Improving Tag Suggestion for Places using Digital Map Data

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Abstract: Today, tagging photos and website bookmarks is widely used. Geographical data is an additional type of resource which can be tagged. Locations representing geographic information can be tagged depending on activities done there. In this paper we present an explorative study to answer the question whether geographical map data can be used to describe similarities between places. When map data can be used to identify similar places services like tag suggestion could be improved. For the study very detailed crowd-sourced map data was used. In a period of four month places were manually tagged with activities done. A measurement for finding places which are similar in the sense of tagging is also presented. To evaluate our idea, we trained three machine learning classifiers (Decision Tree, Support Vector Machine, Naive Bayes). With a precision of 73% and a recall of 65% Decision Tree performed best. Our results indicate that crowd-based map data can assist in tagging geographical resources and can improve tag suggestion services.

1 INTRODUCTION

To simplify retrieval of information resources needs to be structured. Besides static hierarchies keywords and tags can be used. This tagging process dynamically structures data. It is implemented by many applications, e.g. website bookmarking[1], photo management[2] and scholarly reference management[3].

Our work concentrates on tagging spatial data, particularly places. The idea is to facilitate tag suggestion for places. Our main application example is personal life logging. Here the user records his movement over a longer period of time. Visited places can be tagged in a ways similar to photos. We concentrate on tags for activities done at locations. Our work is not restricted to personal life logging because once tags found for locations information can be used for all geo-annotated resources, like photos, videos and texts.

With an explorative study we investigate the question whether tag suggestion for places is possible especially using map data. To define similarities between places geographic data is needed. Our general question can be translated into the question whether there is a similarity measure for places.

To find similar places we extract features from map data. Afterwards we use machine learning to find structures in places tagged equally. When a structure for equal tags can be found, a machine learning classifier will be able to separate places of different types successfully. In this case we can estimate that tag suggestion for places is possible using map data.

This paper is organized in the following way. Section 2 summarizes existing work in the field of tag suggestion and tagging of place with semantic meaning. Section 3 states more precisely which activities and places we are interested in. Data source and a similarity measure is presented in Section 4. Classification and evaluation approach is also explained in this section. An analysis of the collected tagged places is given in Section 5. Steps for data preparation, classification results and a discussion is presented in Section 6. Finally in Section 7 we draw conclusions and give an outlook.

2 RELATED WORK

This work can be categorized between two main research topics. On the one hand the aim is to tag resources and suggest tags which is a research topic in the web information retrieval area. But here mainly web resources are analyzed and no map data. On the other hand in our study activities are classified which is a topic in activity recognition.

[1] www.del.icio.us
[2] www.flikr.com
[3] www.citeulike.com

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2.1 Tag Suggestion

Research work having similar goals as we have is (Lin et al., 2010). There users annotate places in a social network scenario. The check-in behavior is used to describe places and their similarities. Places can be annotated by users. Many places are annotated but there are also many places with tags missing. For these places tags could be suggested. The work differs from ours in the way that we use map features extracted from a geographical database. Lin et al. extract only temporal features, like *maximum number of check-ins by a single visitor*. Another research work (Moxley et al., 2008) developed the SpiritTagger system. This tool suggests tags for photos while considering geographical aspects. They mined tags from Flikr and created a database of images, extracted features and geographic locations. Photos are filtered by geographic location. Only tags from similar photos nearby are suggested. In this work tags are suggested but no map data is used. They only respect geographical nearness.

A research area near to our activity is activity recognition (AR). In the field of AR activities are recognized and predicted. These activities can much differ in scale of time and space. Depending on the situation information can be presented in a proper way and more selective. Detecting moving or transportation type is done by (Ermes et al., 2008; Zheng et al., 2008; Zheng et al., 2010). These activities are of large geographical scale. We concentrate on activities in a smaller geographical area, building scale. Very similar to our work the authors of (Liao et al., 2005) want to label locations automatically. Using supervised learning a model is created with can label locations as ”AtHome”, ”AtWork”, ”Shopping”, ”DiningOut”, ”Visiting” and ”Others”. They also use some geographic evidence, e.g. is a restaurant in a certain range. The work differs to ours in the way that we are not restricted to a preset of tags.

2.2 Sematics of Place Tags

Different types of tags can be extracted when analyzing tagging behavior of users without any restriction which tags to use. The question how to tag places was examined in (Rattenbury and Naaman, 2009). The authors answer the question which type of tags can describe semantics of places. As a result of the work tag distribution has to concentrate on the geographical small region to represent a place tag. We will use this definition later one to classify tags in our study. Another work with location-based social networking services is (Lin et al., 2010). Tags used for location sharing were classified as semantic or geographic information. The geographic tags are of different scale, e.g. floor or city, and have different sub-classes. Some of these can also be found in our study. Our works differs in that we also collected activity tags.

