A Study on the Role of Similarity Measures in Visual Text Analytics

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Abstract: Text Analytics is essential for a large number of applications and good approaches to obtain visual mappings of text are paramount. Many visualization techniques, such as similarity based point placement layouts, have proved useful to support visual analysis of documents. However, they are sensitive to data quality, which, in turn, relies on a critical preprocessing step that involves text cleaning and in some cases term detecting and weighting, as well as the definition of a similarity function. Not much has been discussed on the effect of these important similarity calculations in the quality of visual representations. This paper presents a study on the role of different text similarity measurements on the generation of visual text mappings. We focus mainly on two types of distance functions, those based on the well-known text vector representation and on direct string comparison measurements, comparing their effect on visual mappings obtained with point placement techniques. We find that both have their value but, in many circumstances, the vector space model (VSM) is the best solution when discrimination is important. However, the VSM is not incremental, that is, new additions to a collection force a recalculation of the whole feature space and similarities. In this work we also propose a new incremental model based on the VSM, which is shown to present the best visualization results in many configurations tested. We show the evaluation results and offer recommendations on the application of different text similarity measurements for Visual Text Analytics tasks.

1 INTRODUCTION

Producing visualizations from textual documents requires a pre-processing step in which similarity evaluation plays a fundamental role. Often, a Vector Space Model (VSM) (Salton et al., 1975) that considers the frequency of relevant words is created, over which cosine distance approximates text dissimilarity. Little is known about how this pre-processing affects the outcome of text visualization techniques.

The VSM poses many limitations for visualization purposes, as it fails to capture semantics implicit in the relationships among words and terms. Moreover, in building a meaningful VSM several preprocessing operations require parameter settings that may affect the outcome considerably. Resulting models are typically described by very high-dimensional feature spaces, which suffer from drawbacks globally referred to as 'the curse of dimensionality' (Huang et al., 2005) that result in low discrimination power by most techniques.

VSM models may be avoided altogether by using direct string comparison functions (Telles et al., 2007). Adding documents to a collection does not impact the underlying model, since it suffices to compare the new document with the existing ones. Many such measures have been defined, for different purposes and applications. Again, there is little record on how their choice affects text analytics, visual or otherwise, and the question remains on how they compare with cosine distances calculated over the VSM.

We are concerned with assessing how the choice of a (dis)similarity function affects the output of content-based visualization techniques. We consider visualizations that lay out documents as points on a plane based on their similarity, to verify how the choice of a similarity function affects their quality in terms of discriminating groups of text files with highly related content. We also address the additional limitation that computing a VSM requires the complete collection to be available *a priori*, rendering it incapable of handling streaming text. This paper investigates these issues, reporting on the following questions:

1. are string distance measures suitable for text visualizations based on similarity? which

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measures may be considered and how their choice affects the visualizations?
2. how do string distances compare with the traditional cosine distance computed over the VSM regarding visualization quality?
3. is it possible to represent a dynamic collection, updating a vector model as documents are added? how visualizations built from such a model compare to those obtained with the conventional VSM and with string distances?

2 RELATED WORK

The VSM with *tf-idf* measure of terms deemed relevant is the typical input representation to most text visualization and text clustering techniques. Visualizations may be derived directly from such representations, e.g. as in various *Multidimensional Scaling* (MDS) approaches (Wise et al., 1995; Paulovich et al., 2008; Paulovich and Minghim, 2008). Hierarchical similarity-based layouts have also been proposed and illustrated for visualizing textual documents, e.g. the Neighbor-Joining tree (Cuadros et al., 2007).

The Incremental Board - *incBoard* (Pinho et al., 2009) and the *Incremental Space* (Pinho et al., 2010) also derive text collection visualizations. They are, by design, more suited for handling dynamic collections in which documents are added gradually. These techniques inspired the Incremental Vector Space Model (iVSM) introduced in Section 4.

Alternatively, vector models may be derived with topic extraction techniques such as *Latent Semantic Analysis* (Landauer et al., 2007) and *Latent Direchlet Allocation* (LDA) (Blei et al., 2003), usually producing lower-dimensional feature spaces. Topics are also often extracted to annotate similarity-based visualizations, based, for instance, on LDA (Wei et al., 2010) or on association rule mining (Lopes et al., 2007) to derive topic-oriented views.

Streamit shows real-time views of streaming documents (Alsakran et al., 2012) built from a dynamic 2D similarity layout computed with a fast implementation of a force-based projection. Handling streams poses additional challenges to text visualizations based on content similarity. In this solution text documents are described by dynamic keyword vectors, and in computing the cosine similarity a parameter I_k is introduced to account for the importance of a keyword k at a particular time. Importance may be determined automatically based on various parameters and it may be modified by users based on their perception. LDA is employed to reduce feature space dimensionality. Each topic is associated with a set of keywords, and documents are represented by a vector of the probable weights of their topics. Besides reducing dimensionality, the topics are at a higher semantic level than terms and likely to produce more meaningful document clusters. However, the topic model is extracted from an existing similar collection, as the collection displayed is not available initially.

