

Contribution to Clustering Benchmark Challenge - IFCS 2019, selected on 04/29/2019

EVALUATION OF TEXT CLUSTERING METHODS AND THEIR DATASPACE EMBEDDINGS: AN EXPLORATION.

Alain Lelu, rtd, Université de Franche-Comté¹

Martine Cadot, LORIA²

Abstract

Fair evaluation of text clustering methods needs to clarify the relations between 1)pre-processing, resulting in raw term occurrence vectors, 2)data transformation, and 3)method in the strict sense. We have tried to empirically compare a dozen well-known methods and variants in a protocol crossing three contrasted open-access corpora in a few tens transformed dataspace. We compared the resulting clusterings to their supposed "ground-truth" classes by means of four usual indices. The results show both a confirmation of well-established implicit combinations, and good performances of unexpected combinations, mostly in spectral or kernel dataspace. The rich material resulting from these some 450 runs includes a wealth of intriguing facts, which needs further research on the specificities of text corpora in relation to methods and dataspace.

1 - Introduction : motivations and goals.

Evaluation of text clustering methods is one of the key issues in the problem of bibliometric delineation of scientific fields. As co-authors of [Zitt et al. 2019] we have tried to test seventeen clustering methods with a publicly available real-life test set, the Reuters' test bench [Lewis et al. 2004] which adds up several difficulties of text clustering, i.e. mainly strongly unbalanced man-made classes (the targeted "ground-truth"), and texts of unbalanced sizes. Our report is accessible online [Cadot, Lelu 2018] as a supplementary material to the above-mentioned book chapter. An unexpected result was that antique agglomerative methods, especially Ward hierarchical clustering, performed better than many more recent ones. Was it the case for all types of corpora? Above all we realized that for the sake of fair comparisons, as well as conceptual clarity, we should clearly separate the transformations of the raw word-count data (for example into Salton tf-idf vector representation, or Laplacian spectral space, etc.) from the algorithms in the strict sense, instead of using long-time accepted implicit combinations. For example, no rational reasons forbid using e.g. Non-negative Matrix Factorization in a spectral space. This consideration is in line with the conceptual clarifications operated in [VanMechelen et al. 2018]; last, but not least, unexpected recommendations may proceed from non-classic combinations. This clarification is one of our guiding threads in the present research.

Though restricting our scope to text clustering, it is clear that many types of texts need now to be processed: abstracts or plain texts of scientific papers, which are our primary scientific interest, or journal or legal documents, or texts originating in the social nature of Internet communications, such as contributions to

¹ Alelu@orange.fr

² Martine.Cadot@loria.fr - corresponding author

forum discussions, or social networks. We decided to base our present survey on three typical and contrasted test sets: a full-text scientific database, a wire of press agency, and an Internet discussion forum. It is clear that the complete text preprocessing chain is out of the goal of our research, so we have to rest on one same linguistic – or weakly linguistic – term, lemma or stem extraction scheme, and same elimination of infrequent or too frequent words. This point must not keep us from exploring the influence of truncating the remaining vocabulary in chosen distribution quantiles. Usual benchmark studies mention an absolute occurrence threshold, period... All these specifications led us to the choices we expose in the methodology section.

Of course the options on methods and types of dataspace to be considered are inevitably somehow arbitrary: we tried to take account of the most usual algorithms, or method families, such as K-means, hierarchical agglomerative clustering, spectral clustering, graph clustering, kernel clustering, and we added two more specific methods, i.e. Non-negative Matrix Factorization (NMF) and Latent Dirichlet Allocation (LDA), which amounts to a dozen methods and variants.

Concerning dataspace, we chose to add to the plain term occurrence vector space the transformed spaces by Salton's and Okapi's tf-idf weighting schemes, by chi-square and Hellinger metrics, by Laplacian spectral decomposition, by Correspondence Analysis, and last by order-2-polynomial kernel expansion. These transformations are referenced and formally presented in the next section.

Given the combinatorics of the three main elements – text types, dataspace and algorithms – our research study could be nothing but an exploration, strongly constrained by available resources. However, some interesting conclusions will be drawn out this exploration. In the final conclusion, we will deal with what may be continued and deepened in our perspective, given the results.

