IRIT at TREC 2014 Contextual Suggestion Track

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Abstract. In this work, we give an overview of our participation in the TREC 2014 Contextual Suggestion Track. To address the retrieval of attraction places, we propose a fuzzy-based document combination approach for preference learning and context processing. We use the open web in our submission and make use of both criteria users preferences and geographical location criteria.

1 Introduction

TREC[3] 2014 Contextual Suggestion track examines search techniques that aim to answer complex information needs that are highly dependent on context and user interests. Roughly speaking, given a user, the track focuses on travel suggestions (e.g., attraction places, restaurants, pizzeria, etc) based on two dependent relevance criteria: (1) users' interests which consist of his personal preferences and past history; (2) his geographical location.

For the sake of addressing this challenge, we used the open web to search for relevant places according to the given contexts of the track. This track was an opportunity for us to test a previous approach on multidimensional (personalized) relevance combination [2, 3]. The aggregating operator proposed here is able to offer insight to humans about why some relevance criteria were weighted more highly than other ones and is able to personalize the majority preference regarding the IR task specificity as well as the user preferences.

The remainder of the paper is organized as follows. Section 2 describes our approach for the retrieval of contextual suggestions. In Sections 3 and 4, we describe the used data, the experimental setup and we discuss the obtained results. Section 5 concludes the paper.

2 The Contextual Retrieval Framework

We address here the contextual retrieval problem as a multi-criteria decision making (MCDM) problem. The difficulty here is to: (i) correctly identifying

[3] http://trec.nist.gov

which criterion need to be enhanced *vs.* weakened regarding both user's preference and context; and to (ii) accurately combining these criteria. We rely on the Choquet operator as an aggregation operator. This mathematical function is built on a fuzzy measure μ, defined below.
Let $I_{\mathcal{C}}$ be the set of all possible subsets of criteria from $\mathcal{C}$.

A fuzzy measure is a normalized monotone function μ from $I_{\mathcal{C}}$ to $[0\ldots1]$ such that:
$\forall I_{C_1}, I_{C_2} \in I_{\mathcal{C}}$, if $(I_{C_1} \subseteq I_{C_2})$ then $\mu(I_{C_1}) \leq \mu(I_{C_2})$, with $\mu(I_{\varnothing}) = 0$ and $\mu(I_{\mathcal{C}}) = 1$. $\mu(I_{C_i})$ will be denoted by μ_{C_i}. The value of μ_{C_1} can be interpreted as the importance degree of the interaction between the criteria involved in the subset C_1. The personalized Choquet integral based-relevance aggregation function is defined as follows:
$RSV^u_{\mathcal{C}}(q, d_j)$ is the d_j document personalized relevance score for user u *w.r.t* the set of relevance criteria $\mathcal{C} = \{c_1, c_2\}$ defined as follows:

$$\begin{aligned} RSV^u_{\mathcal{C}}(q, d_j) &= Ch_\mu(RSV^u_{c_1}(q, d_j), RSV^u_{c_2}(q, d_j)) \\ &= \sum_{i=1}^{2} \mu^u_{\{c_i,\ldots,c_N\}}.(rsv^u_{(i)j} - rsv^u_{(i-1)j}) \end{aligned} \tag{1}$$

Where Ch_μ is the Choquet function, $rsv^u_{(i)j}$ is the i^{th} element of the permutation of $RSV(q, d_j)$ on criterion c_i, such that $(0 \leq rsv^u_{(1)j} \leq \ldots \leq rsv^u_{(N)j})$, $\mu^u_{\{c_i,\ldots,c_N\}}$ is the importance degree of the set of criteria $\{c_i, \ldots, c_N\}$ for user u. In this way, we are able to automatically adjust the ranking model's parameters for each user and make results dependent on its preferences over the considered criteria. Note that if μ is an additive measure, the Choquet integral corresponds to the weighted mean.

Considering a user, the typical training data required for learning the criteria importance for each user requires a set of training queries and for each query, a list of ranked documents represented by pre-computed vectors containing performance scores; where each document is annotated with a rank label (*e.g.,* relevant or irrelevant). The general methodology is detailed in figure 1. As most of required information are not present in the TREC collection, we are based on a basic idea, which assign all users the same preferences. However, based on an analysis on the TREC 2013 Contextual Suggestion track data [3], we have found that for most contexts, the users preferences criterion is more important than localisation. Therefore, we assign importance degrees equals to 0.7 and 0.3 for both criteria respectively.

