Extracting Named Entities. A Statistical Approach

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Résumé - Abstract

Les entités nomées et plus généralement les multi-mots sont des ressources importantes pour plusieurs applications. Cependant, les méthodes d’extraction automatique, indépendentes de la langue, de multi-mots, ne nous donnent pas des données 100% fiables. Dans ce papier nous proposons premièrement une méthode pour sélectionner entités nomées d’entre les multi-mots extraits automatiquement et, deuxièmement, une méthode de groupement des entités nomées non-supervisionnée et indépendante de la langue, en utilisant de la statistique. La deuxième phase de groupement rend l’évaluation humaine plus simple. Les traits utilisés pour le groupement sont décrits et motivés. L’analyse faite pour le groupement nous a permis d’obtenir différents groupes d’entités nomées. La méthode a été appliquée sur le bulgare et l’anglais. La précision obtenue pour certains groupes a été très haute. D’autres groupes doivent être encore rafinés. Par ailleurs, les traits discrimants appris pendant la phase de groupement nous permettent de classifier de nouvelles entités nomées.

Named entities and more generally Multiword Lexical Units (MWUs) are important for various applications. However, language independent methods for automatically extracting MWUs do not provide us with clean data. So, in this paper we propose a method for selecting possible named entities from automatically extracted MWUs, and later, a statistics-based language independent unsupervised approach is applied to possible named entities in order to cluster them according to their type. Statistical features used by our clustering process are described and motivated. The Model-Based Clustering Analysis (MBCA) software enabled us to obtain different clusters for proposed named entities. The method was applied to Bulgarian and English. For some clusters, precision is very high; other clusters still need further refinement. Based on the obtained clusters, it is also possible to classify new possible named entities.
1 Introduction

This paper aims at proposing a methodology for clustering named entities. A language independent method is explained for extracting relevant multiword units (MWUs) (Silva et al., 1999) in section 2. As it is shown in section 3, from these MWUs, possible named entities are filtered using simple heuristics. Attributes used for clustering them are described in section 4. Clustering methodology and results are presented in section 5. A method for classifying new named entities is shown in section 6, and related work and conclusions in section 7.

2 Extracting MWUs from the Corpus

Three tools working together, are used for extracting MWUs from any corpus: the LocalMaxs algorithm, the Symmetric Conditional Probability (SCP) statistical measure and the Fair Dispersion Point Normalization (FDPN) (Silva et al., 1999). Thus, let us take an n-gram as a string of n words in any text. So, isolated words are 1-grams and the string President of the Republic is a 4-gram. One can intuitively accept that there is a strong cohesion within the 4-gram United Nations General Assembly, but not in the 4-gram of that but not. LocalMaxs algorithm is based on the idea that a MWU should be an n-gram whose cohesion is higher than any (n − 1)-gram contained in the n-gram; and should also be higher than the cohesion of all the (n + 1)-grams containing that n-gram. Thus, LocalMaxs needs to compare cohesions of n-grams having different sizes: (n+1), n and (n−1) and sharing all but one word in the borders, as we are interested on sequential n-grams. However, for determining the cohesion of an n-gram, we need to transform it into a pseudo-bigram. So, identical weight is given to every possible contiguous bigram in the n-gram by calculating the arithmetic mean show in equation 1. This corresponds to the FDPN concept applied to the SCP(.), and then, a new measure, SCP_f(.), is obtained (Silva et al., 1999).

\[
SCP_f(w_1\ldots w_n) = \frac{p(w_1\ldots w_n)^2}{\frac{1}{n-1} \sum_{i=1}^{n-1} p(w_1\ldots w_i) \cdot p(w_{i+1}\ldots w_n)}
\]  

where \( p(w_1\ldots w_j) \) is the probability of the n-gram \( w_1\ldots w_j \) in the corpus. So, \( SCP_f(.) \) reflects the average cohesion between any two adjacent contiguous sub-n-gram of the original n-gram.

3 Filtering MWUs

For testing our approach we used an English corpus with 10,506,267 words and a Bulgarian corpus with 4,110,838 words. LocalMaxs extracted 207,088 MWUs from the first corpus and
164,655 MWUs from the second. These MWUs include named entities among other multi-words. After separating those MWUs whose first and last words start with a capital letter, the number of MWUs decreased to 50,558 for English and 11,498 for Bulgarian. Since named entities in these languages usually have no long non-capital words with low probability, a second filter was applied by calculating the following value for each MWU:

$$
\text{minPL}(w_1 \ldots w_n) = \min_i (PL(w_i)) \quad \text{where} \quad PL(w_i) = \frac{\text{freq}(w_i)}{N \times \text{length}(w_i)} \quad . \quad (2)
$$

And \(\text{freq}(w_i)\) is the frequency of the \(i\)-th non-capital word of the MWU in the corpus; \(N\) stands for the corpus size we are working with, and \(\text{length}(w_i)\) is the number of characters of word \(w_i\). Then, MWUs having \(\text{minPL}(w_1 \ldots w_n)\) greater than a threshold were taken as good named entities, since they have no long non-capital words with medium or low probability. The threshold found seemed to be the same for both languages: 0.0053 (Kozareva et al., 2004).