We are unaware of previous studies on how the choice of the similarity function affects the outcome of text visualizations. There are, however, studies that report comparisons of string distance functions in other application domains. (Cohen et al., 2003) compare the performance of several distance metrics for the tasks of matching and clustering lists of entity names. *SecondString* is an open-source Java toolkit that incorporates several string metrics for matching names and records, including some novel hybrids of well-known methods. Authors computed three evaluation measures, the non-interpolated average precision, the maximum F1 score and the interpolated precision at eleven recall levels. In general, the best results were obtained with the hybrid distances proposed by them.

(Kempken et al., 2006) compare the performance of selected distances to support retrieval of historical spelling variants in historical text documents. Experiments were conducted on a dataset of historical spellings manually collected from historical German documents, containing a list of word pairs. Distances were evaluated with the precision and recall measures, and the best performance was obtained with a stochastic distance.

3 STRING SIMILARITY MEASURES

String distance functions map a pair of strings X and Y to a real number r, where higher values of r indicate greater dissimilarity between X and Y. String similarity functions, on the other hand, return higher values for r as X and Y are more similar, and distances may be generated taking the value $1-r$. In this section we briefly present string distance and similarity functions employed in this study.

One important class of string distance functions are the so-called *edit distances*, which return the minimum number of editing operations required to transform a string into the other. Typical editing operations are character insertion, deletion and substitution, and each one is assigned a cost. Two strings X and Y may also be considered as multisets of words (substrings or tokens), and several token-based mea-

Table 1: Token-based measures. Function $Q(\cdot)$ returns the number of tokens in the input string, $P(\cdot)$ returns the number of characters, $qG(\cdot)$ returns the number of substrings of length q, XY stands for a concatenation of X and Y, and $C(\cdot)$ returns the size, in bytes, of the compressed input string.

Name	Similarity	
Dice's Coefficient	$\frac{2*Q(X'\cap Y')}{Q(X')+Q(Y')}$	(1)
Cosine	$\frac{Q(X'\cap Y')}{\sqrt{Q(X')*Q(Y')}}$	(2)
Matching Coefficient	$\frac{Q(X'\cap Y')}{\max\{Q(X'),Q(Y')\}}$	(3)
Overlap Coefficient	$\frac{P(X'\cap Y')}{\min\{P(X'),P(Y')\}}$	(4)
Q-gram	$\frac{2*qG(X'\cap Y')}{qG(X')+qG(Y')}$	(5)
NCD	$\frac{C(XY)-min\{C(X),C(Y)\}}{max\{C(X),C(Y)\}}$	(6)
NCDs	$NCD(X,Y)+\frac{NCD(X,X)+NCD(Y,Y)}{2}$	(7)

sures are defined. Given two token sets X' and Y' derived from X and Y several similarity functions may be defined, as described in Table 1. In Section 6 we compare these and other distance measures in generating (dis)similarity-based visualizations of text collections.

4 iVSM: A DYNAMIC VECTOR SPACE MODEL

The *Incremental Vector Space Model (iVSM)* has been proposed to represent text documents of an incremental collection (Pinho et al., 2010). As in the original VSM, each dimension represents the *tf-idf* frequency of a relevant term. As not all documents are known *a priori*, an initial representation of the unknown collection is approximated from the VSM constructed for a similar known collection (e.g., news, or scientific papers). This approximate initial representation is called a 'language model', and provides an initial set of relevant terms, their frequency (TF) and the number of documents in which they occur (DF). The iVSM is constructed by continuously updating the language model (the TF and DF term countings) as new documents are added to the collection (or existing documents are removed).

The process is illustrated with a hypothetical collection with N documents and M terms, for which a VSM has been created, as shown in Table 2, where α_{ij} stands for the frequency count of term t_j in document d_i. A so-called *language model* for this collection is defined as shown in Table 3. DF_j is the number documents that include the term j, and TF_j is the frequency of term j, as computed by Eq. 8.

Table 2: Vector space model (VSM) representation of a collection with N documents. Rows refer to documents and columns to terms that occur in the documents: α_{ij} denotes the frequency of term t_j in document d_i.

	t_1	t_2	$\dots$	t_M
d_1	α_{11}	α_{12}	$\dots$	α_{1M}
d_2	α_{21}	α_{22}	$\dots$	α_{2M}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
d_N	α_{N1}	α_{N2}	$\dots$	α_{NM}

Table 3: Language model of the collection: each row represents a VSM term, as shown in Table 2. Column TF informs overall term frequencies and column DF informs how many documents include the corresponding term.

Term	TF	DF
t_1	TF_1	DF_1
t_2	TF_2	DF_2
$\vdots$	$\vdots$	$\vdots$
t_M	TF_M	DF_M

$$TF-IDF_j = \frac{\sum_{i=1}^{N}\alpha_{ij}}{\log\frac{N}{DF_j}} \tag{8}$$

The language model in Table 3 provides the departing point to build the iVSM for a dynamic collection. This is done by incrementally updating the initial language model whenever a new document arrives. The underlying rationale is very simple: if a term t present in the incoming document also occurs in the language model, its corresponding TF and DF values are incremented accordingly (DF only once for each document). Otherwise, the new term is introduced in the language model, and its TF_t and DF_t values are initialized, i.e., $DF \leftarrow 1$, $TF \leftarrow 1$.

