Semantic-Based Multilingual Document Clustering via Tensor Modeling
Salvatore Romeo, Andrea Tagarelli, Dino Ienco

To cite this version:
Abstract

A major challenge in document clustering research arises from the growing amount of text data written in different languages. Previous approaches depend on language-specific solutions (e.g., bilingual dictionaries, sequential machine translation) to evaluate document similarities, and the required transformations may alter the original document semantics. To cope with this issue we propose a new document clustering approach for multilingual corpora that (i) exploits a large-scale multilingual knowledge base, (ii) takes advantage of the multi-topic nature of the text documents, and (iii) employs a tensor-based model to deal with high dimensionality and sparseness. Results have shown the significance of our approach and its better performance w.r.t. classic document clustering approaches, in both a balanced and an unbalanced corpus evaluation.

1 Introduction

Document clustering research was initially focused on the development of general purpose strategies to group unstructured text data. Recent studies have started developing new methodologies and algorithms that take into account both linguistic and topical characteristics, where the former include the size of the text and the type of language, and the latter focus on the communicative function and targets of the documents.

A major challenge in document clustering research arises from the growing amount of text data that are written in different languages, also due to the increased popularity of a number of tools for collaboratively editing through contributors across the world. Multilingual document clustering (MDC) aims to detect clusters in a collection of multilingual documents written over the same set of classes (Ni et al., 2011; Yogatama and Tanaka-Ishii, 2009) without any restriction about translation or perfect correspondence between documents. To mine this kind of corpus, external knowledge is employed to map concepts or terms from a language to another (Kumar et al., 2011c; Kumar et al., 2011a), which enables the extraction of cross-lingual document correlations. In this case, a major issue lies in the definition of a cross-lingual similarity measure that can fit the extracted cross-lingual correlations. Also, from a semi-supervised perspective, other works attempt to define must-link constraints to detect cross-lingual clusters (Yogatama and Tanaka-Ishii, 2009). This implies that, for each different dataset, the set of constraints needs to be redefined; in general, the final results can be negatively affected by the quantity and the quality of involved constraints (Davidson et al., 2006).

Contributions. We address the problem of MDC by proposing a framework that features three key elements, namely: (1) to model documents over a unified conceptual space, with the support of a large-scale multilingual knowledge base; (2) to decompose the multilingual documents into topic-cohesively segments; and (3) to describe the multilingual corpus under a multi-dimensional data structure.

Through machine translation techniques based on a selected anchor language. Conversely, a comparable corpus is a collection of multilingual documents written over the same set of classes (Ni et al., 2011; Yogatama and Tanaka-Ishii, 2009) without any restriction about translation or perfect correspondence between documents. To mine this kind of corpus, external knowledge is employed to map concepts or terms from a language to another (Kumar et al., 2011c; Kumar et al., 2011a), which enables the extraction of cross-lingual document correlations. In this case, a major issue lies in the definition of a cross-lingual similarity measure that can fit the extracted cross-lingual correlations. Also, from a semi-supervised perspective, other works attempt to define must-link constraints to detect cross-lingual clusters (Yogatama and Tanaka-Ishii, 2009). This implies that, for each different dataset, the set of constraints needs to be redefined; in general, the final results can be negatively affected by the quantity and the quality of involved constraints (Davidson et al., 2006).
The first key element prevents loss of information due to the translation of documents from different languages to a target one. It enables a conceptual representation of the documents in a language-independent way preserving the content semantics. BabelNet (Navigli and Ponzetto, 2012a) is used as multilingual knowledge base. To the extent of our knowledge, this is the first work in MDC that exploits BabelNet.

The second key element, document segmentation, enables us to simplify the document representation according to their multi-topic nature. Previous research has demonstrated that a segment-based approach can significantly improve document clustering performance (Tagarelli and Karypis, 2013). Moreover, the conceptual representation of the document segments enables the grouping of linguistically different (portions of) documents into topically coherent clusters.

The latter aspect is leveraged by the third key element of our proposal, which relies on a tensor-based model (Kolda and Bader, 2009) to effectively handle the high dimensionality and sparseness in text. Tensors are considered as a multi-linear generalization of matrix factorizations, since all dimensions or modes are retained thanks to multi-linear structures which can produce meaningful components. The applicability of tensor analysis has recently attracted growing attention in information retrieval and data mining, including document clustering (e.g., Liu et al., 2011; Romeo et al., 2013) and cross-lingual information retrieval (e.g., Chew et al., 2007).