### 4 Attributes

Proper features were needed for clustering filtered named entities. As shown in (Kozareva et al., 2004), the best features found were **Permanency** and **PLStdDev**.

$$
\text{Permanency}(w_1 \ldots w_n) = \frac{1}{n} \sum_{i=1}^{n} \frac{f(w_i)}{f^*(w_i)} \quad . \quad (3)
$$

where \(f(w_i)\) is the frequency of the word \(w_i\) in the corpus, while \(f^*(w_i)\) is the frequency of the same word but taking all occurrences of case insensitive forms (ex: life, Life, LIFE). This feature helps to distinguish names of persons (where **Permanency** is close to 1, as they occur written the same way) from other types of named entities. The second attribute is based on the standard deviation concept taking the probability and the length of words in the named entity.

$$
\text{PLStdDev}(w_1 \ldots w_n) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (PL(w_i) - \overline{PL}(w))^2} \quad \overline{PL}(w) = \frac{1}{n} \sum_{i=1}^{n} PL(w_i) \quad . \quad (4)
$$

Equation 2 gives \(\overline{PL}(\cdot)\). \(\text{PLStdDev}\) is useful for distinguishing named entities such as Republic of Bulgaria from others like Bulgarian Parliament. These named entities have different variation on the probability and length of their words. Here, we present the standardization to assign the same discriminant power to every attribute.

$$
z_{k,i} = \frac{x_{k,i} - \overline{x}_{k,i}}{\text{std}(x_k)} \quad x_{k,i} = \frac{1}{l} \sum_{i=1}^{l} x_{k,i} \quad \text{std}(x_k) = \sqrt{\frac{1}{l} \sum_{i=1}^{l} (x_{k,i} - \overline{x}_{k})^2} \quad . \quad (5)
$$

\(z_{k,i}\) is the standardized value for the \(i\)-th element of the attribute \(k\) \((x_{k,i})\); \(\overline{x}_{k,i}\) is the mean value of the elements for the same attribute and \(l\) is the number of elements; \(\text{std}(x_k)\) holds as the standard deviation of the same set.

### 5 Clustering Named Entities

Then, having a matrix of named entities characterized by previous 2 features, clustering is done using Model Based Clustering Analysis (MBCA) software. Different models are “simulated” for the input matrix, and the most likely model is proposed by this approach. Due to limitations imposed by the heavy clustering calculations done by MBCA, we clustered just a representative 1000 elements sample from the initial set of named entities for each corpus.
5.1 Results of the Clustering

As shown in (Kozareva et al., 2004), for each corpus (English and Bulgarian), MBCA proposed 5 clusters. Here, we present three elements randomly taken from each cluster.

Cluster e1: HUMANITARIAN AID, ANNUAL REPORT, SECTOR UNDERSTANDING ON EXPORT CREDITS.
Cluster e2: Media Markets, Management Committee, White Cement Committee.
Cluster e3: Vega Cueva, Herrenbuck Herrenstuck Hex, Glatzen Harstell.
Cluster e4: Health and Social Services, Northern Ireland Office Crown, Bayer France and Bayer Spain.
Cluster e5: Department of Tourism and Transport, Republic of Trinidad and Tobago, Secretary-General of the United Nations.
Cluster b1: Dobromir Krystew Atanasow, Simeon Zahariew Simeonow, Diliana Kirilowa Ignatova.
Cluster b2: MINERALNA WODA OT WODOIZTOCHNIK TK-1 (MINERAL WATER FROM WATER TANK TK-1), ZAKANATA S PRESTAPLENIE TRIABWA DA SE RAZGRANICHAWA (THREATENING WITH CRIME SHOULD BE DISTINGUISHED), DYRJAWNA SOBSTWENOST (STATE PROPERTY).
Cluster b3: Emil Georgiew Mihow i Walentin Minchew (Emil Georgiew Mihow and Walentin Minche), Boris i Stefan Hadjiw, Konstantin Petrow Mochikow i Kiril Iwanow Okow.
Cluster b4: Diakowa ot Sliwen (Diakowa from Sliwen), Pechew ot Warna, Ugyrchin i Iablanica (Ugyrchin and Iablanica).
Cluster b5: Sweta Nedelia, Dolno Kozarewo, Georgi Todorow Jilow.