If terms are continuously added, the dimensionality of the vector space keeps increasing, which is not desirable. In order to keep dimensionality under control, the set of relevant terms is updated by setting appropriate Luhn Cut thresholds, according to Eqs. 9 and 10, where N' stands for the maximum value of DF in the current language model. Finally, the iVSM for a particular document is computed considering the *tf-idf* count of each term t_j currently in the language model, as presented in Eq. 11, where tf_{ij} stands for the number of occurrences of term t_j in document D_i.

$$LC_{lower} = \begin{cases} 3, & \text{if } LC_{lower} < 3 \\ \text{llc\% of } N', & \text{if } LC_{lower} > 5\% \text{ of } N' \\ & \text{or } LC_{lower} < 1\% \text{ of } N' \end{cases} \tag{9}$$

$$LC_{upper} = \begin{cases} \text{luc\% of } N', & \text{if } LC_{upper} < 90\% \text{ of } N' \\ & \text{or } LC_{upper} > N' \end{cases} \tag{10}$$

$$iVSM_{ij} = \begin{cases} tf_{ij} * \log \dfrac{N'}{DF_j}, & \text{if } DF_j \geq LC_{lower} \\ & \text{or } DF_j \leq LC_{upper} \\ zero, & \text{otherwise} \end{cases} \quad (11)$$

with *llc* and *luc* standing for the chosen lower and upper cut Luhn's thresholds, respectively. In the studies reported in Section 6 these were set to 2% and 95%, respectively. When applying this model to streaming text similarity measures may be updated as needed by the underlying layout technique. Its usage in tandem with incremental algorithms, e.g., *incBoard* and *incSpace*, was envisioned to require only partial recalculation of similarity measures as the collection changes over time, as required by those algorithms.

5 STUDY SET-UP

Our goal is to investigate how the choice of representation model and dissimilarity function affect the quality of layouts output by point-placement techniques applied to textual collections. Assessing quality of point-placement layouts is a difficult issue, as analysis depends on the tasks the layout is meant to support. We believe important tasks are related with the layout's capability of preserving meaningful text clusters, i.e., to which extent it favors data grouping and group segregation; alternatively analysts may desire layouts capable of preserving as much as possible the original distances, or dissimilarity relations.

Some objective quality measures may be applied to compare different layouts in this context. We consider the *Silhouette Coefficient* (Tan et al., 2005), that attempts to quantify the quality of clusters identifiable in the feature space or in a layout derived from it, and the *Neighborhood Hit* curve (Paulovich et al., 2008), which attempts to quantify to which extent a layout preserves known classes.

The *silhouette coefficient SC* of a cluster is computed as the average of the silhouette coefficient computed for its individual points. The silhouette of a particular data point p_i, belonging to a cluster C_i is computed according to Equation (12):

$$SC_{p_i} = \frac{(b_i - a_i)}{max(a_i, b_i)} \quad (12)$$

where a_i is the average distance from p_i to all the other data points in C_i and b_i is the minimum average distance from p_i to the other clusters, obtained after computing the average distance from p_i to all the data points in a cluster C_j, for all $j \neq i$. *SC* takes values in the range $[-1, 1]$. Negative values indicate that $a_i > b_i$, whereas the opposite is desirable. Notice that *SC* assumes its maximum value when $a_i = 0$.

The *Neighborhood Hit* (NH) is a curve that conveys the layout's capability of preserving class structure. The NH value for an individual data point is computed by counting number of its neighbors on the projected layout that belong to its same label or class. The curve is obtained by averaging the NH measure computed for all individual data points, for a varying number of neighbors to the point, from 1 to a maximum.

We compared layouts obtained with two representative point-placement techniques. The *Least Square Projection* (LSP) (Paulovich et al., 2008) is a multidimensional projection technique, whereas the Neighbor-Joining Tree (Cuadros et al., 2007) generates a hierarchy from a given dissimilarity matrix.

LSP attempts to generate a layout that preserves neighborhood groupings in the feature space. It first obtains a subsample of the data points, called control points, that is hopefully representative of its overall spatial distribution, and then computes neighborhoods for this sample points. The control points are projected first with a precise technique, and their projected coordinates, plus the neighborhoods, provide information to build a linear system model that is solved to obtain the projected coordinates of all data points. LSP takes as input parameters a pairwise distance matrix computed for the collection, the number of control points, and the number of neighbors to consider in defining neighborhoods.

The Neighbor-Joining (NJ) tree is inspired on algorithms for building phylogenetic trees in Biology. It builds a tree that describes ancestrality relations between species, given a matrix of pairwise distances between them. Then, a tree layout algorithm is employed to display the resulting hierarchy. NJ takes as input a pairwise distance matrix of the collection and requires no additional parameters. Whereas LSP shows a global view that attempts to convey meaningful groups of texts that have similar content, the branches and sub-branches in the tree view allow a user to infer levels or degrees of similarity between the texts.

Studies were conducted on textual datasets[1] [2] of scientific papers and news articles, summarized in Table 4.

