Estimation of Web Contents Geographic Provenience Exploiting Creative Commons Licensed Pages for Training Set Aggregation

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Abstract

Geographic scope estimation is a fairly recent problem which is gaining increasing attention due to the broad implications in many different fields, ranging from the development of better search engines to the need to assess specific content production on a geographical basis. However, geographic scope is a concept that can be interpreted in many different ways, ranging from the expected target scope of a specific content to the country where the content originated. The latter, in particular, albeit difficult to address, is of great importance for many reasons, such as, for example, market inquiries or anytime estimates on content production in specific countries are needed. Search engines may also be affected by the knowledge of the various kinds of geographic scopes, to better tune their responses to queries, e.g. according to (but not restricted to) the geographic proximity with the user location. However that information is rarely available and must be inferred in the vast majority of the cases. In this paper we propose a technique, grounded into the machine learning theory, to estimate source geography of web pages by means of a classifier learned on a specially constructed training set. The training set, consisting of a number of features extracted from web pages and the corresponding source-geography label (i.e. the country of origin of the web page) is automatically built by exploiting the wide number of pages with contents licensed under a localized Creative Commons (CC) license. The model thus learned is then used to classify unlabeled records and our tests showed a mean accuracy of 81% with a standard deviation of 0.9.

1 Introduction

Search engines are probably the most used and famous information retrieval application, offering efficient finding and fruition of specific information that is by its nature widely spread across the World Wide Web.

However, most search engines typically exploit simple textual queries to find pertinent documents containing specific weighted *keywords* via an inverted index, which maps terms to web pages. These kind of tools may also take into consideration other parameters such as, for example, language, file type, and usage rights. Moreover, a user might want to restrict searches to pages having a specific geographical origin

or scope, which, in general, may be different from the physical location of the server hosting the resources to be searched. In fact, a user may want to search for specific content from a specific country, such as Italian recipes or, say, mp3 files, or search for a certain keyword in the web when within a certain geographic scope.

In recent years the problem of inferring geographical information contained in web pages in order to determine the geographic context of their content gained increasing attention. The extraction of this kind of information is mostly aimed at allowing web applications, such as search engines or intelligent agents, to retrieve information and compute relevance with respect to a specific query including (but not restricted to), for example, the geographic proximity with the user location. Moreover, the possibility to associate a web page with its geographic scope can also allow to estimate and collect location wise statistics in order to understand the global or local importance of a web site considering its geographical popularity, given by the distribution all over the world of other sites linking to it. Last but not least, knowing the geographic scope and the origin of web pages may be of great importance for market analysts seeking information about interests and needs in specific geographic regions.

However, despite its simple definition, the problem is not an easy one to address, especially if specific metadata (which would render the problem almost trivial) are lacking. In principle, it is already possible to tag specific resources with proper metadata specifying their geographical origin ([1, 2, 3]), but, like most other initiatives on metadata, it suffers for the chicken and egg problem and thus, to date, most of the available content on the web lacks this kind of information which, at best, has to be inferred from contextual information.

Moreover, the geographic context problem is manyfolds: in fact the geographic scope of the audience seeking specific resources might be different from their geographical origin, which, in turn is, in general, different from their physical location.

[4] and [5] already came up with at least two different definitions of geographic context, namely the *target-geography*, or *content-based* geographic context, which relates to the geographical scope of a web page content and the *source-geography*, or *entity-based* geographic context, which, on the other hand, refers to the geographic context where the content was created, which typically means the location associated with its author or the website.

Given the broad implications and aspects of the problem, past literature mostly focused either on determining the geographical location of the hosting services or on extracting geographical information from the web pages' textual content, i.e., estimating geographic context based on the content, the rationale being that the geographical scope of a page is strictly correlated with the locations it refers to.

Buyukokkten *et al.* [6] extracted the area codes from the publicly available phone numbers of all the network administrators for the Class A and B domains; each area code was then mapped to cities, counties and states which were considered to be the geographic scopes of the corresponding IP addresses.

[4] used simple heuristics to infer the geographic information associated with servers and web sites from the output of standard network tools such as `traceroute` and `whois`, and the names, addresses, postal codes, and telephone numbers in the textual content.

