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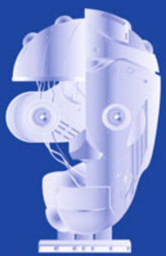

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A Personality-Based Recommender System for Semantic Searches in Vehicles Sales Portals

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Abstract. This work proposes a personality-based recommender system to implement semantic searches on Internet Vehicles Sales Portals. The system is based on a typical recommender system architecture that has been extended to combine a hybrid recommendation approach with a machine learning classifier technique (k-NN). It proposes a combination of the Five Factor Model (Big Five Model) with a correlation between car fronts and power and sociability perceptions. A prototype was implemented to answer the semantic searches considering personality-based user's profiles and a set of Brazilian cars. After each search, a questionnaire was provided for the users to verify how successful the recommendations were for them. The prototype received web searches during a period of 15 days. The final report showed that 77.67% of the users accepted the personality-based recommendations, what indicates that the proposed approach could be promising to improve the quality of the recommendations on the user's point of view.

Keywords: Recommender system · Personality traits · Semantic searches

1 Introduction

A recent report [1] has estimated that a massive part of car sales portals users (90%) gather information on the Internet when they think about to buy a car. Considering this group of 90%, something between 20% to 30% of them have visited several web portals in order to compare the information supplied in the different websites before choosing a specific car. Vehicles sales portals offer services that involve more than simple web searches. Some services may be so complex that they could be considered semantic web search services.

Semantic search aims to determine the contextual meaning of the words that a user is using for searching [2]. In general, search engines are evolving towards semantic search in two different ways. The first way is the use of tags or label parts of a webpage. The other way is the use of hybrid approaches using computational intelligence techniques. One of these hybrid approaches is the hybrid recommender system guided by semantic information [3].

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Recommender systems are filtering systems that seek to predict preferences that user would give to an item. They have emerged as one successful approach to tackle the problem of information overload [4,5]. Recommender systems have become extremely common and they have been applied in a variety of applications. Some of these recommender systems may use optimization techniques such as the ones used by Machine Learning [6], Swarm Intelligence [7] or combinations of them to make smarter recommendations.

A hybrid recommender system typically combines content-based and collaborative methods, but it may also includes other techniques such as the ones used in machine learning or data mining to provide learning functionalities. There are many approaches in the literature considering hybrid recommender systems that are capable of learning in some degree along its operation to provide better recommendations. According to literature, they have used techniques such as Naive Bayes [8], Clustering [9], Neural Networks [10] etc.

Some studies have considered addressing the recommendation problem from the users' psychological characteristics. Personality is an important aspect that influences people's behavior and their interests. These studies have shown a promising opportunity for recommender systems to enhance recommendation quality and user's experience. The question is how to incorporate personality to cars in the context of car sales portal recommender systems.

A possible alternative may be in the recent researches [11–13] about human sensitivity to features in human faces and their information on sex, age, emotions and intentions. In [12], for example, it is demonstrated that automotive features and proportions do covary with trait perception in a manner similar to that found with human faces.

This work proposes a personality-based recommender system to implement semantic web searches to find "best buy opportunities" about cars. The prototype is based on a typical recommender system architecture that has been adapted to include a recommendation engine that combines a hybrid recommendation approach with a machine learning algorithm. The work uses k-Nearest Neighbors (k-NN) to classify the users' personality traits (Five Factor Model) and a correlation between car fronts and personal preferences, according to [12].

The paper is organized as follows: in Sect. 2, it is provided a brief background in order to introduce the basic concepts. Section 3 presents the functionalities of the proposed recommendation engine. Section 4 presents the scenario used for the experiments and discusses the results obtained. Finally, in Sect. 5, the final considerations are presented to conclude the work.

2 Background

Recommender systems provide suggestions of personalized items for users according to their interests. "Item" is a general term used to represent what the system recommends. For example, recommendations are related to many decision-making processes, such as what book to read, what movie to watch, or what vehicle to buy.

In [4], it is proposed a taxonomy that may be used to distinguish recommendation techniques. They are classified in six different categories: (1) collaborative, (2) content-based, (3) demographic, (4) knowledge-based, (5) community-based and (6) hybrid. However, in recent years, several papers have used a new recommendation technique known as personality-based recommendation.