We computed 15 distinct pairwise dissimilarity matrices for the datasets, using the following string distance or similarity functions[3]: Block, Jaccard, Cosine, Euclidean, JaroWrinkler, Dice Coefficient,

[1] http://infoserver.lcad.icmc.usp.br/infovis2/DataSets

[2] http://www.daviddlewis.com/resources/testcollections/reuters21578

[3] http://sourceforge.net/projects/simmetrics

Table 4: Text datasets.

Name	Description	General Content	# docs	# classes
CBR-ILP-IR	case based reasoning, inductive logic programming and information retrieval	scientific papers	574	3
news2011	RSS news feeds (AP, CNN, Reuters and BBC)	news	1,771	23
ReutersNews	subset from Reuters21578 collection (newswire articles)	news	3,988	7

Levenshtein, Matching Coefficient, SmityWaterman, Jaro, QGram, Soundex, NeedlemanWunch, Monge and Overlap Coefficient. Their choice was based on a survey of existing alternatives for string comparison.

After inputting the distance matrices to LSP (considering two distinct configurations for the number of control points and neighborhood size) and to the NJ-tree, resulting layouts were compared to identify the functions with the best results on the CBR-ILP-IR data, by conducting a subjective evaluation of their visual quality and also comparing their corresponding NH curves. This preliminary analysis identified five best performing string measures for further investigation, namely Cosine Similarity, Dice's Coefficient, Matching Coefficient, Overlapping Coefficient and QGram.

In all cases some text-preprocessing has been applied, which varied on different test cases, due to the nature and goals of different functions. Luhn's cutting thresholds, stopwords removal and Porter stemming were employed when appropriate, as detailed in the Results section.

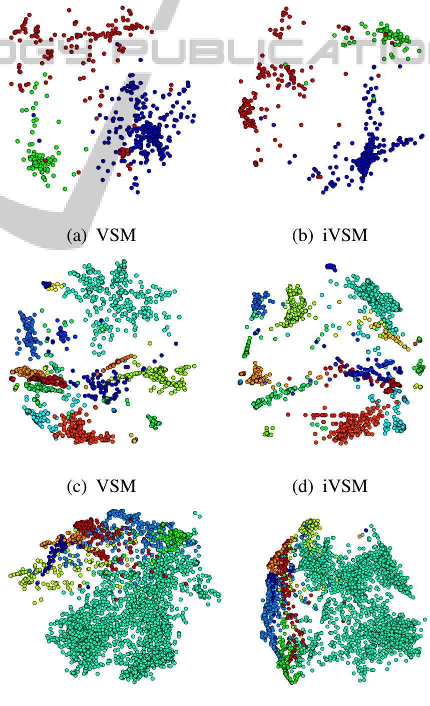
In a subsequent step, we compared the previous five string measures, plus *Normalized Compression Distance* (NCDs) (Telles et al., 2007), with the conventional approach for generating similarity-based layouts from text, namely the Cosine similarity applied over a VSM vector representation. Finally, we included in the comparison the Cosine similarity applied over the iVSM model introduced in Section 4. Precision results are shown in Section 6, processing times are given in Table 5.

Table 5: Processing times (in seconds) for computing dissimilarity matrices with the distinct string dissimilarity functions.

Measure	CBR-ILP-IR	News2011	ReutersNews
Cosine Distance	750	41	2,331
Dice's coefficient	715	41	2,344
Matching's coefficient	1,588	73	4,761
Overlap's coefficient	758	41	2,319
Qgram Distance	16,744	1,215	52,877
NCDs	1,350	10,038	63,109

6 RESULTS

Figure 1 shows the layouts obtained with LSP and with NJ using as input dissimilarity matrices computed employing the cosine distance over the VSM and iVSM representations, respectively, for the three datasets considered. The LSP input parameters were set to 57, 177 and 398 control points, respectively, for CBR-ILP-IR, News2011 and ReutersNews, and to 15 nearest-neighbors in all cases. Figure 2 shows the corresponding NJ tree layouts, created with the NJ implementation by (Paiva et al., 2011), which is faster than the original one (Cuadros et al., 2007)[4]. In the visualizations each circle represents a document and color maps the document class. One may visually assess the degree of class separation inspecting the spatial distribution of colors in the LSP layouts, or the distribution of colors in the branches and sub-branches of the NJ-tree layouts.



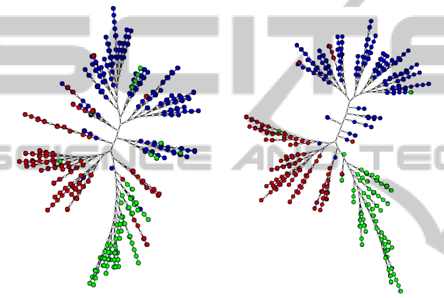
(a) VSM (b) iVSM
(c) VSM (d) iVSM
(e) VSM (f) iVSM

Figure 1: LSP layouts generated for text datasets: CBR-ILP-IR (top), News2011 (middle) and NewsReuters (bottom), using the VSM and iVSM representations and the cosine distance. Circle color maps document class.

