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Visualizing Serendipitous Recommendations in User Controlled Recommender System for Learning

Ahmad Hassan Afridi*

Institute of Managment Sciences, Peshawar Pakistan

Abstract

In this paper, we report on a preliminary study about user preferences for recommender system visualizing serendipitous recommendations . A focus group study of fifty nine users (students) was studied for recording their preferences. The focus group was shown and explained the interaction with six(6) common recommender system visualization techniques. Multivariate analysis and LDA (Linear Discriminant Analysis) and Clustering were performed to compute various visualization significance against various recommender systems attributes. The results showed there is difference in various types of recommender visualization when presenting/generating recommender results facilitating serendipity. This research enables software engineers and data scientist to design visualizations for recommender systems that focus users that need serendipitous recommendations presentation along with accuracy

Keywords: Recommender System, Visualization, Serendipity

1. Introduction

Surpriseful recommendations are investigated for their impact as recommender systems are being used to discover novel and useful resources [1]. In technology enhanced learning its can be used to discover novel study material and encourage exploration. It is therefore important to understand how user needs to visualize the serendipity when

* Corresponding author. Tel.: +92-333-9216682
E-mail address: ahmad.afridi@gmail.com, ahmad.afridi@acm.org

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recommenders generate serendipitous recommendations. In this research , we conducted focus Group study to solicit preferences of users for accuracy and serendipitous recommendations visualization. We studied 59 participants of a focus group (students) . The results of focus group study showed new insights about accuracy and serendipity oriented visualizations. This paper is divided into five sections. Section 2 discuss the background related to serendipitous recommender system and visualization in interactive recommender systems. Section 3 covers problem description in detail and Section 4 discusses research approach. Section 5 discuses the results in detail and presents how the results are useful in learning technology domain .

2. Background

Serendipity has been studied in recommender system for surpriseful effects [9][7][1][2][5][13][3][10] . Serendipity is defined as surprising recommendations to user not discovered by itself [4].Serendipity along with other attributes of recommender system has to be studied to observe that how recommender can recommend user items , taking them out of the loop of accuracy. The serendipities recommendation helps user to observe and explore novel but useful items. Visualization serendipity can be a challenge as there is no definitive guideline to design and develop such visualization for recommender systems. Further there are very few studies that have been carried out in serendipitous recommender system [6]. Serendipity in recommender systems create new challenges to the users , as serendipitous can cause uncertainty [8] .Directing users form accuracy to serendipity shifts the research focus to interactive recommender systems. Visualization in recommender systems has taken major share of recommender system studied as human-recommender interaction have demonstrated phenomenon growth over past years [6]. Interactivity is useful in generating serendipitous recommendations for user. Recommender system , when used to direct students to discover new learning resources via serendipity yields good results [1][2]. Chen he and Katrina Verbert [6] have surveyed and discussed interactive recommender systems in detail. The analysis of recommender system reveals that there are six visualization objectives of the recommender system . They are transparency, justification, controllability , diversity , cold start and context. Visualization techniques include node-link diagram, set based view, radial view , table and scatter plot, icon and flowchart. Evaluation matrices for recommender system include satisfaction, trust and usefulness. Data collection methods includes questionnaires. State of the art revel the following points about serendipitous recommendations and visualizing it.

- Most studies are centred around the accuracy oriented visualization of recommender system.
- There is need for exploration of serendipitous (non-accuracy) computing by enhancing user control and transparency.
- As serendipity is a subjective , there is need to for problem understanding paradigm and problem solving paradigm in recommender system visualization. The experiments reported contain small sample size of recommender systems users. There is a need for increasing of sample size to validate Visualization prototype design and classify types of learners.
- Recommendation visualization requires developing of new models and paradigm for serendipity . These developments include the accuracy and serendipity orientation keeping in view the objectives of interaction design .