Some researchers [14,15] have considered incorporating personality aspects into recommender systems to personalize recommendations and enhance both recommendation quality and users' experience. Other researches [16–18] believe that machine learning is the answer for the main research problems in recommender systems such as cold start, data sparsity and over-specialization. Cold start refers to the difficulty in bootstrapping the recommender systems for new users or new items. Data sparsity occurs when users in general rate only limited number of items. Over-specialization occurs when the recommended items are similar to those previously rated by the user.

Machine learning is a subfield of computer science that improves computer algorithms with the ability to learn without being explicitly programmed [19]. There are several approaches to combine machine learning with recommender system [20–22]. According to a review [23], the most used algorithms to improve recommender systems are: bayesian networks, decision tree, matrix factorization-based algorithms, artificial neural networks, neighbor-based algorithms and rule learning. The choice for the best machine learning algorithm will depend on the specific application of the recommender system to be developed. This work considers a recommendation engine improved with a machine learning algorithm known as k-NN. It is used as a classifier, so that the output data is associated to a personality traits group.

A semantic search is normally defined as a kind of data searching technique in which a query aims not only to find keywords matches, but to determine essentially the contextual meaning of the words that a user is considering for searching.

Personality is defined as a set of consistent behavior patterns and intrapersonal processes that characterizes individuals and impact on their thinking process and decision making. There are several studies [12,15,24,25] that propose to use personality traits to increase the performance of recommender systems.

In [12], for example, there is an approach that is based on the assumption that every human is unique and all of them have common and individual traits. It considered a methodology in which these individuals were asked to report the characteristics, emotions, personality traits, and attitudes they attribute to car fronts, and then used geometric morphometrics and multivariate statistical methods to determine and visualize the corresponding shape information according these characteristics. The research proved that automotive shapes do covary with trait perception in a manner similar to that found with human faces.

Other approaches use a Five Factor Model personality traits [26] to implement personality-based recommended systems [15,24,25] considering five dimensions used to describe human personality. These dimensions are labeled OCEAN: Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism.

The main problem with these approaches is that they cannot accurately predict any single specific behavior, since human behavior is based on many dimensions. It is limited and does not help in the understanding of culturally-specific, gender specific and age-specific personality expressions. These limitations suggest that a combination of different approaches should be to implement personality aspects in recommender systems.

3 Proposed Method for Recommendation

This work considers a typical architecture [27] as the starting point to develop a variant approach in which a recommendation engine component is changed to incorporate machine learning capabilities that enable semantic searches behind the car sales portal. It is a hybrid approach to recommend items that considers content-based and collaborative-based recommendations combined with a k-NN algorithm to implement a Recomendation Engine Component that is based on a personality-based context in which semantic searches that are constrained to the personality traits of the users and the cars available in the user's countries.

The recommendation component computes the degree of the users' interest in order to estimate how a vehicle may be interesting for them, according to Eq. 1. A vehicle is considered interesting when the value of the interest exceeds a certain threshold θ ($\theta = 3.0$). The degree of interest is computed based on the priorities defined for the users' profile and it considers the following attributes which are obtained from benchmarks portal: (1) vehicle purchasing price, (2) fuel consumption, (3) insurance price, (4) depreciation index, (5) satisfaction index with authorized dealer, (6) reparability index, (7) standard equipment, (8) reselling price, (9) the vehicle using cost, (10) vehicle warranty and (11) price of auto parts. Equation 1 is used to compute the degree of interest of the user u related to vehicle v.

$$\varphi(u, v) = \frac{\sum_{i=1}^{n} b_i * p_i}{\sum_{i=1}^{n} p_i} \tag{1}$$

where b_i is the evaluation value which is defined by the benchmark portal to attribute i, p_i the weight of the priority that the user associated to attribute i. As the vehicles are evaluated according to 11 benchmarks, then we have defined $n = 11$. Personality-based recommendation utilizes the personality scores to calculate the similarity between users. For this, the recommendation engine component implements k-NN algorithm to find k nearest users, i.e., those with the shortest distance. The metric used to determine the neighborhood of user u is the Euclidean Distance according to Eq. 2.

