

# Information Extraction for Inclusive Recommender Systems

Noemi Mauro<sup>a</sup>, Liliana Ardissono<sup>a</sup>, Stefano Cocomazzi<sup>a</sup> and Federica Cena<sup>a</sup>

<sup>a</sup>Computer Science Department, University of Torino, Corso Svizzera 185, Torino, I-10149, Italy

## Abstract

Inclusive recommender systems should take both user preferences and the compatibility of items with the user into account in order to generate suggestions that can be appreciated and smoothly experienced at the same time. For instance, considering people in the Autism Spectrum Disorder, the sensory features of a place that is potentially interesting to the user are important to predict whether it might make her/him uncomfortable when visiting it. However, information about users' experience with items can hardly be found in the metadata provided by online geographic sources.

In order to address this issue, we suggest to retrieve it from the consumer feedback collected by location-based services that publish item reviews. This type of feedback represents a sustainable information source because it is supported by people through a continuous reviewing activity. Thus, it deserves special attention as a potential data source. In this paper, we outline how this type of information can be retrieved and we discuss its benefits to Top-N recommendation of Points of Interest.

## Keywords

Recommender Systems, Geographic Information Systems, People with Autism

## 1. Introduction

In the development of inclusive recommender systems, multiple factors have to be taken into account to support a positive user experience with the suggested items. For instance, in Points of Interest (PoIs) recommendation, accessibility issues, such as architectural barriers, should be considered to avoid imposing extra fatigue on the user, or making it hard to reach the place, if (s)he is phys-

ically impaired. Moreover, if the user is in the Autism Spectrum Disorder (ASD), the sensory features of places have to be taken into account to suggest PoIs that are compatible with her/his aversions. However, physical and sensory features of items are only a part of a broader scope of characteristics that can negatively influence user experience. For instance, cultural aspects might impose constraints on garment styles to be considered in order to avoid offending the user with proposals that (s)he cannot accept.

These examples support the idea that both *user preferences*, and the *compatibility* of items with the user are key to the suggestion of items that (s)he can like and smoothly experience at the same time. Different compatibility aspects might be modeled within a recommender system, depending on its goals, such as impairments, sensory aversions, cultural principles, and so forth. The basic difference with respect to preference modeling

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✉ noemi.mauro@unito.it (N. Mauro);  
liliana.ardissono@unito.it (L. Ardissono);  
stefano.cocomazzi@edu.unito.it (S. Cocomazzi);  
federica.cena@unito.it (F. Cena)

ORCID 0000-0001-8234-3266 (N. Mauro);  
0000-0002-1339-4243 (L. Ardissono);  
0000-0003-3481-3360 (F. Cena)

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is that the system should not assess whether the user likes more or less a property of an item, but if that property can cause any discomfort, or difficulties, to her/him. Thus, for instance, a single, totally incompatible feature might make an item unsuitable for the user, even though its other features would satisfy her/him very well.

A few mobile guides propose models for the evaluation of items compatibility with users in personalized recommendation. For instance, INTRIGUE [1] focuses on physical accessibility of items, while PIUMA [2, 3] investigates their compliance with the sensory aversions of people. In both works, the collection of information about items supporting compatibility evaluation is a problematic task. Specifically, while geographic information sources provide some accessibility data (e.g., wheelchair support), they typically offer standard types of information which can hardly represent the user experience with items in a complete way. Moreover, metadata do not always reflect real user experience. For instance, even though a hotel claims that it offers Wi-Fi, the quality of internet access can only be measured when visiting the place.

In order to address this issue, we want to investigate the descriptive power of consumer feedback collected by location-based services that publish online item reviews. Specifically, we want to study the extraction of data about sensory features from textual comments in order to check whether leveraging this type of information in Top-N recommendation improves the suggestion of places.

## 2. Background and related work

As discussed by Ghose and Ipeirotis in [4], online reviews are a precious source of information about products and services because they describe previous consumers' experience with items. Notice also that, as reviews are voluntarily provided by people all over the world, and they are continuously uploaded, they represent an ideally unlimited source of up-to-date information about items that can be used to feed a recommender system.

A lot of work has been carried out to extract relevant data from online reviews with the purpose of personalizing recommendation to the individual user [5, 6], or to assess review helpfulness [4, 7, 8, 9, 10]. Moreover, a parallel research thread applies opinion mining to identify pros and cons of items, as observed by consumers, with the aim of highlighting aspects that can be improved or promoted. For instance, see [11], [12], and [13]. However, those works rely on statistical analyses of text and they focus on the most frequently reported aspects of items, such as the price and cleanliness of a hotel, or the quality of the food served by a restaurant.

In contrast, compatibility evaluation is related to individual idiosyncrasies. For this reason, it should be based on a deep investigation of users' perceptions of items, regardless of how many people highlight the various issues in their reviews. For instance, even though a single person points out that a restaurant is challenging for somebody who uses a wheelchair because the tables are too close to each other, this information should be recorded and taken into account by the system. For this reason, instead of identifying the main item properties that emerge from a statistical analysis of consumer feedback (bottom-up), we aim to start from the

identification of the types of features that can determine a compatibility problem. Then, we want to search for these features in the reviews (top-down). We hypothesize that this approach has the advantage that isolated opinions can bring useful data to be used in the cautious type of recommendation we pursue.

### 3. Item recommendation

We plan to exploit the feature values extracted from consumer feedback to evaluate the compatibility of each feature  $f$  of an item  $i$  with a user  $u$ , taking her/his aversions into account. Following the approach presented in [2], we will combine the compatibility of the features of  $i$  with  $u$ 's preference for the category of  $i$  to obtain the final score of the item. Compatibility and preference information can be integrated in different ways. For instance, in [2] we proposed to compute an overall compatibility value  $comp$  for the item and to combine it with  $u$ 's preference  $pref$  for the category  $c$  of  $i$  (e.g., cinema, park, etc.) in order to estimate the rating  $\hat{r}$  of  $i$ :

$$\hat{r} = \alpha * comp + (1 - \alpha) * pref \quad (1)$$

where  $\alpha \in [0, 1]$  tunes the influence of compatibility and preference information in rating estimation. However, other methods can be applied, which we plan to investigate.

### 4. Extraction of compatibility features from online reviews

In order to support a top-down search of compatibility features in item reviews, we plan to identify the words that refer to such features and to map words to feature values.

Then, we plan to use Natural Language Processing tools to extract the occurrences of such words from the bulk of reviews associated with each individual item. In this way, we can build an item profile that specifies, for each feature, the mean value emerging from the complete set of occurrences of the associated words.

Firstly, we will focus on sensory features to use them in compatibility evaluation of PoIs in relation to people with autism. For this purpose, we are investigating online review repositories providing consumer feedback about PoIs, such as Yelp [14], TripAdvisor [15], and Google Maps [16]. However, we will extend our analysis to other types of features, such as those related to physical accessibility, in order to complement the standard type of information provided by data-sources such as OpenStreetMap [17] with the perceptions of previous visitors.

We also plan to combine the extracted information with other data sources. For instance, we will consider OpenStreetMap for metadata provision and possibly crowdsourcing platforms such as Maps4All [18], which support a flexible type of geo-data mapping. In this way, we will possibly obtain richer item profiles to be used for personalized recommendation. We are aware that is hard to collect real, objective sensory features of PoIs, since the same place can be perceived differently from person to person, especially with notable differences between individuals with autism or not. However, we think that, by merging a large amount of different points of view on the same place, as provided by online reviews, we will be able to obtain an image as similar as possible to its real characteristics.

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