Ding *et al.* [7] described both an estimation technique to exploit the geographic position of sites linking a specific page thus analyzing its area of interest, and an alternative method to extract all the references to geographic locations from the textual content using a named-entity tagger; the scope was then computed by assigning a different weight to each reference to disambiguate and rank them. Both [8] and [9] used an ontology to model geographic areas and relationships between locations to compute scopes by means of some measures on the semantic links between the references; moreover [9] put a specific emphasis on context computation via a graph ranking algorithm.

Particular attention to geographic terms disambiguation and false-positive avoidance was given in [5], where a gazetteer and confidence scores are used for each reference.

All the above techniques focus on computing and exploiting the geographical location in the broad-

est sense, allowing for more efficient information retrieval processes, thus offering more powerful tools than plain queries relying on simple *"keywords + location"* matches, instead leveraging on the geographical scope of a resource to rank results according to some proximity metrics.

However, it is noteworthy to say that ambiguities can lead to wrong classifications when no distinction is made between the *target* geography and the *source* geography or under the assumption that albeit being different concepts they always bear the same value. Most previous works strongly relied on the analysis of the web page textual content, thus focusing only on the former kind of context, i.e., target geography.

In this paper we focus on *source* geography, thus aiming at estimating the geographic *provenience* of a web page irrespective of its specific content which is not assumed to be always correlated with the source-geography. Interestingly enough, source-geography scope is always present and well defined, albeit difficult or impossible to determine, unlike the *target* one, because a web page may not contain any geographical references or may not be aimed at a specific target area, but it is nearly always created and published from a precise geographical region. However, source-geography is usually unrelated with the specific content or subject of a web page. Thus, source-geography context is more difficult to infer reliably.

In this paper we use well-known machine learning techniques to infer the source-geography of a page. More specifically, a classifier is learned on a training set of pre-labeled data and then used to perform online classification. Since harvesting and hand-labeling a properly sized training set would be impractical, we exploit the widespread adoption of localized Creative Commons licenses [10] (for the sake of simplicity, CC in the following).

The contributions of this paper are, thus, two-fold: first, we devise a way to build a proper training set, and secondly we propose a method to infer the source geography of a web page.

The rest of this paper is organized as follows: key ideas and the proposed technique are introduced in Section 2, and results are presented in Section 3, finally, conclusions are drawn in Section 4.

2 Proposed technique

The source geography scope tagging problem can easily be cast into a classification task where, given a web resource, one wants to infer the class to which it belongs, where the class here is the country where the resource was produced. We experimented with two simple classifiers, i.e., Naive Bayes [11] (due to its simplicity and low complexity) and Hidden Naive Bayes [12] (an improvement over the simpler Naive Bayes which takes into account interdependency across the features by conditioning on a latent unobservable variable).

2.1 Training set

As a first step, a set of features has to be chosen and collected to train a proper classifier on a set of pre-labeled data. However, harvesting a proper training set and hand-labeling each resource with the proper class is impractical and time-consuming due to the large number of classes (countries) and the need to have a sufficiently diverse collection of resources for each class.

To overcome this problem we propose an automatic and more efficient technique exploiting the page licensing information (if present).

CC licenses have gained momentum and are being adopted by content producers across the world, due to their simplicity and the wide range of readily available licensing possibilities. These copyright licenses provide a set of predefined options (and the corresponding legal code) to grant some rights to the public, allowing to share, reuse and remix creative works, also regulating commercial uses. They typically represent a convenient solution for non-professional contents creators, i.e., for some free and open contents based business models. Thus, many different kinds of digital objects have currently been put under a CC licensing scheme, ranging from entire blogs, and books, to music, film footage and paintings, a significant part of which has been published on the web.

Even more interestingly from our standpoint is the fact that CC licenses have been localized to the diverse jurisdictions of many countries; to date 51 country-specific versions of the licenses [13] are avail-

able by volunteers's team. These countries comprise most of the main contributors of online contents and can be considered sufficient and significant for our application. Localized licenses cover almost 20% [14] of all the CC licensed contents (which currently amounts to more than 100 millions [15]), thus representing a valid source of information.

Under the reasonable assumption that a localized CC license is usually applied only to a content "*belonging*" to the country it refers to, it can be safely used to label freely available licensed content. Moreover, we assume that pages with CC-licensed contents, while diverse and heterogeneous, are not different (feature-wise) from pages with no reference to a CC license.