Let us close this introduction saying that we are indebted to the remarkable initiative of the Brazilian LABIC team [Rossi et al. 2013] who homogeneously pre-processed [LABIC stemmer] some forty text collections and made the document by term matrices available online on their site [LABIC data].

2 - Methodology

Drawn from our experience of clustering methods, our first claim is that using the supervised learning methodology for comparing non-supervised methods is in any case better than relying on unfounded claims or comparisons to be suspected of author's bias. In relation to the issue of author's bias, let us state that, though being authors of a few clustering algorithms (Axial K-means, Local Component Analysis, Gemen), we have excluded these algorithms of our survey. This supervised methodology may at least result, in default of a universal ranking of methods, in fruitful reflections on the typology of texts, or the nature of the human categorization and abstraction process and its similarities and differences with methods mostly optimizing an intrinsic objective function.

Another core imperative we have set is transparency and reproducibility: in addition to the direct link to the document by term matrices we have provided above, a complementary material HAL site [HAL CNRS] will gather the data and code we used. Though most algorithms are theoretically insensitive to the ordering of input vectors, in practice we experienced that tied effects, among others, could affect the results. This is why we have randomly scrambled the data vectors, and will drop our scrambled data and label files on the above-cited site.

1.1 - Choice of test corpora

The three "prototype" test corpora mentioned in the introduction are, first, Reuters' "ModApté Split" [Apté et al. 1994] limited to the eight most important classes ("Re8" in the present study), second, the ACM

collection made of the proceedings of forty conferences in different computer science areas, third, the "20 Newsgroups" collection ("Ng20") is composed of some 19 000 messages posted in twenty Usenet groups. The size of the man-made reference classes is strongly unbalanced in the case of Re8 (two of them constitute 81% of the documents), roughly equal in the case of ACM and Ng20.

It is to be noted that the sole Reuters' class labels are issued from a direct manual indexing. The two others origin in the concatenation of sub-corpora of comparable size. They could therefore be considered as "semi-real-world data", not really representative of real-life non-annotated corpora. Note also that the mean "Silhouette" coefficient [Kogan, 2007], which measures the inter-class contrasts, is higher (.89) in the case of Re8 than in Ng20 (.80) and ACM (.75) ones.

1.2 - Truncating the vocabularies

As the size of the vocabularies are unbalanced (Re8: about 8900 terms, ACM: 60 800 terms, Ng20: 45 000 terms) but extensive (the hapaxes, i.e. terms of total occurrence one, are included in this count), we decided a common scheme for a vocabulary-independent truncation by thresholds: in addition to the basic option of retaining the whole vocabulary, we built two sub-corpora per test corpus retaining the third quartile of the term distribution (25% of the total occurrences), and the seventh "octile" (12.5%).

1.3 - Choice of clustering methods

- Plain *K-means clustering* ("KM"), see [Mac Queen 1967] algorithm (in the adaptive case) and [Forgy 1965] (in the usual iterative case), initialized by randomly drawing data vectors - we had an unconvincing experience of K-means++ initialization in the context of text clustering. We implemented 20 elementary runs, or "passes", per run, selecting the "best" one in terms of the local optimum of the K-means objective function (sum of squared intra-cluster Euclidean distances).

- *Hierarchical agglomerative clustering* with two linkage variants: average link ("HCa"), and Ward ("HCw") [Ward 1963]. Originally in $O(\#\text{documents}^3)$ time complexity, the more recent contributions [Murtagh 1984] and [Müllner 2013] have lowered this constraint to $O(\#\text{documents}^2)$.

- *Spectral clustering* [Meila, Shi 2000]: we used the "standard" combination K-means/Laplacian spectral dataspace, but also explored (with success, see below) many other combinations.

- *Graph clustering methods*: we chose the two most broadly recognized ones, i.e. *Louvain* [Blondel et al. 2008] and *InfoMap*. [Rosvall, Bergstrom 2007]. Note that these methods, in contrast to all the other tested ones, do not need fixing a desired number of clusters, hence a major operational advantage when no idea of the "true number of clusters" is known beforehand - hierarchical clustering being in an intermediate position, as in one run it leaves the choice of the cluster number to the user.