3. Problem Statement

As most of recommender systems are focusing on the accuracy oriented visualizations of recommendations. There is need of visualization of recommendation that are serendipity oriented . In order to know what kinds of visualizations are suitable to visualize serendipitous recommendations , we formulate three hypothesis. Our hypothesis are as follows:

(H1) There is significant difference in visualizations when used for accuracy and serendipity of recommendations
(H2) Serendipitous recommendations visualization can be well presented with only a certain type of visualization
(H3) There are different clusters of visualizations based on user control , serendipity and transparency and trust ?

Based on these Hypothesis , our research questions are as follows:

(RQ1) Is there any significant difference in visualizations when used for accuracy and serendipity of recommendations?
(RQ2) Is there any certain type(s) of visualization through which Serendipitous recommendations visualization can

be well presented ?
(RQ3) What are the clusters based on user control , serendipity and transparency and trust ?

4. Our Approach

The research approach was based on Pu.et al [12] and serendipity based recommender systems work [1]. The focus group consisted of under graduate level students. The questionnaire was based on user centric evaluation framework by Pu.et al [11]. We categorized six (6) recommender system visualization , attributes and evaluation criteria based on He and Verbert [6]. We conducted focus group of 60 users in learning environment (Institute of Management Sciences, Peshawar, Pakistan). These students (users) were in final semesters of their four(4) year degree, so they had better understanding of the learning materials and need for serendipity when out of loop recommendations are required. The data was collected and recorded to perform statistical analysis. We performed MVA(Multi Variant Analysis) and LDA on Dataset for 4 dependant and 6 independent variables. This work is based on Pu.et al [12] and serendipity based recommender systems work [1]. Further we performed Tree Classification for Analysis of different recommender system visualization preferences by users. We developed four questions for each of six(6) visualization for the focus Group. The questions were about recommender systems attributes such as user control , usefulness, Serendipity and transparency. The questions were asked on Likert scale form strongly disagree (SD) , Disagree(D) , Natural (N) , Agree (A), and Strongly Agree (SA). The users were shown all six visualization , explained and discussed in context of serendipity and user control . SPSS 16 was used to perform all statistical test and data operations. The questionnaire for our research is based on Pu et.al [11].

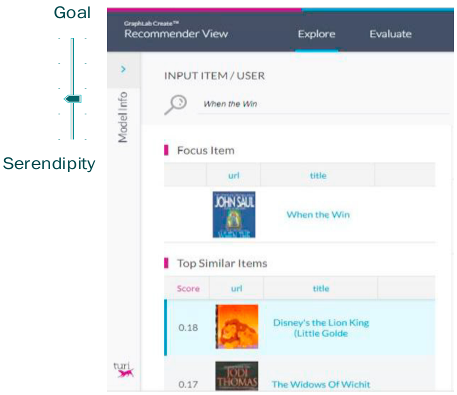
Table 1. Questionnaire for Focus Group

Attribute	Scale				
Q1: The visualization helps me choose (Control) selecting accurate or serendipitous recommendations	SD	D	N	A	SA
Q2: The visualizations are useful in identifying the serendipitous recommendations	SD	D	N	A	SA
Q3: The visualizations of recommender can be trusted for Serendipity	SD	D	N	A	SA
Q4: The visualizations convey transparency of serendipity recommendations	SD	D	N	A	SA

Six Visualization were studied for visualizing serendipity and accuracy oriented visualization. These visualization techniques were based on He. et.al [6] They are :

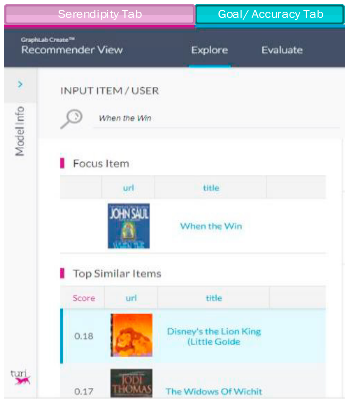
- Slider Table Visualization
- Tab -Table Visualization
- Pie Chart Visualization
- Tab -Table Visualization
- Scatter plot Visualization
- Set Based Visualization
- Graph-node Based Visualization