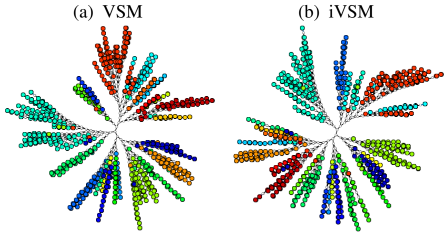
In order to generate the visualizations, textual data was preprocessed with stopwords removal, Porter's stemming and definition of Luhn's thresholds. We removed the usual stopwords, such as articles and

[4] http://infoserver.lcad.icmc.usp.br/infovis2/NeighborJoiningTree

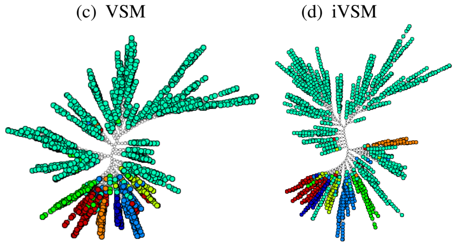
prepositions, and also a few domain specific words when handling scientific papers or news, e.g., for papers added stopwords included ‘press’, ‘proceedings’, ‘proc’, ‘vol’ and ‘year’. In generating the VSM models we set Luhn’s lower cut to 10, and applied no upper cut threshold. In generating the iVSM models, Luhn’s thresholds were defined according to Equations 9 and 10. For the CBR-ILP-IR data the starting language model was generated from an available data set of 2,814 scientific papers (All.zip) from multiple conferences and journals on Visualization, available at the same site as the CBR-ILP-IR data set. For News2011 and Reuters the starting language model has been computed from an existing collection with news from April 2006 (AP_BBC_CNN_Reuters.zip), again available at the same site.



(a) VSM (b) iVSM



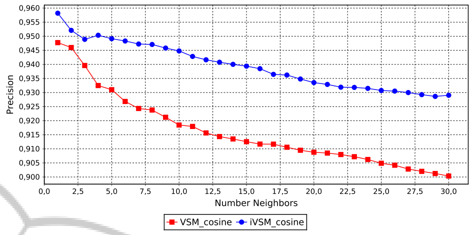
(c) VSM (d) iVSM



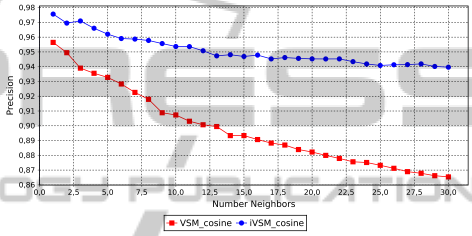
(e) VSM (f) iVSM

Figure 2: NJ-tree layouts for text datasets: CBR-ILP-IR (top), News2011(middle) and NewsReuters (bottom), using the VSM and iVSM representations and the cosine distance. Circle color maps document class.

Figures 3, 4 and 5 show the neighborhood preservation curves of the layouts depicted in the previous figures, for each dataset. One observes that for CBR-ILP-IR the iVSM model does a considerably better job as far as neighborhood preservation is concerned, both for LSP and NJ layouts. This is not true for the news collections: in News2011 LSP with VSM does better, whereas both VSM and iVSM curves relative to the NJ layouts are very similar, although iVSM does slightly better. For NewsReuters NJ with iVSM does better, whereas LSP with iVSM performs better up to 7 neighbors, then VSM starts doing better.

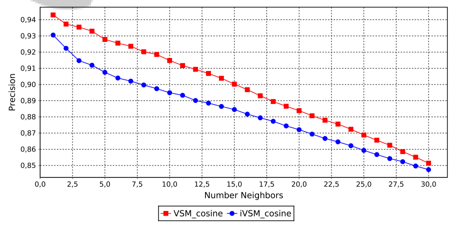


(a) LSP

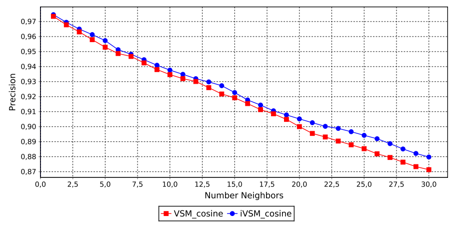


(b) NJ

Figure 3: NH graphs of LSP and NJ layouts of CBR-ILP-IR built with the VSM and iVSM models and cosine similarity.



(a) LSP

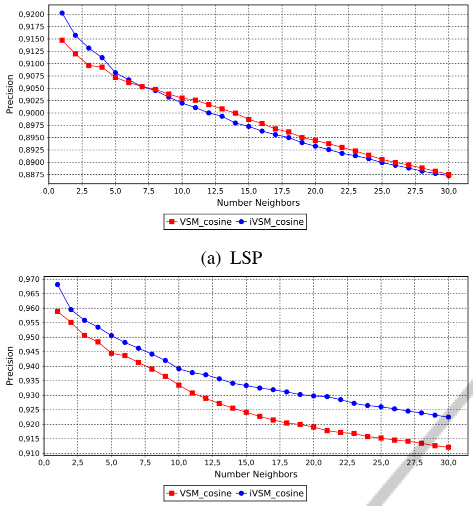


(b) NJ

Figure 4: NH graphs of LSP and NJ layouts of News2011 built with the VSM and iVSM models and cosine similarity.

