Automatically Georeferencing Textual Documents

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Abstract

Most documents can be said to be related to some form of geographic context and the development of computational methods for processing geospatial information, as embedded into natural language descriptions, is a cardinal issue for multiple disciplines. In the context of my M.Sc. thesis, I empirically evaluated automated techniques, based on a hierarchical representation for the Earth's surface and leveraging linear classifiers, for assigning geospatial coordinates of latitude and longitude to previously unseen documents, using only the raw text as input evidence. Noting that humans may rely on a variety of linguistic constructs to communicate geospatial information, I attempted to measure the extent to which different types (i.e., place names versus other textual terms) and/or sources of textual content (i.e., curated sources like Wikipedia, versus general Web contents) can influence the results obtained by automated document geocoding methods. The obtained results confirm that general textual terms, besides place names, can also be highly geo-indicative. Moreover, text from general Web sources can be used to increase the performance of models based on curated text. The best performing models obtained state-of-the-art results, corresponding to an average prediction error of 88 Kilometers, and a median error of just 8 Kilometers, in the case of experiments with English documents and when leveraging Wikipedia contents together with data from hypertext anchors and their surrounding contexts. In experiments with German, Spanish and Portuguese documents, for which I had significantly less data taken only from Wikipedia, the same method obtains average prediction errors of 62, 166 and 105 Kilometers, respectively, and median prediction errors of 5, 13, or 21 Kilometers.

Keywords: Document Geocoding , Natural Language Processing , Hierarchical Text Classification , Processing Geospatial Language , Geo-Indicativeness of Textual Contents

Resumo

A maioria dos documentos estão relacionados de alguma forma com um contexto geográfico, sendo o desenvolvimento de métodos computacionais para processar informação geoespacial, proveniente de discursos de linguagem natural, uma tarefa fundamental para várias áreas científicas. No contexto da minha tese de mestrado, avaliei empiricamente, técnicas automáticas, baseadas numa representação hierárquica da superfície terrestre, para atribuir coordenadas de latitude e longitude a documentos, usando apenas o seu texto. Sabendo que os seres humanos podem utilizar uma variedade de construções linguísticas para comunicar informação geoespacial, eu tentei medir até que ponto diferentes tipos (i.e., nomes de locais ou outros termos textuais) e/ou diferentes fontes de conteúdo textual (i.e., fontes como a Wikipédia ou conteúdos gerais da Web), podem influenciar os resultados obtidos pelos métodos automáticos de geocodificação. Os resultados obtidos confirmam que termos textuais comuns, para além de nomes de locais, também podem ser altamente geo-indicativos. Para além disso, texto de fontes gerais da Web pode ser usado para melhorar os resultados obtidos por métodos de geocodificação automática dos documentos da Wikipédia. Obtiveram-se resultados de acordo com o estado-da-arte da geocoficação de documentos da Wikipédia, nomeadamente um erro médio de 88 Kilómetros e um erro mediano de 8 Kilómetros, para o caso das experiências da Wikipédia Inglesa, juntamente com o texto de âncoras hipertextuais e o seu contexto envolvente. Relativamente às experiências com os documentos da Wikipédia Alemã, Espanhola e Portuguesa, para os quais existem menos dados, retirados apenas da Wikipédia, o mesmo método obteve erros médios de 62, 166 e 105 Kilómetros, respetivamente, e erros medianos de 5, 13 e 21 Kilómetros.

Keywords: Geocodificação de Documentos , Processamento de Linguagem Natural , Classificação Textual Hierárquica , Processamento de Linguagem Geoespacial , Geo-Indicatividade de Conteúdos Textuais

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Chapter 1

Introduction

Most documents, from different application domains, can be said to be related to some form of geographic context. In the recent years, given the increasing volumes of unstructured information being published online, we have witnessed an increased interest in applying computational methods to better extract geographic information from heterogeneous and unstructured data, including textual documents. Geographical Information Retrieval (GIR) has indeed captured the attention of many different researchers that work in fields related to language processing and to the retrieval and mining of relevant information from large document collections. Much work has, for instance, been done on extracting facts and relations about named entities. This includes studies focused on the extraction and normalization of named places from text, using different types of natural language processing techniques (DeLozier *et al.*, 2015; Roberts *et al.*, 2010; Santos *et al.*, 2014; Speriosu & Baldridge, 2013), studies focusing on the extraction of locative expressions beyond named places (Liu *et al.*, 2014; Wallgrün *et al.*, 2014), studies focusing on the extraction of qualitative spatial relations between places from natural language descriptions (Khan *et al.*, 2013; Wallgrün *et al.*, 2014), or studies focusing on the extraction of spatial semantics from natural language descriptions (Kordjamshidi *et al.*, 2011, 2013).

Computational models for understanding geospatial language are a cardinal issue in multiple disciplines, and they can provide critical support for multiple applications. The task of resolving individual place references in textual documents has specifically been addressed in several previous studies, with the aim of supporting subsequent GIR processing tasks, such as document retrieval or the production of cartographic visualizations from textual documents (Lieberman & Samet, 2011; Mehler *et al.*, 2006). However, place reference resolution presents several non-trivial challenges (Amitay *et al.*, 2004), due to the inherent ambiguity of natural language discourse (e.g., place names often have other non geographic meanings, different places are often

referred to by the same name, and the same places are often referred to by different names). Moreover, there are many vocabulary terms, besides place names, that can frequently appear in the context of documents related to specific geographic areas. People may, for instance, refer to vernacular names (e.g., *The Alps* or *Southern Europe*) or vague feature types (e.g.,*downtown*) which do not have clear administrative borders, and several other types of natural language expressions can indeed be geo-indicative, even without making explicit use of place names (Adams & Janowicz, 2012; Adams & McKenzie, 2013). A phrase like *dense traffic in the streets as people rush to their jobs in downtown's high-rise buildings* most likely refers to a large city, while the phrase *walking barefoot in the grass and watching the birds splash in the water* is rather associated with a natural park. Instead of trying to resolve the individual place references that are made in textual documents, it may be interesting to instead study methods for assigning entire documents to geospatial locations (Wing & Baldridge, 2011).

1.1 Thesis Proposal and Validation Plan

In the context of my M.Sc. thesis, relying on recent technical developments in the problem of document geocoding (Melo & Martins, 2015; Wing & Baldridge, 2014), I propose to evaluate automated techniques for assigning geospatial coordinates of latitude and longitude to previously unseen textual documents, using only the raw text of the documents as input evidence. Noting that humans may rely on a variety of linguistic constructs to communicate geospatial information, one can perhaps measure to which extent different types (i.e., place names versus other textual terms) and/or sources of textual content (i.e., curated sources like Wikipedia, versus general Web contents) can influence the results obtained by automated document geocoding methods. I also proposed to measure the effectiveness of the proposed document geocoding method on two Twitter datasets, namely a dataset distributed over the Globe, and a dataset only containing tweets from the United States.

The general document geocoding methodology, proposed in the context of this thesis, relies on a hierarchy of linear models (i.e., classifiers based on support vector machines or logistic regression) together with a discrete hierarchical representation for the Earth's surface, known in the literature as the HEALPix approach. The bins at each level of this hierarchical representation, corresponding to equally-distributed curvilinear and quadrilateral areas of the Earth's surface, are initially associated to textual contents (i.e., all the documents from a training set that are known to refer to particular geospatial coordinates are used and, each area of the Earth's representation is associated with the corresponding texts). For each level in the hierarchy, linear classification models are built using the textual data, relying on a bag-of-words representation, and using

the quadrilateral areas as the target classes. New documents are then assigned to the most likely quadrilateral area, through the usage of the classifiers inferred from training data. Finally documents are assigned to their respective coordinates of latitude and longitude, with basis on the centroid coordinates from the quadrilateral areas.

The main research hypothesis behind this work was that it is possible to achieve state-of-the-art results in the task of georeferencing textual documents, by using a carefully tuned hierarchical classifier.

Experiments with different collections of Wikipedia articles, containing documents written in English, German, Spanish or Portuguese, were performed in order to access the performance of the proposed geocoding methods. I also attempted to quantify the geoindicativeness of words that are not place names. To execute this experiment, the words that are considered to be part of place names were removed through Named Entity Recognition (NER) methods, and the remaining contents were used for training the document geocoding classifiers. The obtained results show that reasonably good results can still be achieved, thus supporting the idea that general textual terms can also be highly geo-indicative. The best performing methods leveraged the full textual contents, obtaining an average prediction error of 82 Kilometers, and a median prediction error of just 8 Kilometers, in the case of documents from the English Wikipedia collection. For the German, Spanish and Portuguese Wikipedia collections, which are significantly smaller, the same method obtained an average prediction error of 62, 166 or 105 Kilometers, respectively, and a median error of 5, 13 or 21 Kilometers. These results are slightly superior to those reported in previous studies by other authors (Wing & Baldridge, 2011, 2014), although the datasets used in our experiments may also be slightly different, despite with a similar origin. After removing place names, the median prediction errors increased to 28, 5, 21 and 37 Kilometers, respectively in the English, German, Spanish and Portuguese Wikipedia collections. Regarding the Twitter datasets, the best results for the WORLD dataset correspond to a mean of 1496 and a median of 497 Kilometers, while a mean of 732 and a median of 234 Kilometers were achieved for the US dataset.

In a second set of experiments, the focus was put on the English language and in the possibility of including different sources of textual contents to improve the document geocoding task. We specifically considered different sources as either a complement or as a replacement to the contents from the English Wikipedia, namely: (a) phrases from hypertext anchors, collected from the Web as a whole and pointing to geo-referenced pages in the English Wikipedia, and (b) phrases from the hypertext anchors together with other words appearing in the surrounding context. The obtained results show that text from general Web pages can be used to complement contents

from Wikipedia, although the performance drops significantly when using these contents in isolation. The best performing model combined the Wikipedia contents with text from hypertext anchors and words from the surrounding contexts, achieving a median error of 88 Kilometers and an average error of 8 Kilometers.

1.2 Contributions

The research made in the context of this thesis has produced the following main contributions:

- State-of-the-art results in the task of document geocoding were achieved, through the use of Hierarchical Equal Area isoLatitude Pixelization (HEALPix) scheme to divide the Earth's surface in subregions, together with a hierarchical classifier based on linear Support Vector Machines.

- Even after removing place names from the Wikipedia contents, good results are still achieved in the document geocoding task, which indicates that even common works may be highly geoindicative.

- Part of the research reported in this dissertation has been accepted for presentation at the 17th EPIA, an international conference on artificial intelligence in Portugal.

The main novel aspects that were introduced in the context of my research are as follows:

- Testing the application of the HEALPix scheme, which produces equal-area discretizations for the surface of the Earth, in the task of document geocoding;

- Testing the use of a greedy hierarchical procedure, relying on support vector machine classifiers, in the task of document geocoding;

- Experimented with datasets in multiple languages (i.e., English, Spanish, Portuguese and German) and from multiple domains (i.e., Wikipedia and Twitter) to evaluate the performance of the proposed document geocoding method. Some of these experiments also involved extended datasets that considered Web anchor text in order to replace or the complement geo-referenced data from Wikipedia.

1.3 Document Organization

The rest of this document is organized as follows: Chapter 2 describes the fundamental concepts involved in (i) representing text for computational analysis, (ii)document classification, and (iii) geospatial data analysis. The chapter ends with the description of studies that have previously addressed the problem of georeferencing textual contents . Chapter 3 details the contributions of this thesis, namely (i) the use of the HEALPix scheme in order to discretize the Earth's surface, and (ii) the application of hierarchical classification in the document geocoding task. Finally, Chapters 4 and 5 present the experimental evaluation and the summary of the obtained results, together with possible paths for future work.

Chapter 2

Concepts and Related Work

This chapter presents the fundamental concepts and the most important related work, in order to facilitate the understanding of my thesis proposal.

2.1 Concepts

This section presents the main concepts required to fully understand the proposed work, namely text representations for supporting computational analysis, document classification methods, and elementary notions from the geographical information sciences.

2.1.1 Representing Text for Computational Analysis

In this section I will describe some of the most common approaches in order to represent text for computational analysis, namely (i) Bag-of-Words, (ii) The Vector Space Model, and (iii) Other Approaches For Representing Text

2.1.1.1 Bag-of-Words

Most studies concerned with the analysis of textual contents use the bag-of-words (BoW) representation model (Maron & Kuhns, 1960), where the semantics of each document are only captured through the words that it contains. In order to represent a document using the BoW method, one is first required to split a document into its constituent words. This process is called tokenization.

One simple way of tokenizing text is to split a document by the white-space characters (i.e., spaces, new lines, and tabs). However, this procedure may result in representations that may not be the best for several tasks (e.g, this will not capture multi-word expressions such as *Los Angeles*). Other tokenization approaches are instead based on n-grams of characters or of words, considering to some extent the order of the words.

Using a BoW representation, there are several ways to measure the similarity between pairs of documents. One such way involves using the Jaccard similarity coefficient. Given two documents A and B, (i.e., given two sets of representative elements such as words or n-grams), we have that the Jaccard similarity is given by:

$$\text{Jaccard}(A, B) = \frac{|A \cap B|}{|A \cup B|} \text{ and thus } \ 0 \leq \text{Jaccard}(A, B) \leq 1 \tag{2.1}$$

2.1.1.2 The Vector Space Model

A related representation to the BoW method is the Vector Space Model (Salton *et al.*, 1975). Given a vocabulary $T = t_1, t_2, ..., t_n$ with all the representative elements that exist, in a given document collection, a document A can be represented as a vector $d_A =< w_{t1}, w_{t2}, ..., w_{t_n} >$. The components w_{t_n} represent the weight of element t_n for document A. These weights w_{t_n} can be as simple as the frequency with which an element occurs in the document. However, this simple weighting approach may give high scores for terms that exist in almost every document, or low scores to rare terms, i.e., the weights are given by looking only at a specific document, discarding the rest of the documents in a collection, from the computation.

One weighting scheme that attempts to give weights according to the term's rarity in the corpus of documents is the term frequency $\times$ inverse document frequency procedure (TF-IDF) (Salton & Buckley, 1988), that calculates the importance of a term t in a document d, contained in the corpus of documents D.

TF-IDF is perhaps the most popular term weighting scheme, combining the individual frequency for each element i in the document j (i.e, the Term Frequency component or TF), with the inverse frequency of element i in the entire collection of documents (i.e., the Inverse Document Frequency). The TF-IDF weight of an element i for a document j is given by the following formula:

$$\text{TF–IDF}_{i,j} = \log_2(1 + \text{TF}_{i,j}) \times \log_2\left(\frac{N}{n_i}\right) \tag{2.2}$$

In the formula, N is the total number of documents in the collection, and n_i is the number of

documents containing the element i.