3 Data Preparation and Indexing

To fetch for the candidate suggestion places, we crawl the open web through the Google Place API[4]. As for most of the TREC Contextual Suggestion track

[4] https://developers.google.com/places

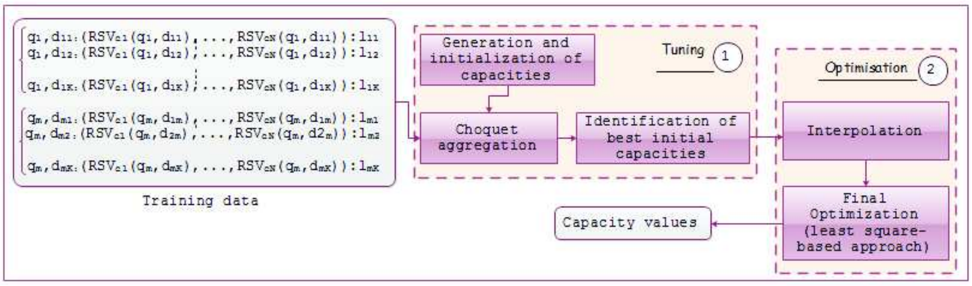

Fig. 1: General Paradigm of Training the criteria importance (users interest and location).

participants, we start by querying the Google Place API with the appropriate queries corresponding to every context based on the location. This API returns up to 60 suggestions, thus, we search again with different parameters, like place types that are relevant to the track (e.g., restaurant, cafe, museum, etc.). Beyond the type of the place, we have also give the latitude and longitude as parameters to Google places to obtain results w.r.t the searched context.
To obtain the document scores *w.r.t* the geolocalisation criterion, we compute the distance between the retrieved places and the context, whereas we exploit the cosine similarity between the candidate suggestions description and the user profile to compute the user interest score. User profiles are represented by vectors of terms constructed from his personal preferences on the example suggestions. The description of a place is the result snippet returned by the search engine Google[5] when the URL of the place is issued as a query.

4 Runs and Evaluation Results

The TREC 2014 Contextual suggestion data set which includes the following characteristics:

- **Users**: The total number of users is 115. Each user is represented by a profile reflecting his preferences for places in a list of 100 example suggestions. An example suggestion is an attraction place expected to be interesting for the user. The preferences, given on a 5-point scale, are attributed for each place description including a title, a brief narrative description and a URL website. Positive preferences are those having a relevance judgment degree of about 3 or 4 *w.r.t* the above features. Ratings of 0 and 1 on example suggestions are viewed as non relevant and those of 2 are considered as neutral.
- **Contexts and queries**: A list of 100 contexts is provided, where each context corresponds to a particular city location, described with longitude and latitude parameters. Given a pair of user and context which represents

[5] https://www.google.com

a query, the aim of the task is to provide a list of 50 ranked suggestions satisfying as much as possible the considered both relevance criteria.

- **Relevance assessments**: Relevance assessments of this task are made by both users and NIST assessors. The user corresponding to each profile, judged suggestions in the same way as examples, assigning a rating of $0-4$ for each title/description and URL, whereas NIST assessors judged suggestions in term of geographical appropriateness on a 3-point scale (2, 1 and 0). A suggestion is relevant if it has a relevance degree of about 3 or 4 $w.r.t$ user interests (profile) and a rating of about 1 or 2 for geolocalisation criterion.

In the present work, we followed the guidelines described in the TREC website [1] and we submitted only one run. Table 1 shows the retrieval performances obtained using our operator. From Table 1, we can see that the performance of our approach w.r.t the measure $P@5$ is about 0.21 whereas it is about 0.33. $P@5$ measures the number of relevant suggestions within the top-5 results for which the user preferred a document satisfying both the description and the geographical location criteria. As described in the track guidelines, the MRR score is computed as $1/k$, where k is the rank of the first relevant attraction found, while TBG uses the time for measuring effectiveness.

	Measures		
Run	**P@5**	**MRR**	**TBG**
choqrun	0.2194	0.3331	0.7252

Table 1: Retrieval effectiveness of our approach wrt the three used evaluation measures.

5 Conclusion and Future Work

We presented a novel method relying on the Choquet mathematical operator to tackle the problem of contextual suggestion using the Google place API. In future, we plan to extend the approach to take into account the types of places the users preferred in their profiles and try to apply the aggregation in this level, in order to learn the preferences for each type.

References

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