3 DEFINITIONS

Semantics of ”places” can differ in many ways. The term can be used to describe for example a city, a country or a house. In the following we substantiate the term ”place” to make clear what kind of resources were tagged in the study. Similarly the term ”activity” can have several meanings. For a better understanding of activity tags later used we also clarify the term ”activity”.

3.1 Definition of Geographic Places

The term ”place” can be used in many different ways. There is no common definition. We will motivate our definition from the application perspective.

Aim of life logging is to document life. Visited places can be tagged with activity descriptions. Places can have different geographical scales. For example Lin et al. (Lin et al., 2010) analyzed users tagging behavior for places. They classified tags into categories ”floor/room”, ”house/building”, ”street/intersection”, ”region/neighborhood”, ”city” and ”state”. Users regard all these categories as places.

We concentrate on scale ”house/building” for several reasons. We use map data which has most information of level ”house/building” and larger scale. When looking for floor plans many malls and public buildings offer such a plan but often only in a format usable for humans and not for automatic analysis. Thus, we do not incorporate this information in our study. Furthermore, in our scenario places are not of scale ”city” or ”state” because the study took place in only one city. Scales ”street/intersection” and ”region/neighborhood” do not have clear boundaries which can be described to users.

3.2 Definition of Activities

When choosing activity tags for places a substantiation is necessary. Which activities and therefore which tags should be used? In our study we focused on activity tags and place tags. Activities can be done in different time and spatial scale. What we are not interested in are activities of transportation mode, like driving or walking (Liao et al., 2007). Our activities are limited to geographical building size dimensions.

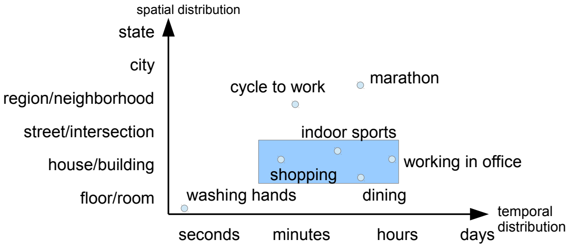

Figure 1: Space-time diagram for activity classification with examples. We are interested in activity lying inside solid area.

Figure 1 shows the category of activities we are interested in. In the figure a categorization of temporal and spatial distribution is made. We are interested in activities which lie within the solid area. These activities last from some minutes, e.g. shopping, to several hours, e.g. working. Also the spatial distribution is limited. This is directly linked to our definition of places. Activities like "cycle to work" are not in our focus because they do not take place in a building scale location. To explain which activities should be tagged scenario of life logging is used. When users do many activities in one place they have to choose for themselves how to tag this. One possibility is to tag this place with the most important activity. Another way is to tag all activities done there. The preferred habit of tagging depends on the user.

The tags in the study were explicitly not restricted on a preset of activities. This decision was also motivated by the scenario of tagging every day life and findings of (Lin et al., 2010). They discovered that every user has its own way of tagging, its own way of abstraction level and its own way of how to remember places. Our question was: What is a user tagging when there are no restrictions?

4 SIMILARITY OF PLACES

4.1 Spatial Data Source

To compute similarity between places a detailed geographical data source is needed. Such data can be found in "point of interest" (POI) databases, e.g. Yellow Pages[4] or Google Places[5]. Points of interest are locations which are of any interest. Popular examples are restaurants or gas stations. In general these databases save detailed information about object interesting for people. For example a restaurant object can have additional information about opening hours and wheelchair accessibility. Representing locations geographical is done by a latitude, longitude tuple. Boundaries of POI object are not known.

[4]www.yellowpages.com

[5]www.google.com/places/

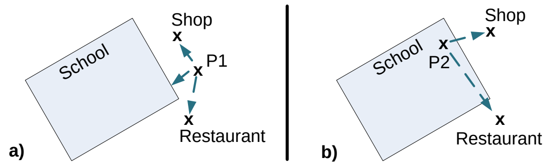

Figure 2: Distance calculated between objects. Figure a) shows that distance from place $P1$ to *School* border. In b) $P2$ has distance 0 for *School* because it lies within.

Our approach is to use hybrid maps. These maps contain information about POIs and additionally geographical information like building outlines. One examples of this category is OpenStreetMap (OSM). The database of OSM enables POIs to be represented by centroid and also as geographical polygon. One effect of such a grassroot approach is that details on the map vary much depending on the region. In large cities many people contribute and thus create very detailed map information whereas in less populated areas only a few information is available.

