

A Bayesian User-Controllable Recommender System

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ABSTRACT

In this research, we propose a Bayesian User-Controllable Recommender System. Our approach allows the user to control the contextual information, i.e., the user can define the content (other users and items) and parameters (users, items, novelty and popularity) used by the recommender to compute predictions. To demonstrate the usefulness of our proposal, we present different scenarios where we change the context configuration and discuss the system outputs.

1. MOTIVATION AND RESEARCH CHALLENGES

Historically, the main goal of the Recommender Systems (RS) have been increasing the accuracy of the recommendation [8]. However, the RS's accuracy is not always correlated with a good user experience with the system [10]. User experience is defined as the analysis of the human factors captured through user's interaction with the RS, e.g., user satisfaction and user engagement [8]. A strategy to enhance the user experience in RS is to give the control of the system to the user. For example, Knijnenburg et al. [7] allow users to order the recommendation list according to different attributes in a RS of best practices for energy efficiency. Some approaches allow their users to modify the content that will be used by the RS [2, 6]. Another line of work, using hybrid models, allows their users to modify the weights assigned to each recommender via sliders, e.g., [10, 4]. However, the effects caused by giving the control to the users and how they are related to the user characteristics are issues that still need investigation.

In this research, we address these issues by proposing an approach to RS that allows the user to control the system. Our research challenges are: (i) How to define the RS elements controllable by the user? (ii) How to design a user interface to capture the user's preferences? (iii) How to define the computational techniques used in the RS? (iv) How to represent the items and users in the system? and (v) How to validate our approach via user study? Until now, we have defined a Bayesian user-controllable model and apply it in the scientific paper recommendation. Our proposal is based on the concept of context, Context-Aware RS make use of contextual information with the aim of improving the recommendation. Contextual information is any information that could be used to impact the accuracy of recommen-

dation, e.g., climate weather information, demographic information [1]. In our model, users can control the elements (researchers and papers) that will be used as content to generate the recommendations. Furthermore, users can setting up the parameters weights of the RS, such as, users, items, novelty and popularity. To demonstrate the utilization of our approach, we present scenarios where we illustrate the use of the system, i.e., showing the system inputs and discussing the outputs. In summary, we aim to achieve the following contributions for the field: (i) a new recommendation method to capture user preferences; (ii) a new user interface for RS; and (iii) we intend to bring more evidence on the relationship among the size of the control given to the user, the user experience and the user characteristics.

2. RELATED WORK

The analysis of the controllability in RS is a relatively recent topic at the same time that is gaining more attention from the academy. Knijnenburg et al. [7] study the effects of different mechanisms of interaction in a RS for energy saving. They conclude that the best interaction mechanism depends on the user characteristics: more experienced users, who had more domain knowledge had preferences for more controllable interfaces, e.g., hybrid and explicit mechanisms. In contrast, less experienced users opted for interfaces with less controllable, e.g., non-personalized methods.

Bostandjiev et al. [2] present the TasteWeights, a controllable hybrid RS of music that integrates the content from three sources, Wikipedia, Facebook and Twitter. Their results indicate that using their proposed interface to explain the hybrid process of recommendation increased the user satisfaction. Knijnenburg et al. [6] also explore the TasteWeights, they use the musics liked by the user in Facebook (items) and the user's Facebook contacts (users). They conclude that the controllability led to a better user experience, however the differences between the two types of control, items and users, was not statistically significant.

Harper et al. [4] study the user controllability in the context of movie recommendation using the MovieLens system. They allow the users to control the weight of two variables, the popularity of the movie and and the year of movie release. They did not find an overall optimization of parameters that works for all users, simply, some users prefer to change the configuration of the recommendation list and others not. Also considering the MovieLens system, the work of Ekstrand et al. [3] allows the user to choose among four algorithms, one to be used. However, the authors found no evidence that would lead a user to choose a particular al-

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gorithm.

