Language Identification of Search Engine Queries

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Abstract

We consider the language identification problem for search engine queries. First, we propose a method to automatically generate a data set, which uses click-through logs of the Yahoo! Search Engine to derive the language of a query indirectly from the language of the documents clicked by the users. Next, we use this data set to train two decision tree classifiers; one that only uses linguistic features and is aimed for textual language identification, and one that additionally uses a non-linguistic feature, and is geared towards the identification of the language intended by the users of the search engine. Our results show that our method produces a highly reliable data set very efficiently, and our decision tree classifier outperforms some of the best methods that have been proposed for the task of written language identification on the domain of search engine queries.

1 Introduction

The language identification problem refers to the task of deciding in which natural language a given text is written. Although the problem is heavily studied by the Natural Language Processing community, most of the research carried out to date has been concerned with relatively long texts such as articles or web pages which usually contain enough text for the systems built for this task to reach almost perfect accuracy. Figure 1 shows the performance of 6 different language identification methods on written texts of 10 European languages that use the Roman Alphabet. It can be seen that the methods reach a very high accuracy when the text has 100 or more characters. However, search engine queries are very short in length; they have about 2 to 3 words on average, which requires a reconsideration of the existing methods built for this problem.

Correct identification of the language of the queries is of critical importance to search engines. Major search engines such as Yahoo! Search (www.yahoo.com), or Google (www.google.com) crawl billions of web pages in more than 50 languages, and about a quarter of their queries are in languages other than English. Therefore a correct identification of the language of a query is needed in order to aid the search engine towards more accurate results. Moreover, it also helps further processing of the queries, such as stemming or spell checking of the query terms.

One of the challenges in this problem is the lack of any standard or publicly available data set. Furthermore, creating such a data set is expensive as it requires an extensive amount of work by human annotators. In this paper, we introduce a new method to overcome this bottleneck by automatically generating a data set of queries with language annotations. We show that the data generated this way is highly reliable and can be used to train a machine learning algorithm.

We also distinguish the problem of identifying the textual language vs. the language intended by the users for the search engine queries. For search engines, there are cases where a correct identifi-
cation of the language does not necessarily im-
ply that the user wants to see the results in the
same language. For example, although the textual
identification of the language for the query “homo
sapiens” is Latin, a user entering this query from
Spain, would most probably want to see Spanish
web pages, rather than web pages in Latin. We ad-
dress this issue by adding a non-linguistic feature
to our system.

We organize the rest of the paper as follows:
First, we provide an overview of the previous re-
search in this area. Second, we present our method
to automatically generate a data set, and evaluate
the effectiveness of this technique. As a result of
this evaluation, we obtain a human-annotated data
set which we use to evaluate the systems imple-
mented in the following sections. In Section 4, we
implement some of the existing models and com-
cpare their performance on our test set. We then
use the results from these models to build a deci-
sion tree system. Next, we consider identifying the
language intended by the user for the results of the
query, and describe a system geared towards this
task. Finally, we conclude our study and discuss
the future directions for the problem.

2 Related Work

Most of the work carried out to date on the writ-
ten language identification problem consists of sup-
ervised approaches that are trained on a list of
words or n-gram models for each reference lan-
guage. The word based approaches use a list of
short words, common words, or a complete vocab-
ulary which are extracted from a corpus for each
language. The short words approach uses a list of
words with at most four or five characters; such as
determiners, prepositions, and conjunctions, and
is used in (Ingle, 1976; Grefenstette, 1995). The
common words method is a generalization over
the short words one which, in addition, includes
other frequently occurring words without limiting
them to a specific length, and is used in (Soutter et
al., 1994; Cowie et al., 1999). For classification,
the word-based approaches sort the list of words in
descending order of their frequency in the corpus
from which they are extracted. Then the likelihood
of each word in a given text can be calculated by
using rank-order statistics or by transforming the
frequencies into probabilities.

The n-gram based approaches are based on the
counts of character or byte n-grams, which are se-
quences of n characters or bytes, extracted from
a corpus for each reference language. Different
classification models that use the n-gram features
have been proposed. (Cavnar and Trenkle, 1994)
used an out-of-place rank order statistic to mea-
sure the distance of a given text to the n-gram
profile of each language. (Dunning, 1994) pro-
posed a system that uses Markov Chains of byte n-
grams with Bayesian Decision Rules to minimize
the probability error. (Grefenstette, 1995) simply
used trigram counts that are transformed into prob-
abilities, and found this superior to the short words
technique. (Sibun and Reynar, 1996) used Rela-
tive Entropy by first generating n-gram probability
distributions for both training and test data, and
then measuring the distance between the two prob-
ability distributions by using the Kullback-Liebler
Distance. (Poutsma, 2001) developed a system
based on Monte Carlo Sampling.