4.2 Similarity Measure

Similarity of places needs to be calculated for later tag suggestion. With machine learning, classifiers try to find similarities between places. A place is described by its surrounding area. Figure 2 describes two examples. The description includes a list of nearby objects and their distance to the current place. In Figure 2 places $P1$ and $P2$ can be described with their distances to the objects $(Shop, Restaurant, School)$. In Figure 2 a) the distance from $P1$ to *School* is the shortest path between polygon and point. In 2 b) the distance between $P2$ and *School* is 0. Possible distance vectors for $P1$ and $P2$ are:

$$\begin{pmatrix} Shop \\ Restaurant \\ School \end{pmatrix} P1 = \begin{pmatrix} 10 \\ 13 \\ 11 \end{pmatrix} P2 = \begin{pmatrix} 15 \\ 35 \\ 0 \end{pmatrix}$$

Working with polygons has advantages when working with large buildings and large areas in general, e.g. shopping mall or zoo. As distance measure we use euclidean distance. All geographical objects within a radius of 100 meters where considered to characterize a place.

4.3 Classification & Evaluation

The data we are working with are tagged places. Tag suggestion can be evaluated when user tag resources and the system suggests new tags. Afterwards the number of suggested tags and the number of accepted tags is compared. An ideal tag suggestion algorithm suggests tags which are all accepted by the user. Dealing with classifiers these tags are true positives (TP). Tags not accepted by users are false positives (FP). Tags not suggested but manually added by users are called false negatives (FN). Tags of category true negatives (TN) are not suggested and not assigned.

For every tag one classifier is trained. In general there is no best classifier. It always depends on the data. We learned three different classifiers (Decision Tree, Naive Bayes, Support Vector Machine), and compared their performance. We used LinearForwardSelection algorithm (Gutlein et al., 2009) for feature selection.

5 DATASET

For our study moving data had to be collected, places extracted and annotated. In a four month period one person collected movement data using an external GPS receiver (Columbus V900). At the end of each day the user had to extract places from movement data and annotate these. The user had to tag with life logging scenario in mind. Our aim was to analyze which tags for activities were done at which locations. We made no further restrictions on deciding which places to extract. This lack of conceptual clarity was intended. We wanted to know which type of places and activities the user would choose and what level of granularity makes sense for the user. At the end of the study a dataset of 90 different tags and 157 places were created.

Evaluating tagged places it was interesting to see that the user tagged some places with place descriptions or meanings but not with the actual activity he did. One prominent example is the tag *home*. At this location the user decided not to describe activities for this location but generalizing these with a place name. Another finding was that activity tags often occurred in addition to place description tags. For example *shopping* as activity tag and *bakery* as place description or *supermarket*.

A plot showing tags and their usage can be found in Figure 3. The graphic shows how often tags were used. The x and y-axes are in logarithmic scale. The data shows a typical power-law distribution seen in many other applications (Capocci and Caldarelli, 2008) using tags.

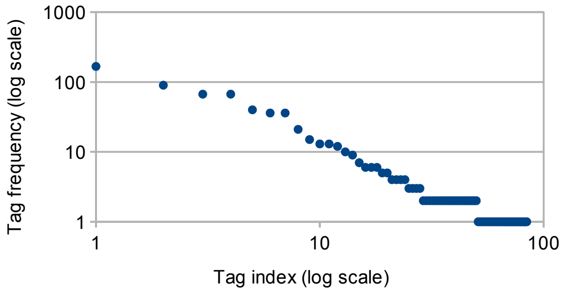

Figure 3: Tag frequency: power-law distribution.

6 EVALUATION

In the following we present steps to prepare classification followed by results of classification task and a discussion.

6.1 Preparation

Before classification data needs to be prepared. We need to train classifiers using training sets and test the created models using testing sets. For this 10-fold cross-validation was used.

We build one classifier for each tag. Tags only used at one place, e.g. *home*, cannot be learned by our classifiers. Learning these tags would result in an unbalanced dataset with one *home* place and 156 *other* places. Many classifiers have problems with unbalanced data (Chawla, 2010). To solve this oversampling or undersampling can be used. Oversampling items which were tagged only less would result in duplicated items and therefore results in over-fitting. We used undersampling (Chawla et al., 2002). The disadvantage is that potentially useful items are ignored. But this is a small disadvantage compared to disadvantages of oversampling.

6.2 Classification

If a tag is used many times for the same location we count it only once because over-fitting would influence our classification results. Preparing classification process Feature Selection was done. This reduces the amount of all features (233) to the relevant ones.

