Automatic generation of human-like route descriptions: a corpus-driven approach

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Abstract—Most of Web applications combines different services, features and contents in order to enable the creation of new features and services. Such systems are called mashups. One of the most popular kind of mashups are the location ones that use geographic data to provide functionalities to users. The RotaCerta is a location system that uses the Google Maps and perform Natural Language Generation to provide textual descriptions of routes between two different locations. The great advantage of RotaCerta is the use of points of interest (POI) to describe routes. POIs help the user to understand and assimilate the route. However, RotaCerta suffers from a several limitation: the need for manually updating of a POIs dataset. Such work is exhausting, costly and greatly limits their use. Another point to highlight is the poor linguistic variability of texts it provides. In this work, we propose a mechanism to enable automatic feeding of POIs and a corpus-driven approach to enhance the linguistic variability of location mashups such as RotaCerta. We adopt both manual and automatic generation of new textual templates. In order to assess the quality of the routes descriptions, we use TF-IDF and cosine distance to calculate the similarity between descriptions of routes created by human volunteers and descriptions generated by the proposed approach. Route generation examples have been performed for three different brazilian cities. We also show that the text generated from the new template base is more similar to the texts used by people when describing routes if compared to Google Maps.

Index Terms—Mashups, Location Systems, Natural Language Generation, Points of Interests

I. INTRODUCTION

There is a wide variety of mobile devices as mobile phones, smartphones, tablets and PDAs supporting alternative communication facilities such as WiFi, 3G and GPS. Many applications make use of these technologies in order to provide new services and features. One of these services are location systems, which are used to determine a user’s position on a map and route between two geographic points. Google Maps\textsuperscript{1} is one of the most popular location system. However, the routes descriptions are far from the way people use to communicate. By providing information about location of establishments, people often make use of landmarks/reference (Points of Interest - POI) to facilitate the assimilation of the route by the concerned person. The sentence “Go on The Street Y and after passing by the Pharmacy X, turn on the right.”, for instance, seems to be more intuitive than something like “Go on The Street northbound for 500 meters and then turn right”. Coordinates and cardinal notion of distance are far more difficult for human understanding.

Some approaches in the concerned literature aim to propose the inclusion of POIs on route suggestions in order to improve the description for the user. One of these systems is the GuiaMais\textsuperscript{2}. Although it is quite similar to Google Maps in defining routes, it allows for the searching of POIs. The user provides the type of property he/she is looking for, such as pizzerias, bars, restaurants or shopping malls at a specific neighborhood, city or state. The system returns a map of the area with several POIs as requested. A great limitation of GuiaMais is that the POI information is not incorporated into the description of routes.

The system Already Talking Points \cite{1} describes an urban orientation system based on reference points. The authors advocate the idea that a walking route may be better presented with the aid of POIs. In addition to include reference points in the descriptions of routes, the system provides an vocal-enabled interface. This allows its use primarily by the visually impaired. However, the feeding of POIs should be done manually, which requires enourmous effort and limits its usage.

Another system that uses POIs on its route suggestions are proposed by \cite{2}. The author emphasizes the advantages of using POIs in the description of the routes, both to provide confirmation that the user is going in the right direction and also to facilitate the memorization of routes. The system implements an algorithm that weights references according to their characteristics in order to select the points that can be more easily identified by people. However, the basis of POIs only contains data regarding Australia.

RotaCerta \cite{3} incorporates information of POIs on route suggestions. The system has its own built-in POIs and uses techniques from Natural Language Generation (NLP) along with the Google Maps API to describe routes in a way similar to that used by people on a day-to-day. Although its interesting results, the RotaCerta

\textsuperscript{1}http://maps.google.com

\textsuperscript{2}http://www.guiamais.com.br/
suffers from problems of maintainability and updating the database of POIs. The feeding of POIs database is manually done, which considerably limits system scalability. Another limitation to highlight is the low linguistic variability of the text generated to describe the routes.

This paper extends the work of RotaCerta [3] along three different axis: (i) proposal of an automated mechanism to update the POI database, (ii) improve the NLG module in order to augment the linguistic variability of the set of pre-defined templates that constitute the description of the route and, finally, (iii) perform an assessment of the quality of the generated text. The goal is to ensure that the system can be used to generate more human-like route descriptions to any place of interest. Unlike the original work, our approach considers the integration with the Google Places system, which consists of a collaborative system for adding POIs of several countries, and a new approach to associate POI to generated routes. The approach used to enhance linguistic variability is corpus-driven. A web page was created to allow the collection of route descriptions provided by volunteers. The extraction of new templates has been performed in two different ways: (i) manually and (ii) automatically, by the adaptation of the algorithm to generating paraphrases described in [4].