Linguini, a system proposed by (Prager, 1999),
combines the word-based and n-gram models us-
ing a vector-space based model and examines the
effectiveness of the combined model and the in-
dividual features on varying text size. Similarly,
(Lena Grothe and Nrnberger, 2008) combines both
models using the ad-hoc method of (Cavnar and
Trenkle, 1994), and also presents a comparison
study. The work most closely related to ours is
presented very recently in (Hammarström, 2007),
which proposes a model that uses a frequency dic-
tionary together with affix information in order to
identify the language of texts as short as one word.

Other systems that use methods aside from the
ones discussed above have also been pro-
posed. (Takci and Sogukpinar, 2004) used letter
frequency features in a centroid based classifica-
tion model. (Kruengkrai et al., 2005) proposed a
feature based on alignment of string kernels us-
ing suffix trees, and used it in two different clas-
sifiers. Finally, (Biemann and Teresniak, 2005)
presented an unsupervised system that clusters the
words based on sentence co-occurrence.

Recently, (Hughes et al., 2006) surveyed the
previous work in this area and suggested that the
problem of language identification for written re-
sources, although well studied, has too many open
challenges which requires a more systematic and
collaborative study.

3 Data Generation

We start the construction of our data set by re-
trieving the queries, together with the clicked urls,
from the Yahoo! Search Engine for a three months
time period. For each language desired in our data
set, we retrieve the queries from the corresponding
Yahoo! web site in which the default language is the same as the one sought. Then we preprocess the queries by getting rid of the ones that have any numbers or special characters in them, removing extra spaces between query terms, and lowering all the letters of the queries. Next, we aggregate the queries that are exactly the same, by calculating the frequencies of the urls clicked for each query.

As we pointed out in Section 1, and illustrated in Figure 1, the language identification methods give almost perfect accuracy when the text has 100 or more characters. Furthermore, it is suggested in (Levering and Cutler, 2006) that the average textual content in a web page is 474 words. Thus we calculate a weight \( w_{q,l} \) for each mapping of a query \( q \) to a language \( l \) as:

\[
\begin{align*}
  w_{q,l} &= \frac{f_l}{F_q} \\
  F_q &= \sum_{l \in L_q} f_l
\end{align*}
\]

where \( F_q \), the total frequency of a query \( q \), is defined as:

\[
  F_q = \sum_{l \in L_q} f_l
\]

where \( L_q \) is the set of languages for which \( q \) has a mapping. Having computed a weight \( w_{q,l} \) for each mapping, we introduce our first threshold parameter, \( W \). We eliminate all the queries in our data set, which have weights, \( w_{q,l} \), below the threshold \( W \).

Second, even though some of the queries map to only one language, this mapping cannot be trusted due to the high frequency of the queries together with too few distinct urls. This case suggests that the query is most likely navigational. The intent of navigational queries, such as “ACL 2009”, is to find a particular web site. Therefore they usually consist of proper names, or acronyms that would not be of much use to our language identification problem. Hence we would like to get rid of the navigational queries in our data set by using some of the features proposed for the task of automatic taxonomy of search engine queries. For a more detailed discussion of this task, we refer the reader to (Broder, 2002; Rose and Levinson, 2004; Lee et al., 2005; Liu et al., 2006; Jansen et al., 2008).

Two of the features used in (Liu et al., 2006) in identification of the navigational queries from click-through data, are the number of Clicks Satisfied (nCS) and number of Results Satisfied (nRS). In our problem, we substitute nCS with \( F_q \), the total click frequency of the query \( q \), and nRS with

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**Algorithm 1**: Join Tables \( T1 \) and \( T2 \), group by query and language, aggregate distinct url and frequency counts.

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**Input**: Tables \( T1\{q, u, f_u\}, T2\{u, l\} \\
**Output**: Table \( T3\{q, l, f_q, c_q, u_l\} \\

CREATE VIEW T3 AS 
SELECT 
  T1.\( q, T2.\ l, COUNT(T1.\ u) \ AS c_{u,l}, \) SUM(T1.\( f_u) \ AS f_l \)
FROM T1 
INNER JOIN T2 
ON T1.\ u = T2.\ u 
GROUP BY \( q, l \);

---

\( 1 \)We do not make a distinction between the different dialects of the same language. For English, Spanish and Portuguese we gather queries from the web sites of United States, Mexico, and Brazil respectively.

