Ricochet: Context and Complementarity-Aware, Ontology-based POIs Recommender System

Chun Lu[1], Philippe Laublet[2], Milan Stankovic[1,2]

[1] Sépage S.A.S, 96 bis boulevard Raspail, 75006 Paris, France
[2] STIH, Université Paris-Sorbonne, 28 rue Serpente, 75006 Paris, France
chun@sepage.fr, philippe.laublet@paris-sorbonne.fr, milstan@sepage.fr

Abstract. In this paper we propose a new approach for improving the personalization of POIs recommender system. Existing context-aware POIs recommender systems usually take into account only peripheral contextual variables. We present Ricochet, an ontology-based system that refines the recommendation results by implementing an inter-POI parameter that we call the "complementarity". We show how this new parameter can generate more effective recommendations. Our experiments are grounded using data from the location-based social network (LBSN) Yelp.com.

Keywords: POI, Recommender system, Context, Complementarity, Ontology

1 Introduction

Recommender systems have changed the way people find products, information and even other people. They provide personalized recommendations and predictions over a large amount of information.

Places of interest, also called points of interest (POIs), are geographical marks that represent a certain importance for people because they play a specific role in the city. For example, places where we eat (restaurant), where we sleep (hotel), where we spend a good moment (bar) or where we participate in cultural activities (museum, theater).

With the rapid growth of location-based social networks (LBSNs), POIs recommender systems are becoming increasingly popular. Various types of approaches can be found both in academic literature (such as context-aware approach [1, 3, 10, 12]), and in commercialized applications and Web sites (Foursquare[1], Yelp[2], Facebook places[3]) that mostly rely on collaborative filtering. However, most of these systems do not take into account the dynamic nature of the user's preferences, and assume that the user is likely to accept recommendations in the same way in any situation, regardless of the POI he is currently in, or that he just visited.

---

[1] https://www.foursquare.com/
[2] http://www.yelp.com/
[3] https://www.facebook.com/

The research questions driving our work are: *why do people go from one POI to another? Is there a link between these two POIs?*

The contributions of this paper are two-fold:

- A set of recommendation criteria for constructing a relevant POIs recommender system, derived from a qualitative user study, based on interviews of 12 users of LBSN applications such as Foursquare and Yelp.
- An ontology of POIs compatible with Yelp taxonomy of place categories. A Semantic Web-based approach that is capable of re-ranking Yelp's recommendations by taking into account the complementarity parameter.

The rest of the paper is organized as follows. In section 2, we present the state of the art. In section 3, we detail the "Ricochet" system. In section 4, we present the evaluation methodology and we report the results. In section 5, we summarize the outcome of this work and we mention some future work.

2 State of the art

The POIs recommender systems are a recent but important research domain that attracts contributions from academic research institutions and companies constructing novel user applications.

In [10], the authors present a location-based POIs recommender system which infers a user's preferences by mining this person's social network profile and by considering the physical constraints delimited by the location and the form of transportation. The system also takes into account how the user is feeling at the moment. We drove this notion of feeling further by studying the impact of the feeling that POIs provoke to the choice and the complementarity of future POIs. In [1, 3, 12], the authors propose context-aware POIs recommender systems. In [1] we find the thoroughest set of contextual variables: distance to POI, temperature, weather, season, companion, time day, weekday, crowdedness, familiarity, mood, budget, travel length, means of transport, travel goal. But for us, these variables are peripheral. Our work enriches the set of contextual variables with the inter-POIs parameter "complementarity". Another difference is that these systems do not use Semantic Web technologies.

In [2, 4, 7, 8, 9], the authors use Semantic Web technologies in different recommender systems: adaptive hypermedia systems, hotel search, POIs recommender system for drivers etc. The data are grounded with the ontology that provides a very well semantic support for developing and improving personalized functionalities such as recommendations. In our work, we also use these technologies because of the power and facility in the knowledge representation and the inference.

In [13] and [14], the authors use sentiment analysis techniques to study user's comments of a venue. [13] concentrates on the general polarity and [14] on the different appreciations about different items at a venue. These approaches can contribute to a better user preference profile. But they need detailed comments and cannot help the decision of the immediate recommendation. [5] studies the temporal effects for the location recommendation, more precisely on correlations between a user's check-in time and the corresponding check-in preferences. In our work, we study the immediate effect caused by the check-in activity and thus recommend complementary POIs that best respond to this effect.