Table 2: Serendipitous Recommendations Visualizations list



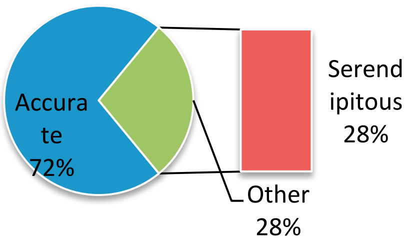
Slider Table Visualization

Visualization Type	Slider Table
Interaction Method	Slider Control
Working Mechanism	User Control/ Algorithmic
Platforms	Desktop/ Mobile
Architecture	App/ Web



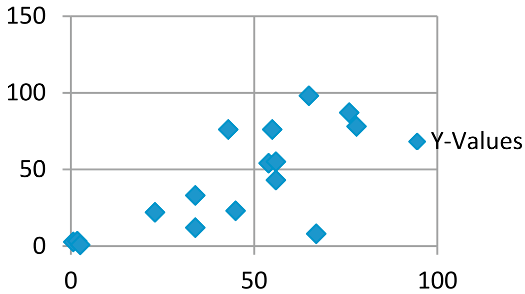
Tab -Table Visualization

Visualization Type	**Tab -Table Visualization**
Interaction Method	Chart Touch Interaction
Working Mechanism	User Control/ Algorithmic
Platforms	Desktop/ Mobile
Architecture	App/ Web



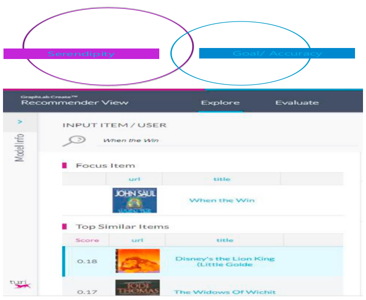
Pie Chart Visualization

Visualization Type	Pie-Chart
Interaction Method	Chart Touch Interaction
Working Mechanism	User Control/ Algorithmic
Platforms	Desktop/ Mobile
Architecture	App/ Web



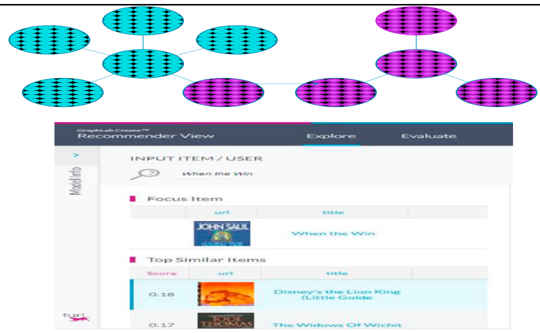
Scatter plot Visualization

Visualization Type	**Scatter plot Visualization**
Interaction Method	Chart Touch Interaction
Working Mechanism	User Control/ Algorithmic
Platforms	Desktop/ Mobile
Architecture	App/ Web



Set Based Visualization

Visualization Type	**Set Based Visualization**
Interaction Method	Chart Touch Interaction
Working Mechanism	User Control/ Algorithmic
Platforms	Desktop/ Mobile
Architecture	App/ Web



Graph-node Based Visualization

Visualization Type	**Graph-node Based Visualization**
Interaction Method	Chart Touch Interaction
Working Mechanism	User Control/ Algorithmic
Platforms	Desktop/ Mobile
Architecture	App/ Web

5. Results

The multivariate analysis shows significance between different subjects. The analysis involved 6 independent (Visualizations) and 4 dependant (Recommender systems Attributes) variables. The results are as follows. We Performed Discriminant Analysis for Grouping variable (0-5) Visualizations and 4 Independents (User Control, Serendipity, Transparency and Usefulness). The Discriminant Analysis results are presented in Table 3 and Table 4 as shown below. The Box M test shows equal population covariance matrices and Wilkes Lambda significant from 1-4 .

Table 3: Test Results

Box's M		69.101
F	Approx.	1.342
	df1	50
	df2	2.195E5
	Sig.	.054

Tests null hypothesis of equal population covariance matrices.