The remainder of this paper is organized as follows. In Section II, we describe the background technologies used to the system development: Mashups, Natural Language Generation and Generation of Paraphrase-based data. Section III presents implementation details and highlight the differences to previous system. Performed experiments, results and discussions are shown in section IV. Finally, in Section V we conclude the work and discuss some possible extensions and future investigations.

II. TECHNOLOGICAL BACKGROUND

A. Mashups

The term Web 2.0 is commonly associated with Web applications that facilitate the sharing of information interactively such as forums, Web sites, social networks, blogs and mashups [5]. Although the concept of Web 2.0 suggest a new version of the World Wide Web, this does not refer to any change concerning technical specifications, but rather in the way that developers and end-users use the Web [6].

Originally, the term mashup was used to describe mixing or blending of two or more music tracks, commonly used by DJ’s. In the context of Web, mashups are simply a new way of developing applications by combining services, features and content already available. Such elements can be formatted as RSS feeds, XML and its derivatives, HTML, Flash or any other type of graphics.

The mapping mashups are one of the most popular forms of mashups. Its main feature is the use of maps, usually used to determine routes between two points. Based on an initial geographical reference (longitude and latitude), these systems are able to describe a route to a target location. The result of this application is typically a graphical representation of the path and textual description. Currently, 81.82% of mapping mashups make use of the Google Maps API [7]. The availability of such an API [8] can be seen as a major factor for such indices [3].

Among the services provided by Google Maps API, can be highlighted: (1) the creation of paths based on source and destination addresses using the Google Directions, (2) calculate the distance between two points, (3) information of latitude and longitude, (4) coordinates of a given address through the Reverse Geocode, and (5) detailed information of a specific point such as street name, number, city, neighborhood, zip code and country.

B. Natural Language Generation

Natural Language Generation (NLG) is a field of Artificial Intelligence that addresses computational systems able to produce understandable texts in a particular human language, starting from non-linguistic data. NLG systems use knowledge about language and the application domain to automatically produce documents, reports, and other [9].

Figure 1 gives an example of a system for generating natural language descriptions of weather events from daily meteorological records [10]. Note that from daily records of temperature and rainfall it is possible to produce textual summarization of climatic events occurred in the month.

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3http://code.google.com/apis/maps/documentation/places/
for which it is being generated, and (4) appear fluent enough to avoid a mechanical communication [11]. Another aspect that can be taken into account is the generated text format. This can be raw text or include more sophisticated formatting elements to meet specific interface requirements, HTML, VXML, LaTeX, and others.

NLG systems is usually classified into 03 (three) categories (in decreasing order of complexity): (1) use of preprogrammed responses (canned text), (2) use of standardized sentences (template) and (3) phrase-based text generation. Each of these differ by their complexity and flexibility of results [3].

The basic idea behind canned text is to associate to each possible systems response at a given context, an answer in natural language. This method is satisfactory when it provides a small number of answers. As the number of system settings increases, this technique tends to become impracticable due to the huge amount of combinatorial results [3].

NLG systems based on templates map the input data to a linguistic structure [12]. This linguistic structure may contain gaps or slots. The output result is obtained when all slots are filled or replaced by the language structures that do not have slots [13]. Suppose we want a system based on NLG templates be able to generate sentences to a train station. The description of such system can be seen in [12] and can start from a semantic representation informing that the train 306 leaves Aberdeen at 10:00 AM:

\[
\text{Departure(train}_{306}, \text{location}_{abdn}, \text{time}_{1000}),
\]

which is directly associated with a template such as:

\[
\text{[train] is leaving [town] now}
\]

The slots represented by [train] and [town] are filled by relevant information obtained from a table. This template is used only when the time said (10:00 AM) is close to the announcement message. Other templates should be used to create ads for the past or future.