\( 2 \)In this study, we only considered languages that use the Roman alphabet.

\( 3 \)Although not done in this study, the urls of web pages that have less than a defined number of words, such as 100, can be discarded to ensure a higher confidence.
The parameters $F$, $U$, and $W$ are actually dependent on the size of the data set under consideration, and the study in (Silverstein et al., 1999) suggests that we can get enough click-through data for our analysis by retrieving a large sample of queries. Since we retrieve the queries that are submitted within a three-month period, for each language, we have millions of unique queries in our data set. Investigating a held-out development set of queries retrieved from the United States web site (www.yahoo.com), we empirically decided the following values for the parameters, $W = 1$, $F = 50$, and $U = 5$. In other words, we only accepted the queries for which the contents of the urls agree on the same language, that are submitted less than 50 times, and at least have 5 unique urls clicked.

The filtering process leaves us with 5-10% of the queries due to the conservative choice of the parameters. From the resulting set, we randomly picked 500 queries and asked a native speaker to annotate them. For each query, the annotator was to classify the query into one of three categories:

- **Category-1**: If the query does not contain any foreign terms.

- **Category-2**: If there exists some foreign terms but the query would still be expected to bring web pages in the same language.

- **Category-3**: If the query belongs to other languages, or all the terms are foreign to the annotator.\(^4\)

\(^{4}\)We do not expect the annotators to know the etymology of the words or have the knowledge of all the acronyms.

90.6% of the queries in our data set were annotated as Category-1, and 94.2% as Category-1 and Category-2 combined. Having successful results for the United States data set, we applied the same parameters to the data sets retrieved for other languages as well, and had the native speakers of each language annotate the queries in the same way. We list these results in Table 1.

The results for English have the highest accuracy for Category-1, mostly due to the fact that we tuned our parameters using the United States data. The scores for German on the other hand, are the lowest. We attribute this fact to the highly multilinguality of the Yahoo! Germany website, which receives a high number of non-German queries. In order to see how much of this multi-linguality our parameter selection successfully eliminate, we randomly picked 500 queries from the aggregated but unfiltered queries of the Yahoo! Germany website, and had them annotated as before.

As suspected, the second annotation results showed that, only 47.6% of the queries were annotated as Category-1 and 60.2% are annotated as Category-1 and Category-2 combined. Our method was indeed successful and achieved 29.2% improvement over Category-1, and 27% improvement over Category-1 and Category-2 queries combined.

Another interesting fact to note is the absolute differences between Category-1 and Category-1+2 scores. While this number is very low, 3.8%, for English, it is much higher for the other lan-

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
Language & Category-1 & Category-1+2 & Category-3 \\
\hline
English & 90.6% & 94.2% & 5.8% \\
French & 84.6% & 93.4% & 6.6% \\
Portuguese & 85.2% & 93.4% & 6.6% \\
Spanish & 86.6% & 97.4% & 2.6% \\
Italian & 82.4% & 96.6% & 3.4% \\
German & 76.8% & 87.2% & 12.8% \\
Dutch & 81.0% & 92.0% & 8.0% \\
Danish & 82.4% & 93.2% & 6.8% \\
Finnish & 87.2% & 94.0% & 6.0% \\
Swedish & 86.6% & 95.4% & 4.6% \\
\hline
Average & 84.3% & 93.7% & 6.3% \\
\hline
\end{tabular}
\caption{Annotation of 500 sample queries drawn from the automatically generated data.}
\end{table}

\[T4: \text{Tables } T1, T2, T3 \]
Table 2: Properties of the test set formed by taking 350 Category-1 queries from each language.

| Language | MinC | MaxC | μC | MinW | MaxW | μW |
|----------|------|------|----|------|------|----|
| English  | 7    | 46   | 21.8 | 1    | 6    | 3.35 |
| French   | 6    | 74   | 22.6 | 1    | 10   | 3.38 |
| Portug.  | 3    | 87   | 22.5 | 1    | 14   | 3.55 |
| Spanish  | 5    | 57   | 23.5 | 1    | 9    | 3.51 |
| Italian  | 4    | 51   | 21.9 | 1    | 8    | 3.09 |
| German   | 3    | 53   | 18.1 | 1    | 6    | 2.05 |
| Dutch    | 5    | 43   | 16.3 | 1    | 6    | 2.11 |
| Danish   | 3    | 40   | 14.3 | 1    | 6    | 1.93 |
| Finnish  | 3    | 34   | 13.3 | 1    | 5    | 1.49 |
| Swedish  | 3    | 42   | 13.7 | 1    | 8    | 1.80 |
| Average  | 4.2  | 52.7 | 18.8 | 1    | 7.8  | 2.63 |

guages. Through an investigation of Category-2 non-English queries, we find out that this is mostly due to the usage of some common internet or computer terms such as "download", "software", "flash player", among other native language query terms.