$$d(u, w) = \sqrt{(p_u^1 - p_w^1)^2 + (p_u^2 - p_w^2)^2 + ... + (p_u^n - p_w^n)^2} \tag{2}$$

where $d(u, w)$ represents the distance between users u and w. Here, the neighborhood of the user u is determined for $k = 3$ and n is the number of attributes used to represent the vector of the user's personality. This vector is defined by the Five Factor Model as $p_u = (p_u^O, p_u^C, p_u^E, p_u^A, p_u^N)$ for user u and, therefore, $n = 5$. In this work, $p_u^O, p_u^C, p_u^E, p_u^A, p_u^N$ represent the values in the dimension of Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism respectively.

To complement the recommendation process, the component builds a list D containing vehicles that can be used to add diversity in recommendations that are offered for users. The list D is presented as Eq. 3:

$$D = \{v_i | v_i \in G \wedge \varphi(u, v_i) > \theta\} \tag{3}$$

where v_i is a vehicle used to add diversity into recommendation list, G is a set that represents vehicles which the user has sympathy, u is the user who receives recommendations containing diversity, and $\varphi(u, v_i)$ is the interest of u by v_i.

Generally, typical car sales portals perform searches within their databases considering simple attributes such as price, model, mileage, manufacture year and brand. However, other attributes can be used to improve the quality of the recommendations such as reselling price, depreciation index, insurance price, reparability index etc. There is an essential difference between the typical car sales portals and the prototype that is proposed here. The proposed prototype is supposed to collect information from other portals such as car sales ads to increase the possibility of finding updated good offers. Another difference is that the proposed prototype uses ontologies. An ontology defines common vocabulary for people who need to share information in the domain. The use of ontology is a good alternative for sharing understanding of the structure of information among people or software agents, enabling the reuse of the domain knowledge and separating the domain knowledge from the operational knowledge.

The prototype uses also a web robot to extract ads from known car sales portals. Next, it populates the ontologies that represent the necessary information to enable the recommendation. In order to identify good offers for users, the prototype is integrated with three kinds of portals such as references, benchmarks and ads portals. A car sales reference portal centralizes and shares information about minimum, average and maximum price for different cars available in Brazil. They are used as a reference to evaluate the acceptable prices for a specific vehicle searched on the market. A benchmark portal is used to compare cars according to a set of features. This comparison information estimates the better cost-benefit analysis necessary for recommendations. The car sales portals are used to offer ads representing business opportunities for new and used vehicles. For each kind of service, some famous portals in Brazil have been chosen such as FIPE (www.fipe.org.br), QuatroRodas (www.quatrorodas.abril.com.br), OLX (www.olx.com.br), and iCarros (www.icarros.com.br).

FIPE portal is used here as a reference to evaluate the average price of a specific vehicle. QuatroRodas portal is used here to acquire benchmarks. It evaluates many vehicles categories. The evaluation considers the following criteria:

vehicle purchasing price, fuel consumption, insurance price, depreciation index, parts replacements, satisfaction index with authorized dealer, reparability index, standard equipment, reselling price, vehicle using cost, vehicle warranty and price of auto parts. OLX and iCarros portals are used here to provide car sales ads. OLX portal hosts ads in several categories including vehicles. iCarros portal is a specialized in ads to buy and sell new and semi-new vehicles.

A Recommendation Engine is a component inside a typical recommender system architecture that is used to predict items on which a user may be interested in using different techniques based on several different knowledge sources. This component depends on the type of necessary recommendation inside a real application of the architecture.

Figure 1 presents the basic functionality for the new recommendation engine. It shows three subcomponents that implement the recommendation process in three steps to generate two groups of recommendations. They are: (a) ads that match the restrictions defined by the current search and user's preferences (content-based filtering) – moreover, a similarity analysis is performed with information gathered from personality tests for Five Factor Model dimensions (collaborative filtering); (b) ads that match the classifier that associate users according to their preferences to car front shapes and that associate cars [12].