We also compared the neighborhood preservation capability of layouts obtained using distance matrices computed with distinct string similarity measures, plus the cosine similarity computed over the VSM and iVSM models, for the three datasets.

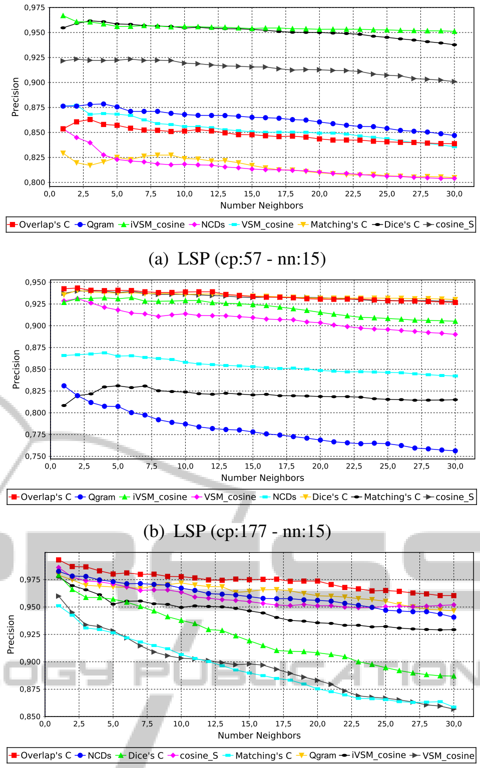
Results are shown in Figure 6 for the CBR-ILP-IR data. We considered two configurations of LSP,



(a) LSP

(b) NJ

Figure 5: NH graphs of LSP and NJ layouts of NewReuters built with the VSM and iVSM models and cosine similarity.



(a) LSP (cp:57 - nn:15)

(b) LSP (cp:177 - nn:15)

(c) NJ

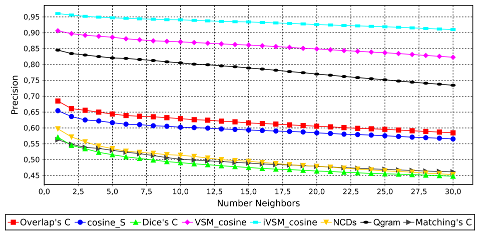
Figure 6: NH graphs of LSP and NJ layouts of CBR-ILP-IR obtained with 8 distinct distance matrices: 6 string functions plus the VSM and iVSM with cosine dissimilarity.

with 57 and 177 control points, both with 15 nearest-neighbors. The text preprocessing applied varied depending on the dissimilarity measure employed. In generating the VSM and iVSM models we applied general and domain specific stopword removal and no stemming. For VSM a lower Luhn's cut was set to 10 and no upper cut was adopted; for iVSM the thresholds were computed automatically as defined in Equations 9 and 10, and the language model has been computed from the same All.zip dataset. For the string distance matrices, pre-processing procedures also varied. General and specific stopwords were removed from the input strings when using the string-based Cosine distance, as well as Dice's Coefficient, Overlap Coefficient and Qgram. No stopword removal was applied when using the Matching Coefficient and the NCDs measures. The choice of applying (or not) stopwords removal has been made after verifying which alternative produced the best NH curves.

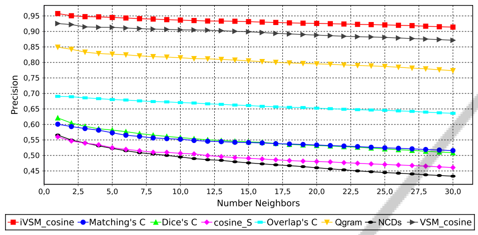
In the first LSP configuration, shown in Figure 6(a), best results regarding class segregation capability were obtained with the cosine distance over the iVSM model (referred to in the figures as iVSM_cosine) and with string-based Dice's Coefficient. The string-based Cosine also did well, the three graphics show curves with values above 0.9. Despite their inferior performance as compared to the previous ones, all the other distance measures produced curves with values above 0.8. The curves of the second LSP configuration (Figure 6(b)) shows that best results were achieved with string-based Overlap Coefficient and with iVSM_cosine and VSM_cosine – again all curves roughly remaining above the 0.9 threshold. The worst results were given by string-based Matching Coefficient and Qgram. For the NJ layouts results are quite different: the best performing measures are string-based, namely Overlap Coefficient, Qgram, NCDs and Cosine. VSM_cosine and string-based Matching Coefficient displayed the worst performances. iVSM_cosine did considerably better than VSM_cosine, and although not top ranked it comes close to the top ranked ones.

For the News2011 collection we employed LSP with 177 control points and 15 nearest-neighbors, and with 150 control points and 20 nearest-neighbors. The resulting NH graphs, for the LSP (two versions) and NJ layouts are shown in Figure 7. Preprocessing steps were the same as for CBR-ILP-IR, and the language model for iVSM has been computed from the AP_BBC_CNN_Reuters.zip dataset. As for the string distances, general and specific stopwords removal was employed for Dice's Coefficient, Matching Coefficient, Overlap Coefficient and Qgram. No stopword removal was applied to the string-based Cosine and the NCDs distance.