Phrase-based text generation use an indirect mapping between input data and linguistic form. Such systems take as input a semantic representation of data. This is then subject of successive transformations until a linguistic structure is produced. Various system components can operate on this NLG defining, for instance, that 10:00 AM is the estimated time for the ad to be displayed and thereby transforming the input into an intermediate representation such as follows:

\[
\text{Leave}_{\text{present}}(\text{train}_{\text{demonstrative}}, \text{Aberdeen}, \text{now})
\]

It is possible to note that the lexical items were determined when the linguistic morphology was still missing. This intermediate representation, in turn, can be transformed into an appropriate sentence such as:

\[
\text{This train is leaving Aberdeen now}
\]

The details of the sentence may vary. Such systems may contain several intermediate representations.

C. Paraphrase generation based on data

The paraphrase is usually considered a way for preserving meaning. If we are dealing with a essentially linguistic textual form, then we can say that the text A and B are paraphrases of each other, if both texts A and B have the same meaning [14]. In other words, the paraphrase is an alternative way of rewriting a text in the same language, without losing the semantic content of the original text.

Paraphrases may exist at the level of words, also known as lexical paraphrase, in which the most common are synonyms, for example, (car, automobile) and (dog, puppy). The hypernym is another example of lexical paraphrase. In this case, a word is more general or specific than the other, as in the examples (shoes, boots) and (fruit, orange).

Paraphrasing is also present at the level of sentences, as in the examples (I finished my work, I finished my task). At this level, it is possible to generate paraphrases by simply replacing one or more words in the original phrase by others with the same meaning.

The concept of distributional similarity, extremely popular technique used in the generation of paraphrase, states that words or phrases that share the same distribution - the same set of words in the same context in a set of texts written in a language that serves as a database for linguistic research (corpus) tend to have similar meanings [15]. A commonly used model for calculating the similarity is the N-gram model.

The N-gram model aims to compute the probability of finding a word W given a history H, or \( P(W | H) \). Such assumption that the probability of a word depends only on the previous word is called Markov assumption [16]. Markov models are a class of probabilistic models that assume that we can calculate the probability of any future unity using only the near past. We can generalize the Bigram (which takes into account only one word history) for Trigram (which takes into account two word history) and thus for the N-gram (which takes into account N - 1 words of the history).

As an example of an N-gram model, suppose that a history H is the sentence "Please turn off your mobile" and we want to compute the probability that the next word is phone:

\[
P(\text{phone} | \text{Please turn off your mobile}).
\]

The number of parameters needed to calculate this probability increases exponentially with the number of words in the history H. For the above example we have the following N-gram models:

- Unigram: \( P(\text{phone}) \)
- Bigram: \( P(\text{phone} | \text{mobile}) \)
- Trigram: \( P(\text{phone} | \text{your mobile}) \)

The algorithm of Pasca and Dienes [17] uses as input corpus a vast collection of Web documents retrieved from Google search engine. First, all n-grams of a specific type for each sentence are computed. Next, a set of anchors (distribution) of each sentence is created and the tuple (Anchors, phrase) is then stored in a list. A count of how many anchors are shared for each pair of
sentences is also done. As in the case of distributional similarity, the greater the number of anchor phrases that are common to two candidates, the greater the likelihood that they paraphrases each other. Finally, the resulting list of paraphrases undergoes a filter in order to eliminate those that are less likely to be similar.

Lin and Pantel [4] discuss how to measure the distributional similarity through paths in dependency trees to induce generalized paraphrases templates as:

\[ X \text{ found an answer to } Y \Leftrightarrow X \text{ solves } Y \]

A dependency relationship is an asymmetric binary relation between a word called "head" and another word called "modifier". The structure of a sentence can be represented by a set of dependency relationships in a tree structure. A word in this phrase may have various modifiers but, often, each word is the modifier of just another word. The root of the dependency tree does not modify any other word. Figure 2 shows the dependency tree generated for the sentence "Mary found an answer to the problem". Arrows represent a dependency relationship between the head and the modifier whereas the name above them indicates the type of relationship found [4].

![Figure 2. Example of a Dependency Tree](image)

In a dependency tree there are two types of semantic relationship: (i) the direct and (ii) indirect. A direct relationship is represented by the arrows in the figure above (links) and the indirect relationship is represented by a path that connects two words. This path is defined by concatenating dependency relationships with the words found throughout these, excluding the ends. For the sentence of figure 2, the path between words "Mary" and "problem" is represented as follows:

\[ N:\text{sujeito}\rightarrow V:\text{encontrou} \rightarrow O:\text{objeto}\rightarrow N:\text{resposta} \rightarrow N:\text{para}\rightarrow N, \]

which means "X found an answer to Y". The words at the extremities of the phrase are called slots that are filled with path context. For example, the slots X and Y of the template extracted from the path above could be filled with the words "Mary" and "problem", respectively.