Thus, we developed a web spider to crawl the web collecting pages containing CC licensing information. This kind of information is usually encoded in the page by means of either RDF [16] expressed in XML and inserted into HTML comments, or via RDFa [17] as recommended by Creative Commons [18]. If no metadata are present it is still possible to simply check for back-links to the license deeds hosted on the CC website. Each time a web page is analyzed, it is labeled according to its license and, along with a number of specific features (irrespective of its licensing scheme) it is added to the training set.

2.2 Feature selection

The relevant features to infer source geography scope can be roughly divided into two categories, i.e., information about the server hosting the content and information extracted from the content itself.

The first set of features includes the physical location of the server hosting a particular page and can be obtained by checking its Fully Qualified Domain Name (FQDN), especially the top level domain part, and its IP address. When a page is crawled and analyzed, the WHOIS [19] protocol is used to obtain from the WHOIS official databases the information about the country of the site domain name and the corresponding IP address owners. Analogously, the IP address of the server hosting the page can be mapped to a country by means of the MaxMind GeoIP's APIs [20].

Class	*Number or records*
ARGENTINA	142
AUSTRALIA	679
BRAZIL	830
CANADA	244
CHINA	444
FRANCE	798
GERMANY	1310
ITALY	1274
JAPAN	866
MEXICO	113
SPAIN	2527
SWEDEN	202
SWITZERLAND	166
UNITED KINGDOM	495
UNITED STATES	1270
OTHER	856
TOTAL	12216

Table 1: Total number of unique records per country in the training set.

Furthermore, often some sort of load-balancing at the name server (DNS) is performed to distribute the load more fairly across different servers. As a consequence, the same name is resolved at each request to a (possibly) different list of IP addresses, which are ranked either at random or according to a sequential "round robin" policy over the set of available servers. Clients typically choose to use the first address of the list. Thus, we had to take into considerations all the IP addresses corresponding to a given FQDN, to map them to their geographic location and, in case they did not belong to the same country, consider the more frequent one in the set.

Some relevant information is also provided by certain features of the page content and the Uniform Resource Locator (URL), especially from the top level domain name if it matches a country code.

In fact the content itself, along with its language, are also very important to assess the source geography, although they may still lead to some ambiguity, especially for certain languages which are widely spoken in different countries. However, language is often

strongly related to the information we seek. Thus, both the character set and an estimate of the language in which the page is written, along with explicit language declarations, if any, are considered as important features.

[21] describes how to express the language information with HTTP headers and into the HTML documents in many ways and with slightly different meanings. In fact, the intended audience language about the document as a whole, for high level processing purposes, is typically described the `Content-Language:` HTTP header. HTML may also include information about the text-processing language, as internal language declarations in the HTML metadata to specify the language for portions of the text and allow tools such as voice browsers and spell checkers to handle the content appropriately.

Moreover, language itself can be declared in various ways in documents written either in the HTML or the XHTML dialects, the latter being compliant to XML. In fact, while on one hand language can be specified by using the `lang` and `xml:lang` attributes of XHTML elements and is inherited by their descendants; if the attribute is used on the `<html>` tag it sets the language for the whole document, however the declaration can be overridden by a similar one in a descendant element. Typically, `lang` is used for HTML pages, `xml:lang` for XHTML pages used for derive an XML document, while both can be used in XHTML served as a text/HTML document, as in the Web scenario. On the other hand, it is also possible to use a meta element which sets the tag `http-equiv` to `Content-Language` or, albeit being less common, using the Dublin Core `language` element [22].

The `Content-Language` meta element and the HTTP header are specifically designed to express the language of the intended audience and they typically consists of set of values (i.e. "de, fr, it") but they can also bear information about the source geography.

Lastly, language information can be inferred by applying natural language processing techniques such as N-Gram based text categorization [23] to the textual content of the requested resource. N-Gram based text categorization extracts a text language profile which is then used to find the best match with a number of pre-calculated profiles of different languages.

Character encoding is usually present in the HTTP headers, more specifically in the `Content-Type` line [24] and should also always be specified, as recommended by the World Wide Web Consortium (W3C), into the `<head>` portion of HTML (or XHTML) documents.

Although language cannot be directly inferred from the character encoding, because there is not a one-to-one mapping, the choice of a specific encoding could give hints about the language and the region of provenience.