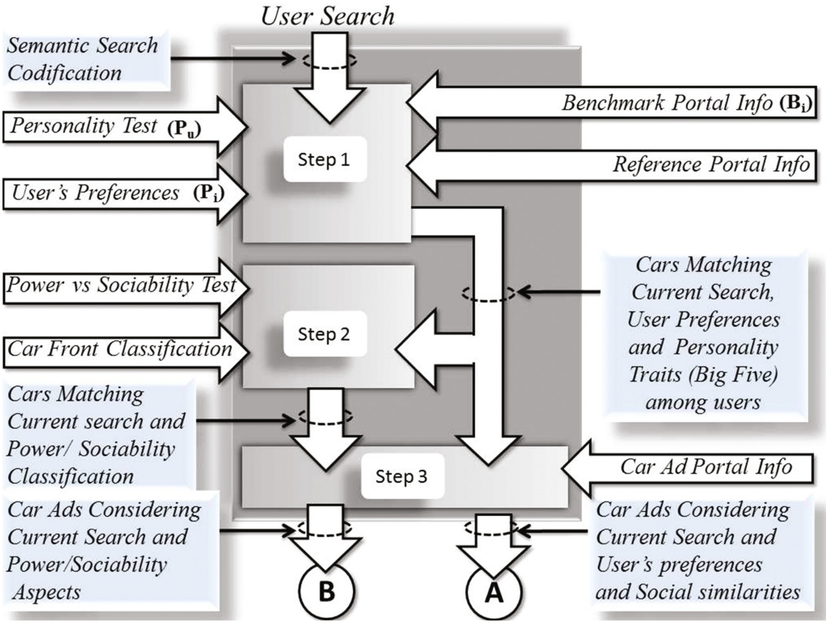


Fig. 1. Recommendation engine component funcionality.

In the first step, the parameters for the search are received from the Internet portal interface. These parameters will be used according to the user's profile and the personality information previously collected from the user. The main objective of this step is to identify a car (or set of cars) that matches the semantic search initially provided on Internet portals. In order to accomplish this objective, the system accesses the benchmark and reference information available on defined links for specialized portals.

Imagine, for example, that the user is asking the following question in the first step: "What is the best sedan for me, considering my profile information, budget (R$ 50,000.00) and personality traits?". The first step is supposed to select, among all the available cars in the sedan category, those cars that are compatible with the budget and personality traits of similar users according to Big Five Model.

In the second step, the main objective is to find alternatives that could improve car recommendations with other personality aspects such as power/sociability association with car front shapes. In order to accomplish this objective, two sets of information are previously collected: (a) information about the users' preference for a degree of variation in a power/sociability personality test; (b) information about how Brazilian cars are classified in an similarity analysis with the cars classified in reference [12]. The output of this step is a car (or set of cars) that complements the set initially provided by step one.

In the last step, a data mining procedure is made on Internet to collect ads for the cars recommended after steps one and two. The final output is supplied to the user by the Internet portal using dynamic web pages.

4 Experiments

A prototype for recommendation of vehicles ads was implemented in Java language and MySQL database. An ontology that includes concepts related to vehicles domain was developed in Protégé. This ontology is named Vehicle Ads Ontology (VAO) and its implementation is based on the reuse of some ontologies such as GoodRelations, Vehicle Sales Ontology and Schema.

Two sets of experiments were used to evaluate the prototype. In the first, the users evaluated a hybrid prototype that combines collaborative filtering and content-based recommendations. In the second, the users evaluated the proposed prototype which offers recommendations based on personality traits.

It is important to note that for each car front available in Brazil, in this work one of four car fronts shapes (1 – narrow and short; 2 – wide and short; 3 – narrow and tall; and 4 – wide and tall) is associated according to similarity aspects. In order to validate the proposed prototype, a scenario that represents a common situation in vehicles sales portal is described. This scenario consists of a user who searches for car ads belonging to a specific category such as hatch, sedan, sport car etc. The implementation of this scenario is shown in Fig. 2.

When the user indicates the year of manufacture (Fig. 2C), the prototype queries the references portal and returns the average price of the vehicle on the national market (Fig. 2D). Next, the user indicates the price range that he/she intends to pay for the selected car (Fig. 2E). Finally, ads portals integrated into the prototype are visited and a recommendation list is produced.

