SVD has achieved the best results. In almost all questions, related to these metrics, SVD recommender has overcome the other recommenders. For positively-formulated questions, i.e., Q1, Q6, Q7, Q9, and Q10, majority of users has chosen this recommender as the best among three recommenders. For one of the negatively-formulated questions, i.e., Q2, minority of the users has chosen this recommender which again indicates the excellent performance of this recommender. The only exception is Q8, formulated negatively and user decided that Co-clustering is the best. This question asks about the recommendation list that represents more mainstream preferences than the users preferences. The least percentage of users chose Co-Clustering which means that recommender algorithm generates a more specific recommendations than others. This is an unexpected outcome and we will investigate it more in our follow-up studies.

In terms of diversity, the SVD did not perform well in comparison to the other recommenders, i.e., KNN With Baseline and Co-Clustering. For questions Q3 and Q4, both of the KNN and Co-Clustering recommenders similarly performed well. For question Q5, which is positively-formulated, majority of users chose KNN With Baseline as the best recommender. This questions asks about the recommendation list that has countries who match a wider variety of preferences. Accordingly, the KNN With Baseline is capable of generating recommendations matching a divers range of preferences.

In terms of novelty, again SVD did not perform well, while the other recommenders performed well side-by-side. Indeed, each of these algorithms achieved the best results for 2 out of 4 questions. For questions Q13 and Q14, KNN With Baseline outperformed other recommenders whereas for questions Q11 and Q12, Co-Clustering achieved the best results. Hence, the users found suggestions based on KNN With Baseline being more pleasantly surprising and containing more new suggestions. On the other hand, users found Co-Clustering recommending countries that users did not expect and hence look like more novel.

Overall, these promising results are very interesting; they show that there is no always-winning recommender algorithm in terms of all evaluation metrics. The results also clearly represent a trade-off between (a) accuracy of recommendation, in one side, and (b) novelty and diversity in an other side.

5 CONCLUSIONS

We have developed a novel RS that can be a support in the decision making process of people who might be willing to immigrate to a new country. The system can elicit preferences of such people and learn from the elicited preferences and ultimately build predictive models that can generate personalized recommendations.

We have evaluated the system through an evaluation methodology which consists of offline and online experiments. The results have shown that different recommender algorithms could optimize a different evaluation metric. While certain algorithms (such as SVD) could result in higher recommendation accuracy and

Table 3: Online evaluation: comparison of different recommender algorithms, based on the opinion of real users. ***pos*****: positively-formulated question,** ***neg*****: negatively-formulated question.**

Metric	Question		Co-Cluster	KNN Baseline	SVD
	Num	Type	[% users]	[% users]	[% users]
Accuracy	Q1	*pos*	33	29	**38**
	Q2	*neg*	59	31	**10**
Diversity	Q3	*neg*	**26**	**26**	48
	Q4	*pos*	**42**	40	18
	Q5	*pos*	24	**47**	29
Understand Me	Q6	*pos*	18	26	**56**
	Q7	*pos*	21	24	**55**
	Q8	*neg*	**15**	24	61
Satisfaction	Q9	*pos*	14	40	**46**
	Q10	*pos*	19	19	**62**
Novelty	Q11	*pos*	**55**	33	12
	Q12	*neg*	**23**	29	48
	Q13	*pos*	25	**49**	26
	Q14	*neg*	29	**17**	54

improved perceived satisfaction, however, they may fall short in properly diversifying the recommendations.

It is worth noting that the research field of immigration is highly complex and sensitive. Indeed, this work is an initial step towards exploring the potentials of the recommender systems in this domain. Recommendation approach we have utilized in this work elicits *explicit* ratings as proposed in classical literature of the recommender systems community. This can be a limitation of our approach. Design and development of more transparent form of preference elicitation can be an interesting direction of research to follow. This can be performed by eliciting a more diverse and novel set of user preferences that can better picture the actual needs and constrains of users.

For future work, we plan to re-design our prototype and implement a new version of the system with a novel user interface offering further functionalities. An example of such functionalities could be critiquing and explanation mechanisms where the users could provide feedback on the recommendation and fine-tune it according to their needs and constrains [7].

We also plan to conduct more experiments while collecting a larger dataset that contains different forms of user preferences. We will compare a wider range of recommender algorithms capable of better learning from different sources of user data, e.g., personality traits and social media profiles.

REFERENCES

[1] Shaha T Al-Otaibi and Mourad Ykhlef. 2012. A survey of job recommender systems. *International Journal of Physical Sciences* 7, 29 (2012), 5127–5142.