The rest of the paper is organized as follows. Section 2 provides an overview of BabelNet and basic notions on tensors. We describe our proposal in Section 3. Data and experimental settings are described in Section 4, while results are presented in Section 5. We summarize our main findings in Section 6, finally Section 7 concludes the paper.

2 Background

2.1 BabelNet

BabelNet (Navigli and Ponzetto, 2012a) is a multilingual semantic network obtained by linking Wikipedia with WordNet, that is, the largest multilingual Web encyclopedia and the most popular computational lexicon. The linking of the two knowledge bases was performed through an automatic mapping of WordNet synsets and Wikipages, harvesting multilingual lexicalization of the available concepts through human-generated translations provided by the Wikipedia interlanguage links or through machine translation techniques. The result is an encyclopedic dictionary containing concepts and named entities lexicalized in 50 different languages.

Multilingual knowledge in BabelNet is represented as a labeled directed graph in which nodes are concepts or named entities and edges connect pairs of nodes through a semantic relation. Each edge is labeled with a relation type (is-a, part-of, etc.), while each node corresponds to a BabelNet synset, i.e., a set of lexicalizations of a concept in different languages.

BabelNet can be accessed and easily integrated into applications by means of a Java API provided by the toolkit described in (Navigli and Ponzetto, 2012b). The toolkit also provides functionalities for graph-based WSD in a multilingual context. Given an input set of words, a semantic graph is built by looking for related synset paths and by merging all them in a unique graph. Once the semantic graph is built, the graph nodes can be scored with a variety of algorithms. Finally, this graph with scored nodes is used to rank the input word senses by a graph-based approach.

2.2 Tensor model representation

A tensor is a multi-dimensional array \( T \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_M} \). The number of dimensions \( M \), also known as ways or modes, is called order of the tensor, so that a tensor with order \( M \) is also said a \( M \)-way or \( M \)-order tensor. A higher-order tensor (i.e., a tensor with order three or higher) is denoted by boldface calligraphic letters, e.g., \( \mathcal{T} \); a matrix (2-way tensor) is denoted by boldface capital letters, e.g., \( \mathbf{U} \); a vector (1-way tensor) is denoted by boldface lowercase letters, e.g., \( \mathbf{v} \). The generic entry \( (i_1, i_2, i_3) \) of a third-order tensor \( T \) is denoted by \( t_{i_1i_2i_3} \), with \( i_1 \in [1..I_1], i_2 \in [1..I_2], i_3 \in [1..I_3] \).

A one-dimensional fragment of tensor, defined by varying one index and keeping the others fixed, is a 1-way tensor called fiber. A third-order tensor has column, row and tube fibers. Analogously, a two-dimensional fragment of tensor, defined by varying two indices and keeping the rest fixed, is a 2-way tensor called slice. A third-order tensor has horizontal, lateral and frontal slices.

The mode-\( m \) matricization of a tensor \( T \), denoted by \( T_{(m)} \), is obtained by arranging the mode-\( m \) fibers as columns of a matrix. A third-order tensor \( T \in \mathbb{R}^{I_1 \times I_2 \times I_3} \) is all-orthogonal if \( \sum_{i_1i_2} t_{i_1i_2i_3} \alpha_{i_1i_2} \beta_{i_1i_2} = \sum_{i_1i_3} t_{i_1i_3i_2} \alpha_{i_1i_3} \beta_{i_1i_2} = \sum_{i_2i_3} t_{i_2i_3i_1} \alpha_{i_2i_3} \beta_{i_2i_1} = 0 \) whenever \( \alpha \neq \beta \). The mode-\( m \) product of a tensor \( T \in \mathbb{R}^{I_1 \times I_2 \times \cdots \times I_M} \) with a matrix \( \mathbf{U} \in \mathbb{R}^{J_x \times I_m} \), denoted by \( T \times_m \mathbf{U} \), is a tensor of dimension \( I_1 \times \cdots \times I_{m-1} \times J \times I_{m+1} \times \cdots \times I_M \) and can be expressed in terms of matrix product as \( \mathbf{Y} = T \times_m \mathbf{U} \), whose mode-\( m \) matricization is \( Y_{(m)} = \mathbf{U}^T \times_m T \).