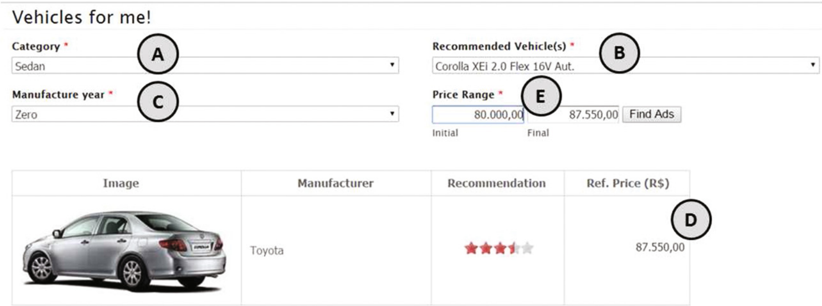
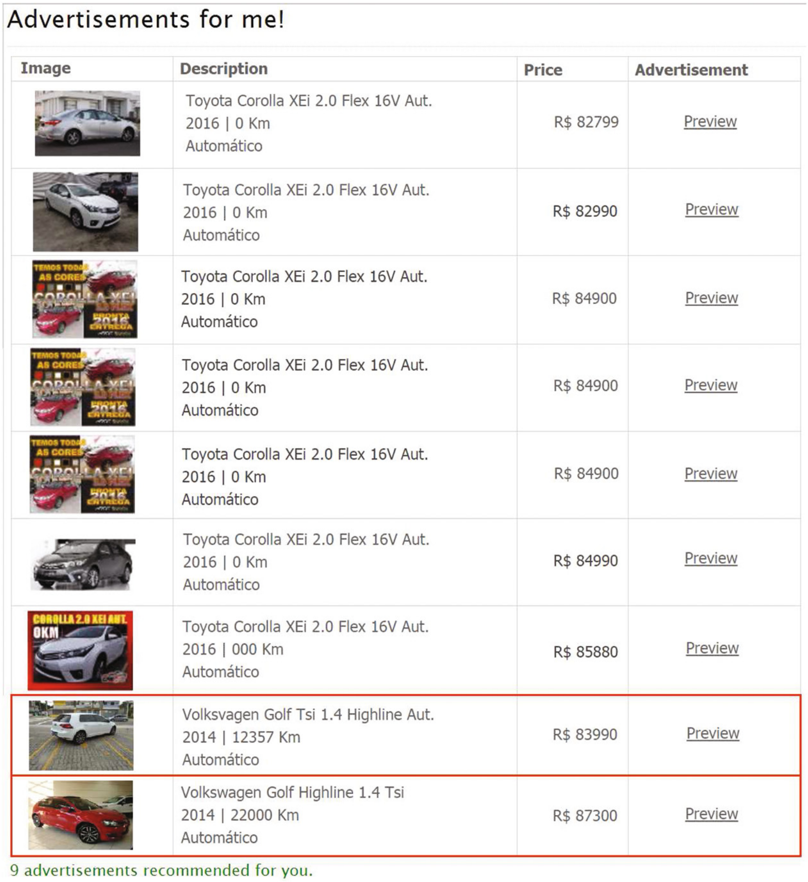


Fig. 2. Searching ads for Toyota Corolla XEi 2.0.



Advertisements for me!

Image	Description	Price	Advertisement
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 0 Km Automático	R$ 82799	Preview
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 0 Km Automático	R$ 82990	Preview
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 0 Km Automático	R$ 84900	Preview
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 0 Km Automático	R$ 84900	Preview
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 0 Km Automático	R$ 84900	Preview
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 0 Km Automático	R$ 84990	Preview
	Toyota Corolla XEi 2.0 Flex 16V Aut. 2016 | 000 Km Automático	R$ 85880	Preview
	Volksvagen Golf Tsi 1.4 Highline Aut. 2014 | 12357 Km Automático	R$ 83990	Preview
	Volkswagen Golf Highline 1.4 Tsi 2014 | 22000 Km Automático	R$ 87300	Preview

9 advertisements recommended for you.