[2] Farshad Bakhshandegan Moghaddam and Mehdi Elahi. 2019. Cold Start Solutions For Recommendation Systems. In *Big Data Recommender Systems, Recent Trends and Advances.* IET.

[3] Yolanda Blanco-Fernandez, Jose J Pazos-Arias, Alberto Gil-Solla, Manuel Ramos-Cabrer, and Martin Lopez-Nores. 2008. Providing entertainment by content-based filtering and semantic reasoning in intelligent recommender systems. *IEEE Transactions on Consumer Electronics* 54, 2 (2008), 727–735.

[4] George J. Borjas. 2014. *Immigration Economics.* Harvard University Press. http://www.jstor.org/stable/j.ctt6wprgr

[5] Dario Cavada, Mehdi Elahi, David Massimo, Stefano Maule, Elena Not, Francesco Ricci, and Adriano Venturini. 2018. Tangible tourism with the internet of things. In *Information and Communication Technologies in Tourism 2018.* Springer, 349–361.

[6] Ingrid A Christensen and Silvia Schiaffino. 2011. Entertainment recommender systems for group of users. *Expert Systems with Applications* 38, 11 (2011), 14127–14135.

[7] Paolo Cremonesi, Mehdi Elahi, and Franca Garzotto. 2017. User interface patterns in recommendation-empowered content intensive multimedia applications. *Multimedia Tools and Applications* 76, 4 (01 Feb 2017), 5275–5309. https://doi.org/10.1007/s11042-016-3946-5

[8] Paolo Cremonesi, Chiara Francalanci, Alessandro Poli, Roberto Pagano, Luca Mazzoni, Alberto Maggioni, and Mehdi Elahi. 2018. Social Network based Short-Term Stock Trading System. *arXiv preprint arXiv:1801.05295* (2018).

[9] Clare Cummings, Julia Pacitto, Diletta Lauro, and Marta Foresti. 2015. Why people move: understanding the drivers and trends of migration to Europe. *London: Overseas Development Institute* (2015).

[10] Vicente Dominguez, Pablo Messina, Denis Parra, Domingo Mery, Christoph Trattner, and Alvaro Soto. 2017. Comparing neural and attractiveness-based visual features for artwork recommendation. In *Proceedings of the 2nd Workshop on Deep Learning for Recommender Systems.* 55–59.

[11] Anthony Edo, Lionel Ragot, Hillel Rapoport, Sulin Sardoschau, Andreas Steinmayr, et al. 2018. The effects of immigration in developed countries: Insights from recent economic research. *IFO Institute-Leibniz Institute for Economic Research at the University of Munich* 5 (2018), 1–24.

[12] Michael D Ekstrand, F Maxwell Harper, Martijn C Willemsen, and Joseph A Konstan. 2014. User perception of differences in recommender algorithms. In *Proceedings of the 8th ACM Conference on Recommender systems.* ACM, 161–168.

[13] Mehdi Elahi. 2014. *Empirical Evaluation of Active Learning Strategies in Collaborative Filtering.* Ph.D. Dissertation. Ph. D. Dissertation. Free University of Bozen-Bolzano.

[14] Mehdi Elahi, Matthias Braunhofer, Tural Gurbanov, and Francesco Ricci. 2019. User Preference Elicitation, Rating Sparsity and Cold Start. *Collaborative Recommendations: Algorithms, Practical Challenges and Applications. World Scientific* (2019).

[15] Mehdi Elahi, Matthias Braunhofer, Francesco Ricci, and Marko Tkalcic. 2013. Personality-based active learning for collaborative filtering recommender systems. In *Congress of the Italian Association for Artificial Intelligence.* Springer, 360–371.

[16] Simon Funk. 2006. Netflix update: Try this at home. http://sifter.org/~simon/journal/20061211.html.

[17] Damianos Gavalas, Vlasios Kasapakis, Charalampos Konstantopoulos, Konstantinos Mastakas, and Grammati Pantziou. 2013. A survey on mobile tourism recommender systems. In *2013 Third International Conference on Communications and Information Technology (ICCIT).* IEEE, 131–135.

[18] Mouzhi Ge, Mehdi Elahi, Ignacio Fernaández-Tobías, Francesco Ricci, and David Massimo. 2015. Using tags and latent factors in a food recommender system. In *Proceedings of the 5th International Conference on Digital Health 2015.* ACM, 105–112.