Hypothetically, if two paths connecting the same set of words they tend to be similar. Lin and Pantel [4] extend the distributional hypothesis; if two paths tend to occur in similar contexts, thus their meanings tend to be similar. In order to compute the similarity of the extended distributional hypothesis, it is necessary to compute the frequencies of all paths within the corpus and the words that fill their slots. For each instance of a path \( P \) which connects two words \( W_1 \) and \( W_2 \), the frequency counter is incremented for both triples \((P, SlotX, W_1)\) and \((P, SlotY, W_2)\), where \((SlotX, W_1)\) and \((SlotY, W_2)\) are called characteristics of \( P \). The more characteristics two paths divide, more similar they are. It uses a hash table to accumulate the frequency of all features for the whole set of paths extracted from the corpus. Essentially, two paths are similar if there is a large number of in common features. [4].

The relationship of mutual information between a path slot and a word that fills it can be computed by:

\[
mi(p, Slot, w) = \log \left( \frac{|p, Slot, w|}{|p, Slot|} \times \frac{|w|}{|*|} \right) \tag{1}
\]

The similarity between a pair of slots \((s_1, s_2)\) is defined as:

\[
sim(s_1, s_2) = \frac{\sum_{w \in T(p_1,s)} + Y}{\sum_{w \in T(p_2,s)} + X} \tag{2}
\]

where \(X = mi(p_1, s, w)\) and \(Y = mi(p_2, s, w)\). The similarity between a pair of paths is defined as the geometric mean of the similarities of the slots, such as:

\[
S(p_1, p_2) = \sqrt{\text{sim}(SlotX_1, SlotX_2) \times \text{sim}(SlotY_1, SlotY_2)} \tag{3}
\]

The performance of such algorithm is strongly tied to the type of the word that is associated with the root of the extracted path. For example, whereas the verbs tend to have various modifiers, nouns usually do not have more than one. However, if a word has less than two modifiers, it cannot be root for a path. As a consequence, this algorithm tends to perform better for paths whose regards verbs.

III. THE ROTA FACIL SYSTEM

RotaFacil is an extension of a location mashup system called RotaCerta [3]. The main goal is to automate the updating mechanism of POIs database and improve linguistic variability of templates. It is proposed the use of a collaborative basis of POIs and a corpus-driven approach for template generation to achieve such goals. These tasks are described in the following sections along with a detailed overview of system’s architecture.

A. System’s architecture

The system architecture consists of three modules: (1) Route Generator (GRotas), (2) Reference Generator (GRef) and (3) Text Generator (GText).

The GRotas aims to find a path that connects the origin and destination points and select points along the path so that a pre established minimum distance \( md \) is preserved. This module uses Google Directions API\(^4\).

The GRef has the following functions: (1) obtain reference points for each route point found by GRotas, (2) find addresses for these points, (3) associate the points to

\(^4\)http://code.google.com/apis/maps/documentation/directions/
of POIs extracted from Google Places.

However, using a collaborative approach leads us to an important issue: how to select the appropriate POI? We have adopted a set of constraints in order to determine if such a POI is useful or not to the route description. The first constraint consists of selecting the references according to a distance \( X \) to the point in question. This procedure eliminates remote routes that do not provide an information gain for the textual description. In our experiments, we have empirically defined \( X = 50(\text{meters}) \). Another important constraint is that only commercial or residential establishments are valid POIs; neighborhood streets, avenues and parks are not considered. Finally, references that are not at the same address of both points to which they have been attached are also disregarded.

C. Enhancing linguistic variability of templates

A Web application has been developed so to provide a pre-defined set of six different visual routes of Aracaju/SE city, Brazil. Volunteers were then asked to provide a textual description for each route, as if they were guiding someone else. These descriptions constitute the corpus of routes used in the creation of the templates. The set of POIs provided by the GRef module was available, so the volunteer could use it to enrich the textual description.