3 Our Proposal

3.1 Multilingual Document Clustering framework

We are given a collection of multilingual documents \( D = \bigcup_{l=1}^L D_l \), where each \( D_l = \{d_{l_1}\}_{i=1}^{N_l} \) represents a subset of documents written in the same language, with \( N = \sum_{l=1}^L N_l = |D| \). Our framework can be applied to any multilingual document collection regardless of the languages, and can deal with balanced as well as
unbalanced corpora. Therefore, no restriction is given on both the number of languages and the distribution of documents over the languages (i.e., $N_i \leq N_j$, with $i, j = 1...L, i \neq j$).

Real-world documents often span multiple topics. We assume that each document in $D$ is relatively long to be comprised of smaller textual units, or segments, each of which can be considered cohesive w.r.t. a topic over the document. This represents a key aspect in our framework as it enables the use of a tensor model to conveniently address the multi-faceted nature of the documents.

Our overall framework, named SeMDocT (Segment-based MultiLingual Document Clustering via Tensor Modeling), is shown in Algorithm 1. In the following, we shall describe in details each of the steps involved in SeMDocT.

### 3.1.1 Computing within-document segments

Text segmentation is concerned with the fragmentation of an input text into multi-paragraph, contiguous and disjoint blocks that represent subtopics. Regardless of the presence of logical structure clues in the document, linguistic criteria (Beeferman et al., 1999) and statistical similarity measures (Hearst, 1997; Choi et al., 2001; Cristianini et al., 2001) have been mainly used to detect subtopic boundaries between segments. A common assumption is that terms that discuss a subtopic tend to co-occur locally, and a switch to a new subtopic is detected by the ending of co-occurrence of a given set of terms and the beginning of the co-occurrence of another set of terms.

Our SeMDocT does not depend on a specific algorithmic choice to perform text segmentation; in this work, we refer to the classic TextTiling (Hearst, 1997), which is the exemplary similarity-block-based method for text segmentation.

### 3.1.2 Inducing document segment clusters

The result of the previous step is a collection of document segments, henceforth denoted as $S$. Each segment in $S$ is represented as a vector of feature occurrences, where a feature can be either lexical or semantic. This corresponds to two alternative representation models: the standard bag-of-words (henceforth BoW), whereby features correspond to lemmatized, non-stopword terms, and the obtained feature space results from the union of the vocabularies of the different languages; and bag-of-synsets (henceforth BoS), whereby features correspond to BabelNet synsets. We shall devote Section 3.2 to a detailed description of our proposed BoS representation.

The segment collection $S$ is given in input to a document clustering algorithm to produce a clustering of the segments $C^S = \{C^S_i\}_{i=1}^k$. The obtained clusters of segments can be disjoint or overlapping. Again, our SeMDocT is parametric to the clustering algorithm as well; here, we resort to a state-of-the-art clustering algorithm, namely Bisecting K-Means (Steinbach et al., 2000), which is widely known to produce high-quality (hard) clustering solutions in high-dimensional, large datasets (Zhao and Karypis, 2004). Note however that it requires as input the number of clusters. To cope with this issue, we adopt the method described in (Salvador and Chan, 2004), which explores how the within-cluster cohesion changes by varying the number of clusters. The number of clusters for which the slope of the plot changes drastically is chosen as a suitable value for the clustering algorithm.

### 3.1.3 Segment-cluster based representation

Upon the segment clustering, each document is represented by its segments assigned to possibly multiple segment clusters. Therefore, we derive a document-feature matrix for each of the $k$ segment clusters. The features correspond either to the BoW or BoS model, according to the choice made for the segment representation.

Let us denote with $F$ the feature space for all segments in $S$. Given a segment cluster $C^s$, the corresponding document-feature matrix is constructed as follows. The representation of each document $d \in D$ w.r.t. $C^s$ is a vector of length $|F|$ that results from the sum of the feature vectors of the $d$’s segments belonging to $C^s$. Moreover, in order to weight the appearance of a document in a cluster based on its segment-based portion covered in the cluster, the document vector of $d$ w.r.t. $C^s$ is finally obtained by multiplying the sum of the segment-vectors by a scalar representing the portion of $d$’s features that appear in the segments belonging to $C^s$. The document-feature matrix of $C^s$ resulting from the previous step is finally normalized by column.