Considering article recommendation, Parra and Brusilovsky [10] present the SetFusion, a controllable graphical interface composed by sliders, where the users could assign weights to different RS algorithms. In addition, the interface showed a Venn diagram, indicating which algorithm was predominant on the recommendation calculation. Their results indicated that users were engaged and had a better user experience with the controllable interface, however the effect was significant only in the case that the user has gained experience with the basics of the system, i.e., the users who used the controllable interface after the non-controllable.

3. PROGRESS TO DATE

We define a model that gives the RS control to the users and, thus, they will be able to define the elements and parameters that will be used as input by the recommendation model. We use the following contextual information: **Users** – this variable concerns the researchers who are saved in the system, the user can define which researchers she wants to include into the context. Thus, to calculate the prediction of the items, the RS will give more importance to the items similar to those included researchers. **Items** – this attribute represents the items that the user can insert into the context, thus the RS will search for similar articles to compose the recommendation list. **Novelty** – this variable is related to how much novelty a paper has, e.g., we consider that survey paper have a low level of novelty. Likewise, newer papers receive a higher value than the new older articles. **Popularity** – this attribute is defined by how popular a paper is, we consider that the more citations the article has, the more popular it will be and increase the chance of it being recommended.

Definitions – Let $U = \{u_1, \dots, u_{|U|}\}$, $|U| > 0$ be the set of all users in the systems and let $D = \{d_1, \dots, d_{|D|}\}$ be the set of all documents in the system. Each document $d_j \in D$ has three attributes represented by a 3-tuple $d_j = (s_j, y_j, r_j)$, where s_j represents a textual description of the document, y_j indicates the year that the document was released, and $r_j \geq 0$ indicates the number of citations of the document. Each user $u_i \in U$ has a set $P_i = \{p_{i,1}, \dots, p_{i,|P_i|}\}$, $|P_i| \geq 0$, that represents her portfolio. Each item $p_{i,l} \in P_i$ has two attributes $p_{i,l} = (s_{i,l}, y_{i,l})$, where $s_{i,l}$ represents a textual description of the document and $y_{i,l}$ indicates the year that the item was included in her portfolio. Let $T = \{t_1, \dots, t_{|T|}\}$ be the set of terms used to index the documents and to represent user profiles. So, each document $d_j \in D$ is represented by the vector $\vec{d}_j = (w_{j,1}, \dots, w_{j,|T|})$, where $w_{j,k} \geq 0$ represents the importance of the term $t_k \in T$ to the document d_j . The user $u_i \in U$ has a profile denoted by the vector $\vec{u}_i = (w_{i,1}, \dots, w_{i,|T|})$, where $w_{i,k} \geq 0$ represents the importance of the term $t_k \in T$ to the user u_i . Each user $u_i \in U$ has a set $C_i = \{c_{i,1}, \dots, c_{i,|C_i|}\}$, $0 \geq |C_i| \leq 10$ of contexts, where a context $c_{i,m} \in C_i$ is defined by a 7-tuple $c_{i,m} = \{title_{i,m}, U_{i,m}, D_{i,m}, user_{i,m}, item_{i,m}, nov_{i,m}, pop_{i,m}\}$, where: $title_{i,m}$ – is a not-empty string that represents the context title; $U_{i,m} \subseteq U$, $0 \geq |U_{i,m}| \leq 5$ and $D_{i,m} \subseteq D$, $0 \geq |D_{i,m}| \leq 5$ – are, respectively, the researchers set and the items set inserted by the user u_i into the context $c_{i,m}$; $user_{i,m}$, $item_{i,m}$, $nov_{i,m}$, $pop_{i,m} \in [0, 1]$ – represent, respectively, the weights assigned by the user to the attributes *Users*, *Items*, *Novelty*, *Popularity* of the context $c_{i,m}$. To build the user profiles $\vec{u}_1, \vec{u}_2, \dots, \vec{u}_{|U|}$, we adopt our approach published in [9]. So,

given a user u_i , we create the user portfolio P_i using her curriculum vitae, i.e., resumé, formation, projects and production. We crawl the user curriculum vitae from the CV-Lattes (<http://lattes.cnpq.br/>) and merged it with DBLP publications. To index the items and create the vectors $\vec{d}_1, \vec{d}_2, \dots, \vec{d}_{|D|}$, we use the TF-IDF procedure, more details can be found in [9]. In the rest of this section, when we present the equation *sim*, we are referring to the cosine similarity between two vectors.