4 Language Identification

We start this section with the implementation of three models each of which use a different existing feature. We categorize these models as statistical, knowledge based, and morphological. We then combine all three models in a machine learning framework using a novel approach. Finally, we extend this framework by adding a non-linguistic feature in order to identify the language intended by the search engine user.

To train each model implemented, we used the EuroParl Corpora, (Koehn, 2005), and the same 10 languages in Section 3. EuroParl Corpora is well balanced, so we would not have any bias towards a particular language resulting from our choice of the corpora.

We tested all the systems in this section on a test set of 3500 human annotated queries, which is formed by taking 350 Category-1 queries from each language. All the queries in the test set are obtained from the evaluation results in Section 3. In Table 2, we give the properties of this test set. We list the minimum, maximum, and average number of characters and words (MinC, MaxC, μC, MinW, MaxW, and μW respectively).

As can be seen in Table 2, the queries in our test set have 18.8 characters on average, which is much lower than the threshold suggested by the existing systems to achieve a good accuracy. Another interesting fact about the test set is that, languages which are in the bottom half of Table 2 (German, Dutch, Danish, Finnish, and Swedish) have lower number of characters and words on average compared to the languages in the upper half. This is due to the characteristics of those languages, which allow the construction of composite words from multiple words, or have a richer morphology. Thus, the concepts can be expressed in less number of words or characters.

4.1 Models for Language Identification

We implement a statistical model using a character based n-gram feature. For each language, we collect the n-gram counts (for \( n = 1 \) to \( n = 7 \) also using the word beginning and ending spaces) from the vocabulary of the training corpus, and then generate a probability distribution from these counts. We implemented this model using the SRILM Toolkit (Stolcke, 2002) with the modified Kneser-Ney Discounting and interpolation options. For comparison purposes, we also implemented the Rank-Order method using the parameters described in (Cavnar and Trenkle, 1994).

For the knowledge based method, we used the vocabulary of each language obtained from the training corpora, together with the word counts. From these counts, we obtained a probability distribution for all the words in our vocabulary. In other words, this time we used a word-based n-gram method, only with \( n = 1 \). It should be noted that increasing the size of \( n \), which might help in language identification of other types of written texts, will not be helpful in this task due to the unique nature of the search engine queries.

For the morphological feature; we gathered the affix information for each language from the corpora in an unsupervised fashion as described in (Hammarström, 2006). This method basically considers each possible morphological segmentation of the words in the training corpora by assuming a high frequency of occurence of salient affixes, and also assuming that words are made up of random characters. Each possible affix is assigned a score based on its frequency, random adjustment, and curve-drop probabilities, which respectively indicate the probability of the affix being a random sequence, and the probability of being a valid morphological segment based on the information of the preceding or the succeeding character. In Table 3, we present the top 10 results of the probability distributions obtained from the vocabulary of English, Finnish, and German corpora.

We give the performance of each model on our test set in Table 4. The character based n-gram model outperforms all the other models with the exception of French, Spanish, and Italian on which the word-based unigram model is better.
The word-based unigram model performs poorly on languages that may have highly inflected or composite words such as Finnish, Swedish, and German. This result is expected as we cannot make sure that the training corpus will include all the possible inflections or compositions of the words in the language. The Rank-Order method performs poorly compared to the character based n-gram model, which suggests that for shorter texts, a well-defined probability distribution with a proper discounting strategy is better than using an ad-hoc ranking method. The success of the morphological feature depends heavily on the probability distribution of affixes in each language, which in turn depends on the corpus due to the unsupervised affix extraction algorithm. As can be seen in Table 3, English affixes have a more uniform distribution than both Finnish and German.

Each model implemented in the previous section has both strengths and weaknesses. The statistical approach is more robust to noise, such as misspellings, than the others, however it may fail to identify short queries or single words because of the lack of enough evidence, and it may confuse two languages that are very similar. In such cases, the knowledge-based model could be more useful, as it can find those query terms in the vocabulary. On the other hand, the knowledge-based model would have a sparse vocabulary for languages that can have heavily inflected words such as Turkish, and Finnish. In such cases, the morphological feature could provide a strong clue for identification from the affix information of the terms.