### 3.1.4 Tensor model and decomposition

The document-feature matrices corresponding to the $k$ segment-clusters are used to form a third-order tensor.
Our third-order tensor model is built by arranging as frontal slices the $k$ segment-cluster matrices. The resulting tensor will be of the form $T \in \mathbb{R}^{I_1 \times I_2 \times I_3}$, with $I_1 = |D|$, $I_2 = |F|$, and $I_3 = k$. The proposed tensor model is sketched in Fig. 1.

The resulting tensor is decomposed through a Truncated Higher Order SVD (T-HOSVD) (Lathauwer et al., 2000) in order to obtain a low-dimensional representation of the segment-cluster-based representation of the document collection. The T-HOSVD can be considered as an extension of the Truncated Singular Value Decomposition (T-SVD) to the case of three or more dimensions. For a third-order tensor $T \in \mathbb{R}^{I_1 \times I_2 \times I_3}$ the T-HOSVD is expressed as

$$T = \mathcal{X} \times_1 U^{(1)} \times_2 U^{(2)} \times_3 U^{(3)}$$

where $U^{(m)} = [u_1^{(m)} \ u_2^{(m)} \ \ldots \ u_m^{(m)}] \in \mathbb{R}^{I_m \times r_m}$ ($m = 1, 2, 3$) are orthogonal matrices, $r_m \ll I_m$, and the core tensor $\mathcal{X} \in \mathbb{R}^{r_1 \times r_2 \times r_3}$ is an all-orthogonal and ordered tensor.

3.1.5 Document clustering

The mode-1 factor matrix is provided in input to a clustering method to obtain a final organization of the documents into $K$ clusters, i.e., $C = \{C_1\}_{k=1}^K$. Note that there is no principled relation between the number $K$ of final document clusters and $k$. However, $K$ is expected to reflect the number of topics of interest for the document collection. Also, possibly but not necessarily, the same clustering algorithm used for the segment clustering step (i.e., Bisecting K-Means) can be employed for this step.

3.2 Bag-of-synset representation

In the BoS model, our objective is to represent the document segments in a conceptual feature space instead of the traditional term space. Since we deal with multilingual documents, this task clearly relies on the multilingual lexical knowledge base functionalities of BabelNet. Conceptual features will hence correspond to BabelNet synsets.

The segment collection $S$ is subject to a two-step processing phase. In the first step, each segment is broken down into a set of lemmatized and POS-tagged sentences, in which each word is replaced with related lemma and associated POS-tag. Let us denote with $\langle w, POS(w) \rangle$ a lemma and associated POS-tag occurring in any sentence $sen$ of the segment. In the second step, a WSD method is applied to each pair $\langle w, POS(w) \rangle$ to detect the most appropriate BabelNet synset $\sigma_w$ for $\langle w, POS(w) \rangle$ contextually to $sen$. The WSD algorithm is carried out in such a way that all words from all languages are disambiguated over the same concept inventory, producing a language-independent feature space for the whole multilingual corpus. Each segment is finally modeled as a $|BS|$-dimensional vector of BabelNet synset frequencies, being $BS$ the set of retrieved BabelNet synsets.

As previously discussed in Section 2.1, BabelNet provides WSD algorithms for multilingual corpora. More specifically, the authors in (Navigli and Ponzetto, 2012b) suggest to use the Degree algorithm (Navigli and Lapata, 2010), as it showed to yield highly competitive performance in a multilingual context as well. Note that the Degree algorithm, given a semantic graph for the input context, simply selects the sense of the target word with the highest vertex degree. Clearly, other graph-based methods for (unsupervised) WSD, particularly PageRank-style methods (e.g., (Mihalcea et al, 2004; Girir and Soroa, 2009; Yeh et al., 2009; Tsatsaronis et al., 2010)), can be plugged in to address the multilingual WSD task based on BabelNet. An investigation of the performance of existing WSD algorithms for a multilingual context is however out of the scope of this paper.

4 Evaluation Methodology

In order to evaluate our proposal we need a multilingual comparable document collection with annotated

Figure 1: The third-order tensor model for the representation of a multilingual document collection based on segment clusters.
Table 1: Number of documents for each topic and language.