In the vector space representation, to find the similarity between pairs of documents, d_A and d_B, one simple approach involves computing the cosine of the angle θ formed between the vectors d_A and d_B, given by the formula:

$$\cos(\theta) = \frac{d_A \cdot d_B}{\|d_A\|\|d_B\|} = \frac{d_{A1}d_{B1} + d_{A2}d_{B2} + ... + d_{An}d_{Bn}}{\sqrt{\sum_{i=1}^{n} {d_{Ai}}^2}\sqrt{\sum_{i=1}^{n} {d_{Bi}}^2}} \tag{2.3}$$

2.1.1.3 Other Approaches For Representing Text

Besides the aforementioned approaches based on a bag-of-words, there are other models that use a bag-of-concepts (BoC) (Sahlgren & Cöster, 2004) approach, in which the intuition is that that a document can be represented as a distribution over topics, where each topic is a distribution over a vocabulary.

Latent Dirichlet Allocation (LDA) is a generative probabilistic model that uses the previous notion of BoC, where each document exhibits multiple topics, and thus can be represented as a distribution of those topics (Blei *et al.*, 2003). Imagine a topic such as Computer Science. This topic would have high probability for words such as *computer*, *software* or *program* and low probability for words that are not associated with Computer Science.

A relatively new approach, also corresponding to a BoC model, is the Concise Semantic Analysis (CSA) method, that was proven to achieve good results in terms of accuracy and computational efficiency, when compared with popular alternatives (Li *et al.*, 2011).

Besides LDA and CSA, many other approaches have also been introduced in the recent literature focusing on building document representations. For instance Srivastava *et al.* (2013) introduced a deep learning method, namely a type of Deep Boltzmann Machine, that is suitable for extracting distributed semantic representations from a large unstructured collection of documents, and that was shown to extract features that outperform other common approaches, such as LDA. Criminisi *et al.* (2011) instead proposed approaches based on ensembles of decision trees for learning effective data representations. In the experiments reported in this dissertation, I have only used the BoW approach for representing documents, although other alternatives can be considered for future work.

Besides the aforementioned cosine similarity metric, one other method that can be used to measure the similarity between pairs of documents, represented as vectors that encode probability distributions (e.g., over latent topics) is the Kullback–Leibler divergence. The Kullback–Leibler (KL) divergence measures the distance between two probability distributions, and the smaller the

result, the more similar the distributions are. Given two distributions P and Q, the symmetric Kullback-Leibler divergence is equal to:

$$\mathrm{symKL}(P,Q) = \frac{\mathrm{KL}(P||Q) + \mathrm{KL}(Q||P)}{2}, \quad \text{with} \quad \mathrm{KL}(\mathrm{X}||\mathrm{Y}) = \sum_i \log\left(\frac{\mathrm{X}(i)}{\mathrm{Y}(i)}\right) X(i) \tag{2.4}$$

In the previous formulas $\mathrm{X}(i)$ and $\mathrm{Y}(i)$ are the proportions for the topic i in document representations X and Y, respectively.

2.1.2 Document Classification

Document classification, also known as document categorization, is the task of automatically assigning classes or categories to textual documents. In this section I will describe some of the most commonly used classifiers such as: (i) Naive Bayes Classifier, (ii) Discriminative Linear Classifiers, and (iii) Nearest Neighbor Classifiers

2.1.2.1 Naive Bayes Classifier

Naive Bayes is a simple classifier based on the Bayes theorem (McCallum & Nigam, 1998). The probability of a document d_k, assuming a vocabulary V_{d_k} for the collection of documents, being generated by a class c_i, is computed as:

$$\mathrm{P}(c_i|d_k) \propto \mathrm{P}(c_i) \prod_{w_j \in V_{d_k}} \mathrm{P}(w_j|c_i) \tag{2.5}$$

Document classification according to the Naive Bayes, method can be made by finding the most probable class $\hat{c}$, for a document d_k, expressed in the following equation:

$$\hat{c} = \mathrm{argmax}_{c_i \in G} \mathrm{P}(c_i) \prod_{w_j \in V_{d_k}} \mathrm{P}(w_j|c_i) \tag{2.6}$$

In the previous formula, G represents the set of possible classes. The naive Bayes classifier is called naive because it assumes independence over the features, e.g., in the previous equation it is assumed that the probability of a word w_j appearing in document d_k does not depend on the other words of the document. We know that in a given text, the probability of a word is dependent on the previous words, e.g. due to syntactic rules. However, despite the naive assumptions, Naive Bayes Classifiers are known to perform well on several different tasks.

2.1.2.2 Discriminative Linear Classifiers

Besides Naive Bayes, we also have that linear discriminative classifiers are commonly used in document classification applications. Support Vector Machines (SVMs) are one of the most popular approaches for learning the parameters of linear classifiers from training data. Given n training instances $\mathbf{x}_i \in \mathbb{R}^k$, $i = 1, \ldots, n$, in two classes $y_i \in \{1, -1\}$, SVMs are trained by solving the following optimization problem under the constraints $y_i(\mathbf{w} \cdot \mathbf{x_i} - w_0) \geq 1 - \xi_i$, $\forall 1 \leq i \leq n$, and $\xi_i \geq 0$:

$$\arg \min_{\mathbf{w}, \xi, w_0} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_{i=1}^{n} \xi_i \right\} \tag{2.7}$$

In the formula, the parameters ξ_i are non-negative slack variables which measure the degree of misclassification of the data $\mathbf{x}_i$, and $C > 0$ is a regularization term.

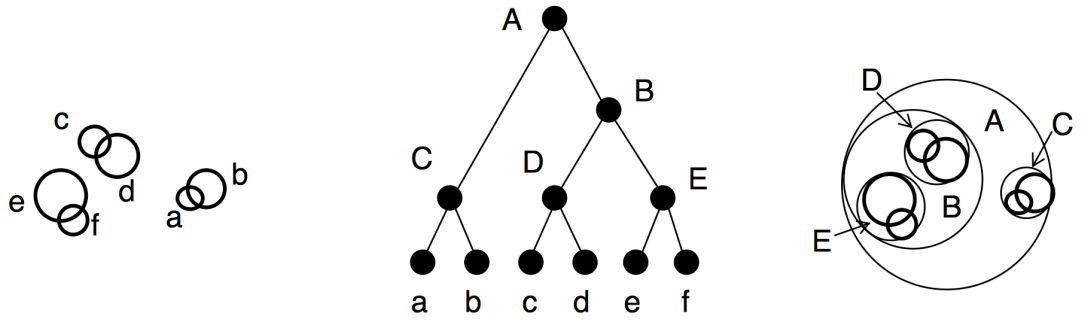
Multi-class classification can also be handled through the procedure above, by first converting the problem into a set of binary tasks through the one-versus-all scheme (i.e., use a set of binary classifiers in which each class is fitted against all the other classes, and finally assigning the class $\hat{y}(\mathbf{x})$ with the highest value from $w_0^y + \sum_{i=1}^{k} w_i^y x_i$).

Logistic regression is an alternative linear classification approach, that can also handle multi-class classification through the one-versus-all scheme. In brief, logistic regression models use the predictor variables to determine a probability, that is a logistic function of a linear combination of them (i.e., logistic regression provides estimates of a-posteriori probability for the class memberships, as opposed to SVMs which are more geometrically motivated and focus on finding a particular optimal separating hyperplane, by maximizing the margin between points closest to the classification boundary). Logistic regression models can be trained by solving an optimization problem that is very similar to that of SVMs, instead considering a loss function that is derived from a probabilistic model:

$$\arg \min_{\mathbf{w}, w_0} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_{i=1}^{n} \log(1 + e^{-y_i(\mathbf{w} \cdot \mathbf{x}_i - w_0)}) \right\} \tag{2.8}$$

Previous studies have argued that SVMs often lead to smaller generalization errors (Caruana & Niculescu-Mizil, 2006), particularly in the case of high-dimensional datasets, but both types of models should nonetheless be compared, as their performances change depending on the task.

Figure 2.1: A metric ball tree, built from a set of balls in the plane. The middle part illustrates the binary tree built from the balls on the left, while the right part of the figure illustrates how space is partitioned with the resulting ball tree.



2.1.2.3 Nearest Neighbor Classifiers

Another frequently used classifier is the k-nn method, that simply consists in finding the document's K nearest neighbours, and then assigning the class with basis on a majority vote. One efficient way of discovering the top-k most similar documents, involves the use of a geometric data structure commonly referred to as the metric ball tree (Omohundro, 1989; Uhlmann, 1991). A ball tree is essentially a binary tree in which every node defines a m-dimensional hypersphere, containing a subset of the instances to be searched. Each internal node of the tree partitions the data points into two disjoint sets which are associated with different hyperspheres. While the hyperspheres themselves may intersect, each point is assigned to one particular hypersphere in the partition, according to its Euclidean distance towards the hypersphere's center. Each node in the tree defines the smallest ball that contains all data points in its subtree. This gives rise to the useful property that, for a given test instance d_i, the Euclidean distance to any point in a hypersphere h in the tree is greater than or equal to the Euclidean distance from d_i to the hypersphere. Figure 2.1, adapted from a figure given in the technical report by Omohundro (1989), shows an example of a two-dimensional ball tree.

The search algorithm for answering k nearest neighbor queries can exploit the distance property of the ball tree, so that if the algorithm is searching the data structure with a test point d_i, and it has already seen some point d_p that is closest to d_i among the points that have been encountered so far, then any subtree whose ball is further from d_i than d_p can be ignored for the rest of the search. Specifically, the nearest-neighbor algorithm can examine nodes in depth-first order, starting at the root. During the search, the algorithm maintains a max-first priority queue Q with the k nearest points encountered so far. At each node h, the algorithm may perform one of following three operations, before finally returning an updated version of the priority queue:

- If the Euclidean distance from the test point d_i to the current node h is greater than the furthest point in Q, ignore h and return Q.
- If h is a leaf node, scan through every point enumerated in h and update the nearest-neighbor queue appropriately. Return the updated queue.
- If h is an internal node, call the algorithm recursively on h's two children, searching the child whose center is closer to d_i first. Return the queue after each of these calls has updated it in turn.

A metric ball tree is usually built offline and top-down, by recursively splitting the data points into two sets. Splits are chosen along the single dimension with the greatest spread of points, with the sets partitioned by the median value of all points along that dimension. A detailed description of the ball tree data structure is given by Omohundro (1989).

2.1.3 Geospatial Data Analysis

This section explains fundamental concepts from the geographic information sciences, related to (i) representing locations over the surface of the Earth, (ii) measuring distances, (iii) discretizing geospatial information and (iv) interpolating geospatial information.

2.1.3.1 Geographic Coordinate Systems and Measuring Distances

Geographic coordinate systems allow us to describe a specific location over the surface of the Earth, as a set of unambiguous identifiers. One of the most common methods to represent a specific location is the use of geographic coordinates of latitude and longitude.

The latitude of a geospatial location (i.e., point) is measured as the angle between an horizontal plane that passes in the equator, and the normal of that geospatial point to an ellipsoid that is an approximation of the shape of the Earth. The latitude varies between -90°, that represents a point in the south pole, to 90°, that corresponds to a point in the north pole.

The longitude of a geographic location (i.e., point) is the angle between a reference meridian (e.g., the Greenwich Meridian), and the meridian of that specific point (i.e., the plane that separates the Earth into two equal semi-ellipsoids and passes through the specific point we are refering). This angle varies between -180°, that correspond to a point in the most extreme West, to 180°, representing points in the most extreme East.

Given two locations represented by their pair of coordinates of latitude and longitude in degrees

(ϕ_1 , λ_1) and (ϕ_2 , λ_2), it is not trivial to calculate an accurate distance between these locations, due to the Earth's curvature.

One approach that calculates the geospatial distance between two points, by approximating the Earth's surface with the surface of a sphere, is the great-circle distance procedure. The first step of this method is to find the central subtended angle $\Delta\sigma$, that is the angle formed between the two lines that link each location to the center of the Earth, given by the formula:

$$\Delta\sigma = \arccos\Big(\sin(\phi_1)\sin(\phi_2) + \cos(\phi_1)\cos(\phi_2)cos(|\lambda_2 - \lambda_1|)\Big) \tag{2.9}$$

After calculating the central subtended angle in degrees, by using the previous formula, the distance between the two locations can be estimated by converting this angle to radians, and multiplying the angle by the radius of the Earth r, i.e. :

$$\text{distance} = \Delta\sigma \times r \times \frac{\pi}{180} \tag{2.10}$$

As the Earth is not exactly a sphere, its radius varies, being slightly smaller at the poles and larger at the equator. For this previous method, it is common to choose the mean Earth radius, that is approximately equal to 6371 km.

Another method to estimate the distance between two coordinates, considering that the Earth can be approximated to an oblate spheroid (i.e., a rotationally symmetric ellipsoid, whose polar axis is smaller than the diameter of its equatorial circle) is Vincenty's inverse method (Vincenty, 1975). In this method we have that a is the length of the semi-major axis of the ellipsoid (i.e., the radius at equator); f is the flattening of the ellipsoid; $b = (1-f)a$ is the length of the semi-minor axis of the ellipsoid (i.e., radius at the poles); $U_1 = \arctan((1-f)\tan(\phi_1))$ and $U_2 = \arctan((1-f)\tan(\phi_2))$ are the reduced latitude (i.e. the latitude on the auxiliary sphere); α is the azimuth at the equator and σ is the arc length between points on the auxiliary sphere. The first step of this algorithm is to calculate U_1 and U_2, and setting $\lambda = \lambda_2 - \lambda_1$, followed by iteratively applying the following equations until λ converges:

$$\sin(\sigma) = \sqrt{(\cos(U_2)\sin(\lambda))^2 + (\cos(U_1)\sin(U_2) - \sin(U_1)\cos(U_2)\cos(\lambda))^2} \tag{2.11}$$

$$\cos(\sigma) = \sin(U_1)\sin(U_2) + \cos(U_1)\cos(U_2)cos(\lambda) \tag{2.12}$$

$$\sigma = \arctan\left(\frac{\sin(\sigma)}{\cos(\sigma)}\right) \tag{2.13}$$

$$\sin(\alpha) = \frac{\cos(U_1)\cos(U_2)\sin(\lambda)}{\sin(\sigma)} \tag{2.14}$$

$$\cos^2(\alpha) = 1 - \sin^2(\alpha) \tag{2.15}$$

$$\cos(2\sigma_m) = \cos(\sigma) - \frac{2\sin(U_1)\sin(U_2)}{\cos^2(\alpha)} \tag{2.16}$$

$$C = \frac{f}{16}\cos^2(\alpha)[4 + f(4 - 3\cos^2(\alpha))] \tag{2.17}$$

$$\lambda = L + (1 - C)f\sin(\alpha)\left(\sigma + C\sin(\sigma)\left(\cos(2\sigma_m) + C\cos(\sigma)(-1 + 2cos^2(2\sigma_m))\right)\right) \tag{2.18}$$

We iterate λ until it converges to our desired degree of accuracy, and then evaluate the following equations:

$$u^2 = cos^2(\alpha)\frac{a^2 - b^2}{b^2} \tag{2.19}$$

$$A = 1 + \frac{u^2}{16384}\left(4096 + u^2\left(-768 + u^2\left(320 - 175u^2\right)\right)\right) \tag{2.20}$$

$$B = \frac{u^2}{1024}\left(256 + u^2\left(-128 + u^2\left(74 - 47u^2\right)\right)\right) \tag{2.21}$$

$$\Delta\sigma = B\sin(\sigma)\left(\cos(2\sigma_m) + \tfrac{1}{4}B\left(\cos(\alpha)(-1 + 2\cos^2(2\sigma_m)) - \tfrac{1}{6}B\cos(2\sigma_m)(-3 + 4\sin^2(\sigma))(-3 + 4\cos^2(2\sigma_m))\right)\right) \tag{2.22}$$

Finally the distance between the two locations is given by:

$$\text{distance} = bA(\sigma - \Delta\sigma) \tag{2.23}$$

2.1.3.2 Calculating the Geographic Midpoint of a Point Set

The geographic midpoint is a method of summarizing information from a set of geospatial coordinates, into a single geospatial location, that corresponds to the point that has the minimum distance to all the original geospatial points. One practical application for the use of a weighted geographic midpoint is in the domain of georeferencing, when there are several possible locations, with different probabilities (i.e. different weights), for an object we are trying to locate.