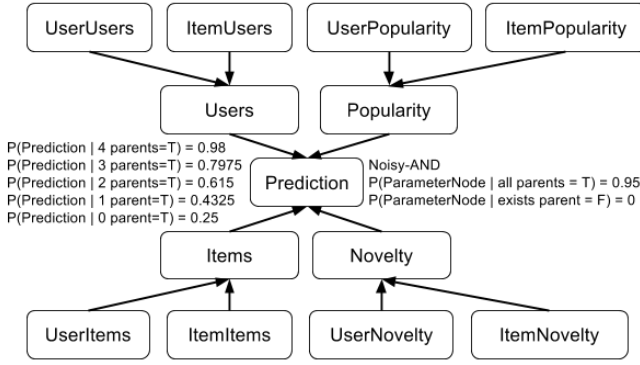
The Bayesian Network – The RS is a Bayesian Network (BN), wherein for each available paper for recommendation is created one BN that calculates its prediction for the given context. This prediction is obtained by the value of the variable *Prediction* of the BN, and it is influenced by four variables of the context, *Users*, *Items*, *Popularity* and *Novelty*. Each context variable, receives the influence of two variables, one corresponding to a user’s preference and another related to an item feature. All BN nodes have two states, *True* and *False*, the BN has four types of node: **Prediction node** – in the BN, only the node *Prediction* is such, it represents the predictive value of an item to a user in a given context. In other words, the higher the value of $P(\text{Prediction})$ greater will be the predicted value of the item to the user. **Parameter nodes** – this type of node represents the parameters used in the RS, the nodes of this type are parents of the node *Prediction*. We define four parameters, *Users*, *Items*, *Popularity* and *Novelty*, so we create a node with the same name for each parameter. Each node of this type has two parents, one representing a user preference and another representing an item feature. **User preference nodes** – this type of node represents the weight given by the user to a specific parameter, i.e., it serves as an interface between the user and the model. There are four nodes of this type, *UserUsers*, *UserPopularity*, *UserNovelty* and *UserItems*. **Item feature nodes** – such node represents a paper feature. There are four nodes of this type, one for each parameter, *ItemUsers*, *ItemPopularity*, *ItemNovelty* and *ItemItems*.

To define the conditional probabilities of the *Prediction* node, we follow the approach defined by Zapata and Greer [12]. Their approach simplifies conditional probabilities definition by simply defining the influence of each parent node on the child node. In this work, we admit that all *Parameter* nodes have a *strong* influence on the *Prediction* node. To define the conditional probabilities of the *Parameter nodes* we use the Noisy-AND strategy with $\alpha = 0.05$ [5]. Figure 1 presents the BN and its conditional probabilities tables.

Computing the item prediction – Firstly, the *user preference* nodes are calibrated by the values given by the user on the context. Then, the weights inserted by the user are mapped to the BN as follows: $P(\text{UserUsers}) = user_{i,m}$, $P(\text{UserItems}) = item_{i,m}$, $P(\text{UserNovelty}) = nov_{i,m}$ and $P(\text{UserPopularity}) = pop_{i,m}$. This configuration of the BN will be valid for the context $c_{i,m}$ while the user does not perform new changes in their weights. Then, for each available paper for recommendation, we make a copy of the BN and modify the weights of its *item feature* nodes according to the paper features. Given a document $d_j \in D$, in the following we present how the *item feature* nodes, *ItemUsers*, *ItemItems*, *ItemNovelty* and *ItemPopularity*, are calibrated.