<table>
<thead>
<tr>
<th>Topic/Corpus</th>
<th>English</th>
<th>French</th>
<th>Italian</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Balanced Corpus</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C15 - PERFORMANCE</td>
<td>850</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>C18 - OWNERSHIP CHANGES</td>
<td>850</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>E11 - ECONOMIC PERFORMANCE</td>
<td>850</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>E12 - MONETARY/ECONOMIC</td>
<td>850</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>M11 - EQUITY MARKETS</td>
<td>850</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>M13 - MONEY MARKETS</td>
<td>850</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>5,100</td>
<td>5,100</td>
<td>5,100</td>
</tr>
<tr>
<td><strong>Unbalanced Corpus</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C15 - PERFORMANCE</td>
<td>850</td>
<td>850</td>
<td>0</td>
</tr>
<tr>
<td>C18 - OWNERSHIP CHANGES</td>
<td>850</td>
<td>850</td>
<td>0</td>
</tr>
<tr>
<td>E11 - ECONOMIC PERFORMANCE</td>
<td>0</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>E12 - MONETARY/ECONOMIC</td>
<td>850</td>
<td>0</td>
<td>850</td>
</tr>
<tr>
<td>M11 - EQUITY MARKETS</td>
<td>0</td>
<td>850</td>
<td>850</td>
</tr>
<tr>
<td>M13 - MONEY MARKETS</td>
<td>850</td>
<td>0</td>
<td>850</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>4,400</td>
<td>3,400</td>
<td>3,400</td>
</tr>
</tbody>
</table>

Table 2: Main characteristics of the corpora.

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Balanced Corpus</th>
<th>Unbalanced Corpus</th>
</tr>
</thead>
<tbody>
<tr>
<td># of docs</td>
<td>15,200</td>
<td>10,200</td>
</tr>
<tr>
<td># of terms</td>
<td>38,825</td>
<td>44,535</td>
</tr>
<tr>
<td># of synsets</td>
<td>16,395</td>
<td>14,339</td>
</tr>
<tr>
<td>BoW Density</td>
<td>1.5 × 10^{-3}</td>
<td>2.0 × 10^{-3}</td>
</tr>
<tr>
<td>BoS Density</td>
<td>2.6 × 10^{-4}</td>
<td>3.1 × 10^{-4}</td>
</tr>
</tbody>
</table>

1http://trec.nist.gov/data/reuters/reuters.html
2012a), (Navigli and Ponzetto, 2012b). In particular, the WSD process tightly depends from the concept coverage supplied from the language-specific knowledge base.

4.2 Competing methods and settings

We compare our SeMDocT with two standard approaches, namely Bisecting K-Means (Steinbach et al., 2000), and Latent Semantic Analysis (LSA)-based document clustering (for short, LSA). Given a number $K$ of desired clusters, Bisecting K-Means produces a $K$-way clustering solution by performing a sequence of $K$-1 repeated bisections based on standard K-Means algorithm. This process continues until the number $K$ of clusters is found. LSA performs a decomposition of the document collection matrix through Singular Value Decomposition in order to extract a more concise and descriptive representation of the documents. After this step, Bisecting K-Means is applied over the new document space to get the final document clustering.

All the three methods, SeMDocT, Bisecting K-Means and LSA are coupled with either BoS or BoW representation models. The comparison between BoS and BoW representations allows us to evaluate the presumed benefits that can be derived by exploiting synsets instead of terms for the multilingual document clustering task.

Both SeMDocT and LSA require the number of components as input; as concerns specifically SeMDocT, we varied $r_1$ (cf. Section 3.1.4) from 2 to 30, with increments of 2. To determine the number of segment clusters $k$, we employed an automatic way as discussed in Section 3.1.2. By varying $k$ from 2 to 40, for Balanced Corpus and Unbalanced Corpus, respectively, the values of $k$ obtained were 22 and 23 under BoS, and 25 and 11 under BoW.

As concerns the step of text segmentation, TextTiling requires the setting of some interdependent parameters, particularly the size of the text unit to be compared and the number of words in a token sequence. We used the setting suggested in (Hearst, 1997) and also confirmed in (Tagarelli and Karypis, 2013), i.e., 10 for the text unit size and 20 for the token-sequence size.

4.3 Assessment criteria

Performance of the different methods are evaluated using two standard clustering validation criteria, namely F-Measure and Rand Index.