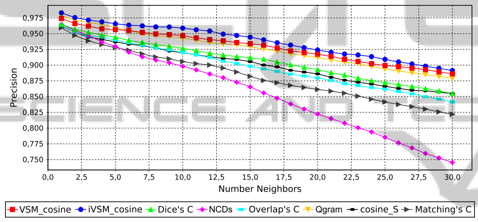
For the first LSP configuration (Figure 7(a)) best results were obtained with cosine distance over the



(a) LSP (cp:177 - nn:15)



(b) LSP (cp:150 - nn:20)

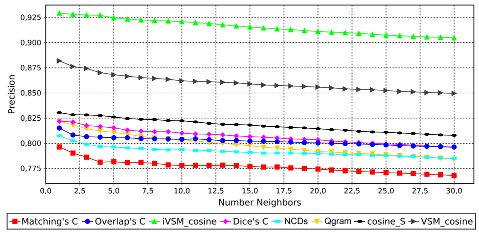


(c) NJ

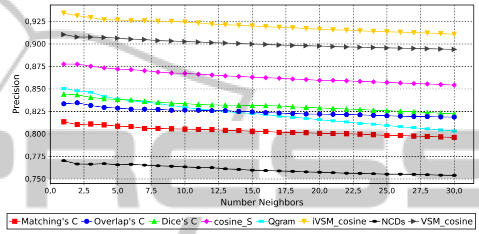
Figure 7: NH graphs of LSP and NJ layouts of News2011 obtained with 8 distinct distance matrices: 6 string functions plus the VSM and iVSM with cosine dissimilarity.

iVSM and VSM models and string-based Qgram, which all show curves with values above 0.73. The string-based Dice's Coefficient, Matching Coefficient and NCDs resulted in the worst performances (curves staying bellow 0.6). In the second LSP configuration, shown in Figure 7(b), one notices that iVSM_cosine, VSM_cosine and Qgram kept the best performances. Note that in this configuration NH curves outperform slightly the ones in Figure 7(a). The worst results were returned by string-based Cosine (identified in the figures as cosine_S) and NCDs. Moreover, all NH curves produced by NJ (Figure 7(c)) achieve similar precision values, above 0.75. Nonetheless, the best results are again by iVSM_cosine, VSM_cosine and Qgram.

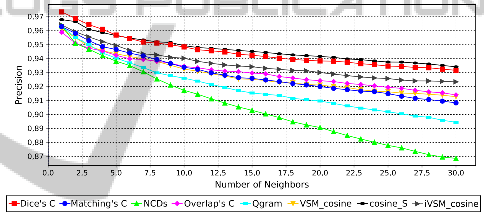
For the NewsReuters collection we employed LSP with 398 control points and 15 nearest-neighbors, and with 200 control points and 20 nearest-neighbors. The resulting LSP and NJ NH curves are in Figure 8. Pre-processing to generate the VSM and iVSM models was applied as described for News2011. As for the string distances, general and specific stopword removal was employed for Cosine Distance, Overlap Coefficient, Qgram and NCDs measures. No stop-word removal was applied to the string-based Dice's Coefficient and Matching Coefficient distance.



(a) LSP (cp:398 - nn:15)



(b) LSP (cp:200 - nn:20)



(c) NJ

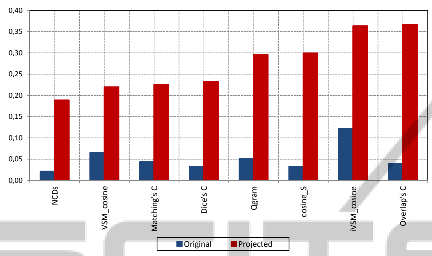
Figure 8: NH graphs of LSP and NJ layouts of NewsReuters obtained with 8 distinct distance matrices: 6 string functions plus the VSM and iVSM with cosine dissimilarity.

Figures 8(a) and 8(b) show the results for the two LSP configurations. In both cases the iVSM produced the highest precision values, followed by the VSM and string-based Cosine, as the NH curves of the latter two are the best in the second configuration (curves stay above 0.85). The worst results were given by string-based Matching Coefficient in the first configuration (Figure 8(a)) and by NCDs in the second (Figure 8(b)). The best NH curves for the NJ layouts were obtained with string-based Cosine, Dice's Coefficient and the iVSM. String-based NCDs and Qgram displayed the worst performances. Despite their inferior performance, these distance measures still produced curves with values above 0.87.

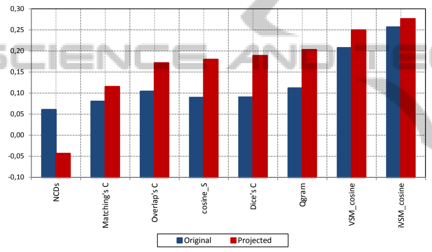
Figure 9 shows the Silhouette Coefficients (*SC*) computed for the datasets considering different distance functions, in the original (blue bars) and in the NJ-tree visual space (red bars). Distances in the NJ-tree are computed considering path lengths. As discussed in Section 5, *SC* values closer to 1.0 indicate highly cohesive and well separated clusters, accord-

Table 6: Ranking of NH curves of layouts obtained with string-based metrics and with the cosine similarity computed over VSM and iVSM on the three datasets.