In this subsection, a simple algorithm to find the geographic weighted midpoint between geospatial coordinates of n locations will be presented, following the description originally provided by (Jeness, 2008).

Given several specific locations represented by their geospatial coordinates of latitude (lat) and longitude (lon), in degrees, and given a weight that represents the importance of each location w_i, the first step when calculating the geographic midpoint between those locations is to convert each of the geospatial coordinates from degrees to Cartesian coordinates. One is first required to convert the coordinates from degrees to radians, which is done by simply multiplying each latitude and longitude coordinate by $\frac{\pi}{180}$. Finally, the Cartesian coordinates are calculated according to:

$$x_i = \cos(lat_i) \times \cos(lon_i) \quad y_i = \cos(lat_i) \times \sin(lon_i) \quad z_i = \sin(lat_i) \tag{2.24}$$

In the previous formula, lat_i and lon_i are the latitude and longitude coordinates for each point i, in radians.

The Cartesian coordinates for the midpoint of the geospatial coordinates that were provided as input, are simply a weighted average of each geospatial point's Cartesian coordinates:

$$x = \frac{(x_1 \times w_1) + (x_2 \times w_2) + ... + (x_n \times w_n)}{w_1 + w_2 + ... + w_n} \tag{2.25}$$

The previous formula shows how to calculate the Cartesian x coordinate for the geospatial midpoint, and the same logic applies for the y and z coordinates.

The final step is the conversion from Cartesian coordinates to latitude and longitude coordinates in degrees, which is done by the following formulas:

$$lat = \mathrm{atan2}(z, \sqrt{x \times x + y \times y}) \times 180 \tag{2.26}$$

$$lon = \mathrm{atan2}(y, x) \times 180 \tag{2.27}$$

In the previous formulas, $\mathrm{atan2}$ is the arctangent function with two arguments.

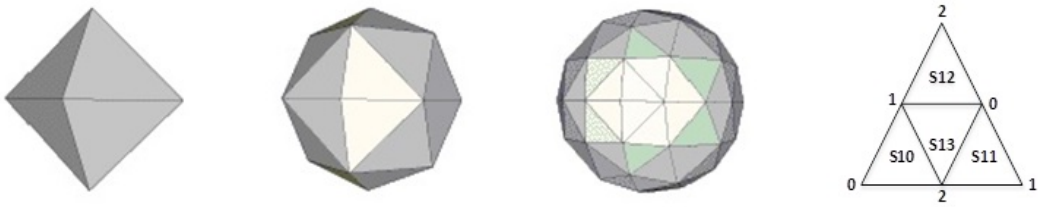


Figure 2.2: The hierarchical triangular decomposition of a sphere associated to the HRM approach.

2.1.3.3 Hierarchical Tessellations for the Earth's surface

In geocoding tasks, it is common to discretize the Earth's surface into several bounded regions. For instance, the Hierarchical Triangular Mesh (HTM) is a multi-level recursive approach to decompose the Earth's surface into triangles with almost equal shapes and sizes (Szalay *et al.*, 2005), while the Hierarchical Equal Area isolatitude Pixelization (HEALPix) is instead based on quadrilateral regions (Górski *et al.*, 2005).

The HTM offers a convenient approach for indexing data georeferenced to specific points on the surface of the Earth, having been used in previous studies focusing on document geocoding (Dias *et al.*, 2012). The method starts with an octahedron, as one can see on the left of Figure 2.2, that has eight spherical triangles, four on the northern hemisphere and four on the southern hemisphere, resulting from the projection of the edges of the octahedron onto a spherical approximation for the Earth's surface. These eight spherical triangles are called the level 0 trixels.

Each extra level of decomposition divides each of the trixels into 4 new ones, thus creating smaller regions. This decomposition is done by adding vertices to the midpoints on each of the previous level trixels, and then creating great circle arc segments to connect these new vertices in each trixel, as one can see in the right part of Figure 2.2. The right part of Figure 2.2 shows an HTM decomposition resulting from dividing the original 8 spherical triangles two times. The total number of trixels n, for the level of resolution k, is given by $n = 8 \times 4^k$.

2.1.3.4 Kernel Density Estimation and Interpolating Spatial Data

A fundamental problem in the analysis of data pertaining to georeferenced samples is that of estimating, with basis on the observed data, the underlying distribution of the samples (i.e., the underlying probability density function). Kernel Density Estimation (KDE) can be seen as a generalization of histogram-based density estimation, which uses a kernel function at each point,

instead of relying on a grid. More formally, the Kernel density estimate for a point (x, y) is given by the following equation (Carlos *et al.*, 2010):

$$\mathrm{f}(x, y) = \frac{1}{nh^2} \sum_{i=1}^{n} \mathrm{K}\left(\frac{d_i}{h}\right) \tag{2.28}$$

In the formula, d_i is the geospatial distance between the occurrence i and the coordinates (x, y), and n is the total number of occurrences. The bandwidth is given by the parameter h, that controls the maximum area in which an occurrence has influence. It is very important to choose a correct h value, because if it is too low, the values will be undersmoothed. The opposite happens when h is too high, resulting in values that will be oversmoothed, since each point will affect a large area. Finally, $\mathrm{K}(.)$ is the kernel function, that integrates to one and controls how the density diminishes with the increase of the distance to the target location. A commonly used kernel is the Gaussian function:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{\frac{-u^2}{2}} \tag{2.29}$$

2.2 Related Work

This section presents the most important previous work that focused in the task of georeferencing textual documents, describing methods that range from simply discretizing the Earth's surface using a grid, estimating a language model for each cell, and finding the most probable cell to each previously unseen document, to more advanced techniques that create clusters in order to keep regions with approximately the same sizes, or that rely on discriminative classifiers.

2.2.1 Early Proposals

This section details two seminal works addressing the problem of document geocoding, namely (i) the GIPSY system described by Woodruff & Plaunt (1994) and (ii) the Web-a-where system described by Amitay *et al.* (2004).

Woodruff & Plaunt (1994) developed the Geo-referenced Information Processing System (GIPSY), as a prototype retrieval service integrating document geocoding functionalities for handling documents related to the region of California. Document geocoding relied on an auxiliary dataset containing a subset of US Geological Survey's Geographic Names Information System (GNIS) database, that contains geospatial point coordinates of latitude and longitude for over 60,000 geographic place names in California. Each possible location for a given place name is associated

with a probabilistic weight that depends on (1) the geographic terms extracted, (2) the position within the document and the frequency of these terms, (3) knowledge of the geographic objects and their attributes on the database, and (4) spatial reasoning about the geographic regions of the object (e.g. *south California*).

GIPSY's document geocoding algorithm can be divided into 3 main steps. Step (i) is a parsing stage, where the document's relevant keywords and phrases are extracted. Terms that are related with geospatial locations in the auxiliary dataset are collected, along with lexical constructs containing spatial information such as *adjacent* or *neighbouring*. In step (ii), in order to obtain the geographic coordinate data, the system uses spatial datasets that have information such as the locations of cities, states, names and locations of endangered species, bioregional characteristics of climate regions, etc. The system identifies the spatial locations that are the most similar with the geographic terms retrieved from step (i). This method also looks for synonym relations (e.g. the latin and the common name of a specie); membership relations (e.g. when we do not have geospatial information about a given subspecie but there is information on a hierarchically superior specie of that subspecie); and geographic reasoning (e.g. *south of California*).

After extracting all the possible locations for all the place names or phrases in a given document, the final step overlays polygons in order to estimate approximate locations. Every combination of place name or phrase, probabilistic weight and geospatial coordinates, is represented as a three dimensional polygon with base on the plane formed by the x, z axes, and that is elevated upward on the y axis according to its weight. Each of the polygons for a given document is added one by one to a skyline that starts empty. When adding a polygon there are three possible scenarios: (i) the polygon to add does not intersect any of the other polygons, and is mapped to $y = 0$ (see Figure 2.3); (ii) the polygon to add is contained in a polygon that has already been added, and its base is positioned in a higher plane (see Figure 2.4); and (iii) the polygon to add intersects, but it is not fully contained by one or more polygons, and the polygon to add is split. The portion that does not intersect any polygon is laid at $y = 0$, and the portions that intersect polygons are put on top of the existing polygons they intersect (Figure 2.5).

When all the polygons for a given document are added to the skyline, one can estimate the geospatial region that best fits a document for example by calculating a weighted average of the regions that have higher elevation in the skyline generated for the document, or for example by assuming the document is located in the higher region of the skyline.

In another seminal publication for this area, Amitay *et al.* (2004) described the Web-a-Where system for associating a geographic region with a given web page. A hierarchical gazetteer was used in this work, dividing the world into continents, countries, states (for some countries only) and cities. The gazetteer contained a total of 40,000 unique places, and a total of 75,000 names

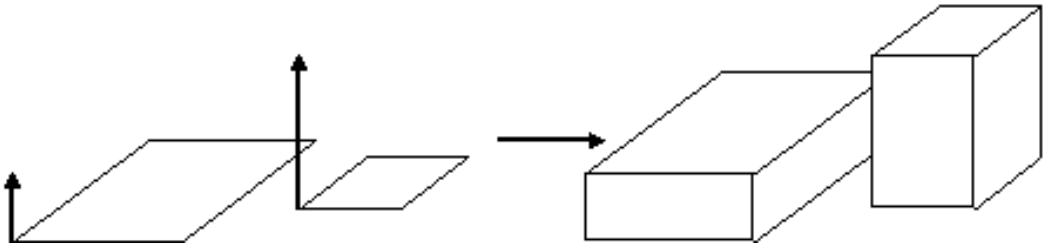


Figure 2.3: Illustration for the case when two polygons do not intersect each other.

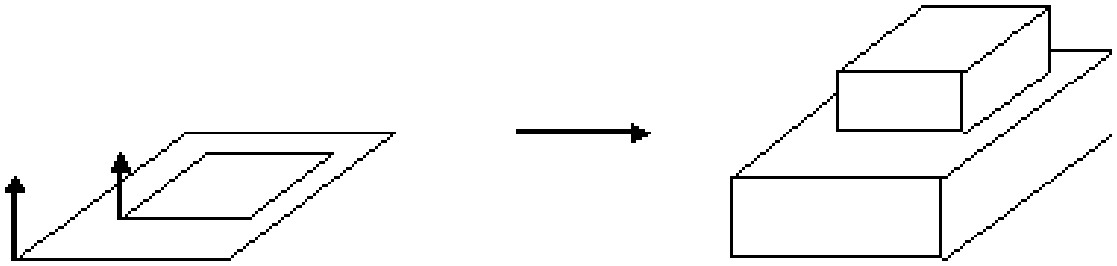


Figure 2.4: Illustration for the case when one polygon is contained in another polygon.

for those unique places, which include different spellings and abbreviations. The geocoding algorithm has 3 main steps, namely (i) spotting, (ii) disambiguation and (iii) focus determination.

On the first step, the goal is to find all the possible locations mentioned in a given web page. There are some terms that are extracted in this early step and that do not correspond to places, so a disambiguation step is needed.

There are two possible ambiguities: geo/geo (for example *London*, England and *London*, Ontario), and geo/non-geo (e.g, as *London* in *Jack London*, which should be considered part of a name). In order to disambiguate possible place names, the surrounding words are analyzed. If a surrounding word is the country, or the state of a place name, a high confidence level is assigned

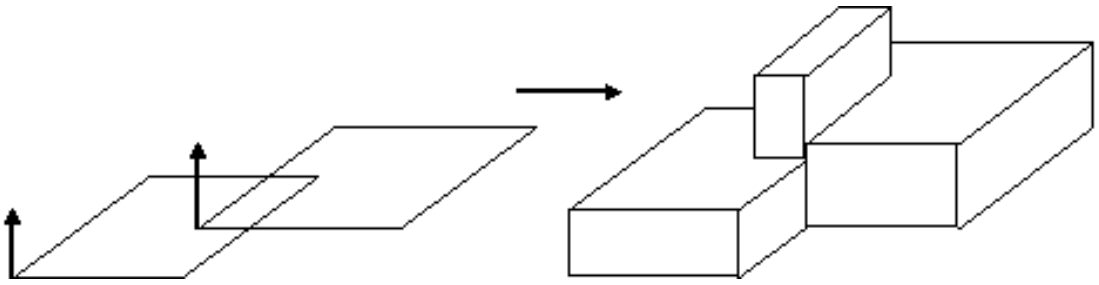


Figure 2.5: Illustration for the case when a polygon partially intersects other polygons.

to that place name. Each spot that is unresolved is assigned a low confidence and is associated with the geographical place with the highest population. When there is already a resolved place name and there are other unresolved occurrences of the same place name, the unresolved place names are assigned the same geographic region of the resolved place name with a middle value for the confidence between. Finally, the algorithm attempts to discover the location of unresolved place names (i.e., those that have a low confidence) through the context. For instance if we have *Hamilton* and *London* , one can infer that the most probable location is *Ontario, Canada*, because it is the only place that has both Hamilton and London as descending cities. In this case the confidence level is increased.

The final step of the geocoding algorithm is to find the focus, i.e. the region that is mostly mentioned in the document (e.g. a page mentioning *San Francisco (California) and San Diego (California)* has the focus as the taxonomy node *California*| *United States* | *North America*, whereas a document mentioning *Italy, Portugal, Greece and Germany* has the focus as the taxonomy node *Europe*). The focus algorithm attempts to be as specific as possible. For instance, if the document mentions several times *Lisbon*, and no other cities, nor countries, nor continents, the focus will be the taxonomy node *Lisbon*| *Portugal* | *Europe* , rather than *Portugal* | *Europe*, or *Europe* that although correct are not that specific as the first taxonomy node.

The authors used a dataset from the Open Directory Project (ODP) that has almost one million English pages with a geographic focus. The Web-a-Where system predicted the country that was the focus of each of these articles with an accuracy of 92%, and a 38% accuracy was measured for the correct prediction of the city that was the focus of each of these articles.