Given a document collection $\mathcal{D}$, let $\Gamma = \{\Gamma_j\}_{j=1}^H$ and $\mathcal{C} = \{C_i\}_{i=1}^K$ denote a reference classification and a clustering solution for $\mathcal{D}$, respectively. The local precision and the local recall of a cluster $C_i$ w.r.t. a class $\Gamma_j$ are defined as $P_{ij} = |C_i \cap \Gamma_j| / |C_i|$ and $R_{ij} = |C_i \cap \Gamma_j| / |\Gamma_j|$, respectively. F-Measure (FM) is computed as follows (Steinbach et al., 2000):

$$F = \frac{\sum_{j=1}^H |\Gamma_j| \max_{i=1..K} \{ F_{ij} \}}{\mid \mathcal{D} \mid}$$

where $F_{ij} = 2P_{ij}R_{ij} / (P_{ij} + R_{ij})$.

Rand Index (RI) (Rand, 1971) measures the percentage of decisions that are correct, penalizing false positive and false negative decisions during clustering. It takes into account the following quantities: $TP$, i.e., the number of pairs of documents that are in the same cluster in $\mathcal{C}$ and in the same class in $\Gamma$; $TN$, i.e., the number of pairs of documents that are in different clusters in $\mathcal{C}$ and in different classes in $\Gamma$; $FN$, i.e., the number of pairs of documents that are in different clusters in $\mathcal{C}$ and in the same class in $\Gamma$; and $FP$, i.e., the number of pairs of documents that are in the same cluster in $\mathcal{C}$ and in different classes in $\Gamma$. Rand Index is hence defined as:

$$RI = \frac{TP + TN}{TP + TN + FP + FN}$$

Note that for each method, results were averaged over 30 runs and the number of final document clusters $K$ was set equal to the number of topics in the document collection (i.e., 6).

5 Results

We present here our main experimental results. We first provide a comparative evaluation of our SeMDocT with the competing methods, on both balanced and unbalanced corpus evaluation cases. Then we provide a per language analysis focusing on SeMDocT.

5.1 Evaluation with competing methods

Evaluation on balanced corpus. Figure 2 shows FM and RI results obtained by the various methods coupled with the two document representations on the Balanced Corpus. Several remarks stand out. First, the BoS space positively influences the performance of all the employed approaches. This is particularly evident for Bisecting K-Means and LSA that clearly benefit from this kind of representation. The former almost doubles its performance in terms of FM and significantly improves its result w.r.t. RI. LSA shows improvements in both cases. SeMDocT-BoS generally outperforms all the competitors for both FM and RI when the number of components is greater than 16. Note that, under the BoW model, SeMDocT-BoW still outperforms the other methods.

Evaluation on unbalanced corpus. Figure 3 reports results for the Unbalanced Corpus. Also in this evaluation, the best performances for all the methods are reached using the BoS representation. SeMDocT-BoS shows similar behavior according to the two measures. It always outperforms the competitors considering a number of components greater than or equal to 12. More precisely, SeMDocT-BoS obtains a gain of 0.047 and 0.103 in terms of FM and 0.066 and 0.058 in terms of RI, w.r.t. LSA-BoW and Bisecting K-Means-BoW, respectively. Similarly, SeMDocT-BoS obtains improvements of 0.05 in terms of FM w.r.t. both BoS
competitors, while in terms of RI the differences in performance are 0.012 and 0.019 for LSA-BoS and Bisecting K-Means-BoS, respectively.

### 5.2 Per language evaluation of SeMDocT-BoS

Starting from the clustering solutions produced by SeMDocT-BoS in both balanced and unbalanced cases, for each language we extracted a language-specific projection of the clustering. After that, we computed the clustering validation criteria according to language specific solutions to quantify how well the clustering result fits each specific language. The results of this experiment are reported in Fig. 4 and Fig. 5.

On the Balanced Corpus, SeMDocT-BoS shows comparable performance for English and French documents, while it behaves slightly worse for Italian texts. This trend is highlighted for both clustering evaluation criteria. Inspecting the results for the Unbalanced Corpus, we observe a different trend. Results obtained for the English texts are generally better than the results for the French and Italian documents. For this benchmark, SeMDocT-BoS obtains similar results for documents written in French and in Italian.