ItemUsers node – Given the users set $U_{i,m} \subset U$ created by the user u_i in the context $c_{i,m}$ and the paper $d_j \in D$, the weight of this node is obtained by the average of the sim-

Figure 1: The Bayesian Recommender System and its conditional probabilities tables.



ilarities between the document d_j and the users $u \in U_{i,m}$:

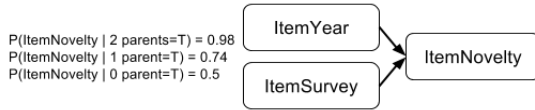
$$P(\text{ItemUsers}) = \frac{\sum_{u \in U_{i,m}} \text{sim}(\vec{d}_j, \vec{u})}{|U_{i,m}|}$$

ItemItems node – Given the items set $D_{i,m} \subset D$ of the context $c_{i,m}$ created by the user u_i , its weight is calculated by the average of the similarities between the document d_j and the documents

$$d' \in D_{i,m}: P(\text{ItemItems}) = \frac{\sum_{d' \in D_{i,m}} \text{sim}(\vec{d}_j, \vec{d}')}{|D_{i,m}|}$$

ItemNovelty node – We calculate its weight using the auxiliary BN presented in Figure 2. The weights of the BN also fol-

Figure 2: Bayesian Network of the ItemNovelty node.



low the Zapata and Greer’s approach [12], where nodes *ItemYear* and *ItemSurvey* have a *strong* influence on the node *ItemNovelty*. We calculate the weight of the node *ItemSurvey* analyzing the document description s_j , if the description contains the terms *survey* or *review*, your weight will be $P(\text{ItemSurvey}) = 0$, otherwise $P(\text{ItemSurvey}) = 1$. The weight of the node *ItemYear* is calculated based on the date of publication y_j of the item d_j : $P(\text{ItemYear}) = 0.9^{y_{\text{now}} - y_j}$, where y_{now} is the current year. **ItemPopularity node** – The weight of this node is proportional to the number of citations r_j of the document d_j . Let $R = (r_1, \dots, r_{|D|})$ be a list of all citation numbers of the papers $d_j \in D$, so, we calculate the probability $P(\text{ItemPopularity})$ according to:

$$P(\text{ItemPopularity}) = \begin{cases} 0 & \text{if } r_j = 0, \\ 0.25 & \text{if } r_j \in]0, Q1(R)], \\ 0.5 & \text{if } r_j \in]Q1(R), Q2(R)], \\ 0.75 & \text{if } r_j \in]Q2(R), Q3(R)], \\ 1 & \text{otherwise,} \end{cases} \quad (1)$$

where $Q1(R), Q2(R), Q3(R)$ are, respectively, the 1st, 2nd and 3rd quartiles of the list R .

Scenarios – For each scenario we present the model input and discuss its outputs. Table 1 presents the papers we

Table 1: Papers used in the scenarios. For $P(\text{ItemPopularity})$ computation we made assumptions for the quartiles.

Id	d_1	d_2	d_3
Reference	[8]	[6]	[10]
Year	2012	2012	2015
#Citation	205	25	7
Survey	Yes	No	No
$P(\text{ItemPopularity})$	1.0	0.75	0.5
$P(\text{ItemNovelty})$	0.492	0.897	0.956
$P(\text{ItemYear})$	0.6561	0.6561	0.9
$P(\text{ItemSurvey})$	0.0	1.0	1.0
$\text{sim}(D.Parra, d_j)$	0.7	0.8	0.9
$P(\text{ItemUsers})$	0.7	0.8	0.9
$\text{sim}([11], d_j)$	0.7	0.9	0.8
$\text{sim}([4], d_j)$	0.7	0.9	0.8
$P(\text{ItemUItems})$	0.7	0.9	0.8

use in the scenarios to compose the recommendation list. Table 2 presents the models outputs for all scenarios.

Scenario 1 – In this first scenario, which consists of the most basic case, we suppose that the user started and saved a context without changing the parameters. So, the context $c_{i,m}$ is set up with the following parameters: $U_{i,m} = \emptyset$, $D_{i,m} = \emptyset$, $user_{i,m} = 0.5$, $item_{i,m} = 0.5$, $nov_{i,m} = 0.5$ and $pop_{i,m} = 0.5$. We can see from the Table 2 that the paper d_2 has the best balance of *Popularity* and *Novelty*, so, therefore it is on the top of the list.