2.2.2 Language Modeling Approaches

Several previous document geocoding methods are instead based on language modelling approaches (Dias *et al.*, 2012; Roller *et al.*, 2012; Wing & Baldridge, 2011). A language modelling approach uses training data in order to estimate the parameters of a model that is able to assign a probability to a previously unseen sequence of words. A language model is thus a generative model, defining a probabilistic mechanism for generating language. One of the most popular language-modeling techniques is the n-gram model, which relies on a Markov assumption in which the probability of a given word at the ith position, can be approximated to depend only on the k previous words, instead of depending on all of the previous words, i.e.:

$$\mathrm{P}(w_i|w_1 w_2 ... w_{i-1}) \approx \mathrm{P}(w_i|w_{i-k} ... w_{i-1}) \tag{2.30}$$

The simplest n-gram model is based on unigrams, where the k of the previous equation is equal to 0, and where the probability of a sequence of words is approximated to the multiplication of the probabilities of each word based on the training data, i.e.:

$$P(w_1 w_2 ... w_n) \approx \prod_i \mathrm{P}(w_i) = \frac{\mathrm{count}(w_i)}{\text{number of tokens}} \tag{2.31}$$

A more sophisticated approach, is the bigram language model, where the probability of a word depends on the previous one, i.e.:

$$\mathrm{P}(w_i|w_1 w_2 ... w_{i-1}) \approx \mathrm{P}(w_i|w_{i-1}) = \frac{\mathrm{count}(w_{i-1}, w_i)}{\mathrm{count}(w_{i-1})} \tag{2.32}$$

According to the previous equation, one estimates the probability of a word by dividing the total number of times word i follows word i-1 by the total number of times word i-1 appears. The same approach can be extended to take into account the last 2 words (the trigram model), the last 3 words (the 4-gram model), etc.

In the previous equation the probability of a word given its previous words is 0 if the event of the word w_{i-1} does not follow the word w_i, which may be due to the effect of statistical variability of the training data. Some sort of smoothing, i.e. adding a small probability to unseen events, is thus required in order to build effective models. One simple method is the Laplace (add-one) smoothing where, as the name suggests, we simply add one to the numerator of the probability of a given word, and add the size of the vocabulary V to the denominator (i.e., unseen events instead of having a probability of 0 will now have a probability of $\frac{1}{V}$. The probability of observing the word w_i in a bigram model, after Laplace add one smoothing is given by:

$$\mathrm{P}(w_i|w_{i-1}) = \frac{\mathrm{count}(w_{i-1}, w_i) + 1}{\mathrm{count}(w_{i-1}) + V} \tag{2.33}$$

The same smoothing procedure can be generalized to an n-gram model, given by the following equation:

$$\mathrm{P}(w_i|w_{i-1} ... w_{i-n+1}) = \frac{\mathrm{count}(w_{i-n+1} ... w_{i-1} w_i) + 1}{\mathrm{count}(w_{i-n+1} ... w_{i-1}) + V} \tag{2.34}$$

In the above equation $\mathrm{count}(w_{i-n+1} ... w_{i-1} w_i)$ is the total of times word w_i is preceded by the sequence of the previous $n-1$ words (i.e., $w_{i-n+1} ... w_{i-2} w_{i-1}$), and $\mathrm{count}(w_{i-n+1} ... w_{i-1})$ is the number of times the sequence of this previous $n-1$ words occurs.

Wing & Baldridge (2011) have for instance investigated the usage of language modelling methods for automatic document geolocation. The authors started by applying a regular geodesic grid,

with the same latitude and longitude (e.g. 1° by 1°), to divide the Earth's surface into discrete rectangular cells. Each of these cells is associated with a *cell-document*, that is a concatenation of all the training documents that are located within the cell's region. The cells that do not contain any training documents are discarded.

The unsmoothed probability of observing the word j in the cell c_i is given by:

$$\tilde{\mathrm{P}}(w_j|c_i) = \frac{\sum\limits_{d_k \in c_i} \mathrm{count}(w_j, d_k)}{\sum\limits_{d_k \in c_i} \sum\limits_{w_l \in V} \mathrm{count}(w_l, d_k)} \tag{2.35}$$

In the previous equation, the unsmoothed probability of observing the word j in the cell c_i is simply calculated by the division of the total number of times word w_j appears in all documents contained in cell c_i, by the total of words from the complete vocabulary V that appear in cell c_i.

An equivalent distribution $\tilde{\mathrm{P}}(w_j|d_k)$ exists for each test document d_k, corresponding to the unsmoothed probability of observing word w_j on document d_k:

$$\tilde{\mathrm{P}}(w_j|d_k) = \frac{\mathrm{count}(w_j, d_k)}{\sum\limits_{w_l \in V} \mathrm{count}(w_l, d_k)} \tag{2.36}$$

In the above equation, the probability of an unseen event (i.e., word w_j not occurring on document d_k) is 0. If we use Naive Bayes as a classifier to evaluate the probability of document d_k having generated another document that contains the word w_j, the probability of the classifier would be 0, simply because document d_k does not contain the word w_j, which may occur frequently in cases where documents are typically short compared to a large vocabulary. The authors solved the previous issue, by applying a smoothing procedure that reserves a small probability for unseen events. The smoothed probability for the word j in document d_k, contained in D, the set of all documents, is given by:

$$\mathrm{P}(w_j|d_k) = \begin{cases} \alpha_{d_k} \frac{\mathrm{P}(w_j|D)}{1 - \sum\limits_{w_l \in d_k} \mathrm{P}(w_l|D)} & \text{if } \tilde{\mathrm{P}}(w_j|d_k) = 0 \\ (1 - \alpha_{d_k}) \tilde{\mathrm{P}}_{(w_j|d_k)} & \text{otherwise} \end{cases} \quad \text{where} \quad \alpha_{d_k} = \frac{|w_j \in V s.t. \mathrm{count}(w_j, d_k) = 1|}{\sum\limits_{w_j \in V} \mathrm{count}(w_j, d_k)} \tag{2.37}$$

In the previous equations α_{d_k} is the probability mass for unseen words, that is equal to the probability of observing a word only once in document d_k, motivated by Good-Turing smoothing. Analogous procedures were applied to the smoothed cell distributions.

The geolocation algorithm attempts to find the *cell-document* that is the most similar with each

of the test documents. Three different supervised methods were applied in order to find the most similar cell for each test document, namely (i) Kullback-Leibler divergence, (ii) Naive Bayes, and (iii) average cell probability.

The Kullback-Leibler (KL) divergence measures how well a distribution encodes another one, and the smaller the value, the closer both distributions are. Each cell c_i has a distribution that represents the probabilities of observing each of the words of the vocabulary, and we can thus find the cell $\hat{c}$ in the grid G, whose distribution best encodes the test document's distribution, given by:

$$\hat{c} = \text{argmin}_{c_i \in G} \sum_{w_j \in V_{d_k}} \text{P}(w_j|d_k) \log \left(\frac{\text{P}(w_j|d_k)}{\text{P}(w_j|c_i)} \right) \tag{2.38}$$

In the above equation, w_j is a word from the vocabulary V_{d_k} of document d_k. In this previous equation, instead of using the vocabulary for all the existent words, the authors included only the vocabulary of a document d_k, because their experiments have proven that the same result is achieved in both situations.

As for Naive Bayes it is a simple generative model, based on unigrams, that assumes that the probability of each word in the document d_k does not depend on the previous ones. The cell $\hat{c}$ with higher probability is, in this case, given by the equation:

$$\text{argmax}_{c_i \in G} \frac{\text{P}(c_i)\text{P}(d_k|c_i)}{\text{P}(d_k)} \tag{2.39}$$

Note that in the previous formula, $\text{P}(d_k)$ is the same for every cell c_i in the grid G, and since the objective is to find the most probable cell, we can remove the denominator of the equation. The probability of document d_k being located in cell c_i is thus calculated by multiplying the probabilities of a cell c_i for each word in document d_k:

$$\hat{c} = \text{argmax}_{c_i \in G} \text{P}(c_i) \prod_{w_j \in V_{d_k}} \text{P}(w_j|c_i)^{\text{count}(w_j, d_k)} \tag{2.40}$$

In the previous equation $\text{P}(w_j|c_i)^{\text{count}(w_j, d_k)}$ is the probability for the word w_j in cell c_i to the power of the total number of times word w_j appears in the contents of document d_k. The authors calculated the probability of the cell c_i (i.e., $\text{P}(c_i)$) as being equal to the number of documents in cell c_i, divided by the total number of documents in the corpus.

Finally, the method based on the average cell probability is given by:

$$\hat{c} = \text{argmax}_{c_i \in G} \sum_{w_j \in V d_k} \text{count}(w_j, d_k) \frac{\text{P}(w_j|c_i)}{\sum_{c_i \in G} \text{P}(w_j|c_i)} \tag{2.41}$$

In the formula $\text{count}(w_j, d_k)$ is the total number of times word w_j appears in the contents of document d_k.

After choosing the most probable cell by one of these methods, the authors assigned to each test document d_k the coordinates of the midpoint of that most probable cell. A prediction error can finally be calculated using the great-circle distance between the predicted location and the actual location of the document in the original dataset.

Wing and Baldridge used two different datasets to compare the proposed methods, namely a full dump of the English version of Wikipedia, from September 2010, and a collection of geotagged tweets collected by Eisenstein et. al. (2010), from the 48 states of the continental USA. Regarding the Wikipedia articles, they were split 80/10/10 into training, development and testing sets, whereas in the collection of tweets, the division of training, development and testing sets was already provided in the data by Eisenstein et. al. (2010). The best results were obtained using the Kullback-Leibler divergence approach, with Naive Bayes as a close second. For the Wikipedia dataset, the best results corresponded to a mean error of 221 km and a median error of just 11.8 km. Regarding the Twitter dataset, the authors report on a mean error of 892.0 km and a median error of 479 km, as the best results that were obtained.

In subsequent work by the same team, Roller *et al.* (2012) reported on two improvements to the previously described method.

The first improvement relates to the use of k-d-trees to construct an adaptive grid (Bentley, 1975). This method deals better with sparsity, producing variable-sized cells that have roughly the same number of documents in them. In order to find the most probable cell for a given document, the authors again used the Kullback-Leibler divergence, given that this was the method that had the most promising results in the previous study.

The second improvement relates to the use of a different measure to choose the location of a cell. Instead of assigning, to the test document, the coordinates of the midpoint of the most probable cell, the authors assigned the centroid coordinates of the training documents in that cell.

The authors used three different datasets in this second study, namely the two datasets described in the previous article, and a third one consisting of 38 million of Tweets located inside North America . Roller *et al.* (2012) improved on the results of Wing & Baldridge (2011), reducing the mean error from 221 km to 181 km and the median error from 11.8 km to 11.0 km, by using k-d trees instead of uniform grids, and using centroid coordinates instead of the midpoint of the

most probable cell. The mean error was further reduced to 176 km, in an approach combining uniform grids with k-d trees, that used, as training data, the cell-documents produced by applying an uniform grid, together with the cell-documents produced by applying a k-d tree. Regarding the Twitter dataset, the best results were obtained using only the k-d trees, and these correspond to a mean error of 860 km and a median error of 463 km.

Dias *et al.* (2012) also evaluated several techniques for automatically geocoding textual documents (i.e., for assigning textual contents to the corresponding latitude and longitude coordinates), based on language model classifiers, and using only the text of the documents as input evidence. Experiments were made using georeferenced Wikipedia articles written in English, Spanish and Portuguese.

These authors used the Hierarchical Triangular Mesh (HTM) method, a multi-level recursive approach to decompose the Earth's surface into triangles with almost equal shapes and sizes (Szalay *et al.*, 2005) to partition the geographic space.

In the experiments made by Dias et al., the resolution that was used in the HTM approach varied from 4 to 10, i.e. from 2048 to 8388608 trixels, that will be associated to language models capable of capturing the most likely regions for a given document.

The documents were first divided into a training set and test sets. The authors then represented the documents through either n-grams of characters or of terms (i.e., using 8-grams of characters or word bi-grams). In what regards the language models based on n-grams of characters, there are essentially generative models based on the chain rule, smoothed by linear interpolation with lower order models, and where there is a probability of 1.0 for the sum of all sequences for a given length. The training documents, associated with the corresponging coordinates, were used to build a language model for each HTM cell, with the occurrence probabilities for each n-gram.

The authors estimated the distribution $\mathrm{P}(c_i)$, and also the probability of a document occurring within the region covered by each specific cell, i.e. $\mathrm{P}(d_k|c_i)$. With these two probabilities, it is then possible to estimate the probability of a document belonging to a specific cell through Bayes theorem, i.e. $\mathrm{P}(c_i|d_k)$. This probability, combined with post-processing techniques, allowed the authors to decide which is the most likely location of a given document.

Every document in the test set is assigned with the most similar(s) region(s) (i.e., the ones with greater $\mathrm{P}(c_i|d_k)$). Lastly the latitude and longitude coordinates of each document (in the test set) can be assigned, for instance with basis on the centroid coordinates of the most similar regions.

Four different post-processing techniques were tested for the assignment of the coordinates to the documents: (i) the coordinates of the centroid of the most likely region, (ii) the weighted geographic midpoint of the coordinates of the most likely regions, (iii) a weighted average of the

coordinates of the neighbouring regions of the most likely region and; (iv) the weighted geographic midpoint of the coordinates of the $k - nn$ most similar training documents, contained in the most likely region for the document.

The 2nd and 3rd techniques require well calibrated probabilities regarding the possible classes, while the approach based on language models that was used by the authors is known to produce extreme probabilities. In order to calibrate the probabilities the authors used a sigmoid function similar to $(\sigma \times score)/(\sigma - score + 1)$, where the σ parameter was empirically adjusted.

The best results were obtained in the English Wikipedia collection, using n-grams of characters, together with the post-processing method that used the $k - nn$ most similar documents. These best results correspond to an average error of 265 km, and a median error of 22 km. For the Spanish and Portuguese collections, the authors obtained an average error of 273 and 278 km, respectively, and a median error of 45 and 28 km, using the same procedures. The errors reported by the authors correspond to the distance between the original document's location and the predicted one, using Vincenty's geodetic formulae (Vincenty, 1975).

2.2.3 Modern Combinations of Different Heuristics

This section details recent studies that introduced innovative ways of geocoding documents, such as (i) combining language models from different sources (Laere *et al.*, 2014c); (ii) testing feature selection methods to improve the prediction of Twitter users' locations (Bo Han & Baldwin, 2014), and (iii) leveraging document representations obtained through probabilistic topic models (Adams & Janowicz, 2012).

We have for instance that Laere *et al.* (2014c) studied the use of textual information from social media (i.e. tags on Flickr and words from Twitter messages), in order to aid in the task of georeferencing Wikipedia documents. The first step of the proposed algorithm is to find the most probable region a for a given document D. Instead of using a fixed grid as Wing & Baldridge (2011), the authors used a k-medoids algorithm, which clusters the training documents into several regions. Each of these k-clusters contains approximately the same number of documents, which means that small areas will be created for very dense regions, and larger areas fore more sparse regions. The k-medoids algorithm is similar to k-means, but more robust to outliers (Kaufman & Rousseeuw, 1987).

After clustering, the authors applied the simple procedure outlined in Algorithm 1 to remove terms that are not geo-indicative (i.e., that are dispersed all over the world and that are not realated with specific locations). This algorithm assigns a score to each term from the vocabullary, and the lower this score is, the more geo-indicative the term is.