Overall 157 tags were used. Only six of them occurred in more than six different places. These can be used for classification as explained in Section 6.1. Classifiers were trained and evaluated for each tag. In Figure 4 precision and recall of different classifiers are presented. In average the Decision Tree (DT) classifier performs best with precision of 0.73 and recall of 0.65. The second best classifier Naive Bayes

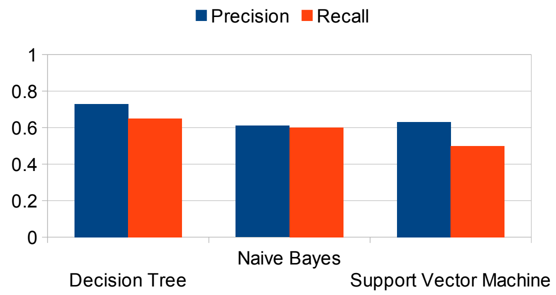

Figure 4: Performance of different classifiers.

(NB) suggested tags with a precision of 0.61 in average and a recall of 0.60. Finally Support Vector Machine (SVM) performs slightly worse with a precision of 0.63 and recall of 0.50. For further details we concentrate on DT because this classifier performed best. For classification and evaluation WEKA data mining software was used.

In Figure 5 precision and recall values of the six classified tags are presented. These tags could be classified best. Precision represents how exact the suggested tags were. In the ideal case precision is 1 which means that all the regarding tags were suggested for places where it was used by the user. The value 0 means it was not suggested or it was suggested on places where the user did not used it. High recall values express that most of the users tagged places were also tagged using the learned classifier. If the classifier suggests too little places for a tag recall value will be low. As Figure 5 shows some tags could be suggested very good. This suggests that map features can assist in tagging. Features used to classify these tags can be learned by classifiers. A structure in geographic data could be found in similar tagged places.

6.3 Discussion

In the four month period 90 different tags were used to annotate activities in places. Not only activity tags were used but also tags describing places. Place tags were used to substantiate activities and in situations where a short activity tag was not usable, e.g. *home*. Only a small part of it, were used in more than six different places. Models learned for each tag can classify half of the tags better than 50% regarding precision and recall. What does it mean for the scenario of tagging places in personal life logs? Our results indicate that detailed map data can assist in creating tag suggestions and therefore help tagging places in personal life logs. It also shows that activities done in many locations can be recognized and used for automatic tagging. Tag suggestion for places is not restricted to life log scenario. It can also be used in applications

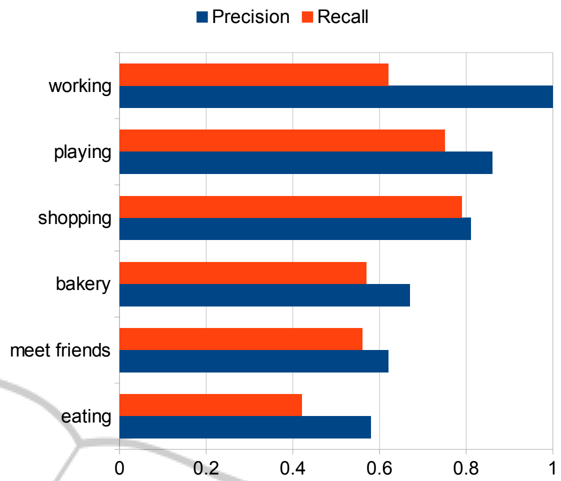

Figure 5: Precision and recall of classified tags using Decision Tree.

when resources have an geographic position associated. For geo-referenced images tags could also be created.

Regarding life logging scenario we only evaluated tags used in different places. Methods to suggest tags for locations often visited but only in one location was not focused in this work. Research on those tags and activities, e.g. *home*, is already done by others, e.g. (Liao et al., 2005). Here algorithms taking time into consideration are more successful.

One shortcoming of our work is that only one person took part in the study. Therefore this work is an explorative study. It is planned to repeat the analysis with a wider range of people.

7 CONCLUSIONS & OUTLOOK

Tags can be used to organize resources, like images and bookmarks. A tag suggestion mechanism can assist in the process and ensure the use of the same words for same facts. Geographical locations can be tagged with activities done there.

We studied tagging behavior of one person in a period of four month in a life logging scenario. The used tags can be classified as tags describing activities and tags describing places. On the one hand place tags were used because they implied activities and on the other hand to refine activity descriptions. To evaluate the possibility of tag suggestion we created different classifiers for each tag. Decision Tree produced the best results with an average precision of 73% and recall of 65%. These results suggest that detailed map data, like OpenStreetMap, should be considered when creating tag suggestions for geographical resources. This can also be used for geographical annotated images and texts.

We plan to repeat the study with more people in different regions. The influence of detailed map data depending on the region has to be evaluated. We also plan to incorporate suggestions for activities which were only done in one place using time-dependent models.

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