Fig. 3. Ads list containing diversity in recommendation.

In order to complement this list, the prototype uses the acquired knowledge about the user to increase the diversity of items and avoid over-specialization. As seen in Fig. 2, the user has requested ads related to *Toyota Corolla XEi 2.0*. However, in Fig. 3, the recommendation list displays two highlighted ads that are related to *Volksvagen Golf Tsi 1.4*. The first 7 cars shown in Fig. 3 represent the ads related to user's query, as Fig. 1A. The two highlighted cars represent ads related to the user's personality aspects, according to Fig. 1B. Regarding these highlighted ads, it can be seen that (a) Golf car does not belongs to the sedan category, (b) Golf car was not chosen in the user's query and, (c) the recommended ads do not offer new cars according to the user's query. However, the prototype considered that these ads may be good opportunities for the user.

An expert in vehicles domain has defined that Golf car can be represented by *car front 3*. Therefore, the recommendation component learned that the user sympathizes with cars that can be associated to this specific car front. Moreover, it calculated the degree of user's interest and verified that Golf car could be interesting.

To perform the experiments, 243 participants (158 males and 85 females) used the prototype. They are aged from 30–60 with different education levels such as PhD, master and bachelor. Each participant (user) created his/her profile. It contains user's information and also 11 attributes that represent the priorities that a user has in relation to the features of a car.

The participants also answered one questionnaire containing 10 questions from BFI-10 Test [28] to assess the values related to five personality dimensions (OCEAN), according to Five Factor Model. They were also invited to select an image that represents a car front which he/she has more sympathy.

An expert in vehicles domain was invited to create a mapping for representing the relationship between the car front and cars. The purpose of this mapping is to enable a strategy which identifies cars that can please the user, even if he/she is not interested in buying them or he/she does not know them. This strategy is implemented using the Eq. 3. It has been used to complement the recommendation list in order to add diversity for recommended items.

According to [29], the user's satisfaction measures the success of a recommender system. Commercial systems measure user's satisfaction by the number of products purchased (and not returned), while noncommercial systems may just ask users how satisfied they are [30]. In [31], the authors used a questionnaire survey to examine how usefulness, novelty and usability are related to the user's satisfaction.

In order to evaluate the user's satisfaction, we invited the participants who answered both the questionnaire related to BFI-10 Test and the form in which they selected a car front that represents his/her sympathy. Unfortunately, only 68.31% (109 males and 57 females) were willing to participate again.

Each user has been instructed to request vehicles recommendations belonging to three categories such as hatch, sedan and sport car. After three recommendation lists are offered to the user (one for each category), he/she is invited to answer another questionnaire containing only five questions. The goal is to

Table 1. Users' satisfaction regarding the recommendations.

Question	Hybrid prototype		Prototype based on personality traits	
	Yes	No	Yes	No
Q1	62.96%	37.04%	88.59%	11.41%
Q2	64.60%	35.40%	75.94%	24.06%
Q3	—	—	74.67%	25.33%
Q4	58.02%	41.98%	69.61%	30.39%
Q5	44.85%	55.15%	68.31%	31.69%

evaluate the user's satisfaction with the prototype. The questions are: *(Q1) I consider the suggested vehicles ideal for me*, *(Q2) The recommended ads meet my expectations*, *(Q3) The highlighted ads are useful for me*, *(Q4) In general, the prototype meets my expectations* and *(Q5) I would use the prototype again*. The answers to these questions are stored into a database to evaluate the user's satisfaction. The results that evaluate the users' satisfaction are presented in Table 1.

The question *Q1* aims to identify the user's satisfaction related to vehicles that have been suggested as appropriate for his/her profile. These suggestions are based on Eqs. 1 and 2. *Q2* aims to verify if the prototype has been able to extract from ads portals offers that meet the user's expectations. *Q3* aims to evaluate if the diversity which is computed using Eq. 3 has satisfied the user. Finally, the questions *Q4* and *Q5* verify the user's satisfaction about the prototype.