Algorithm 1 Geographic spread filtering algorithm (Laere *et al.*, 2014c).

Place a grid over the world map with each cell having sides that correspond to 1 degree latitude and longitude
for each unique term t in the training data **do**
  for each cell $c_{i,j}$ **do**
    Determine $|t_{i,j}|$, the number of training documents containing the term t
    if $|t_{i,j}| \geq 0$ **then**
      for each $c_{i',j'} \in \{c_{i-1,j}, c_{i+1,j}, c_{i,j-1}, c_{i,j+1}\}$, i.e. the neighbouring cells of $c_{i,j}$ **do**
        Determine $|t_{i',j'}|$
        if $|t_{i',j'}| \geq 0$ and $c_{i,j}$ and $c_{i',j'}$ are not already connected **then**
          Connect cells $c_{i,j}$ and $c_{i',j'}$
        end if
      end for
    end if
  end for
  $\mathrm{count} =$ number of remaining connected components
  $\mathrm{score}(t) = \frac{\mathrm{count}}{max_{i,j}|t_{i,j}|}$
end for

Given a clustering A_k and the vocabulary V, it is then possible to estimate language models for each cluster. The authors estimated separate language models from Wikipedia, Flickr and Twitter, using the textual contents from Wikipedia articles and from tweets, and the textual tags assigned to photos in Flickr.

For each test document D, the authors calculated the probabilities for each language model, for each cluster, to have generated that test document D. The next step was to combine the probabilities from the different language models for each cluster, in order to find the region a that has the highest probability of containing the document D.

Naive Bayes was the classifier chosen to find the region $a \in A_k$ to where the document D has the highest probability of belonging to.

The goal is then to find the region a with the highest $\mathrm{P}(a|D)$. After moving the equation to log-space, we have that:

$$a = \mathrm{argmax}_{a \in A} \left(\log\left(\mathrm{P}(a)\right) + \sum_{t \in V_D} \log\left(\mathrm{P}(t|a)\right) \right) \tag{2.42}$$

The probability of a region $\mathrm{P}(a)$ is calculated as the number of training documents associated with the region a, divided by the total number of training documents. The probability of a term t given a region a, i.e., $P(t|a)$, can be calculated by dividing the total number of times the term t appears in the training documents in a, by the total number of terms in a. However if a term t does not appear in the training data, its probability would be 0, so some form of smoothing is required.

The authors applied a Bayesian smoothing procedure with Dirichlet priors:

$$\mathrm{P}(t|a) = \frac{O_{ta} + \mu \mathrm{P}(t|V)}{O_a + \mu} \quad , \text{where} \quad \mu > 0 \tag{2.43}$$

In the formula, the probability of a term given the vocabulary V in the corpus, i.e., $\mathrm{P}(t|V)$, can be calculated by dividing the total number of times the term t occurs in the corpus, by the total number of terms in the corpus. The parameter O_{ta} is the total number of times the term t occurs in area a, and O_a is the total number of terms that occur in area a, i.e. $\sum_{t \in V} O_{ta}$.

The final equation to find the most probable area for document D combines the language models estimated from the different sources S (i.e., from Wikipedia, Twitter and Flickr), and is given by:

$$a = \mathrm{argmax} \left(\sum_{model \in S} \lambda_{model} . \log \left(\mathrm{P}_{model}(a|D) \right) \right) \tag{2.44}$$

In this last formula the weight of a given model can be controlled by the parameter λ_{model}. The authors found that a small weight $\lambda_{Twitter}$ should be assigned, because the Twitter data set contains noisy information.

Due to memory limitations, the authors only calculated and stored the 100 regions with highest probabilities for each test document and for each model. The probability of a given document being in region a is then approximated to:

$$\mathrm{P}_{model}(a|D) = \begin{cases} \mathrm{P}_{model}(a|D) & \text{if } a \text{ in top-100} \\ min_{a'} \text{ in top-100} \mathrm{P}_{model}(a'|D) & \text{otherwise} \end{cases} \tag{2.45}$$

In the previous equation, $\mathrm{P}_{model}(a|D)$ is approximated with the minimum of the top-100 most probable regions for D of that language model, in the cases where $\mathrm{P}_{model}(a|D)$ does not belong to the top-100 most probable areas.

After discovering the area a that best relates with document D, the authors tested three ways of choosing the coordinates for D namely (i) the medoid, (ii) the Jaccard similarity, and (iii) the similarity score returned by a well known information retrieval system named Lucene.

The medoid is calculated by searching the document that is closer to all other documents in a and assigning those coordinates to document D:

$$ma = \mathrm{argmin}_{x \in \mathrm{Train}(a)} \sum_{y \in \mathrm{Train}(a)} \mathrm{d}(x, y) \tag{2.46}$$

In the previous equation, $\mathrm{d}(x, y)$ is the geodesic distance between the coordinates of documents x and y, i.e. the great circle distance.

The Jaccard similarity is based on searching the training document in the region a that is the most similar with D, according to this similarity measure, and then assign its coordinates to D. Finally, the procedure based on Lucene is similar to the previous one, but using Lucene's internal similarity measure, which relies on a dot product between TF-IDF vectors.

In their experiments, the authors started by using the Wikipedia dataset from Wing & Baldridge (2011). However, they detected a number of shortcomings in the previous dataset, such as the absence of a distinction between articles that describe a specific location and articles whose location can't be approximated to a single location, such as countries and rivers. For these reasons, the authors created a new dataset, where every test document has a precise location inside the bounding box of the UK. This dataset has a similar size to the one used by Wing & Baldridge (2011), containing 21 839 test articles and 376 110 training articles.

The authors also created two social media datasets, namely one from Flickr containing 32 million geolocated and tagged photos, and another one from Twitter containing 16 million georeferenced tweets, with at least one hashtag.

The baseline results for geocoding Wikipedia documents corresponded to a median error of 4.17 km when using training documents from the same dataset, 2.5 km using the Flickr dataset, and a median error of 35.81 km for the Twitter dataset. The best results for the combination of Twitter and Wikipedia documents lowered the median error to 3.69 km, while the best combination between Wikipedia and Flickr resulted in a median error of just 2.16 km. When combining Wikipedia, Twitter and Flickr, the best results correspond to a median error of 2.18 km.

Bo Han & Baldwin (2014) also evaluated document geolocation techniques in order to predict Twitter user locations, based on the text of their tweets. The authors tested the use of numerous feature selection methods to extract *Location indicative Words* (*LIWs*) from the tweets, instead of using the full text, and the complete vocabulary.

The following datasets were used in this study: (i) a North American dataset by Roller et. al. (2012) that contains 38 million tweets from 500,000 users from 378 cities (NA); (ii) a worldwide extraction of tweets created by the authors (from 21 September, 2011 to 29 February, 2012) that is split into a dataset containing geotagged data only in the English language (WORLD), a dataset containing English geotagged and non-geotagged data (WORLD + NG), a dataset containing multilingual geotagged data (WORLD + ML) and a dataset containing English geotagged data and metadata, namely the users declared locations, real names, descriptions and time zones; (iii) another worldwide dataset extracted 1 year later than that named WORLD and that is used

only as a test dataset, in order to evaluate the influence of time in the task of predicting Twitter user locations.

The authors describe several feature selection methods in order to select only words that are associated with geographical information such as place names, dialectal words, slang or local references. The information gain ratio was the author's choice for most of the geolocation predictions, which can be computed as:

$$\begin{aligned} \mathrm{IGR}(w) &= \frac{\mathrm{IG}(w)}{\mathrm{IV}(w)} \\ \text{where} \quad \mathrm{IG}(w) &= \mathrm{H}(c) - \mathrm{H}(c|w) \\ \text{and where} \quad \mathrm{IV}(w) &= -\mathrm{P}(w)\log(\mathrm{P}(w)) - \mathrm{P}(\bar{w})\log(\mathrm{P}(\bar{w})) \end{aligned} \tag{2.47}$$

In the previous equation, the Information Gain Ratio (IGR) of a word w is the result of the division between the Information Gain (IG) of that word by the intrinsic entropy (IV) of the word. The parameter IG(w) represents the decrease in class entropy given by the word w, i.e. the difference between the entropy of the class, and the entropy of the class given the word w.

The authors used a city-based representation for most of their work, so each class is a city, and H(c) is the entropy of a given city c. As the final goal is to find which are the top geoindicative words, and since H(c) is equal for all the words, instead of calculating $\mathrm{IG}(w)$, we can only calculate:

$$\mathrm{H}(c|w) = \mathrm{P}(w)\sum_{c\in c}\mathrm{P}(c|w)\log(P(c|w)) + \mathrm{P}(\bar{w})\sum_{c\in c}\mathrm{P}(c|\bar{w})\log(P(c|\bar{w})) \tag{2.48}$$

In the previous equation $\mathrm{P}(w)$ is the probability of finding the word w, whereas $\mathrm{P}(\bar{w})$ is the probability of not finding the word w.

Another method used to find LIWs was the Geographic Density (GeoDen), a strategy for selecting words that occur in dense regions. The GeoDen of a word w is given by:

$$\mathrm{GeoDen}(w) = \frac{\sum\limits_{c\in c'}\mathrm{P}(c|w)}{|c'|^2\frac{\sum\limits_{c_j,c_k\in c' j\neq k}\mathrm{dist}(c_j,c_k)}{|c'|(|c'|-1)}} \tag{2.49}$$

In the above equation $c' \subseteq c$ (i.e., c' is a subset of cities) where word w is used, $\mathrm{dist}(c_j, c_k)$ is the great-circle distance between c_j and c_k, and $\mathrm{P}(c|w)$ is the probability that a word w has in each city $c \in c'$. The denominator of the Geographical Density is a product of the square number of cities where w occurs by the average distance between all cities where w appears.

Table 2.1: Comparison between the selection of Location Indicative Words (LIWs) vs using the full text

Dataset	Features	Acc	Acc@161	Acc@C	Median (km)
NA	Full text	0.171	0.308	**0.831**	571
	IGR	**0.260**	**0.450**	0.811	**260**
	GeoDen	0.258	0.445	0.791	282
WORLD	Full text	0.081	0.200	**0.807**	886
	IGR	**0.126**	0.262	0.684	913
	GeoDen	0.123	**0.266**	0.691	**842**
WORLD + NG	IGR	**0.280**	**0.492**	**0.878**	**170**

Table 2.1 presents the obtained results using Naive Bayes as a classifier and compares the use of the full text against using a method to find LIWs such as the IGR, or the Geographic Density. Acc is the city-level accuracy; Acc@161 is the accuracy within 161km and Acc@C is the country-level accuracy. One can observe that the addition of 182 million non-geotagged Tweets to a dataset of 12 million geotagged Tweets (WORLD + NG) clearly improved the obtained results, demonstrating that non-geotagged Tweets can also be indicative of the user location.

In another previous study, Adams & Janowicz (2012) demonstrated that, besides place names, some natural language expressions are highly geo-indicative. For instance the words *traffic, income, skyline, government, poverty,* or *employment* probably refer to a large city, whereas *park, hike, rock, flow water, above,* or *view* most likely occur in the context of a description for a national park.

In order to test if indeed there are words that are good hints to discover the geographic location associated to a document, the authors relied on experiments with two different data sources, namely travel blog entries and Wikipedia articles. They also removed all the place names from every document (i.e., by using Yahoo's Placemaker[1] Web Service to identify the places mentioned in the documents), deleted non-English documents and words that belong to an English standard stop word list, and stemmed the rest of the words.

Adams & Janowicz (2012) divided the Earth's surface using a geodesic grid with a fixed width and height, based on decimal degrees. Each training document was then assigned to the cell where its location is contained. A cell can be seen as the concatenation of all the training documents contained in its region, similarly to other works that were previously discussed.

After the data pre-processing, Adams & Janowicz (2012) applied the Latent Dirichlet Allocation (LDA) (Blei *et al.*, 2003) technique to discover T latent topics from the corpus of documents D and their coordinates P. The result is a $|T|$-sized vector θ_d, created for each document, with the

[1] `https://developer.yahoo.com/geo/placemaker/`

correspondent probability for each topic. These vectors represent the observed frequency of the topic at the document's location. LDA is a generetive model, that assumes documents are the result from a mixture of topics. Each document has a Dirichlet distribution of the different topics, and each topic has a Dirichlet distribution of all the possible words. This model assumes that words are chosen by first selecting a topic, according to the document's topic distribution, and then by selecting a word according to the selected topic's words distribution.

The following step was to estimate the topic vector for each cell, by calculating a weighted average of the topic values for each document in that given cell. Finally, the centroid point of all the documents in each cell is associated with the cell's corresponding topic vector. The authors calculated, for each different topic, a probability surface, by applying the Kernel Density Estimation (KDE) method, using the cells' centroid points, and the corresponding cell topic values, except all the cell points that have the topic value equal to 0.

As previously discussed in this chapter, Kernel Density Estimation (KDE) can be seen as a generalization of histogram-based density estimation, which uses a kernel function at each point, instead of relying on a grid. More formally, the Kernel density estimate for a point (x, y) is given by the following equation (Carlos *et al.*, 2010):

$$\mathrm{f}(x,y) = \frac{1}{nh^2} \sum_{i=1}^{n} \mathrm{K}\left(\frac{d_i}{h}\right) \tag{2.50}$$

In the formula, d_i is the geospatial distance between the occurrence i and the coordinates (x, y), and n is the total number of occurrences. The bandwidth is given by the parameter h, that controls the maximum area in which an occurrence has influence. It is very important to choose a correct h value, because if it is too low, the values will be undersmoothed. The opposite happens when h is too high, resulting in values that will be oversmoothed, since each point will affect a large area. Finally, $\mathrm{K}(.)$ is the kernel function, that integrates to one and controls how the density diminishes with the increase of the distance to the target location.

Adams & Janowicz (2012) used the Epanechnikov kernel function, given by:

$$\mathrm{K}(u) = \frac{3}{4}(1-u^2) \quad \text{with} \quad |u| \leq 1 \tag{2.51}$$

After having the probability surfaces for each different topic, one can calculate a test document's location. The first step is to create the topic vector for the test document, resulting from LDA, followed by the calculation of a weighted raster overlay via map algebra operations over the topic probability surfaces, where only the topics that have greater probability than random are considered, and where the weight for each for each topic is a product of the test document's topic

weight and its normalized inverse entropy, that measures the topic's geo-indicativeness.

In order to test this method, sets of 200 held-out documents were used from the travel blog and Wikipidia datasets. The best results were obtained when using only the top 30 locations to estimate a document's coordinates. The top-30 locations for the Wikipedia dataset predicted 75 % of the articles within 505 km and 50 % of them were predicted under 80 km from the real location. For the travel blog dataset, half of the instances had their location predicted with an error distance smaller than 1169 km.

2.2.4 Recent Approaches Based On Discriminative Classification Models

In a recent study, Wing & Baldridge (2014) achieved state-of-the-art results on document geocoding by using discriminative classification models. The authors combined a hierarchical division of the Earth's surface with the use of logistic regression, relying on a greedy search procedure over the hierarchy to reduce the time and the storage space required to train and apply the models.