61 route descriptions have been obtained. 36 descriptions have been selected to compose the generation set. The remaining 25 descriptions have been used to evaluate the quality of route descriptions generated by the system. We have defined two different approaches to create the system’s set of templates: (1) manual definition and (2) automated generation of templates.

It is worth point out that RotaFacil works with templates and routes in Brazilian Portuguese language. Thus, examples of route descriptions and templates presented in this paper is in Portuguese language. In some sections we provide the English version of the example in order to favor reading and understanding facilities.
TABLE I.
The result for the manual generation of templates (Examples in Brazilian Portuguese Language)

<table>
<thead>
<tr>
<th>Potential Template</th>
<th>New Template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pegar esquerda e seguir até a D&amp;E</td>
<td>Pegue à esquerda e siga até o [POI]</td>
</tr>
<tr>
<td>Locação de Veículos</td>
<td></td>
</tr>
<tr>
<td>Quando você passar pelo O Blazer,</td>
<td>Quando você passar pelo [POI], entre na próxima</td>
</tr>
<tr>
<td>entra na próxima rua à direita</td>
<td>[STREET] à direita</td>
</tr>
<tr>
<td>Quando chegar no Bobs Aracaju,</td>
<td>Quando chegar no [POI], vire à esquerda na [STREET]</td>
</tr>
<tr>
<td>vira à esquerda na Av. Anízio</td>
<td></td>
</tr>
<tr>
<td>Azevedo</td>
<td></td>
</tr>
<tr>
<td>A casa dela vai estar na próxima</td>
<td>O seu destino estará na próxima rua</td>
</tr>
<tr>
<td>rua após a Seccafé, que é a R.</td>
<td>após [POI], que é a [STREET]</td>
</tr>
<tr>
<td>Cristóvão de Barros</td>
<td></td>
</tr>
<tr>
<td>Entrar na rua da Feeling, que é a</td>
<td>Entre na rua da [POI], que é a [STREET]</td>
</tr>
<tr>
<td>R. Homero Oliveira</td>
<td></td>
</tr>
</tbody>
</table>

TABLE II.
The result for the manual generation of templates (Examples in English)

<table>
<thead>
<tr>
<th>Potential Template</th>
<th>New Template</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pick up left and follows the D &amp; E</td>
<td>Pick up left and follows the [POI]</td>
</tr>
<tr>
<td>E Car Rental</td>
<td></td>
</tr>
<tr>
<td>When you go through Bob's Aracaju,</td>
<td>When you go through [POI], enter the next [STREET]</td>
</tr>
<tr>
<td>turn left on Anízio Azevedo Avenue</td>
<td>on the right</td>
</tr>
<tr>
<td>Her house will be on the next</td>
<td>Her house will be on the next street after [POI],</td>
</tr>
<tr>
<td>street after Seccafé, which is</td>
<td>which is [STREET]</td>
</tr>
<tr>
<td>Cristóvão de Barros Street</td>
<td></td>
</tr>
<tr>
<td>Enter the street where it is located</td>
<td>Enter the street where it is located [POI], which is</td>
</tr>
<tr>
<td>Feeling Shop, which is</td>
<td></td>
</tr>
<tr>
<td>Romero Oliveira Street</td>
<td></td>
</tr>
</tbody>
</table>

Algorithm 1: Lin and Pantel Algorithm Adapted

Data: List of dependency trees for the corpus (ArvDep)

Result: List of similarities between the paths found in each dependency tree

```
foreach tree ∈ ArvDep do
    Paths ← FindPath(tree)
    Remove of Paths all path with less than 3 words
end foreach

foreach p_i ∈ Paths do
    Sim ← SimilarityCalculus(p_i, p_i+1)
    if Sim > 70% then
        Similarity_{i+1} ← Sim
        Adiciona Similarity_{i+1} na SimilarityList
    end if
end foreach
Return SimilarityList
```

Given the dependency trees as input, all the paths (in-direct semantic relationships) with less than three words are removed. Next, we calculate the similarity between all remaining paths by means of Lin and Pantel methodology. Finally, for best results, just the paths with similarity values greater than 70% are considered. For results with more than three words SlotX has been removed.

In order to illustrate the application of the algorithm, let’s consider the description of the route presented in Figure 4. The first step is to extract the dependency tree of this description. For this, we use the tool proposed in [18].