Except for academic papers, there are several commercialized applications Foursquare, Yelp, Facebook places etc. They allow users to do check-ins. Recommendations in these LBSNs usually combine the collaborative filtering and the context. On Foursquare, some recommendations are based on the user's and the user's friends' check-in history. For example, "You haven't been here yet", "Your friends have checked-in here" etc. Foursquare has released a new recommender system recently. Our work was conducted before. These proprietary applications do not use Semantic Web technologies and do not consider the complementarity parameter between POIs. In this paper we demonstrate the importance and advantage of doing so.

3 The Ricochet system

In this section, we describe the Ricochet system. The presentation consists of the following parts: criteria of recommendation, construction of OntoPOI, recommendation engine.

3.1 Criteria of recommendation

We conducted user interviews in order to understand the important elements of POI choice. According to the responses of our interviewees, we cleared 3 types of criteria that people take into account when choosing a POI: contextual criteria, intrinsic criteria of POIs and criteria of complementarity between POIs.

Contextual criteria indicate the weather, the moment of the day etc. Intrinsic criteria of POIs indicate characteristics of POIs, for example, the opening hours, the popular hours, the price, the atmosphere, the comfort, the decoration, the location, the type of food, the quality of food, the quality of the service, the smells etc. Criteria of complementarity indicate relations between POIs and reasons why we go from one POI to another. In order to represent the knowledge about POIs and to do intelligent inferences, we decided to construct an ontology.

3.2 Construction of OntoPOI

Like all ontologies, OntoPOI contains two basic components: classes and properties. The class "Thing" has four sub-classes: "Place", "Context", "Characteristic" and "Complementarity". "Context", "Characteristic" and "Complementarity" correspond with the three types of criteria of recommendation. The sub-classes of "Place" are the taxonomy of entertainment POIs. As we wanted to realize some experiments with Yelp's data, we decided to use the same taxonomy as Yelp: "Active Life", " Arts and Entertainment ", " Beauty and Spas ", "Food", "Nightlife" and "Restaurant". OntoPOI is thus compatible with Yelp's data and can reorganize them in an intelligent way thanks to the good inferring capacity of the logic-based ontology. OntoPOI can be downloaded at: http://sepage.com/ontology/OntoPOI_Ricochet.owl

Some precisions on the representation of criteria of complementarity

In [10], the authors made a filtering based on the feeling of the user. They used the same categorization of POIs as Foursquare. For them, each of POI categories was mapped to a particular feeling:

Arts & Entertainment= "feeling artsy" College & Education="feeling nerdy"
Nightlife="feeling like a party animal" Great Outdoors="feeling outdoorsy"
Shops="feeling shopaholic" Food="feeling hungry"
Home / Work / Other="feeling workaholic"

Our work is aligned to this idea and takes it further. We go to a POI because we have a certain feeling at a given moment. This feeling can be caused by the POI that we just visited and the POI where we decide to go can satisfy this feeling. This feeling can be also interpreted as a need or a sensation. These feelings/needs/sensations can be physiological, as the hunger, the thirst and the elimination. They can also be physical or intellectual. The complementarity can be seen as the link between the POI that causes a need and the POI that satisfies this need. For example, the hunger can be caused by a POI where we make physical efforts and can be satisfied by a POI where we eat. The relation of complementarity between two POIs can be interpreted in the following way:

Figure 1. Principle of criteria of complementarity

In [11], the authors showed that physical activities possessed a specific intensity and this can be assessed. We considered that every entertainment activity possessed an intensity of expressiveness at several levels: cognitive, emotional and physical. This notion concretizes the feeling discussed above. Empirically, we classified our POIs in four intensities of expressiveness: high, moderately high, moderately low and low. We created four sub-classes of "Place": "High Intensity Expressiveness place", "Moderately High Intensity Expressiveness place", "Moderately Low Intensity Expressiveness place", "Low Intensity Expressiveness place". Then, we classified each of the POIs classes according to their intensity of expressiveness. The result of our interviews showed that daily activities required an alternation of different rhythms and intensities. An "X Intensity Expressiveness Place" causes X intensity. X intensity needs to be alternated by Y intensity other than X. Y intensity is provoked by a "Y Intensity Expressiveness place". We can simplify the deduction like this:

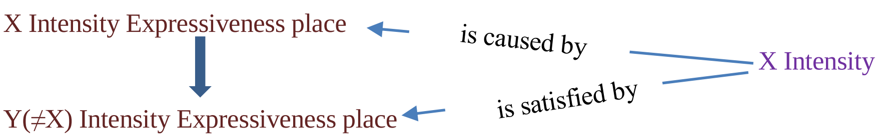

Figure 2. Deduction of the complementarity for its representation in OntoPOI

To represent this in the ontology, we used OWL Full[4]. We created two objectProperties “is caused by” and “is satisfied by” which have the class “Complementarity” as domain and rdfs:Class as range. The class "Complementarity" has four instances: "high intensity", "moderately high intensity", "moderately low intensity", "low intensity". We defined, for each instance, their values of the two properties by applying the process represented on Figure 2. We created some other objectProperties: "is the exposition of" (inside or outside) and "is the time for". We created some datatypeProperties: "has address", "has city", "has phone", "has postal code" etc which are basic informations about POIs.

3.3 Recommendation engine

We used several tools: Yelp API, Jena API and Google Maps API. Firstly, the Java program gets data by accessing to Yelp API that returns 50 POIs near the current location of the user. Secondly, the information of these POIs are translated into RDF triples and stored in Jena RDF repository with OntoPOI. Thirdly, according to the context and the check-in information of the user, we generate SPARQL queries, in order to determine the adequacy of each POI with regards to the user’s situation, according to 3 criteria. The total adequacy is calculated according to the following formula:

$$\text{Total point} = \text{Point of the weather criterion} + \text{Point of the moment of day criterion} \\ +3 * \text{Point of the complementarity criterion.}$$

Ricochet recommends the 10 highest-rated POIs in descending order. The recommended POIs are marked on a local map by using Google Maps API. This process is represented on Figure 3.

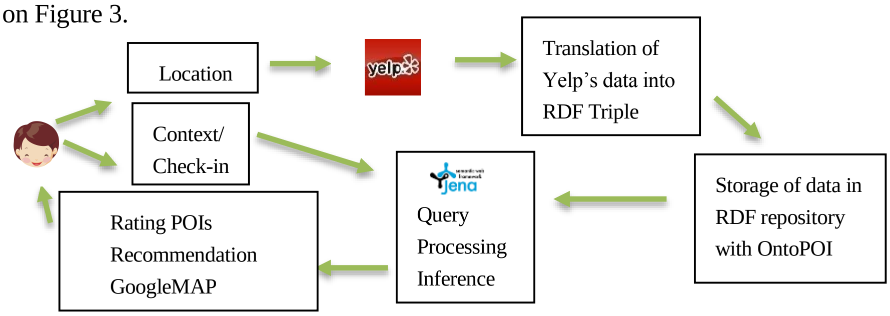

Figure 3. Diagram of the recommendation engine

4 Evaluation

In order to evaluate the effectiveness of our approach, we compared the recommendations produced by two variants of Ricochet. The first (R1) is that described above, the second (R2) is not complementarity-aware. Using these two variants, we could measure if the proposed complementarity-aware system can improve the user perceived relevance of the recommendations with the same data. The evaluations took place at Paris in France with

[4] http://www.w3.org/TR/owl-ref/#OWLFull

the participation of 10 persons. We varied the day time (morning, afternoon, night) and the place (not only downtown). We asked the evaluators to choose a POI nearby in our database and to imagine that they just visited it. We obtained the recommendations for the two variants. Then, we invited our evaluators to rate each recommended POI by referring to the following scale: 0: I won't go there (not relevant); 1: I hesitate (partially relevant); 2: I'll go there without hesitation (definitely relevant). To gauge the relevance, we used the following metrics:

Precision was used to evaluate the quality of the recommendations. It is the number of relevant recommended POIs divided by the total number of recommended POIs. The POI having the score 2 counts for 1 relevant POI, 1 counts for 0.5, 0 doesn't count.

$$\text{Precision} = \frac{\text{Relevant recommended POIs}}{\text{Total recommended POIs}}$$

Recall was used to evaluate the quantity of POIs extracted. We modified the traditional recall. We showed not all the database but only 10 recommended POIs. The evaluators judged the relevance of these shown POIs. We cannot know their appreciation about the non-shown POIs. The modified recall is the number of relevant recommended POIs divided by the total number of relevant recommended POIs of the two variants.