- *Non-negative Matrix Decomposition* ("NMF") [Lee, Seung 1999]: this decomposition is akin to be used as a clustering method, when the label of a document is attributed depending on the axis of its maximum projection. As this method converges to local optima of its objective function, we implemented the same "20 runs" strategy as for K-means. Note that the resulting gradual representation of documents in the clusters is also interesting in that outliers, or even additional cluster seeds, may be identified - one kind of "possibilistic" clustering.

- *Latent Dirichlet Allocation* ("LDA") [Blei et al. 2003] is well-known and much respected as deeply founded in theoretic grounds.

- *Kernel clustering* [Girolami 2002]: thanks to the "kernel trick", a document by document similarity matrix ("Gram matrix") is built without explicit expansion of the raw dataspace by a kernel function. Here we used an order-2 polynomial kernel, which amounts to take into account the wholeness of the 2-term itemsets in

each document when comparing one to another (in addition to standard "1-term" itemsets). In this case the raw dataspace is not made of numeric occurrence vectors, but of binary existence ones.

1.4 - Choice of dataspace:

In addition to the plain term-occurrence vector space, we have considered and built:

- *Salton's vector space*, weighted by the classic tf-idf scheme:

$$x_{ij} = \text{tf idf}$$

$$\text{where tf} = n_{ij}$$

$$\text{idf} = \log n - \log e_j$$

Notations :

N is the document by term matrix, n_{ij} is the occurrence number of term j in document i , n_i is the total occurrences of terms in document i , n_j is the total occurrences of term j , $n_{..}$ is the grand total of occurrences in the corpus, n is the number of documents.

E is a binary document by term matrix, e_{ij} is 1 if term j exists in document i , 0 else, e_i is the total number of terms which appear in document i , e_j is the number of documents in which term j appears, $e_{..}$ is the grand total of term appearances in the corpus.

- *Okapi* (also coined BM25) [Robertson et al. 1994] *vector space*, with a more cryptic, but statistically grounded, weighting scheme [Okapi***]:

$$x_{ij} = \text{tf idf}$$

$$\text{tf} = n_{ij} (a+1) / (n_{ij} + a(1-b+b(n_i/n_{..}))) \quad ; \text{ recommended values: } a=1.2 \quad b=.75$$

$$\text{idf} = \log(n - e_j + .5) - \log(n_i + .5)$$

- *Chi-square metrics*, which amounts to a Euclidean vector space with vectors transformed as suggested in [Legendre, Gallagher 2001]:

$$x_{ij} = n_{..}^{1/2} n_{ij} / (n_i n_j^{1/2})$$

- *Hellinger metrics*, which also amounts to a Euclidean vector space with vectors normalized as suggested in [Legendre, Gallagher 2001]:

$$x_{ij} = (n_{ij} / n_i)^{1/2}$$

Giving rise to systematically poor performances in our first trials, we have eliminated this metric in the sequel.

- *Laplacian spectral space* [Von Luxburg 2007]:

Given **Cos**, the (truncated or not) cosine matrix between the documents, which defines a non-oriented graph, and **s** the sum vector of its rows or columns, the transformed matrix

$$\mathbf{Q}_{\text{lapl}} = \text{diag}(\mathbf{s}^{-1/2}) \mathbf{Cos} \text{diag}(\mathbf{s}^{-1/2}) \quad \text{gives rise to a Singular Value Decomposition (SVD):}$$

$$\mathbf{Q}_{\text{lapl}} = \mathbf{U}_{\text{lapl}} \mathbf{D} \mathbf{V}_{\text{lapl}}$$

The first rank factors concentrate the relevant information. When aiming at k classes, we chose to take into account three configurations of \mathbf{U}_{lapl} , with respectively integer($k/2$), k and $2k$ top-ranking factors.

- *Correspondence Analysis spectral space* [Benzecri 1973]:

The transformed matrix $\mathbf{Q}_{ca} = \text{diag}\{n_i^{-1/2}\} \mathbf{N} \text{diag}\{n_j^{-1/2}\}$ gives rise to a SVD decomposition

$$\mathbf{Q}_{ca} = \mathbf{U}_{ca} \mathbf{L} \mathbf{V}_{ca}$$

resulting in the CA factors:

$$\mathbf{F} = \mathbf{n}^{1/2} \text{diag}\{n_i^{-1/2}\} \mathbf{U}_{ca} \mathbf{L}$$

As the first factor is trivial, we chose to take into account three configurations, with respectively $1 + \text{integer}(k/2)$, $1+k$ and $1+2k$ top-ranking factors.