Scenario 2 – Now, assume that the user has made the following changes in the context. She added the researcher D. Parra, the papers [11] and [4], and changed the configuration to give more importance to the *Users* variable. Thus, the context will have the following configuration: $U_{i,m} = \{D.Parra\}$, $D_{i,m} = \{[11], [4]\}$, $user_{i,m} = 1.0$, $item_{i,m} = 0.3$, $nov_{i,m} = 0.3$ and $pop_{i,m} = 0.3$. Thus, first we calculate the similarities among the papers and the elements that may be used in context, Table 1 displays such similarities. Note that the values shown in Table 1 are illustrative and may vary according to the dataset used. It also presents the probabilities $P(\text{ItemUsers})$ and $P(\text{ItemItems})$. Verifying Table 2, we can see that the recommendation order has been modified, this was because the article d_3 has a greater similarity with the elements in the context.

Scenario 3 – In this scenario, we assume that the user wants to receive more similar items to the papers she inserted into the context. Thus, the user changes the context to: $U_{i,m} = \{D.Parra\}$, $D_{i,m} = \{[11], [4]\}$, $user_{i,m} = 0.3$, $item_{i,m} = 1.0$, $nov_{i,m} = 0.3$ and $pop_{i,m} = 0.3$. We can see in Table 2 that the list ordering has changed and the paper d_2 is on the top of the list, because it has higher similarity with the items $d \in D_{i,m}$.

Scenario 4 – Now, the user is concerned with the popularity of the recommended papers and change the context to the following configuration: $U_{i,m} = \{D.Parra\}$, $D_{i,m} = \{[11], [4]\}$, $user_{i,m} = 0.3$, $item_{i,m} = 0.3$, $nov_{i,m} = 0.3$ and $pop_{i,m} = 1.0$. Analyzing Table 2, we verify that the papers are ordered by the citation number, then the paper with more citations, d_1 , is on the top of the list now.

Scenario 5 – In this last scenario, the user wants more recency papers, i.e., paper with novelty, thus she modifies the context to: $U_{i,m} = \{D.Parra\}$, $D_{i,m} = \{[11], [4]\}$, $user_{i,m} = 0.3$, $item_{i,m} = 0.3$, $nov_{i,m} = 1.0$ and $pop_{i,m} = 0.3$. In this configuration, the paper d_2 assumes the top of

Table 2: Model outputs for different scenarios, for visualization issues we present the values multiplied by 100. Where d_1 : [8], d_2 : [6] and d_3 : [10]

Scenarios	1			2			3			4			5		
	d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3	d_1	d_2	d_3
$P(\text{UserUsers})$	50	50	50	100	100	100	30	30	30	30	30	30	30	30	30
$P(\text{ItemUsers})$	0	0	0	70	80	90	70	80	90	70	80	90	70	80	90
$P(\text{Users})$	0	0	0	66.5	76	85.5	19.9	22.8	25.6	19.9	22.8	25.6	19.9	22.8	25.6
$P(\text{UserPopularity})$	50	50	50	30	30	30	30	30	30	100	100	100	30	30	30
$P(\text{ItemPopularity})$	100	75	50	100	75	50	100	75	50	100	75	50	100	75	50
$P(\text{Popularity})$	47.5	35.6	23.7	28.5	21.4	14.2	28.5	21.4	14.2	95	71.2	47.5	28.5	21.4	14.2
$P(\text{UserItems})$	50	50	50	30	30	30	100	100	100	30	30	30	30	30	30
$P(\text{ItemItems})$	0	0	0	70	90	80	70	90	80	70	90	80	70	90	80
$P(\text{Items})$	0	0	0	19.9	25.7	22.8	66.5	85.5	76	19.9	25.7	22.8	19.9	25.7	22.8
$P(\text{UserNovelty})$	50	50	50	30	30	30	30	30	30	30	30	30	100	100	100
$P(\text{ItemNovelty})$	49.2	89.7	95.6	49.2	89.7	95.6	49.2	89.7	95.6	49.2	89.7	95.6	49.2	89.7	95.6
$P(\text{Novelty})$	23.4	42.6	45.4	14	25.6	27.2	14	25.6	27.2	14	25.6	27.2	46.7	85.2	90.8
$P(\text{Prediction})$	37.9	39.3	37.6	48.5	52.1	52.3	48.5	53.3	51.1	52.2	51.5	47.5	46	53.3	53
List ordering	2	1	3	3	2	1	3	1	2	1	2	3	3	1	2