The probability for a logistic regression model of assigning a binary class $y \in \{1, -1\}$ is equal to:

$$\mathrm{P}(y = \pm 1|x) \equiv \frac{1}{1 + e^{-yw^T x}} \tag{2.52}$$

In the previous equation x is the data instance and $w \in \mathbb{R}^n$ is the weight vector, that is chosen in order to minimize the following equation:

$$\mathrm{P}^{LR}(w) = C \sum_{i=1}^{l} \log\left(1 + e^{-y_i w^T x_i}\right) + \frac{1}{2} w^T w \tag{2.53}$$

In the equation above $C > 0$ is a penalty parameter, and the weights are influenced by the binary training data $\{x_i, y_i\}_{y=1}^{l}, x_i \in \mathbb{R}^n, y_i \in \{1, -1\}$

In order to adapt the previous binary model to a multiclass classification scenario (this is required to determine which is the most probable cell for a given test document), one can create N binary models, where a different model is created for each cell, and where the binary classification task is that of finding the probability of the document belonging to that cell, versus the probability of not belonging to that cell (i.e., belonging to some other). One can than choose the cell that has the highest probability for the test document.

The hierarchical division starts with a root node ($\mathrm{c}_{\mathrm{root}}$) that covers the entire Earth's surface, and from there the authors create a tree of cells, that become smaller from a level to the following. The authors used an approach originally proposed by Silla & Freitas (2011) in which independent

classifiers are learned in each node of the hierarchy. The probability of a node cj in the hierarchy is the product of that node multiplied by the probability of all the ancestors of the node, given by the following recursive equation:

$$\mathrm{P(c_{root})} = 1.0 \qquad \mathrm{P(cj)} = \mathrm{P}(cj| \uparrow cj)\mathrm{P}(\uparrow cj) \tag{2.54}$$

In the previous equation $\uparrow cj$ is cj's parent node in the hierarchy. In order to avoid computing the probability of each leaf cell in Equation 2.54, the authors instead used a stratified beam search where only the b cells with highest probability are kept at each level. A tight beam drastically reduces the number of classifications required.

Different configurations for the division of the Earth's surface were tested, based on either a uniform grid or a k-d tree grid. There are two parameters that influence the grid's size at each level. One of these parameters derives from the classifier being used (logistic regression or Naive Bayes that was employed in this study as a baseline method) and controls the size of the first level division of the grid. The second parameter is a subdivision factor SF, that defines how the subdivision is done from one level to the following.

On the uniform grids, each cell is divided into $SFxSF$ subcells, which in practice is not true because the authors discard every cell that does not contain any training document. For the k-d trees, if a level 1 has a Bucket size of B, level 2 will have a bucket size of B/SF, level 3 will have a bucket size of B/SF^2, etc.

Vowpal Wabbit [1] was the implementation of logistic regression classifiers that was chosen, which leverages an online procedure for model training, together with feature hashing for increased performance. The authors used 24-bit feature hashing and 12 passes over the data for the subcell classifiers in hierarchical classification, and 26-bit features and 40 passes over the data for the remaining classifiers using logistic regression. Feature hashing is a fast way of transforming features such as words from a Bag of Words representation into a fixed-size vector. Feature hashing is an alternative to using a dictionary, because it avoids the process of searching through the text in order to find all different features and then assigning a number to each of them. As the name implies, a hashing function is used to convert a given feature in a number, and the position in the feature vector returned by the hashing function holds a frequency count.

Besides the previously described hierarchical procedure using logistic regression (**HierLR**), the authors also tested three other classification methods for comparison purposes, namely (i) Naive Bayes with Dirichlet smoothing (**NB**); (ii) Naive Bayes with Dirichlet smoothing and with only the top N features obtained by using the Information Gain Ratio (**IGR**); and (iii) a logistic regression

[1] `https://github.com/JohnLangford/vowpal_wabbit`

model applied only to the leaf nodes (**FlatLR**).

The authors tested their geocoding methods on six distinct datasets:

- **TWUS** containing 38 million tweets from 450,000 users, where each of them has at least 1 tweet geotagged whitin the bounding box of the United States;
- **TWWorld** containing 1.4 million users with english geoagged tweets near a city;
- **ENWIKI13** an English version of Wikipedia containing 864 thousands of geotagged articles;
- **DEWIKI14** a German version of Wikipedia containing 324 thousands of geotagged articles;
- **PTWIKI14** a Portuguese version of Wikipedia containing 131 thousands of geotagged articles;
- **COPHIR** a dataset from Flickr containing 2.8 millions of geotagged images together with their correspondent manually-inserted descriptive tags.

The mean, the median and the accuracy at 161 km (**acc@161**) were used as metrics to evaluate the different geolocation strategies.

Tables 2.2, 2.3 and 2.4 present the results obtained for the Wikipedia datasets. BK is the bucket size, SF is the subdivision factor, BM is the beam size and CU is the percentage of the top geoindicative features that were selected. As one can observe, the document geocoding approach that uses a hierarchical classifier, together with a k-d tree as a discretization method achieved the best results for the English and Portuguese versions of Wikipedia, which correspond to an accuracy @ 161 km of 88.9% , a mean error of 168.7 km and a median error of 15.3 km, and an accuracy @ 161 km of 89.5%, a mean error of 186.6 km and a median error of 27.2 km for the Portuguese Wikipedia. In what regards the German version of Wikipedia, the hierarchical geocoder that uses k-d trees to discretize the Earth's surface was still the best geocoder for the accuracy @ 161 km and for the mean error with 90.2% and 122.5 km respectively. As for the median, the best geocoder for the German version of Wikipedia was the one that used Naive Bayes as a classifier, together with k-d trees, achieving a median error of 7.6 km.

2.3 Summary

In this chapter, the most important concepts for understanding the proposed document geocoding method are presented, namely: (i) concepts related to the representation of text for computational analysis, such as the Vector Space Model where a document is represented as a vector

Table 2.2: Results obtained using the English Wikipedia dataset

Corpus		**ENWIKI13**		
Method	Parameters	A@161	Mean	Med
NB Uniform	$1.5°$	84.0	326.8	56.3
NB k-d	BK100	84.5	362.3	21.1
IGR Uniform	$1.5°$, CU96%	81.4	401.9	58.2
IGR k-d	BK250, CU98%	80.6	423.9	34.3
FlatLR Uniform	$7.5°$	25.5	1347.8	259.4
FlatLR k-d	BK1500	74.8	253.2	70.0
HierLR Uniform	$7.5°$, SF3,BM5	86.2	228.3	34.0
HierLR k-d	BK1500,SF12,BM2	88.9	168.7	15.3

Table 2.3: Results obtained using the German Wikipedia dataset

Corpus		**DEWIKI13**		
Method	Parameters	A@161	Mean	Med
NB Uniform	$1°$	88.4	257.9	35.0
NB k-d	BK25	89.3	192.0	7.6
IGR Uniform	$2°$, CU82%	87.1	312.9	68.2
IGR k-d	BK50, CU100%	86.0	226.8	10.9
FlatLR Uniform	$5°$	55.1	340.4	150.1
FlatLR k-d	BK350	82.0	193.2	24.5
HierLR Uniform	$7°$, SF3,BM5	88.5	184.8	30.0
HierLR k-d	BK3500,SF25,BM5	90.2	122.5	8.6

Table 2.4: Results obtained using the Portuguese Wikipedia dataset

Corpus		**PTWIKI13**		
Method	Parameters	A@161	Mean	Med
NB Uniform	$1°$	76.6	470.0	48.3
NB k-d	BK100	77.1	325.0	45.9
IGR Uniform	$2°$, CU54%	71.3	594.6	89.4
IGR k-d	BK100, CU100%	71.3	491.9	57.7
FlatLR Uniform	$2°$	88.9	320.0	70.8
FlatLR k-d	BK25	86.8	320.8	30.0
HierLR Uniform	$7°$, SF2,BM5	88.6	223.5	64.7
HierLR k-d	BK250,SF12,BM2	89.5	186.6	27.2

of components, and the TF-IDF weighting heuristic where the weight that a term has on a given document is a product of its term frequency and its inverse document frequency; (ii) document classifiers such as Support Vector Machines and Logistic Regression; and (iii) concepts related to geospatial data analysis.

This chapter also presented an extensive description of the related work on the field of document geocoding; organizing these previous studies as follows:

- **Early Proposals**, specifically presenting a document geocoding method for the region of California (Woodruff & Plaunt, 1994), and a document geocoding method for assigning the main region described in a given web page (Amitay *et al.*, 2004). Both these approaches leverage on place names recognized in the text
- **Language-modelling approaches** consisting of document geocoding approaches that use a uniform grid, a k-d tree, or a Hierarchical Triangular Mesh to discretize the Earth's surface, together with Naive Bayes or the Kullback-Leibler divergence as a classifier to encounter the most probable region for a given test document (Wing & Baldridge (2011) , Roller *et al.* (2012) Dias *et al.* (2012)).
- **Recent Approaches Based on Discriminative Classification Models**, specifically presenting the previous study by Wing & Baldridge (2014), which achieved state-of-the-art results on document geocoding, by using a hierarchical classifier. This is the work that is the most similiar with the document geociding approach proposed on this thesis, although it differs on the following aspects: 1) the use of HEALPix to divide the Earth's surface instead of a k-d or a uniform grid; 2) the use of TF-IDF or TF-IDF-ICF as document representations instead of term frequency; and 3) the use of Support Vector Machines as the underlying classifiers.

Chapter 3

Geocoding Textual Documents

Most text documents, from different application domains, are related to some form of geographic context. Geographical Information Retrieval (GIR) has recently captured the attention of many different researchers that work in fields related to language processing and to the retrieval and mining of relevant information from large document collections. Some previous works focused on the task of resolving individual place references in textual documents, in order to support following GIR processing tasks, such as document retrieval or the production of cartographic visualizations from textual documents (Lieberman & Samet, 2011; Mehler *et al.*, 2006).

We have, for instance, that the task of resolving individual place references in textual documents has been addressed in several previous works, with the aim of supporting subsequent GIR processing tasks, such as document retrieval or the production of cartographic visualizations from textual documents (Lieberman & Samet, 2011; Mehler *et al.*, 2006). Instead of trying to resolve place references made in textual documents, I will instead study methods for assigning entire documents to correspondent geospatial locations

This chapter presents the geocoding algorithm proposed in the context of my M.Sc. thesis, detailing the method used to divide the Earth's surface into a set of regions, the approach taken in order to transform the text of the documents in representations that the computer may use, and the hierarchical classification approach.

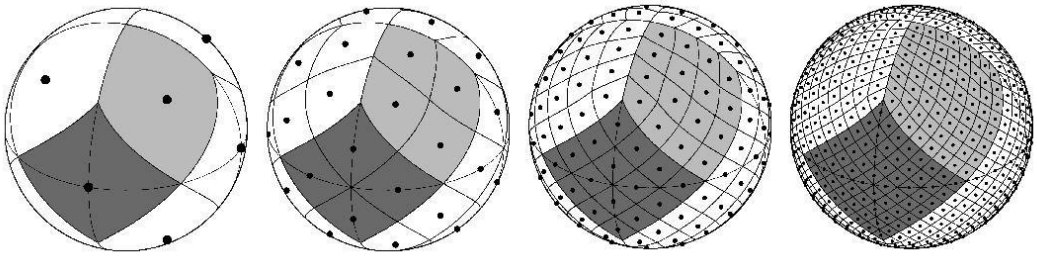


Figure 3.6: Orthographic views associated to the first four levels of the HEALPix sphere tessellation.

3.1 The HEALPix Representation for the Earth's Surface

The general approach considered for geocoding textual documents has been described in a recent publication (Melo & Martins, 2015), and it is based on discretizing the surface of the Earth into sets of regions, each with a different resolution, allowing us to predict locations with standard discriminative classification approaches over discrete outcomes. Unlike previous authors such as Wing & Baldridge (2011), which used a regular grid of squared cells, the HEALPix approach was used to discretize the Earth's surface into curvilinear and quadrilateral regions (Górski *et al.*, 2005). This strategy results in grids that roughly preserve an equal area for each region, instead of variable-size regions that shrink latitudinally, becoming progressively smaller and more elongated the closer they get towards the poles. Notice that the HEALPix discrete representations of the Earth ignore all higher level regions, such as states, countries or continents. Nonetheless, this is appropriate for the geocoding purposes, since documents can be related to geographical regions that do not fit into an administrative division of the Earth's surface.

HEALPix is an acronym for Hierarchical Equal Area isoLatitude Pixelization of a sphere and, as the name suggests, the procedure results on a multi level recursive subdivision for a spherical approximation to the Earth's surface, in which each resulting subdivision covers an equal surface area. HEALPix is used extensively in the context of astrophysics applications, given that the resulting discretization distributes the subregions on lines of constant latitude, and this property is particularly useful for applications involving the analysis of spherical harmonics. Although this property is not explored in the context of the application addressed in this thesis, HEALPix was chosen due to the availability of practical implementations[1], and due to its equal-area and hierarchical self-similarity properties.

With HEALPix, a spherical representation for the Earth's surface can be hierarchically tessellated into curvilinear quadrilaterals. The lowest resolution partition is comprised of 12 base regions

[1] `https://github.com/healpy/healpy`

HEALPix Resolution	4	64	256	1024
Total number of regions	192	49,152	786,432	12,582,912
Approximate area of each region (Km^2)	2,656,625	10,377	649	41

Table 3.5: Number of regions and approximate area for HEALPix grids of different resolutions.

distributed in three rings around the poles and equator, and the resolution of the tessellation increases by the division of each region into four new ones. Figure 3.6, adapted from the original illustration provided in the HEALPix website[1], shows from left to right the resolution increase by three steps from the base level (i.e., a sphere is partitioned, respectively, into 12, 48, 192, and 768 pixels). The light gray shading shows one of the 8 (4 north and 4 south) identical polar base-resolution regions, while the dark gray shading shows one of the 4 identical equatorial base-resolution regions. The cells in the resulting mesh are the regions used in our discrete representation of the Earth and every curvilinear quadrilateral, at any resolution, is represented by a single identifier (ID). For each location given by a pair of geospatial coordinates on the surface of the sphere, there is a discrete ID representing the curvilinear quadrilateral, at a particular resolution, that contains the corresponding point. An hierarchical binary numbering scheme is normally adopted for assigning IDs to each curvilinear quadrilateral, where each two bits represent a pixel number at a given depth (i.e., by shifting off the last two bits one can find the parent pixel number of a pixel). For more details about the HEALPix procedure, please refer to the paper by Górski *et al.* (2005).