Note that Euclidean distances in the complete factor space equal chi-square distances [Benzécri 1973]. Therefore truncating this space in this manner amounts to consider "partial chi-square" distances, *a priori* more relevant than chi-square distances. We will check this below.

These six transformations of a document-by-term matrix are convenient for the KM, NMF, LDA and Spectral Clustering methods. Other methods, such as Hierarchical Clustering, Graph methods and Kernel methods, need a document-by-document similarity (or dissimilarity) matrix. We have derived the distance or cosine matrices for all the above-mentioned dataspace. Depending on each dataspace-method combination, we have used euclidean distance or cosine distance (i.e. 1-cosine, which weighs half of the squared chord distance [Legendre, Gallagher 2001]).

- *Kernel space* [Girolami 2002]:

In matrix notations and in the case of order-2 polynomial kernel, the Gram similarity matrix writes:

$$\mathbf{X}_{k2} = (\mathbf{1} + \mathbf{E} \mathbf{E}')^2 \quad \text{where } \mathbf{X}^2 \text{ means squaring each value of matrix } \mathbf{X}$$

Given the much contrasted values in this matrix, the cosine distance is well-fit to this dataspace.

1.5 - Choice of evaluation measures

We chose the four most usual indices encountered in the evaluation literature, i.e. first, Normalized Mutual Information (NMI) [Cover, Thomas 1991] and Adjusted rand Index (ARI) [Rand 1971], which compute independently from the number and labels of clusters; and second, mean local class vs. cluster F-scores (F) [Van Rijsbergen 1979] and global Purity score (i.e. 1-global error rate) which need the same number of clusters and classes, and same labels. Even when this was not the case (graph methods), we have aligned the k classes and the k most "analogue" clusters, in the sense of local F-scores, by means of the ranking issued from the first non-trivial factor in the Correspondence Analysis of the classes by clusters F-score matrix.

1.6 - Code implementation and computer efficiency

As computer efficiency is out of our goals, we implemented the data transformations, method code, and post-processing code in an Octave environment, on an Intel 6-core I7, 3.33GHz, 48Go RAM computer. Method codes were derived from existing Matlab codes (links to the original pieces of code will be available in the supplementary material). Their degree of computing time optimization varies considerably: e.g. in the case of the 19 000 documents Ng20 test set, from 2 minutes for twenty elementary runs of the standard "litekmeans.m" code, to 6 hours for one run of Louvain method.

2 - Evaluation results for each method

We have tried as much as possible to cross-combine corpora \times data transformations \times methods. This was not always possible, due to constraints such as computing time or resources devoted to systematically poor results.

2.1 – K-means

Altogether with hierarchical agglomerative clustering, this method is an inescapable classic of exploratory data analysis. Our results confirm why it is till now so widely used: good performances ($nmi > .60$ on ACM and Ng20 corpora), low computing complexity $O(\#documents \times \#terms)$, fast runs as noted above.