![Figure 4. Route description from corpus](image)

The dependency tree is thus provided as input to the algorithm described above. Finally, a set of templates is automatically generated as shown in Figure 5. Again, we present the templates in both Brazilian Portuguese and English for clarity.

![Figure 5. Automatically extracted set of templates, using the adapted algorithm.](image)

IV. EXPERIMENTS AND RESULTS

Experiments have been divided into two parts. The first part shows how the automatic POI base updating mechanism of RotaFacil solves the huge limitation of RotaCerta’s, thus enabling the utilization of POIs for whatever intended Brazilian city in the generation of route descriptions. Different paths for three different cities in Brazil have been generated: Aracaju/SE, Belo Horizonte/MG and Porto Alegre/RS. The second part of experiments aims to evaluate the quality of the text generated by RotaFacil. At this stage we use the similarity of texts based on TF/IDF to compare the route descriptions generated by RotaFacil to the set of route descriptions provided by volunteers and stored as test set. The results of these experiments are presented below.
A. The POI collaborative dataset

City 1: Aracaju/SE

Figure 6 illustrates a route generated in the city of Aracaju/SE. The route includes the ordered streets Lagarto and Lorival Chagas. The landmarks between the points A and B represent the POIs selected for this route.

![Figure 6. Screenshot of RotaFacil system for the route in Aracaju/SE](image)

Figures 7 and 8 show the text generated by Google Maps and the RotaFacil, respectively, for the route of Figure 6. Names in italics represent the descriptions of streets and avenues, and the names in bold represent the POIs selected by the system for the route in question.

**Google Maps route description**

(Aracaju/SE)

1. Siga na direção sul na R. Lagarto em direção à Av. Barão de Maruim
2. Vire à direita na Av. Pedro Paes Azevedo
3. Continue para Av. Mariquinha Seixas Dorea
4. Faça um retorno
5. Pegue a primeira à direita em R. Lourival Chagas

![Figure 7. Google Maps route description for Aracaju/SE](image)

Note that the textual description provided by RotaFacil (Figure 8) provides a significant amount of references present in the path that allow the user to evaluate the correctness of his/her displacement at every moment.

For example, if we analyze the description number 13 of RotaFacil: "Arrive at destination that is close to **Marlange Hairdressers** in **Lorival Chagas Street**" (translated into English), it is more informative than the corresponding description in google maps (description number 5: "Take the first right in **Lorival Chagas Street**").

City 2: Belo Horizonte

Figure 9 illustrates a route in the city of Belo Horizonte/MG. The chosen path is located between Falcataes Street and Federal University of Minas Gerais, at Antonio Carlos Avenue.

![Figure 9. Screenshot of RotaFacil system for the route in Belo Horizonte/MG](image)

Again, we present both textual descriptions. In Figure 10, the text generated by Google Maps and Figure 11,
the text generated by RotaFacil with POI information highlighted in bold. Both textual descriptions are for the route shown in Figure 9.

Google Maps Route Description
(Belo Horizonte/MG)
1. Siga na direção leste na Alameda das Falcatas em direção à Alameda dos Coqueiros
2. Vire à direita na Alameda das Latâncias
3. Pegue a primeira à esquerda para pegar a Avenida Coronel José Dias Bicalho
4. Pegue a primeira à direita em Avenida Presidente Antônio Carlos

RotaFacil Route Description
(Belo Horizonte/MG)
1. Siga em direção do New Commerce TI Ltda na Alameda das Falcatas
2. Vire à direita na Alameda das Latâncias
3. Passe por Pierrot Fantasies na Avenida Coronel José Dias Bicalho
4. Continue pela Avenida Coronel José Dias Bicalho passando por Comercial Pandoro Ltda
5. Passe por Colégio Brasileiro de Medicina Estática na Rua Leopoldino dos Passos
6. Chegue no destino que fica próximo a CPEJr - Consultoria e Projetos Elétricos Júnior na Avenida Presidente Antônio Carlos

The chosen example concerns a route with much more guiding details. Google Maps description only considers the names of the avenues. However, the avenues have several points of reference that help the user to verify he/she following the right path. For example, the José de Alencar Street referenced by Google Maps in the description of number 2 (in english: "Turn left at José de Alencar Street") is described in RotaFacil with a set of reference points such as the description of number 13 (in english: "Turn on José de Alencar Street which is near of SIDI medical clinic").