The proposed representation scheme contains a parameter N_{side} that controls the resolution, i.e. the number of divisions along the side of a base-resolution region that is needed to reach a desired high-resolution partition, which naturally will also define the area of the curvilinear quadrilaterals. In the particular application of document classification, having regions from a course grained resolution can lead to very rough estimates, but classification accuracy with a thin-grained resolution can also decrease substantially, due to insufficient data to adjust the model parameters associated to each bin. In order to address this issue, a hierarchical classification approach that leverages 4 different representations of different resolutions was used, equaling the N_{side} parameter to the values of $2^2 = 4$, $2^6 = 64$, $2^8 = 256$ and $2^{10} = 1024$, with $2^0 = 1$ corresponding to a first-level division. Table 3.5 presents the number of regions in each of the considered resolution levels, where the number of regions n for a resolution N_{side} is given by $n = 12 \times N_{side}^2$. Table 3.5 also presents the approximate area, in squared Kilometers, corresponding to each region.

[1] `http://healpix.jpl.nasa.gov`

3.2 Building Representations

Besides the issue of building a hierarchy of discrete representations for the surface of the Earth (i.e., the representations associated to the outcomes, in the context of our classification models), another important question relates to the choice of how to represent the input instances (i.e., the documents to be geocoded). A common representation scheme involves associating each document to a vector of characteristics in a given vector space, in which the dimensionality corresponds to the number of different features. This representation scheme is associated with a well-known model for processing and representing documents in the area of information retrieval, commonly referred to as the vector space model (see section 2.1.1 for a more thorough explanation on how to represent text for computational analysis). TF-IDF is perhaps the most popular term weighting scheme, combining the individual frequency for each element i in the document j (i.e, the Term Frequency component or TF), with the inverse frequency of element i in the entire collection of documents (i.e., the Inverse Document Frequency). In this thesis two approaches for building representations were evaluated, namely (i) the TF-IDF scheme, and (ii) the TF-IDF-ICF scheme, that complements the TF-IDF method with an additional heuristic corresponding to the notion of Inverse Class Frequency (ICF), as previously proposed by Lertnattee & Leuviphan (2012). The idea is to use a simple supervised term weighting scheme (i.e., information on the membership of training documents to classes is used in the process of building the representations) that promotes terms that appear in fewer classes (i.e., in fewer regions of the globe) and demotes terms that appear in many classes. Similar intuitions have already been considered in previous works related to automated document geocoding (Han *et al.*, 2014; Laere *et al.*, 2014a), although only for purposes of term selection instead of term weighting. The TF-IDF-ICF weight of an element i for a document j is given by:

$$\text{TF–IDF–ICF}_{i,j} = \log_2(1 + \text{TF}_{i,j}) \times \log_2\left(\frac{N}{n_i}\right) \times \log_2\left(\frac{N_c}{c_i}\right) \tag{3.55}$$

In the formula, N is the total number of documents in the collection, n_i is the number of documents containing the element i, N_c is the total number of classes (i.e., when building the document representations leveraging the ICF heuristic, we considered documents to be associated to classes corresponding to HEALPix regions with a resolution of 64), and c_i is the number of classes associated to documents j' where $\text{TF}_{i,j'} \geq 0$. Through experiments, we found that both the TF-IDF-ICF and the TF-IDF procedures achieved state-of-the-art results in the task of geocoding documents.

3.3 Geocoding through Hierarchical Classification for the Textual Documents

With the hierarchy of discrete representations given by the HEALPix method, together with the document representations based on TF-IDF or TF-IDF-ICF, we can use linear classification algorithms to address the document geocoding task. A separate classification model is trained for each node in the hierarchy of discrete representations, taking all documents whose coordinates lay within the region corresponding to each node, as the training data for each classifier. When geocoding a test document, the first step is to apply the root classifier to decide the most likely region, and then proceed greedily by applying the classifier for each of the most likely nodes, up to the leafs. After reaching a leaf region from the hierarchical representation, the geospatial coordinates of latitude and longitude are assigned by taking the centroid coordinates of the leaf region.

In what follows, we denote by $\mathcal{X}$ the input set of documents and by $\mathcal{Y}$ our output set of classes (i.e., geospatial regions). Recall that a classifier is any function which maps objects $x \in \mathcal{X}$ onto classes $y \in \mathcal{Y}$ and, for the purpose of understanding classifiers, it is useful to think about each $x \in \mathcal{X}$ as an abstract object which is subject to a set of measurements (i.e., each x takes values in $\mathbb{R}^k$), which we refer to as features (e.g., the TF-IDF-CF weights for each term in the document).

The experiments reported on this thesis are based on linear classifiers, which make their decision based on a linear combination of the features, plus a bias term. In the case of binary classification problems where $\mathcal{Y} = \{+1, -1\}$, if $\hat{y}(x)$ is the predicted value for x, if the vector $\boldsymbol{w} =< w_1, \ldots, w_k >$ corresponds to the weights associated to each of the k features, and if w_0 represents the bias term, then we have that:

$$\hat{y}(x) = \text{sign}(w_0 + w_1 x_1 + \ldots + w_k x_k) \tag{3.56}$$

Support Vector Machines (SVMs) are one of the most popular approaches for learning the parameters of linear classifiers from training data. In the experiments described in this thesis, I used the SVM and Logistic Regression implementations from scikit-learn[1]. In the case of logistic regression classifiers, the probability of class membership is given by:

$$\arg\min_{\mathbf{w}, w_0} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 + C \sum_{i=1}^{n} \log(1 + e^{-y_i(\mathbf{w}\cdot\mathbf{x}_i - w_0)}) \right\} \tag{3.57}$$

[1] http://scikit-learn.org/

A separate classification model based on one of the previous linear classifiers is trained for each node in the hierarchy of discrete representations, taking all documents whose coordinates lay within the region corresponding to each node, as the training data for each classifier. When geocoding a test document,the root-level classifier is first applied to decide the most likely region, and then a greedy procedure is followed for each of the most likely nodes, up to the leafs. After reaching a leaf region from the hierarchical representation, the geospatial coordinates of latitude and longitude are then assigned to the test document by taking the centroid coordinates of the leaf region.

3.4 Summary

In this chapter the main ideas behind this thesis are presented, namely the components of a hierarchical geocoder that assigns geospatial coordinates to a given test document based on its textual contents, and on the training data. The chapter started by describing HEALPix, a method for discretizing the Earth's surface into hierarchical curvilinear quadrilaterals. The chapter also explained the text representations used for the proposed document geocoding algorithm, namely TF-IDF and TF-IDF-CF. The chapter ends with a thorough explanation of the hierarchical document geocoding approach, that was tested with out-of-the-box linear classifiers such as the implementations of Support Vector Machines and Logistic Regression from scikit-learn.

Chapter 4

Experimental Evaluation

This chapter, describes the experimental methodology used for comparing different variations of the proposed method, afterwards discussing the obtained results.

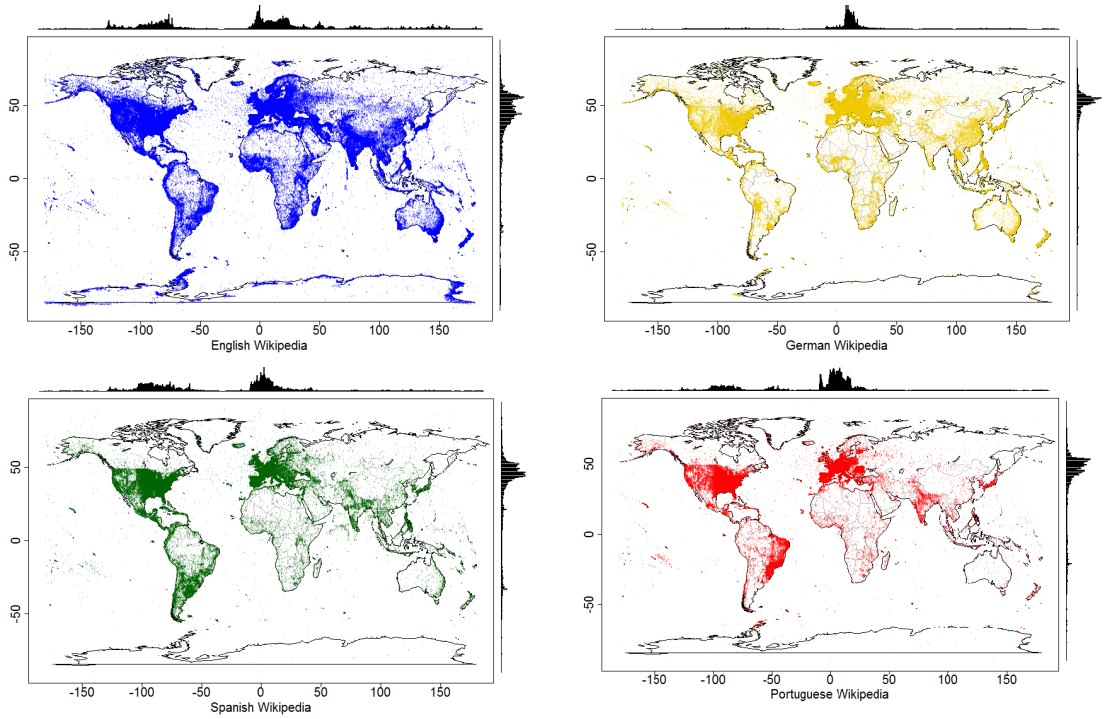
4.1 Datasets and Methodology

For the experiments reported here, I used samples with articles from the English, German, Spanish, and Portuguese Wikipedias, taken from database dumps produced in 2014. These samples include a total of 847,783, 307,859, 180,720 and 131,085 articles, respectively in English, German, Spanish, and Portuguese, associated to latitude and longitude coordinates. Previous studies have already shown that Wikipedia articles are a well-suited source of textual contents for evaluating document geocoding methods (Wing & Baldridge, 2011, 2014).

I processed the Wikipedia collections to extract the raw text from the articles, and for extracting the geospatial coordinates of latitude and longitude, using manually-defined patterns to capture some of the multiple templates and formats for expressing coordinates in Wikipedia. Considering a random order for the articles, about 90% of the geo-referenced articles were used for model training (i.e., a total of 763,005 articles in English, 277,074 in German, 162,649 in Spanish, and 117,977 in Portuguese), and the other 10% were used for model validation (i.e., a total of 84,778, 30,785, 18,071 and 13,108 articles, respectively in English, German, Spanish and Portuguese). Table 4.6 presents a brief characterization these datasets, while Figure 4.1 illustrates the geospatial distribution of the locations associated to the documents.

In Table 4.6, the values corresponding to the total number of place references in the collection, and the number of place references in each document, were obtained from the application of

Figure 4.7: Maps with the geographic distribution for the documents in the Wikipedia collections.



a Named Entity Recognition (NER) system over the texts, in order to extract location names. I have specifically used Stanford NER, together with models trained for each language. In what regards the geospatial distributions of documents, notice that some regions (e.g, North America or Europe) are considerable more dense in terms of document associations than others (e.g, Africa). We can also see that in the Portuguese collection there is a higher concentration of articles in Europe and in South America (i.e., in Brazil), and that in the Spanish collection there is a higher concentration of articles in Europe and in latin South-American countries. Moreover, oceans and other large masses of water are scarce in associations to Wikipedia documents. This implies that the number of classes that has to be considered by this model is much smaller than the theoretical number of classes given in Table 3.5. In the English dataset, there are a total of 286,966 bins containing associations to documents at resolution of 1024, and a total of 82,574, 15,065, and 190 bins, respectively at resolutions 256, 64, and 4. These numbers are even smaller in the other collections, e.g. with just 98,139, 100,335 and 72,109 bins containing associations to documents in a resolution of 1024, respectively in the case of the German, Spanish and Portuguese collections.

In order to evaluate the effectiveness of the proposed document geocoding approach, I also used a dataset from Roller *et al.* (2012) named Twitter-US that contains 38 million tweets 450 thousand users. In the dataset, a document is the result of the concatenation of all tweets by

EN Wikipedia	Train	Test
Documents	763,005	84,778
Terms	279,886,310	30,936,884
Place References	11,326,826	1,289,530
Avg. Terms/Doc.	366.821	364.916
St.Dev. Terms/Doc.	767.537	739.657
Avg. Places/Doc.	14.845	15.211
St.Dev. Places/Doc.	26.080	25.460

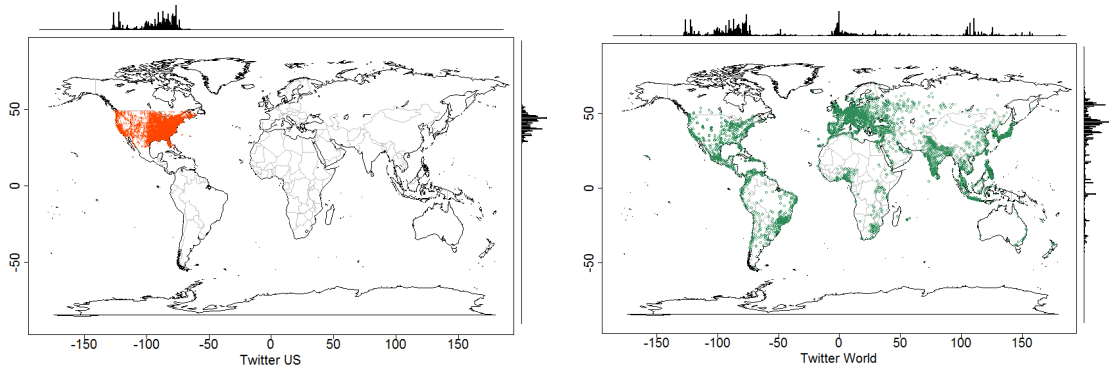
DE Wikipedia	Train	Test
Documents	277,074	30,785
Terms	132,464,428	14,614,460
Place References	4,023,883	446,339
Avg. Terms/Doc.	478.083	474.727
St.Dev. Terms/Doc.	869.365	815.676
Avg. Places/Doc.	14.523	14.499
St.Dev. Places/Doc.	27.751	26.632

ES Wikipedia	Train	Test
Documents	162,649	18,071
Terms	57,067,617	6,304,936
Place References	1,431,185	173,642
Avg. Terms/Doc.	350.864	348.898
St.Dev. Terms/Doc.	880.160	893.109
Avg. Places/Doc.	8.779	9.609
St.Dev. Places/Doc.	19.166	21.173

PT Wikipedia	Train	Test
Documents	117,976	13,108
Terms	21,424,167	2,397,775
Place References	479,602	52,958
Avg. Terms/Doc.	181.598	182.925
St.Dev. Terms/Doc.	606.659	587.515
Avg. Places/Doc.	4.065	4.040
St.Dev. Places/Doc.	8.688	8.072

Table 4.6: Statistical characterization for the Wikipedia collections used in our experiments.

Figure 4.8: Maps with the geographic distribution for the documents in the Twitter collections.



a given user, that has at least one geotagged tweet with specific coordinates of latitude and longitude. The earliest geotagged tweet from a given user is considered the user's location. In this dataset, tweets outside a bounding box covering the United States were discarded, together with potential spammers or robots (given the number of tweets, followers and followees). I used another dataset from Twitter, named Twitter-World, collected from Han & Baldwin (2012), that is similar from the previous, but instead has geotagged tweets that cover the Earth's surface and it only has geotagged tweets. The authors also removed non-english tweets, tweets that are not near a city, short tweets and non-aphabetic tweets. The resulting dataset has 12 million tweets from 1.4 million users. Figure 4.1 shows the geospatial distribution for Twitter-US and Twitter-World datasets.