We gained an insight into the above discussed performance behaviors by computing some additional statistics that we report in Table 5: for each language and each dataset, the size of the term and synset dictionaries and the average number of synsets per lemma ($\beta$) we retrieved with BabelNet according to the related corpus. More in detail, $\beta$ is the ratio between the BoS and the BoW dictionaries. This quantity roughly evaluates how many synsets are produced per term during the multilingual WSD process (Section 3.2). As we can observe, this value is always smaller than one, which means that not all the terms have a corresponding mapping to a synset. The $\beta$ ratio can explain the discrep-

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Language</th>
<th>BoW size</th>
<th>BoS size</th>
<th>avg # synsets per term ($\beta$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Balanced</td>
<td>English</td>
<td>29,999</td>
<td>12,065</td>
<td>0.4021</td>
</tr>
<tr>
<td></td>
<td>French</td>
<td>17,826</td>
<td>5,310</td>
<td>0.2978</td>
</tr>
<tr>
<td></td>
<td>Italian</td>
<td>18,931</td>
<td>4,571</td>
<td>0.2837</td>
</tr>
<tr>
<td>Unbalanced</td>
<td>English</td>
<td>19,432</td>
<td>10,387</td>
<td>0.5342</td>
</tr>
<tr>
<td></td>
<td>Italian</td>
<td>14,744</td>
<td>4,012</td>
<td>0.2721</td>
</tr>
</tbody>
</table>

Table 5: Balanced corpus: language statistics.
Figure 4: Average F-Measure (a) and Rand Index (b) for language specific solutions on the Balanced Corpus obtained by SeMDocT-BoS.

Figure 5: Average F-Measure (a) and Rand Index (b) for language specific solutions on the Unbalanced Corpus obtained by SeMDocT-BoS.

To compute the SVD, we used the svds() function of MATLAB R2012b, which is based on an iterative algorithm. Experiments were carried out on an Intel Core i7-3610QM platform with 16GB DDR RAM.

Figure 6 shows the execution time of the SVD over the mode-1 matricization of our tensor for the Balanced Corpus, by varying the number of components, for both BoW and BoS representation models. As it can be observed, in both cases the runtime is linear in the number of components. However, the SVD computation in the BoS setting is one order of magnitude faster than performance in the BoW setting. This is mainly due to a large difference in size between the feature spaces of BoW and BoS (cf. Table 2), since the selected number of segment clusters ($k$) was nearly the same (25 for BoW, and 22 for BoS). Therefore, by providing a more compact feature space, BoS clearly allows for a much less expensive SVD computation for our tensor decomposition.

5.3 Runtime of tensor decomposition

As previously discussed, T-HOSVD of a third-order tensor can be computed through three standard SVDs. Furthermore, for clustering purposes, we considered only the mode-1 factor matrix of the decomposition.

To compute the SVD, we used the svds() function of MATLAB R2012b, which is based on an iterative algorithm. Experiments were carried out on an Intel Core i7-3610QM platform with 16GB DDR RAM.

Figure 6 shows the execution time of the SVD over the mode-1 matricization of our tensor for the Balanced Corpus, by varying the number of components, for both BoW and BoS representation models. As it can be observed, in both cases the runtime is linear in the number of components. However, the SVD computation in the BoS setting is one order of magnitude faster than performance in the BoW setting. This is mainly due to a large difference in size between the feature spaces of BoW and BoS (cf. Table 2), since the selected number of segment clusters ($k$) was nearly the same (25 for BoW, and 22 for BoS). Therefore, by providing a more compact feature space, BoS clearly allows for a much less expensive SVD computation for our tensor decomposition.

5.3 Runtime of tensor decomposition

As previously discussed, T-HOSVD of a third-order tensor can be computed through three standard SVDs. Furthermore, for clustering purposes, we considered only the mode-1 factor matrix of the decomposition.
7 Conclusion

In this paper we proposed a new approach for multilingual document clustering. Our key idea lies in the combination of a tensor-based model with a bag-of-synsets description, which enables a common space to project multilingual document collections. We evaluated our approach w.r.t. standard document clustering methods, using both term and synset representations. Results have shown the benefits deriving from the use of a multilingual knowledge base in the analysis of comparable corpora, and also shown the significance of our approach in both a balanced and an unbalanced corpus evaluation. Our tensor-based representation of topically-segmented multilingual documents can also be applied to cross-lingual information retrieval or multilingual document categorization.

References


Young-Min Kim, Massih-Reza Amini, Cyril Goutte, and Patrick Gallinari. 2010. Multi-view clustering...