[19] Thomas George and Srujana Merugu. 2005. A scalable collaborative filtering framework based on co-clustering. In *Fifth IEEE International Conference on Data Mining (ICDM'05).* IEEE, 4–pp.

[20] Jonathan L. Herlocker, Joseph A. Konstan, Loren G. Terveen, and John T. Riedl. 2004. Evaluating Collaborative Filtering Recommender Systems. *ACM Transaction on Information Systems* 22, 1 (January 2004), 5–53.

[21] Mei-Hua Hsu. 2008. A personalized English learning recommender system for ESL students. *Expert Systems with Applications* 34, 1 (2008), 683–688.

[22] Dietmar Jannach, Markus Zanker, Alexander Felfernig, and Gerhard Friedrich. 2010. *Recommender Systems: An Introduction.* Cambridge University Press.

[23] Yehuda Koren. 2008. Factorization meets the neighborhood: a multifaceted collaborative filtering model. ACM, New York, NY, USA, 426–434. https://doi.org/10.1145/1401890.1401944

[24] Jinjiao Lin, Haitao Pu, Yibin Li, and Jian Lian. 2018. Intelligent Recommendation System for Course Selection in Smart Education. *Procedia Computer Science* 129 (2018), 449–453.

[25] David Massimo, Mehdi Elahi, Mouzhi Ge, and Francesco Ricci. 2017. Item Contents Good, User Tags Better: Empirical Evaluation of a Food Recommender System. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization.* ACM, 373–374.

[26] Joseph F McCarthy. 2002. Pocket restaurantfinder: A situated recommender system for groups. In *Workshop on Mobile Ad-Hoc Communication at the 2002 ACM Conference on Human Factors in Computer Systems.* 8.

[27] Pablo Messina, Vicente Dominguez, Denis Parra, Christoph Trattner, and Alvaro Soto. 2019. Content-based artwork recommendation: integrating painting metadata with neural and manually-engineered visual features. *User Modeling and User-Adapted Interaction* 29, 2 (2019), 251–290.

[28] Ali Akbar Niknafs and Mohammad Ebrahim Shiri. 2008. A new restoration-based recommender system for shopping buddy smart carts. *International Journal of Business information systems* 3, 3 (2008), 284–299.

[29] Pearl Pu, Li Chen, and Rong Hu. 2011. A user-centric evaluation framework for recommender systems. In *Proceedings of the fifth ACM conference on Recommender systems.* ACM, 157–164.

[30] Roi Reshef. 2015. *How do you build a "People who bought this also bought that"-style recommendation engine.* https://datasciencemadesimpler.wordpress.com/tag/co-clustering/

[31] Francesco Ricci, Lior Rokach, and Bracha Shapira. 2011. Introduction to recommender systems handbook. In *Recommender systems handbook*. Springer, 1–35.

[32] J Ben Schafer, Joseph Konstan, and John Riedl. 1999. Recommender systems in e-commerce. In *Proceedings of the 1st ACM conference on Electronic commerce*. 158–166.

[33] Markus Schedl, Peter Knees, Brian McFee, Dmitry Bogdanov, and Marius Kaminskas. 2015. Music recommender systems. In *Recommender systems handbook*. Springer, 453–492.

[34] Markus Schedl, Hamed Zamani, Ching-Wei Chen, Yashar Deldjoo, and Mehdi Elahi. 2018. Current challenges and visions in music recommender systems research. *International Journal of Multimedia Information Retrieval* 7, 2 (2018), 95–116.

[35] UsNews. 2019. Quality of Living City Ranking. https://www.usnews.com/news/best-countries/quality-of-life-rankings. Accessed: 2019-09-22.

[36] Roland Verwiebe, Steffen Mau, Nana Seidel, and Till Kathmann. 2010. Skilled German migrants and their motives for migration within Europe. *Journal of International Migration and Integration/Revue de l'integration et de la migration internationale* 11, 3 (2010), 273–293.

[37] Kangning Wei, Jinghua Huang, and Shaohong Fu. 2007. A survey of e-commerce recommender systems. In *2007 international conference on service systems and service management*. IEEE, 1–5.

[38] Wikipedia. 2019. Mercer Quality of Living Survey. https://en.wikipedia.org/wiki/Mercer_Quality_of_Living_Survey. Accessed: 2019-09-30.

[39] Frans Willekens, Douglas Massey, James Raymer, and Cris Beauchemin. 2016. International migration under the microscope. *Science* 352, 6288 (2016), 897–899.