2.3 The classifier

It should be noted that none of the above features, if taken alone, can unequivocally determine the source geography scope of a web page, but all of them bear some information. Moreover, part of the information brought to bear by the attributes is redundant, and the contributions of different features partly overlaps.

In addition, all the considered attributes have a variable degree of reliability: the country which hosts the server often has no relationship with the users who use it to publish contents, language metadata are often missing, certain top level domain are either too generic, such as the case of *.com* and *.org* or are misused (*.tv* and *.tk*), thus reducing their relationship with the source geography.

Due to this problems source geography can not be deterministically decided simply by looking at a single feature. Thus to obtain a robust and reliable estimate a probabilistic approach should be used, because no feature can completely discriminate across the classes.

Learning a Bayesian model implies the computation of the conditional probability for every possible combination pair of the features values, which, in general, leads to high computational cost; thus we adopted a simpler model called Naive Bayes. The Naive Bayes approach assumes that all the features are conditionally independent.

Obviously the assumption of conditional independence across the features is a rough approximation which deliberately ignores the mutual information *between* the features, i.e., their relative redundancy which, in our case, is always greater than zero. To

Model	*Mean Accuracy*	*Standard deviation*
Naive Bayes	**79.395%**	0.951
Hidden Naive Bayes	**80.675%**	0.916

Table 2: Mean accuracy of the tested classifiers is presented along with the corresponding standard deviation.

overcome this problem we also experimented with the *Hidden Naive Bayes*[12] which relies on weaker assumptions about independence across the features by introducing a latent, hidden parent feature for each observable one, defined by means of a weighted one-dependence estimators, encoding the *importance* of each attribute, thus playing a key role in the learning process.

3 Results

A set of about 1.5 million web pages from all over the world was collected by means of our crawler which also recorded the attributes needed to perform classification. However, most of these pages were redundant, often because they belonged to the same site, thus, the set was deeply pruned down to a subset of 12.216 pages not sharing the second level domain name (in order to avoid multiple samples like `bob.blog.com` and `alice.blog.com` with similar characteristics), except for web pages sharing some domain names but with a different class, i.e., which belong to different countries. Table 1 shows the number of records per country we collected this way.

Pruning however left many countries with very few samples, clearly insufficient to perform training properly, so we decided to limit the number of classes by lumping into one single class all the classes corresponding to countries with fewer than 100 distinct samples. We also noticed how the ratios between country samples number in this set became close to the ratio of the number of licensed contents per jurisdiction as estimated by the Creative Commons organization [15] and by some previous works [14]. This suggests that our content harvesting techniques did not introduce any particular bias into the distribution of the training samples.

Our algorithm was tested by means of 10 runs of a 10-fold cross validation, i.e., the training set [1] (after pruning and class lumping) was first divided into 10 almost equally-sized subset, which were in turn used as test sets for a model learnt on the remaining nine. After each run, records were randomly sorted. At the end of the whole evaluation process mean accuracy and standard deviation were computed, both for the Naive and the Hidden Naive Bayes classifiers. In Table 2 results for both methods are shown. The simpler Naive Bayes model achieved a mean accuracy of 79.395%, while Hidden Naive Bayes accuracy increased of 1.3%, up to a mean value of 80.675%. Interesting enough, the standard deviation is about 0.9 for both classifiers, showing that classification performance is quite stable across the training set.

It is noticeable how most misclassifications belong to the UNITED STATES class. This happens because of the great number of contents outside the United States sharing many features typical of pages actually coming from the USA, such as being written in English language and hosted on a server located in the USA.

4 Conclusions

In this paper we presented an algorithm to automatically classify web contents with their country of origin. This classification is made by means of a supervised learning algorithm which is used to build up a probabilistic model starting from a set of already labeled records. For this purpose, we also proposed a technique to build the training set automatically by exploiting Creative Commons licensed web pages in fact, the web was harvested and for each page found we extracted the nationality and a set of geographically meaningful features. Two different probabilistic

[1] The training set is available for download at: `http://nexa.polito.it/nexafiles/geoweb_tr_set.zip`

models, a simpler Naive Bayes and a Hidden Naive Bayes models were trained and used to perform classification,

Results show that the Hidden Naive Bayes model successfully classified unlabeled contents with an accuracy of about (mean ± standard deviation) 81% ± .9.

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