5.2 Discussion

Clusters were proposed by MBCA considering VVV (Variable volume, Variable shape and Variable orientation) the best model for both languages; details in (Fraley and Raftery, 1998). This shows that clusters are not always spherical and have not the same volume. Person names tend to have frozen writing, which is detected by Permanency attribute: cluster e3 for English 90% precision (table 1) and clusters b1 and b3 for Bulgarian (100% precision). However, for
Bulgarian person names, those having no small and frequent words, that is, low $PLStdDev$ values, were put in cluster $b1$; those having high $PLStdDev$ values are in cluster $b3$. So, for person names, we have 1 cluster for English and 2 for Bulgarian. This is due to the very different nature of the corpora (Silva et al., 2004). Wrong written named entities are rare events corresponding to low Permanency values: cluster $e1$ (97% precision) and cluster $b2$ (94% precision). The results of the other clusters require future work. They tend to have institutions and city names: clusters $e2$, $e4$ and $e5$ with 22%, 29% and 50% precision respectively, and clusters $b4$ and $b5$ with 25% and 49% precision. Precision and recall values were calculated on the basis of majority of specific type of named entities clustered. So, if in the cluster of person names occurred a name of an enterprise, this would count as failure.

6 Classifying New Named Entities

Although we have just clustered a representative sample of the initial set of named entities the remaining elements must be also classified, concerning the clusters obtained. Beside that, we must be able to classify new named entities that did not occur in our corpus. So, every unclassified element must be part of any class represented by one of the already formed clusters, or be clearly out of those clusters. During the process of classifying new named entities we used the Discriminant Quadratic Score in order to indicate “how close” a named entity represented by the vector $\vec{y}$ is to a class $i$.

\[
d_Q^i(\vec{y}) = -\frac{1}{2} \ln |\Sigma_i| - \frac{1}{2} (\vec{y} - \vec{\mu}_i)^T \Sigma_i^{-1} (\vec{y} - \vec{\mu}_i) + \ln p_i.
\]

Covariance matrix $\Sigma_i$ is associated with the attributes that characterize the elements from the class $i$, and it is estimated by the covariance matrix taking the elements (named entities) of cluster $i$ (see details on (Silva et al., 2004)). For Discriminant Quadratic Score, the most important factor is the Mahalanobis Distance between the named entity $\vec{y}$ and the vector of means of class $i$, $(\vec{\mu}_i)$, represented by the vector of means of cluster $i$ $(\vec{c}_i)$ (see details on (Silva et al., 2004)). This lower this factor is, the higher the Quadratic Score. So, let $\vec{y}$ be a vector that represents an element to be classified, and $\pi_r$ a class represented by cluster $r$ that contains named entities $(\vec{e}_1, \vec{e}_2, \ldots, \vec{e}_n)$. Then $\vec{y}$ belongs to class $\pi_r$ if and only if

\[
d_Q^r(\vec{y}) = \max_i d_Q^i(\vec{y}) \land d_Q^r(\vec{y}) \geq \min_j d_Q^r(\vec{e}_j)
\]

where $i = 1, 2, \ldots, g$; $g$ is the number of classes (clusters), and $j = 1, 2, \ldots, n$, where $n$ is the number of named entities of the cluster. Equation (7) describes a criterion for classifying new named entities. This corresponds to the Minimum Total Probability of Misclassification Rule for Normal Populations criterion, but with an extra condition we added: $d_Q^r(\vec{y}) \geq \min_j d_Q^r(\vec{e}_j)$.

This condition sets that an element $\vec{y}$ belongs to class $r$ if its Quadratic score is also higher or equal than the Quadratic Score of all elements of cluster $r$. This prevents a very “distant” and “strange” element to be classified as a member of any class represented by the clusters. A detailed explanation about the components of the vector $\vec{y}$, representing the new named entity, is given in (Silva et al., 2004). Although we have done just a few tests on classification, for Bulgarian named entities this classifier showed 100% precision for person names and 60% for institution names and city names. Similar values were obtained for English.
7 Related Work, Conclusions and Future Work

Recently, some Machine Learning approaches such as (McNamee and Mayfield, 2002) have been used to extract named entities. However, these systems usually require a set of labeled data to be trained on, and this may not be available or be expensive to obtain. Other systems are language oriented such as (Carreras et al., 2003), or symbolic dependent such as (Poibeau et al., 2003). This paper points to an unsupervised statistics-based and language independent approach for clustering named entities. Firstly, thousands of MWUs were extracted from corpora using LocalMaxs algorithm. Possible named entities were filtered and clustered using just two attributes. This methodology was applied on 2 different corpora (English and Bulgarian) and similar results were obtained in both languages for some clusters. The best number of clusters was automatically calculated by Model-Based Cluster Analysis. The results are encouraging, since about 95% of the person names and misspelled expressions were correctly grouped. However, there are problems to solve: it is not possible to distinguish São Paulo as a person name and São Paulo as a location name, unless we use semantic information and look at the neighbourhood of the MWU São Paulo in the corpus. Besides, Permanency attribute does not work if the language is not alphabetic or if it does not use upper-case for person names. So future work has to be done, concerning other attributes and other kind of informations.

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