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Pairwise Comparisons in a Logic-Based Recommender System

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Abstract. In this paper, we propose a recommender system using pairwise comparisons as the main source of information in the user preference elicitation process. We use a logic-based approach implemented in APARELL, an inductive learner modelling the user's preferences in description logic. A within-subject preliminary user study with a large dataset from a real-world domain (car retail) was conducted to compare pairwise comparison interface to one using standard product list search. The results show the users' preference for the interface based on pairwise comparisons, which has proven significantly better in a number of ways.

Keywords: pairwise comparisons · inductive learning · logic based approach.

1 Introduction

The idea to use pairwise comparisons in Recommender Systems (RS) is quite recent, and still under explored, despite showing promise. The pairwise comparisons approach first proposed by Balakrishnan and Chopra [1] reduces the user's input to a binary choice between two items. Other pairwise recommender systems were also proposed by Pan et al. [2]; Jensen et al. [3]; and Rokach and Kisilevich [4]. Most studies in RS, particularly those which use pairwise comparisons, use statistical machine learning approaches. At the same time, there is a potential advantage from applying a logic-based approach with its more expressive representation. There is growing demand for transparency through explanations [5].

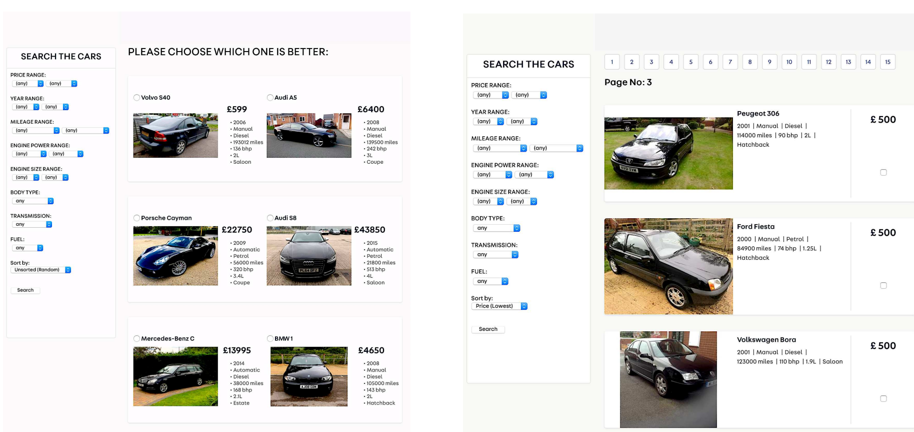
In this paper, a real-world recommender system application has been implemented to help the users find their preferred items through a set of pairwise comparisons. The rest of the paper is organised as follows: in Section 2 we explain the system design. We then discuss the user study evaluation and the result analysis in Section 3. Finally, we conclude our work and provide our plan for further work in Section 4.

2 System Design

The proposed system is composed of the two main modules that, collaboratively, allow the system to select a set of pairs from the triple store database for annotation by the users, from which the system can generate a set of recommendations. The two main modules implemented in our system are:

1. Learning module
   The learning algorithm used in this module is based on Inductive Logic Programming in Description Logic and is described in [6],
2. Recommender module
   The system will find the best items for the given user based on the rules which are produced by the learning algorithm. The following steps are used to produce a recommendation:
   – The learning algorithm output is used as input to the recommendation algorithm.
   – A directed graph is built to express the order of preferences based on the rules produced by the learner.
   – Obtain the definition (as a combination of features) describing the concept of items not dominated by any other item in the user's preferences.
   – Find all items matching the above description.

We use the machine learning algorithm APARELL (Active PAirwise RELation Learner), an Inductive Logic Programming (ILP) algorithm using Description Logics (DL) to represent data and models. It has been shown that APARELL outperforms several popular classification algorithms (Decision trees, SVM, Aleph) on the task of learning models of pairwise preferences [6].



(a) Pairwise comparisons user interface (b) Standard list user interface

Fig. 1: Pairwise comparisons vs standard list user interface

3 Evaluation and Analysis

The study, which took place in Nov 2017, was designed by following the user-centric evaluation framework of recommender systems (**ResQue**) [7] to evaluate a recommender system's quality from the user's perspective. There were 24 participants recruited among students and staff in the University. The number of cars available in the system is 7,360 with descriptions as seen on the Autotrader.co.uk website. The users in our study were asked to evaluate the pairwise interface as shown in Figure 1a and compare it with the standard list interface as shown in Figure 1b. The user study was conducted with a within-subjects, counter-balanced design.

Each interface was used to complete a specific task. The two tasks were separated, thus producing different results, but otherwise they were of similar nature. The two tasks were: (1) find up to three cars suitable for daily commutes between home and office, and (2) find up to three cars suitable for weekend shopping for a household of four people.

After using each interface, the user was asked to fill in a five-point Likert scale questionnaire (1 strongly disagree up to 5 strongly agree) to evaluate the interface he/she just tested. Details of the questions are described in [8]. We measure quality of recommended items (Q1-Q4), interaction adequacy (Q5), interface adequacy (Q6), perceived ease of use (Q7), perceived usefulness (Q8), control/transparency (Q9), attitudes (Q10-Q12) and behavioural intentions (Q13-Q14). Finally, all participants were asked to answer a questionnaire about their preferences with those two interfaces in terms of five aspects: general preference, informativeness, usefulness, better at recommending, and better at helping perceived diversity.

The ordinal values of all participants' responses for each question were averaged and the difference between the pairwise and standard list interface responses were tested using a paired sample t-test. The average values of each question are shown side by side between pairwise and standard list in Figure 2 to see how they differ. The final questionnaire consisted of an evaluation of five different factors and the results of the interface preferences are presented in Figure 3. The graph shows that pairwise interface gained more vote than list interface, except in the better at recommending which is a tie.

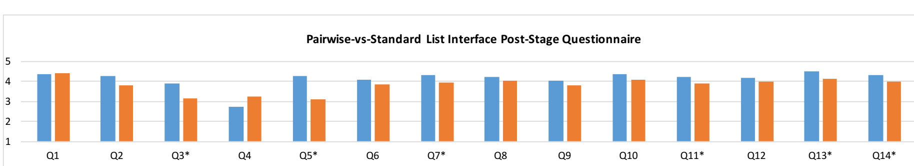


Fig. 2: Usability and user satisfaction assessment results

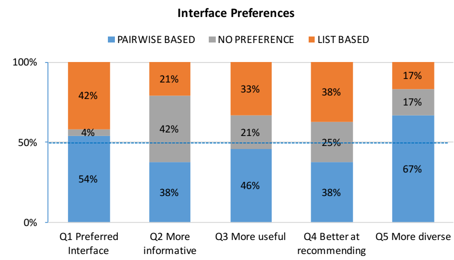


Fig. 3: Interface preferences questionnaire results

4 Conclusion and Future Work

In this paper, a novel algorithm for learning in logic, APARELL, was applied to a real-world used car recommender system. The system evaluation has shown that the combination of a logic-based, relational learner and a pairwise interface results in a recommender system can provides a better alternative to the commonly used list-based interfaces. Following this preliminary user study, we plan to conduct another user study by inviting a larger number of participants.

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