B. Assessing the quality of generated text

In this section, we present the results of the evaluation of the quality of texts generated by RotaFacil using both template generation approaches: (i) automatic extraction (RotaFacil AT) and (ii) manual creation (RotaFacil MA). By hypothesis, it is assumed that the RotaFacil MA produces texts that are more similar to the corpus if compared to RotaFacil AT system which is, in turn, assumed to have greater similarity to Google Maps. In other words, the hypothesis is that the generation of routes in natural language using manually built templates is the closest to the way people usually guide other people to move between different points of a city.
The quality measurement of the RotaFacil system has been made by comparing the generated descriptions to the texts of the test set. This is done by computing the similarity between texts. For that, we have used the statistical measure Term Frequency - Inverse Document Frequency (TF-IDF). TF-IDF is a value that represents how a word is relevant for such a document in regards to a collection (corpus). This importance increases proportionally with the number of times the word appears within the document and decreases according to the frequency of the word throughout the collection [19].

TF (term frequency) corresponds to the number of times the term occurs in the document normalized according to the document size and is calculated by:

$$t_{f_{i,j}} = \frac{n_{i,j}}{\sum_{k=1}^{n} n_{k,j}}$$  \hspace{1cm} (4)

where \(n_{i,j}\) is the number of occurrences of the term \(i\) in the document \(j\) and the denominator is the number of occurrences of all terms in the document \(j\).

The IDF (Inverse Document Frequency) evaluates the importance of the term in the collection and is given by:

$$idf_{i} = \log \left( \frac{|D|}{|\{d_j : t_i \in d_j\}|} \right)$$  \hspace{1cm} (5)

where \(|D|\) is the total number of documents in the corpus and \(|\{d_j : t_i \in d_j\}|\) is the number of documents where the word \(t_i\) appears. The TF-IDF is calculated by multiplying the equations 4 and 5, such that:

$$t_{f_{i,j}} = t_{f_{i,j}} * idf_{i}$$  \hspace{1cm} (6)

Each term within a document is associated to a weight given by the value TF-IDF, computed for the whole corpus. Then, each document \(d\) is represented by a vector \(\vec{v}(d)\) of real numbers concerning the weights TF-IDF of its terms. Given two documents \(d_1\) and \(d_2\), the similarity between them is given by:

$$\text{simCos}(d_1, d_2) = \frac{\vec{v}(d_1) \cdot \vec{v}(d_2)}{|\vec{v}(d_1)| \cdot |\vec{v}(d_2)|}$$  \hspace{1cm} (7)

where \(\vec{v}(d_1)\) e \(\vec{v}(d_2)\) are the term vectors of documents \(d_1\) and \(d_2\), respectively.

We have provided 6 route descriptions using the points of origin and destination described in Table III. These routes were the same used for the generation of the corpus. Since each route has more than one description within the corpus, the texts of RotaFacil have been compared with each of these descriptions.

<table>
<thead>
<tr>
<th>Route Type</th>
<th>Source Address</th>
<th>Destination Address</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Rua Gérus</td>
<td>Rua Aquidabá</td>
</tr>
<tr>
<td>B</td>
<td>Rua Ananias de Azevedo</td>
<td>Rua Ns. Sra. das Dores</td>
</tr>
<tr>
<td>C</td>
<td>Rua Piru Paulo</td>
<td>Rua Cristóvalo de Barros</td>
</tr>
<tr>
<td>D</td>
<td>Rua Lúcio Mota</td>
<td>Rua Moro Cam Wandeley</td>
</tr>
<tr>
<td>E</td>
<td>Rua Manoel Eudes de Oliveira</td>
<td>Rua João Vitório de Matos</td>
</tr>
</tbody>
</table>

The test set consists of 6 descriptions of type A, 5 descriptions of type B, 6 descriptions of type C, 6 descriptions of type D and 2 descriptions of type E, totaling 25 route descriptions. Obviously, route descriptions have been compared within its particular type (same source and destination addresses).

Tables IV, V, and VI show the results of similarity to Google Maps, RotaFacil MA and RotaFacil AT, respectively, when compared with the descriptions of test set.