$$\text{Recall (modified)} = \frac{\text{Relevant recommended POIs}}{\text{Total relevant recommended POIs of the 2 variants}}$$

normalized Discounted Cumulative Gain (nDCG) was used to evaluate the quality of the ranked list. The nDCG value of a ranking list at position *n* is calculated in the following way:

$$\mathrm{N(n)} \equiv \mathrm{Z_n} \sum_{\mathrm{j=1}}^{\mathrm{n}} \begin{cases} 2^{\mathrm{r(j)}} - 1, \mathrm{j} = 1 \\ \dfrac{2^{\mathrm{r(j)}} - 1}{\log(\mathrm{j})}, \mathrm{j} > 1 \end{cases}$$

where *r*(*j*) is the rating of the j-th document in the ranking list, and the normalization constant $\mathrm{Z_n}$ is chosen so that the perfect list gets a nDCG score of 1 ([5]).

The results are shown on Figure 4.

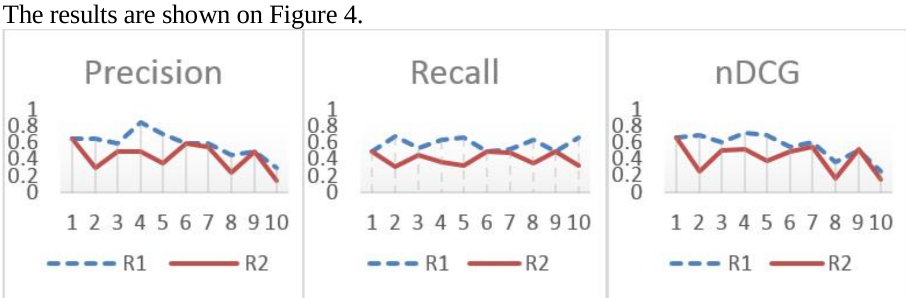

Figure 4. Results of the precision, the recall and the nDCG

R1 is the first variant, R2 the second. 1-10 are the numbers of the ten evaluations. We can see clearly that the performance of R1 is generally better than that of R2 in terms of the quality, the quantity and the ranking. For 1 (a park), the two performances are the same. It was the dinner time. During the mealtime, the rank of the food POIs is largely elevated. The rest of the evaluations were done outside the mealtime where Ricochet privileged the complementarity parameter. The evaluators were pleased to be recommended complementary POIs. For 2 (a coffee), 8 (a massage center), we are well rested and often want a more intense activity, R2 recommended a beauty spa, a day spa, a massage, a tea room which have a similar intensity, R1 recommended only more intense POIs like a park, a dance studio, a museum etc. For 4 (a cinema), R2 recommended another cinema. For 5 (a gym club), 7 (a swimming pool), 10 (a tennis court), we normally feel tired, but R2 recommended still wearying POIs like a swimming pool, a gym club, a bike rental, a museum, R1 recommended more relaxing POIs, like a juice bar, a cinema, a cosmetic beauty supply, a coffee-tea. For 3 (a museum) and 6 (a hair salon), 9 (a musical venue), the performances are close. As before, Ricochet recommended complementary POIs that have a different intensity. But it turned out that the proposed intensity was not always suitable. People often need to change rhythm between two activities. But every individual has his own rhythm. The change of the rhythm seems to be submitted to a modulation according to the psyche of the individual. For example, some people like only the restful activities, for them, we would do better to eliminate the tiring activities. Others like all the activities, light as intense. For the latter, the range of the recommendations would deserve to be more refined. In our current system, there is only one rule on the change of rhythm. However the appropriateness of a POI with regards to the rhythm is important and we intend to further personalize the taking into account of the rhythm, potentially by combining our approach with a machine learning approach.

To conclude this evaluation, even though the number of evaluators was limited, the results showed evidence that considering the complementarity can improve the relevance of the recommended POIs. In our future work we intend to conduct a more complete evaluation with more users and more specific situations.

5 Conclusion and Future work

In this paper, we presented Ricochet an ontology-based POIs recommender system and illustrated the advantage of this approach and the importance of implementing the complementarity parameter when recommending POIs.

In spite of good critics of our evaluators, there are still several weak points in our system to be improved in a future work.