Questions *Q1* and *Q2* have shown the user's satisfaction about the recommendations of vehicles and ads according to his/her profile. The results shown in Table 1 are satisfactory. The evaluation shows that more than 75% of the participants were satisfied by the offered recommendations. We regard that to the hability that the recommendation component has to evaluate vehicles based on benchmarks from specialized portals. However, traditional portals recommend vehicles based on simple features such as price, model, brand, mileage etc.

Question *Q3* aims at evaluating the user's satisfaction when the diversity is applied to the recommendation list. Almost 70% of the participants consider that the diversity of items were useful for the search. Five cars were associated to each car front. Furthermore, we have to evaluate if the quantity of cars associated to the car front is suitable or it might still need some adjustments on this quantity. Thus, new experiments and more participants are extremely important.

Finally, the last two questions show the user's evaluation about the prototype and his/her perspective to use it again, respectively. The results show that more than 68% of the participants evaluated the prototype satisfactorily and that, on another opportunity, they will use it again.

5 Conclusion

This work presented a personality-based recommender system to enable semantic searches to find "best buy" opportunities about cars for sale on the Internet. The prototype combined a hybrid recommendation approach (content-based and collaborative one) with a machine learning algorithm known as k-NN. The results indicate that the proposed approach is promising to improve the quality of the recommendations, even though they may be improved to obtain better satisfaction numbers in the final report.

A possible future approach should consider other personality aspects associated with the reputation of the different vehicles according to the common sense of the users, since in some cases this reputation may result from other sources that are independent from the car front shapes and their dimensions.

References

1. McDonald, M.: Internet reshapes how dealers sell used cars (2012). http://wardsauto.com/dealerships/internet-reshapes-how-dealers-sell-used-cars. Accessed 05 Feb 2014
2. Grimes, S.: Breakthrough analysis: two + nine types of semantic search (2010). http://www.informationweek.com/software/informationmanagement/breakthrough-analysis-two-+-nine-types-ofsemantic-search/d/d-id/1086310. Accessed 09 Feb 2017
3. Zhuhadar, L., Nasraoui, O.: A hybrid recommender system guided by semantic user profiles for search in the e-learning domain. J. Emerg. Technol. Web Intell. **2**(4), 272–281 (2010)
4. Burke, R.: Hybrid web recommender systems. In: Brusilovsky, P., Kobsa, A., Nejdl, W. (eds.) The Adaptive Web. LNCS, vol. 4321, pp. 377–408. Springer, Heidelberg (2007). doi:10.1007/978-3-540-72079-9_12
5. Manchale, P., Bilal, M.: Curated content based recommender system. Int. J. Comput. Sci. Eng. **2**(4), 66–72 (2013)
6. Hariri, N., Castro-Herrera, C., Mirakhorli, M., Cleland-Huang, J., Mobasher, B.: Supporting domain analysis through mining and recommending features from online product listings. IEEE Trans. Softw. Eng. **39**(12), 1736–1752 (2013)
7. Wasid, M., Kant, V.: A particle swarm approach to collaborative filtering based recommender systems through fuzzy features. Procedia Comput. Sci. **54**, 440–448 (2015)
8. Miyahara, K., Pazzani, M.J.: Improvement of collaborative filtering with the simple Bayesian classifier. Inf. Process. Soc. Jpn. **43**(11), 3429–3437 (2002)
9. Pham, M.C., Cao, Y., Klamma, R., Jarke, M.: A clustering approach for collaborative filtering recommendation using social network analysis. J. UCS **17**(4), 583–604 (2011)
10. Vassiliou, C., Stamoulis, D., Martakos, D., Athanassopoulos, S.: A recommender system framework combining neural networks & collaborative filtering. In: Proceedings of the 5th WSEAS International Conference on Instrumentation, Measurement, Circuits and Systems, pp. 285–290 (2006)
11. Matthews, G., Deary, I.J., Whiteman, M.C.: Personality Traits, 2nd edn. University Press, Cambridge (2003)