Table 4: Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 4	.838	61.018	20	.000
2 through 4	.981	6.777	12	.872
3 through 4	.992	2.849	6	.828
4	1.000	.168	2	.919

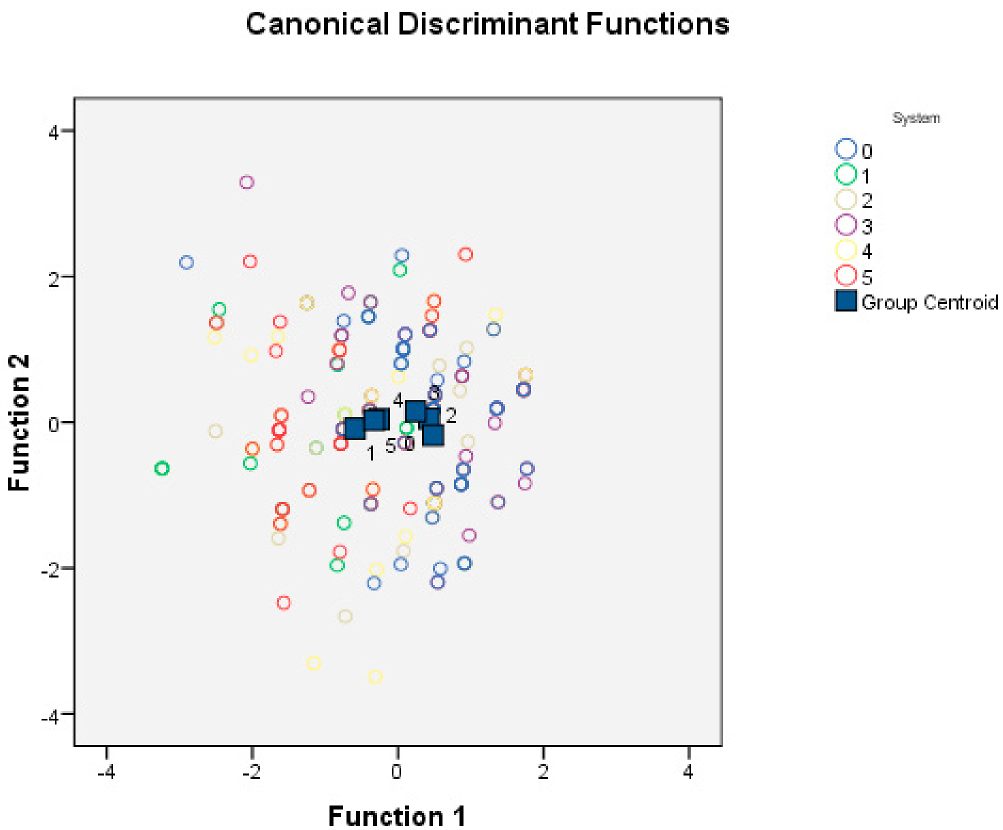


Figure 1 : Canonical Discriminant Function for Visualizations

The Tree Classification for six visualizations and four recommender system attributes shows the following results. CHAID method was used to grow trees.