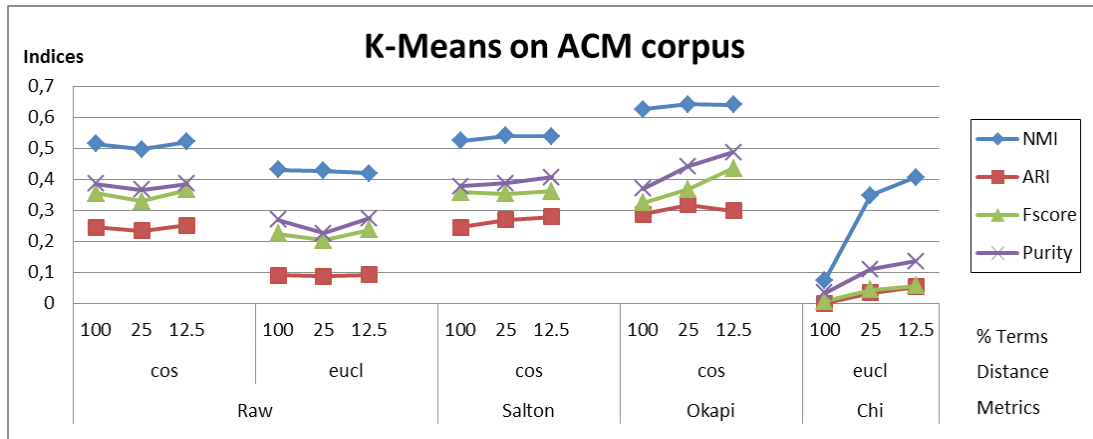


Figure 1: K-means on ACM corpus

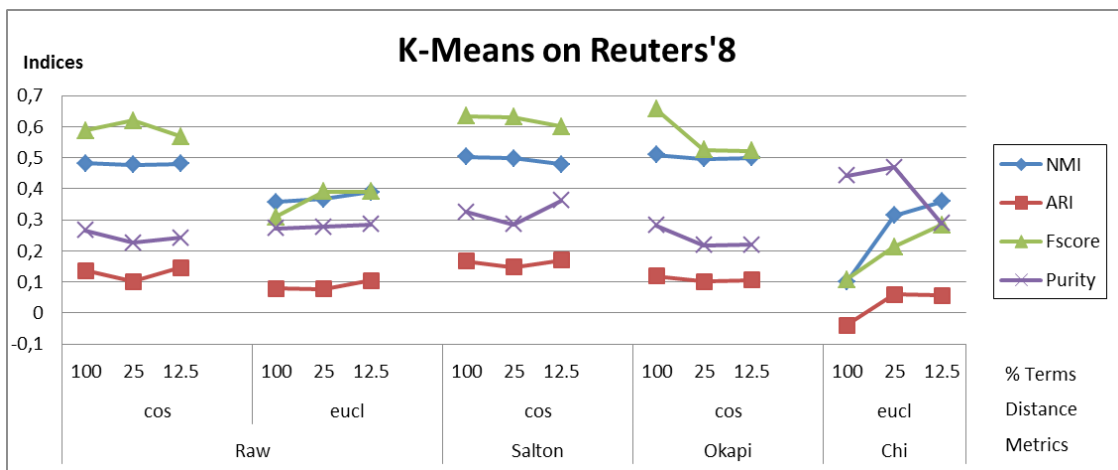


Figure 2: K-means on Re8 corpus

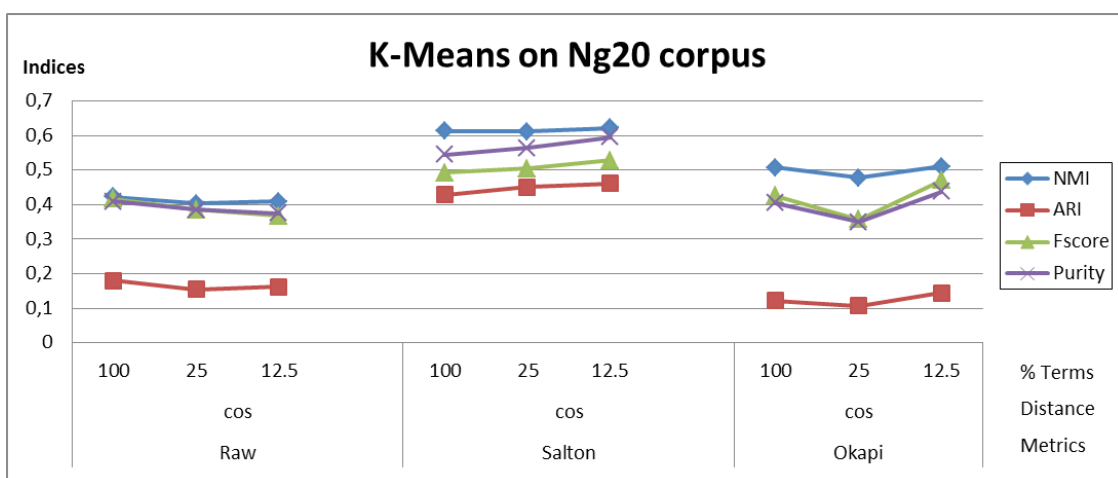


Figure 3: K-means on Ng20 corpus

A remark about evaluation indices: in the case of the two balance-sized corpora, they both globally go much in the same line - a bit more uneven in the case of Re8.