Firstly, being dependent to Yelp API, we cannot have access to all recommendable POIs but to a pre-selection made by Yelp. This also the reason why we didn't compare our results against the baseline ordering from Yelp. This influences on the application of the complementarity parameter and thus on the quality of the results. Secondly, we identified but did not include yet the intrinsic criteria in our system. And nevertheless, these criteria can potentially be useful for refining the results. Thirdly, it could be possible to cover a more complete set of contextual information like in [1]. Fourthly, the notion of complementarity could also be further refined to improve the personalization of the recommendation. The improvement and the personalization require a better knowledge on the user, and more exactly, on the scale of the user's acceptable activities. Fifthly, we can use the technologies installed on today's mobile devices like the wireless accelerometers, the heart rate monitor and the sensor of calories. We can measure the exact intensity of the activity or the number of calories spent. Having these data, we can better recommend appropriated POIs that lead people to a balanced and healthy life. With more and more strongly typed user data available, the use of Semantic Web knowledge structures to make relevant, context-aware recommendations makes more and more sense.

The POIs recommender systems are adopted by the modern society. The personalization of the latter is a largely exploitable field and its future is very promising.

References

1. Baltrunas, L., Ludwig, B., Peer, S., Ricci, F.: Context-Aware Places of Interest Recommendations of Mobile Users. In: Human-Computer Interaction International, pp. 531-540. Heidelberg, Berlin (2011)
2. Brut, M., Sedes, F.: Modélisation basée sur ontologies pour développer des recommandations personnalisées dans les systèmes hypermédia adaptatives. In: INFORSID, pp. 61-76. Marseille (2010)
3. Costa, H., Furtado, B., Pires, D., Macedo, L., Cardoso, A.: Context and Intention-Awareness in POIs Recommender Systems. In: Proc. 6th ACM Conf. on Recommender Systems, 4th Workshop on Context-Aware Recommender Systems, RecSys'12, NY, USA (2012)
4. Debattista, J., Scerri, S., Rivera, I., Handschuh, S.: Ontology-based rules for recommender systems. In: Proceedings of the International Workshop on Semantic Technologies meet Recommender Systems & Big Data, pp. 49-60. (2012)
5. Gao, Huiji, Tang, Jiliang, Hu, Xia, Liu, Huan.: Exploring temporal effects for location recommendation on location-based social networks. In: Proceedings of the 7th ACM conference on Recommender systems, pp. 93-100. ACM, New York, USA (2013)
6. Liu, T.-Y., Xu, J., Qin, T., Xiong, W., Li, H.: Letor: Benchmark dataset for research on learning to rank for information retrieval. In: Proceedings of SIGIR 2008 Workshop on Learning to Rank for Information Retrieval. (2007)
7. Ngamsrithepparit, S. et al.: Rule Management System for Ontology-based Recommendation System. In: The Joint International Symposium on Natural Language Processing and Agricultural Ontology Service 2011, Bangkok, Thailand, Feb 9-10, (2012)
8. Niemann, M., Mochol, M., Tolksdorf, R.: Improving online hotel search - what do we need semantics for? In: Proc. of the Semantics (2006)
9. Parundekar, R., Oguchi, K.: Driver Recommendations of POIs using a Semantic Content-based Approach. In: SeRSy, pp. 13-24. (2012)
10. Savage, N.S. et al.: I'm feeling LoCo: A Location Based Context Aware Recommendation System. In: Advances in Location-Based Services, pp. 37-54. Heidelberg, Berlin (2012)
11. Tapia, E.M. et al.: Real-Time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor. In: Proceedings of the 2007 11th IEEE International Symposium on Wearable Computers, pp. 1-4. (2007)
12. Waga, K., Tabarcea, A., Fränti, P.: Recommendation of Points of Interest from User Generated Data Collection. In: CollaborateCom 2012, Pittsburgh, USA, October (2012)
13. Yang, D., Zhang, D., Yu Z., Wang, Z.: A sentiment-enhanced personalized location recommendation system. In: Proceedings of the 24th ACM Conference on Hypertext and Social Media (HT '13), pp. 119-128. ACM, New York, NY, USA (2013)
14. Yang, D., Zhang, D., Yu, Z., Yu, Z.: Fine-grained preference-aware location search leveraging crowdsourced digital footprints from LBSNs. In: Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp '13), pp. 479-488. ACM, New York, NY, USA (2013)