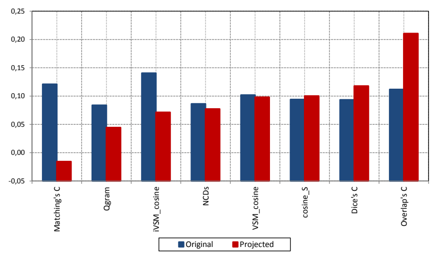
	CBR-ILP-IR			News2011			NewsReuters		
Ranking	LSP (1)	LSP (2)	NJ	LSP (1)	LSP (2)	NJ	LSP (1)	LSP (2)	NJ
1°	iVSM	Dice's C	Overlap's C.	iVSM	iVSM	iVSM	iVSM	iVSM	Cosine
2°	Dice's C	Cosine	Qgram	VSM	VSM	VSM	VSM	VSM	Dice's C
3°	Cosine	Overlap's C.	NCDs	Qgram	Qgram	Qgram	Cosine	Cosine	iVSM
4°	Qgram	iVSM	Cosine	Overlap's C.	Overlap's C.	Dice's C	Dice's C	Dice's C	Overlap's C
5°	VSM	VSM	iVSM	Cosine	Matching's C	Cosine	Overlap's C.	Overlap's C.	VSM
6°	Overlap's C.	NCDs	Dice's C	NCDs	Dice's C	Overlap's C.	Qgram	Qgram	Matching's C
7°	Matching's C	Matching's C	VSM	Matching's C	Cosine	Matching's C	NCDs	Matching's C	Qgram
8°	NCDs	Qgram	Matching's C	Dice's C	NCDs	NCDs	Matching's C	NCDs	NCDs



(a) CBR-ILP-IR



(b) News2011



(c) NewsReuters

Figure 9: Silhouette Coefficients of datasets, in the original feature space and in the NJ-tree visual space (different distance functions).

ing to the distance function considered. One observes how the choice of the distance function affects the grouping of elements based on similarity, in both the original and the visual data spaces.

Ideally, a similarity-based layout should not degrade cluster quality, or even better it could actually improve it, favoring user perception of possibly meaningful structures. Indeed, the figures show that the NJ layout does improve cluster quality relative to the feature space in some cases, in terms of cohesiveness and separation, as measured by the *SC*. Inspecting the bar charts one notices that cluster quality in the feature space may be poor, and some distance functions are more effective than others in identifying better quality clusters.

For the CBR-ILP-IR data, we notice that all distance functions actually contributed to a projected layout with improved cluster quality. In fact, all distances produced very low *SC* values in the feature space, always inferior to 0.1 with the exception of iVSM_cosine. *SC* value in the projected space is better for all functions, with the Overlap Coefficient distance doing the best job in this matter. In the News2011 data, again *SC* values in the feature space are low and improve in the projected layouts, with the exception of layout obtained with the NCDs. The picture is quite different in the NewReuters data, however: most distances produce worse *SC* values in the projected space, with the exception of the string-based Cosine, Dice's Coefficient and Overlap Coefficient. VSM_cosine and NCDs roughly preserve the cluster quality as in the original space. Unlike the other cases iVSM_cosine performed poorly in this data.

It is worth noting that we did not consider the Silhouette Coefficient on the LSP projection because distance computation in 2D space tends to favor round-shaped clusters, and as such it is not necessarily a meaningful measure of cluster quality in the visual space when cluster shapes vary largely.

7 CONCLUSIONS

In our experiments we observed that VSM and iVSM generated visualizations with the best class segregation capability. Similarity-based layouts of text collections obtained using both models were compared using Neighborhood Hit curves, for which values close to 1.0 reflect layouts with good class preservation capability. A global ranking summarizing the major findis is presented in Table 6. The iVSM outperformed, or otherwise stayed close, to the VSM in most cases. Given the observed results, we propose iVSM as a new incremental model based on VSM.

Coupled with incremental MDS techniques, e.g., *incBoard* and *incSpace*, it is well-suited for handling text streams and time-stamped document collections, with limited recalculations.

Some string-based metrics also performed well in the comparisons, in particular Qgram, string based Cosine and Overlapping Coefficient. Their major advantage is not requiring intermediate text representations such as the vector models, althoug distance calculations are computationally expensive. A next step is to evaluate iVSM and string measures in a truly incremental setup, by applying them in displaying text streams with, e.g., *incBoard* or *incSpace*.

The approaches considered disregard any kind of semantic analysis of text. For instance, stemming in preprocessing impacts semantics in a not very predictable manner. Although this type of processing and dissimilarity calculation suffices for many applications, further investigation should be conducted on semantic-based distances, as semantics cannot be ignored in some text analytics applications. The impact of the language model also needs further study.

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