In a second set of experiments, the performance of the document geocoding method was evaluated over different sources of text, taking these sources either as a complement or as a replacement to the geo-referenced contents from the English Wikipedia, using Support Vector Machines

	Corpus size (words)	Vocabulary size	Terms per document	
			Average	St.dev
Wikipedia	311,670,977	7,217,371	367.631	764.793
Anchor text	46,375,708	1,772,058	54.702	389.399
Wikipedia + anchor text	324,378,152	7,243,824	382.619	896.209
Anchor text + context	236,263,101	4,112,659	278.683	5418.008
Wikipedia + anchors + context	514,503,489	9,183,943	606.881	5679.983

Table 4.7: Statistical characterization for the document collections used in our second set of experiments.

as the linear model for the hierarchical classifiers, and TF-IDF-ICF method to build the document representations. Two different sources of text were considered in these experiments:

- Phrases from hypertext anchors, collected from the Web as a whole and pointing to geo-referenced pages in the English Wikipedia. I specifically made use of a dataset released by Google[1], obtained by iterating over this search engine's Web index. I used the text of the hypertext anchors either as a replacement to the Wikipedia contents (i.e., the training instances instead consisted of the title of the Wikipedia pages plus the concatenation of all hypertext anchors), or as a complement to the contents in Wikipedia (i.e., concatenating the hypertext anchors to the Wikipedia documents).

- Phrases from the hypertext anchors together with other words appearing in the surrounding context, as made available in an expanded version of Google's original dataset (Singh *et al.*, 2012). In this expanded version, the text of the hypertext anchors is made available together with the surrounding words (i.e., words either at the left or the right of the anchor text). I again used these contents either a complement or as a replacement to the geo-referenced contents from the English Wikipedia.

  One of the reasons behind experimenting with the usage of these datasets to help geocoding Wikipedia documents is due to the fact the anchor text associated to links towards geo-referenced Wikipedia pages, together with the words from the surrounding context, can offer compact descriptions for the main contents of these pages. We therefore believe that these textual contents can providing some valuable extra information, that can perhaps improve the results of the document geocoding method.

Table 4.7 presents a statistical characterization of the different datasets used in this second set of experiments.

[1] `https://code.google.com/p/wiki-links/`

I also evaluated the performance of the proposed document geocoding method after, (i) removing all the terms that were considered as being part of a place name, with the use of Stanford NER models for each language (dataset **Without Place Names**), (ii) storing the set of all titles for a given Wikipedia collection and then removing all the occurences of a Wikipedia title from each document (dataset **Without Wiki Titles**).

4.2 Experimental Results

Table 4.8 presents the obtained results for geo-referenced documents from the English Wikipedia using , (i) the full content of its pages, (ii) the textual contents without place references, and (iii) the textual contents after removing all matches towards titles of geo-referenced Wikipedia pages. In these experiments I used TF-IDF-CF as a document representation approach, together with SVM classifiers. The prediction errors shown in Table 4.8 correspond to the distance in Kilometers, computed through Vincenty's geodetic formulae, from the predicted locations to the true locations given in the gold standard. The accuracy values correspond to the relative number of times that we could assign documents to the correct bin (i.e., the bin where the document's true geospatial coordinates of latitude and longitude are contained), for each level of hierarchical classification. The table also presents upper and lower bounds for the average and median errors, according to a 95% confidence interval and as measured through a t-test (for the average) or through a sampling procedure (for the median).

As expected, the results from Table 4.8 show that classifiers leveraging the full-contents achieve better results, with a best prediction accuracy of over 0.95 in the task of finding the correct bin with the 1st level classifier, in the case of the English collection, while assigning documents to the correct geospatial coordinates had an average error of 87 Kilometers, and a median error of 8 Kilometers, also in the case of the English collection. Although better results are achieved when using the entire contents of the Wikipedia articles, it should nontheless be noticed that even when using models trained with contents where the place names have been removed or where all the titles were removed from the text of the documents, interesting results were achieved, given the circumstances, thus suggesting that other terms besides place names can also be geo-indicative

The obtained results also attest to the general effectiveness of the proposed document geocoding method, as we have measured slightly inferior errors than those reported in the previous studies by Wing & Baldridge (2011, 2014) in section 2.2. It should nonetheless be noted that the datasets used in our experiments may be slightly different from those used by Wing and Baldridge, despite their similar origin. The hyper-parameters used in the classification approach (i.e., the C

	Classifier accuracy				Errors in terms of distance (Km)	
Full Wikipedia	1st	2nd	3rd	4th	Average	Median
English	0.967	0.786	0.547	0.272	86.616 (± 4.517)	8.308 [5.134 - 14.413]
German	0.974	0.844	0.670	0.423	62.046 (± 6.075)	4.628 [3.432 - 7.150]
Spanish	0.951	0.722	0.446	0.167	184.385 (± 18.223)	12.546 [8.392 - 22.691]
Portuguese	0.954	0.670	0.344	0.112	108.505 (± 10.249)	20.606 [13.105 - 32.020]
	Classifier accuracy				Errors in terms of distance (Km)	
Without Place Names	1st	2nd	3rd	4th	Average	Median
English	0.867	0.548	0.343	0.177	448.892 (± 11.160)	28.015 [12.359 - 68.293]
German	0.949	0.787	0.609	0.376	150.271 (± 10.579)	5.417 [3.759 - 10.422]
Spanish	0.889	0.588	0.349	0.133	357.856 (± 21.949)	21.302 [11.460 - 44.815]
Portuguese	0.912	0.523	0.261	0.094	240.727 (± 16.773)	37.365 [20.623 - 65.839]
	Classifier accuracy				Errors in terms of distance (Km)	
Without Wiki Titles	1st	2nd	3rd	4th	Average	Median
English	0.873	0.553	0.346	0.167	422.966 (± 11.572)	26.871 [12.459 - 63.683]
German	0.940	0.731	0.530	0.305	161.063 (± 10.071)	8.221 [4.734 - 18.681]
Spanish	0.881	0.542	0.305	0.113	372.164 (± 22.627)	29.672 [15.214 - 65.492]
Portuguese	0.906	0.537	0.249	0.079	274.119 (± 20.653)	34.300 [21.0350 - 56.665]

Table 4.8: The results obtained for each different language, with different types of textual contents and when using TF-IDF-ICF representations ans Support Vector Machines as a linear classifier.

regularization term for the SVM classifiers) were also kept at the default values and, for future work, one could use automated procedures to tune the parameters of the classifiers (Claesen *et al.*, 2014), and also to experiment with different hierarchical organizations (i.e., with different numbers of levels and/or with different resolutions in the hierarchical classification procedure).

Table 4.9 presents results for a document geocoding method that represents documents using the TF-IDF method, together with classifiers based on SVMs or logistic regression. The English version of Wikipedia achieved a mean of 83 Km and a median of 9 Km for the approach that uses SVMs as linear classifiers. The German, Spanish and Portuguese versions of Wikipedia achieved means of 63, 166, and 105 Km, and medians of 5, 13, and 22 Km, when using SVMs as linear classifiers. Inferior results were achieved when using logistic regression as linear classifier. As one can observe similar results were achieved both using TF-IDF or TF-IDF-ICF. The first method usually achieves slightly better mean results, whereas TF-IDF-ICF usually achieves slightly better median results.

Table 4.10 describes the results for the Twitter datasets, namely a mean of 1496 km and a median of 497 km for the Twitter-World dataset, and a mean of 732 km, and a median of 234 km for the Twitter-US dataset. This results show that the proposed geocoding method can also be used to geolocate tweets, since we achieved better mean error and similar median error results than Wing & Baldridge (2014), for the Twitter World dataset, that report a mean error of 1670 Km and a median error of 490 Km.

Table 4.11 presents the obtained results when using external datasets as a complement or an

	Classifier accuracy				Errors in terms of distance (Km)	
SVMs	1st	2nd	3rd	4th	Average	Median
English	0.966	0.785	0.540	0.262	82.501 (± 4.340)	8.874 [5.303 - 15.142]
German	0.972	0.832	0.648	0.396	62.995 (± 5.753)	4.974 [3.615 - 8.199]
Spanish	0.950	0.720	0.436	0.157	165.887 (± 16.675)	13.410 [8.392 - 22.691]
Portuguese	0.951	0.667	0.336	0.104	105.238 (± 10.059)	21.872 [13.611 - 33.264]

	Classifier accuracy				Errors in terms of distance (Km)	
LR	1st	2nd	3rd	4th	Average	Median
English	0.950	0.701	0.425	0.168	138.547 (± 7.288)	15.637 [9.344 - 26.682]
German	0.938	0.713	0.505	0.238	251.716 (± 13.943)	11.648 [6.154 - 22.757]
Spanish	0.916	0.591	0.309	0.087	356.162 (± 23.545)	24.901 [14.885 - 45.955]
Portuguese	0.915	0.541	0.246	0.062	335.543 (± 24.858)	34.159 [20.779 - 57.110]

Table 4.9: The results obtained for each different language and for each different linear classifier, and when using TF-IDF representations.

	Classifier accuracy				Errors in terms of distance (Km)	
Twitter Dataset	1st	2nd	3rd	4th	Average	Median
WORLD	0.589	0.205	0.156	0.147	1495.760 (± 53.770)	497.225 [230.603 - 921.458]
US	0.706	0.345	0.216	0.093	732.310 (± 20.276)	234.022 [44.029 - 609.816]

Table 4.10: The results obtained for the Twitter datasets using TF-IDF-CF as the document representation method

alternative to geocode documents from the English version of Wikipedia. The results show that text from general Web pages can be used to complement contents from Wikipedia, although the performance drops significantly when using these contents in isolation. The best performing model for the median error combined the Wikipedia contents with text from hypertext anchors and words from the surrounding contexts, achieving a median error of 8.127 Kilometers, showing that slightly better results can be achieved when combining data from external sources such as general content from the Web.

4.3 Summary

This chapter describes the datasets used in the experiments that were designed for validating the proposed method (i.e., versions of the English, German, Spanish and Portuguese Wikipedias from 2014, and the two datasets from Twitter, namely the WORLD and the US datasets described in the previous study by) in order to test the proposed document geocoding approach. The best performing results for the English version of Wikipedia achieved a mean error of 83 Km and a median error of 8 Km. The German, Spanish and Portuguese versions of Wikipedia achieved

	Classifier accuracy				Errors in terms of distance (Km)	
	1st	2nd	3rd	4th	Average	Median
Wikipedia text	0.967	0.786	0.547	0.272	86.616 (± 4.517)	8.308 [5.134 - 14.413]
Anchors	00.00	00.00	00.00	00.00	273.355 (± 10.13)	44.587 [2.315 - 22.315]
Wikipedia + anchors	0.967	0.786	0.548	0.273	85.808 (± 4.490)	8.299 [4.998 - 14.348]
Anchors + context	0.915	0.644	0.387	0.182	246.102 (± 8.084)	18.583 [9.983 - 33.107]
Wikipedia + anchors + context	0.967	0.790	0.551	0.274	88.068 (± 4.657)	8.178 [5.024 - 14.055]

Table 4.11: The results obtained with different sources of text, used as a complement or as a replacement to Wikipedia.

mean errors of 62, 166 and 105 Km and median errors of 5, 13, and 21 Km respectively, demonstrating that state-of-the-art results were achieved with this document geocoding algorithm. It was also shown that even common words may be highly geoindicative, in an experiment where the place names occurring in the contents of each Wikipedia version were first removed using Stanford NER. The results, after removing place names, for the English version of Wikipedia were a mean error of 449 Km and a median error of 28 Km, and mean errors of 150, 358, and 241 Km, and median errors of 5, 21, and 37 Km respectively for the German, Spanish and Portuguese Wikipedias. I also tested the use of external datasets to complement the geocoding of Wikipedia documents. The best results were achieved with a Google dataset that contains anchors that refer to the English Wikipedia pages, together with surrounding context, and correspond to a mean error of 88 Km, and a median error of 8 Km. The best results for the WORLD Twitter dataset were a mean of 1496 Km and a median error of 497 km, and a mean error of 732 km, while a median error of 234 km for the US Twitter dataset, results that are comparable with the ones reported by (Wing & Baldridge, 2014).

Chapter 5

Conclusions and Future Work

This chapter summarizes the main conclusions from my research work, and presents some suggestions of possible future work on the mining of geospatial information from textual documents.

5.1 Conclusions

Through this study, I empirically evaluated automated methods for document geo-referencing over textual contents of different types (i.e., place names versus other textual terms) and/or from different sources (i.e., curated sources like Wikipedia, versus general Web contents). The results confirm that the automatic identification of the geospatial location of a document, based only on its text, can be performed with high accuracy by using out-of-the-box implementations of well-known supervised classification methods, and leveraging a discrete binned representation of the Earth's surface based on the HEALPix scheme. The results also show that reasonably good results can still be achieved when place names are removed from the textual contents, thus supporting the idea that general textual terms can be highly geo-indicative. When comparing the performance of models trained with contents from different sources, we saw that text from general Web pages (i.e., text from hypertext anchors point to geo-referenced Wikipedia documents, and words from the contexts surrounding these hypertext links) can be used to complement contents from Wikipedia, although the performance drops significantly when using these contents in isolation. One of the best performing approaches leveraged SVMs classification models and text representations based on TF-IDF-ICF achieving a median error of 87 Km and an average error of 8 Km in the task of geocoding English Wikipedia documents. Regarding the Twitter datasets,

over the Twitter-World dataset I achieved a mean eror of 1496 Km, and a median error of 497 Km, whereas in the Twitter-US dataset I achieved a mean error of 732 Km, and a median error of 234 Km. The results show that this geocoding approach can be used for geocoding tweets sinced it achieved similar results with the ones reported by (Wing & Baldridge, 2014).

5.2 Future Work

The general approach proposed here is simple to implement, and both training and testing can be easily parallelized, in order to scale to very large document collections. The most effective strategy uses contents from sources that are readily available and easy to collect, and I therefore believe that automated document geocoding can easily be integrated into other geographic information retrieval applications. Still, despite the interesting results, there many possible paths for future improvements. Taking inspiration on the previous work by Laere *et al.* (2014b), it would be interesting to see if contents from Flickr could still be used to further improve the results of our best performing models. Instead of ICF, other supervised term weighting schemes can also be devised, for instance through the usage of geographic spread heuristics, or through Rippley's K function for quantifying spatial homogeneity (Laere *et al.*, 2014a).

Although identifying a single location for an entire document can provide a convenient way for connecting texts with locations, useful for many different applications, for some studies it may instead be more interesting to consider the complete resolution of place references in the text (Lieberman & Samet, 2011; Santos *et al.*, 2014). For future work, it may be interesting to revisit the place reference resolution problem, taking inspiration on recent developments within the general area of entity linking in text. The estimations provided by our method can, for instance, be used to define a document-level prior for the resolution of individual place names. Finally, in terms of future work, I would also like to experiment with other types of classification approaches (e.g., with models based on ensembles of classifiers), as well as with methods for dealing with class imbalancement (Chawla *et al.*, 2002).

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