### 4.2 Decision Tree Classification

Noting the fact that each model can complement the other(s) in certain cases, we combined them by using a decision tree (DT) classifier. We trained the classifier using the automatically annotated data set, which we created in Section 3. Since this set comes with a certain amount of noise, we pruned the DT during the training phase to avoid overfitting. This way, we built a robust machine learning framework at a very low cost and without any human labour.

As the features of our DT classifier, we use the results of the models that are implemented in Section 4.1, together with the confidence scores calculated for each instance. To calculate a confidence score for the models, we note that since each model makes its selection based on the language that gives the highest probability, a confidence score should indicate the relative *highness* of that probability compared to the probabilities of other languages. To calculate this relative highness, we use the *Kurtosis* measure, which indicates how peaked or flat the probabilities in a distribution are compared to a normal distribution. To calculate the Kurtosis value, $\kappa$, we use the equation below.

$$\kappa = \frac{\sum_{l \in L} (p_l - \mu)^4}{(N - 1)\sigma^4}$$

where $L$ is the set of languages, $N$ is the number of languages in the set, $p_l$ is the probability for language $l \in L$, and $\mu$ and $\sigma$ are respectively the mean and the the standard deviation values of $P = \{p_l | l \in L\}$.

We calculate a $\kappa$ measure for the result of each model, and then discretize it into one of three categories:

- **HIGH:** If $\kappa \geq (\mu' + \sigma')$
- **MEDIUM:** If $[\kappa > (\mu' - \sigma') \land \kappa < (\mu' + \sigma')]$
- **LOW:** If $\kappa \leq (\mu' - \sigma')$

where $\mu'$ and $\sigma'$ are the mean and the standard deviation values respectively, for a set of confidence scores calculated for a model on a small development set of 25 annotated queries from each language. For the statistical model, we found $\mu' = 4.47$, and $\sigma' = 1.96$, for the knowledge
Table 5: Evaluation of the Decision Tree Classifier with varying sizes of training data.

| Language | 500   | 1,000 | 5,000 | 10,000 |
|----------|-------|-------|-------|--------|
| English  | 78.6% | 81.1% | 84.3% | 85.4%  |
| French   | 83.4% | 85.7% | 85.4% | 86.6%  |
| Portuguese | 81.1% | 79.1% | 81.7% | 81.1%  |
| Spanish  | 77.4% | 79.4% | 81.4% | 82.3%  |
| Italian  | 90.6% | 89.7% | 90.6% | 90.0%  |
| German   | 81.1% | 82.3% | 83.1% | 83.1%  |
| Dutch    | 86.3% | 87.1% | 88.3% | 87.4%  |
| Danish   | 86.3% | 87.7% | 88.0% | 88.0%  |
| Finnish  | 88.3% | 88.3% | 89.4% | 90.3%  |
| Swedish  | 81.4% | 81.4% | 81.1% | 81.7%  |
| Average  | 83.5% | 84.2% | 85.3% | 85.6%  |

Hence, for a given query, we calculate the identification result of each model together with the model’s confidence score, and then discretize the confidence score into one of the three categories described above. Finally, in order to form an association between the output of the model and its confidence, we create a composite attribute by appending the discretized confidence to the identified language. As an example, our statistical model identifies the query "the sovereign individual" as English (en), and reports a $\kappa = 7.60$, which is greater than or equal to $\mu' + \sigma' = 4.47 + 1.96 = 6.43$. Therefore the resulting composite attribute assigned to this query by the statistical model is "en-HIGH".

We used the Weka Machine Learning Toolkit (Witten and Frank, 2005) to implement our DT classifier. We trained our system with 500, 1,000, 5,000, and 10,000 instances of the automatically annotated data and evaluate it on the same test set of 3500 human-annotated queries. We show the results in Table 5.

The results in Table 5 show that our DT classifier, on average, outperforms all the models in Table 4 for each size of the training data. Furthermore, the performance of the system increases with the increasing size of training data. In particular, the improvement that we get for Spanish, French, and German queries are strikingly good. This shows that our DT classifier can take advantage of the complementary features to make a better classification. The classifier that uses 10,000 instances gets outperformed by the statistical model (by 4.9%) only in the identification of English queries.