<table>
<thead>
<tr>
<th>Route Type</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.01</td>
<td>0.008</td>
<td>0.03</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
</tr>
<tr>
<td>B</td>
<td>0.10</td>
<td>0.02</td>
<td>0.05</td>
<td>0.01</td>
<td>0.05</td>
<td>-</td>
<td>0.04</td>
</tr>
<tr>
<td>C</td>
<td>0.03</td>
<td>0.08</td>
<td>0.11</td>
<td>0.16</td>
<td>0.12</td>
<td>0.01</td>
<td>0.08</td>
</tr>
<tr>
<td>D</td>
<td>0.07</td>
<td>0.16</td>
<td>0.09</td>
<td>0.10</td>
<td>0.03</td>
<td>0.12</td>
<td>0.09</td>
</tr>
<tr>
<td>E</td>
<td>0.01</td>
<td>0.03</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table VII shows the comparative result between RotaFacil MA, the RotaFacil AT and Google Maps. As seen earlier, each route type has different amounts of

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TABLE V. SIMILARITY BETWEEN ROTA FACIL MA AND THE TEST SET

<table>
<thead>
<tr>
<th>Route</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.05</td>
<td>0.13</td>
<td>0.15</td>
<td>0.08</td>
<td>0.03</td>
<td>0.17</td>
<td>0.10</td>
</tr>
<tr>
<td>B</td>
<td>0.18</td>
<td>0.08</td>
<td>0.07</td>
<td>0.02</td>
<td>0.20</td>
<td>-</td>
<td>0.11</td>
</tr>
<tr>
<td>C</td>
<td>0.08</td>
<td>0.07</td>
<td>0.10</td>
<td>0.12</td>
<td>0.06</td>
<td>0.08</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>0.59</td>
<td>0.17</td>
<td>0.11</td>
<td>0.14</td>
<td>0.12</td>
<td>0.13</td>
<td>0.13</td>
</tr>
<tr>
<td>E</td>
<td>0.02</td>
<td>0.03</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.03</td>
<td></td>
</tr>
</tbody>
</table>

TABLE VI. SIMILARITY BETWEEN ROTA FACIL AT AND THE TEST SET

<table>
<thead>
<tr>
<th>Route</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.04</td>
<td>0.07</td>
<td>0.05</td>
<td>0.10</td>
<td>0.01</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>B</td>
<td>0.14</td>
<td>0.03</td>
<td>0.10</td>
<td>0.03</td>
<td>0.20</td>
<td>-</td>
<td>0.10</td>
</tr>
<tr>
<td>C</td>
<td>0.03</td>
<td>0.04</td>
<td>0.14</td>
<td>0.13</td>
<td>0.10</td>
<td>0.10</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>0.12</td>
<td>0.19</td>
<td>0.15</td>
<td>0.16</td>
<td>0.12</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>0.08</td>
<td>0.04</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.06</td>
<td></td>
</tr>
</tbody>
</table>

In this paper, we presented the mashup location system RotaFacil. RotaFacil provides natural language descriptions of route, considering Points of Interest (POI). We detail its automated mechanism for automatic feeding of the POI database system and two different approaches for the creation of language templates from a corpus of route descriptions provided by volunteers. A first approach is to manually identify common patterns of text. The second approach is an adaptation of an algorithm for generating paraphrases and enables the automatic identification of such patterns, thus lowering human effort.

The POI base updating mechanism has proved to be effective for generating natural route descriptions regardless of region and independent from human intervention. We present examples for three different Brazilian cities.

The corpus-driven approach to provide linguistic templates in support of generation of route descriptions has shown good results. The set of templates has been improved both quantitatively and in terms of linguistic variability. The quality of generation provided by RotaFacil was evaluated by measuring the similarity of generated route descriptions with a test set containing textual descriptions of same routes provided by volunteers. Experiments have shown that both manual and automatic approaches to creation of linguistic templates, proposed in this paper, lead to generation of route descriptions much closer to the way people actually orient others and themselves in their way if compared to Google Maps.

Once the results has shown no significant difference between both approach, we conclude that the automatic approach for creating linguistic templates should be prioritized, since it considerably reduces human effort.

A known limitation is that although both mechanism for POI base updating and automatic generation of template is language independent, current version of RotaFacil cannot provide route descriptions in any language other than Portuguese. We are working to extend its template base to other languages.

A mobile version of RotaFacil which takes GPS data of user’s current location is also being considered.

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REFERENCES


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<td>413</td>
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