12. Windhager, S., Slice, D., Schaefer, K., Oberzaucher, E., Thorstensen, T., Grammer, K.: Face to face: the perception of automotive designs. Human Nat. **19**(4), 331–346 (2008)
13. Windhager, S., Booksteina, F.L., Grammera, K., Oberzauchera, E., Saidd, H., Slicee, D.E., Thorstensenb, T., Schaefera, K.: Cars have their own faces: cross-cultural ratings of car shapes in biological (stereotypical) terms. Evol. Hum. Behav. **33**(2), 109–120 (2012)
14. Nunes, M.A.S., Hu, R.: Personality-based recommender systems: an overview. In: Proceedings of the Sixth ACM Conference on Recommender Systems, RecSys 2012, pp. 5–6. ACM, New York (2012)
15. Tintarev, N., Dennis, M., Masthoff, J.: Adapting recommendation diversity to openness to experience: a study of human behaviour. In: Proceedings of User Modeling, Adaptation, and Personalization, pp. 190–202 (2013)
16. Ericson, K., Pallickara, S.: On the performance of distributed clustering algorithms in file and streaming processing systems. In: Fourth IEEE International Conference on Utility and Cloud Computing (UCC 2011), pp. 33–40. IEEE (2011)
17. Ericson, K., Pallickara, S.: On the performance of high dimensional data clustering and classification algorithms. Future Gener. Comput. Syst. **29**(4), 1024–1034 (2013)
18. Panda, M., Patra, M.R., Dehuri, S.: Building recommender systems for network intrusion detection using intelligent decision technologies. In: Intelligent Techniques in Recommendation Systems: Contextual Advancements and New Methods, pp. 49–62. IGI Global (2015)
19. Samuel, A.L.: Some studies in machine learning using the game of checkers. IBM J. Res. Dev. **3**(3), 210–229 (1959)
20. Kelley, P.G., Hankes Drielsma, P., Sadeh, N., Cranor, L.F.: User-controllable learning of security and privacy policies. In: Proceedings of the 1st ACM Workshop on AISec, pp. 11–18. ACM (2008)
21. Marović, M., Mihoković, M., Mikša, M., Pribil, S., Tus, A.: Automatic movie ratings prediction using machine learning. In: MIPRO: Proceedings of the 34th International Convention 2011, pp. 1640–1645. IEEE (2011)
22. Takács, G., Pilászy, I., Németh, B., Tikk, D.: Scalable collaborative filtering approaches for large recommender systems. J. Mach. Learn. Res. **10**, 623–656 (2009)
23. Portugal, I., Alencar, P., Cowan, D.: The use of machine learning algorithms in recommender systems: a systematic review. arXiv:1511.05263 (2015)
24. Roshchina, A., Cardiff, J., Rosso, P.: TWIN: personality-based intelligent recommender system. J. Intell. Fuzzy Syst. **28**(5), 2059–2071 (2015)
25. Wu , W., Chen, L.: Implicit acquisition of user personality for augmenting movie recommendations. In: Proceedings of User Modeling, Adaptation and Personalization, Dublin, Ireland, pp. 302–314 (2015)
26. Gosling, S.D., Rentfrow, P.J., Swann, W.B.: A very brief measure of the big-five personality domains. J. Res. Pers. **37**, 504–528 (2003)
27. Paiva, F.A.P., Costa, J.A.F., Silva, C.R.M.: A hierarchical architecture for ontology-based recommender systems. In: Proceedings of the Computational Intelligence and 11th Brazilian Congress on Computational Intelligence (2013)
28. Rammstedt, B., John, O.P.: Measuring personality in one minute or less: a 10-item short version of the big five inventory in English and German. J. Res. Pers. **41**(1), 203–212 (2007)

29. Ziegler, C.-N., McNee, S.M., Konstan, J.A., Lausen, G.: Improving recommendation lists through topic diversification. In: Proceedings of the 14th International Conference on World Wide Web, pp. 22–32. ACM, New York (2005)
30. Herlocker, J.L., Konstan, J.A., Terveen, L.G., Riedl, J.T.: Evaluating collaborative filtering recommender systems. ACM Trans. Inf. Syst. **22**(1), 5–53 (2004)
31. Swearingen, K., Sinha, R.: Beyond algorithms: an HCI perspective on recommender systems. In: Proceedings of Workshop on Recommender Systems, vol. 13, No. 5–6, pp. 393–408 (2001)