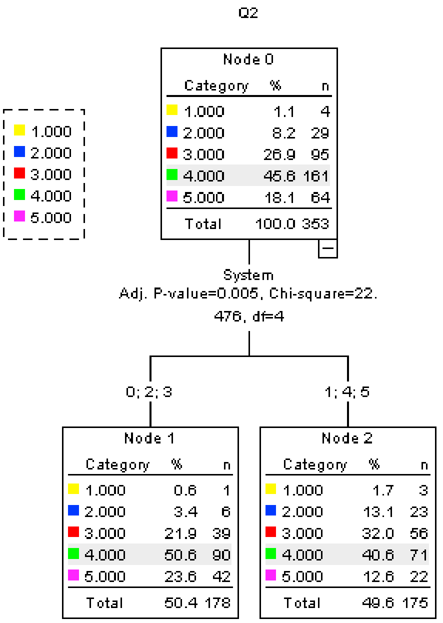


Figure 2: Serendipity and Visualizations Tree

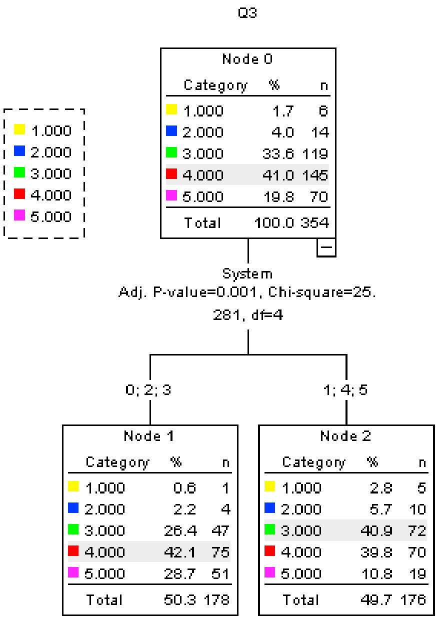


Figure 3 : Trust and Visualizations Tree

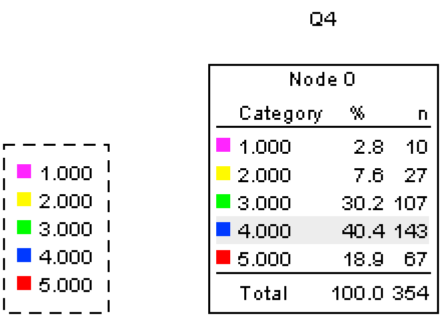


Figure 4 : Transparency and Visualizations Tree

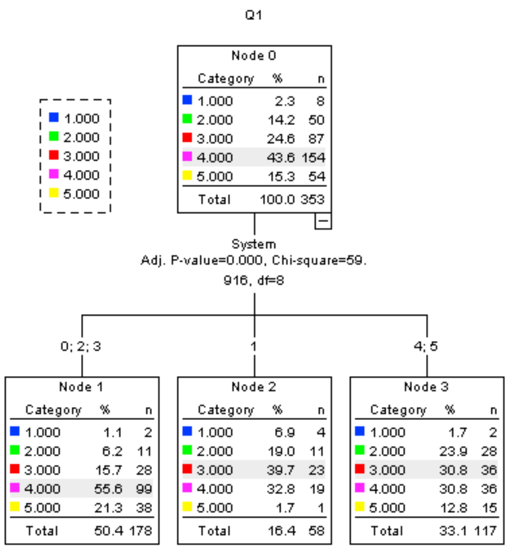


Figure 5: User Control and Visualizations Tree

(RQ1) **Is there any significant difference in visualizations when used for accuracy and serendipity of recommendations?** There is significant difference in various visualizations when serendipitous recommendations are under consideration . This is shown by multivariate analysis and Wilkes lambda. The canonical discriminant functions shows that visualizations 1 and 5 (table-bar and Set based views) are more clustered and 0, 2,3,4 are more clustered . **(RQ2) Is there any certain type(s) of visualization through which Serendipitous recommendations visualization can be well presented ?** As explained in Figure 8, there is clear tree structure for Serendipity oriented visualization are 0, 2 and 3 (Bar-table, Tab-table and pie-chart for Serendipity-Accuracy oriented visualization.

(RQ3) What are the clusters based on user control , serendipity and transparency and trust ?For user control its same 0, 2 and 3 (Bar-table, Tab-table and pie-chart. For Transparency its Bar-table view and for Trust its 0, 2 and 3 (Bar-table, Tab-table and pie-chart.

6. Conclusions

Therefore we conclude that serendipity oriented visualization are more user friendly when appropriate visualizations are used. Recommender system when can show significance utility when serendipity and accuracy are both options are provided at interface level. Further we suggest there must be more long duration studies with users using recommender system in their learning environment. This study can be particularly beneficial to more recommender system user interfaces.

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