In order to evaluate the significance of our improvement, we performed a paired t-test, with a null hypothesis and $\alpha = 0.01$ on the outputs of the statistical model, and the DT classifier that uses 10,000 training instances. The test resulted in $P = 1.12 \times 10^{-10} \ll \alpha$, which strongly indicates that the improvement of the DT classifier over the statistical model is statistically significant.

In order to illustrate the errors made by our DT classifier, we show the confusion matrix $M$ in Figure 2. The matrix entry $M_{i,j}$ simply gives the number of test instances that are in language $l_i$ but misclassified by the system as $l_j$. From the figure, we can infer that, Portuguese and Spanish are the languages that are confused mostly by the system. This is an expected result because of the high similarity between the two languages.

4.3 Towards Identifying the Language Intent

As a final step in our study, we build another DT classifier by introducing a non-linguistic feature to our system, which is the language information of the country from which the user entered the query. Our intuition behind introducing this extra feature is to help the search engine in guessing the language in which the user wants to see the resulting web pages. Since the real purpose of a search engine is to bring the expected results to its users, we believe that a correct identification of the language that the user intended for the results when typing the query is an important first part of this process.

To illustrate this with an example, we consider the query, "how to tape for plantar fasciitis", which we selected among the 500 human-annotated queries retrieved from the United States web site. This query is labelled as Category-2 by the human annotator. Our DT classifier, together with the statistical and knowledge-based models, classifies this query falsely as a Portuguese query, which is most likely caused due to the presence of the Latin phrase "plantar fasciitis".

In order to test the effectiveness of our new feature, we introduce all the Category-2 queries to our
Table 6: Evaluation of the new feature and the two decision tree classifiers on the new test set.

| Language     | New Feat. | Classifier-1 | Classifier-2 |
|--------------|-----------|--------------|--------------|
| English      | 74.9%     | 82.8%        | 89.5%        |
| French       | 77.0%     | 85.6%        | 93.7%        |
| Portuguese   | 79.1%     | 78.1%        | 93.3%        |
| Spanish      | 84.1%     | 80.7%        | 94.2%        |
| Italian      | 90.6%     | 86.7%        | 96.3%        |
| German       | 80.2%     | 80.7%        | 94.2%        |
| Dutch        | 91.6%     | 85.8%        | 95.3%        |
| Danish       | 88.6%     | 87.0%        | 94.9%        |
| Finnish      | 94.0%     | 87.7%        | 97.9%        |
| Swedish      | 87.9%     | 80.9%        | 95.3%        |
| Average      | 85.0%     | 83.6%        | 94.5%        |

5 Conclusions and Future Work

In this paper, we considered the language identification problem for search engine queries. First, we presented a completely automated method to generate a reliable data set with language annotations that can be used to train a decision tree classifier. Second, we implemented three features used in the existing language identification methods, and compared their performance. Next, we built a decision tree classifier that improves the results on average by combining the outputs of the three models together with their confidence scores. Finally, we considered the practical application of this problem for search engines, and built a second classifier that takes into account the geographical information of the users.

Human annotations on 5000 automatically annotated queries showed that our data generation method is highly accurate, achieving 84.3% accuracy on average for Category-1 queries, and 93.7% accuracy for Category-1 and Category-2 queries combined. Furthermore, the process is fast as we can get a data set of size approximately 50,000 queries in a few hours by using only 15 computers in a cluster.

The decision tree classifier that we built for the textual language identification in Section 4.2 outperforms all three models that we implemented in Section 4.1, for all the languages except English, for which the statistical model is better by 4.9%, and Swedish, for which we get a tie. Introducing the geographical information feature to our decision tree framework boosts the accuracy greatly even in the case of a noisier test set. This suggests that the search engines can do a better job in presenting the results to their users by taking the non-linguistic features into account in identifying the intended language of the queries.

In future, we would like to improve the accuracy of our data generation system by considering additional features proposed in the studies of automated query taxonomy, and doing a more careful examination in the assignment of the parameter values. We are also planning to extend the number of languages in our data set. Furthermore, we would like to improve the accuracy of Classifier-2 with additional non-linguistic features. Finally, we will consider other alternatives to the decision tree framework when combining the results of the models with their confidence scores.

6 Acknowledgments

We are grateful to Romain Vinot, and Rada Mihalcea, for their comments on an earlier draft of this paper. We also would like to thank Sriram Cherukiri for his contributions during the course of this project. Finally, many thanks to Murat Birinci, and Seçkin Kara, for their help on the data annotation process, and Cem Sözgen for his remarks on the SQL formulations.
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