the list, because it is a relatively new paper and it is not a survey, and it presents a good balance among variables.

4. FUTURE WORK

For future work, we aim two steps, the first one is to define a controllable interface for the user to manage her contexts. Basically, the interface must provides the following features to the users: (i) create a context; (ii) set up a context (iii) save a context; (iv) delete a context; (v) duplicate a context; and (vi) provide feedback on the recommendation. In the second step, we aim to perform a user study in laboratory. Thus, we must define the experiment planning, i.e., define the procedure, subjects, variables, statistical tests, etc.

References

- [1] G. Adomavicius and A. Tuzhilin. *Recommender Systems Handbook*, chapter Context-Aware Recommender Systems, pages 217–253. Springer US, Boston, MA, 2011.
- [2] S. Bostandjiev, J. O’Donovan, and T. Höllerer. Tasteweights: A visual interactive hybrid recommender system. In *Proceedings of the Sixth ACM Conference on Recommender Systems*, RecSys ’12, pages 35–42, New York, NY, USA, 2012. ACM.
- [3] M. D. Ekstrand, D. Kluver, F. M. Harper, and J. A. Konstan. Letting users choose recommender algorithms: An experimental study. In *Proceedings of the 9th ACM Conference on Recommender Systems*, RecSys ’15, pages 11–18, New York, NY, USA, 2015. ACM.
- [4] F. M. Harper, F. Xu, H. Kaur, K. Condiff, S. Chang, and L. Terveen. Putting users in control of their recommendations. In *Proceedings of the 9th ACM Conference on Recommender Systems*, RecSys ’15, pages 3–10, New York, NY, USA, 2015. ACM.
- [5] M. Henrion. Some Practical Issues in Constructing Belief Networks. In L. N. Kanal, T. S. Levitt, and J. F. Lemmer, editors, *Uncertainty in Artificial Intelligence 3*, pages 161–173. North-Holland, 1989.
- [6] B. P. Knijnenburg, S. Bostandjiev, J. O’Donovan, and A. Kobsa. Inspectability and control in social recommenders. In *Proceedings of the Sixth ACM Conference on Recommender Systems*, RecSys ’12, pages 43–50, New York, NY, USA, 2012. ACM.
- [7] B. P. Knijnenburg, N. J. Reijmer, and M. C. Willemsen. Each to his own: How different users call for different interaction methods in recommender systems. In *Proceedings of the Fifth ACM Conference on Recommender Systems*, RecSys ’11, pages 141–148, New York, NY, USA, 2011. ACM.
- [8] J. A. Konstan and J. Riedl. Recommender systems: From algorithms to user experience. *User Modeling and User-Adapted Interaction*, 22(1-2):101–123, Apr. 2012.
- [9] J. Magalhães, C. Souza, E. Costa, and J. Fechine. Recommending scientific papers: Investigating the user curriculum. In *The Twenty-Eighth International Flairs Conference*, 2015.
- [10] D. Parra and P. Brusilovsky. User-controllable personalization: A case study with setfusion. *International Journal of Human-Computer Studies*, 78:43 – 67, 2015.
- [11] N. Tintarev and J. Masthoff. Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction*, 22(4-5):399–439, Oct. 2012.
- [12] J.-D. Zapata-Rivera and J. E. Greer. Interacting with inspectable bayesian student models. *International Journal of Artificial Intelligence in Education*, 14(2):127–163, 2004.