The vocabulary truncation does not seem to be quite influential, except in the case of the Chi-square space. So one recommendation may be drawn: a 12,5% threshold seems good enough for acceptable results, resulting in a lighter processing task.

Examining performances, the results are surprising: Okapi dataspace performs best for ACM, Salton's one for Ng20, and both perform equally for Re8, as well as raw occurrence dataspace. Conclusions would need a specific study of the peculiarities of text corpora with regard to these disorientating kinds of observations.

2.2 - NMF

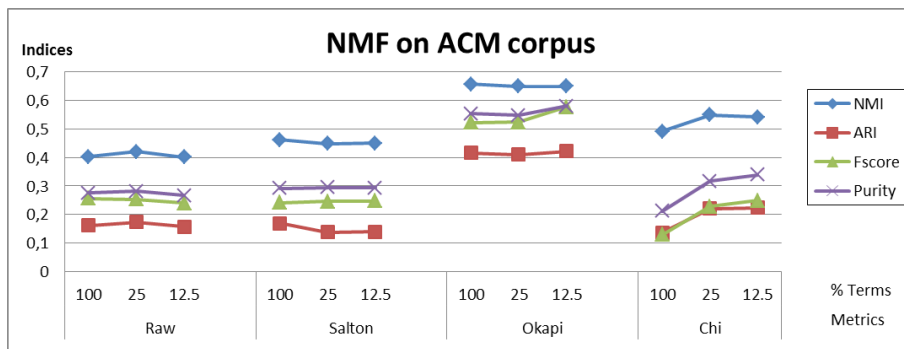


Figure 4: NMF on ACM corpus

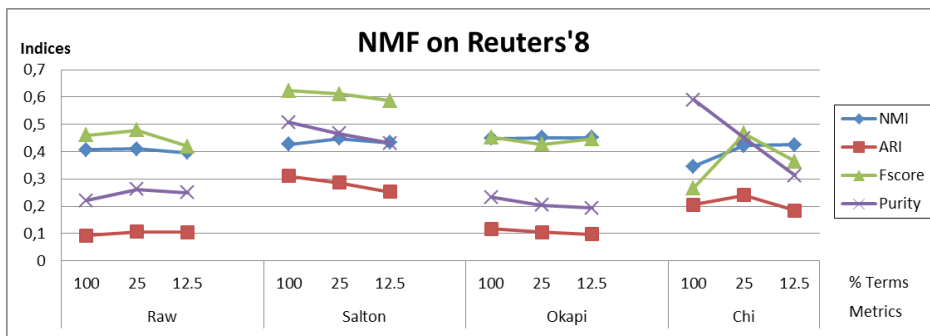


Figure 5: NMF on Re8 corpus

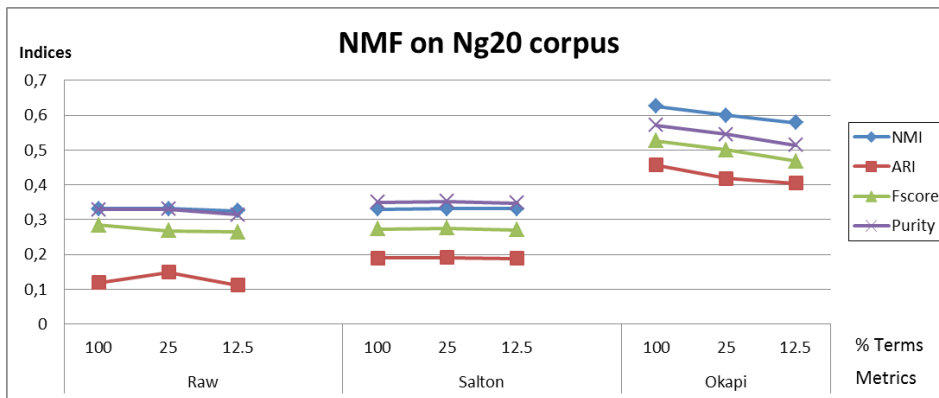


Figure 6: NMF on Ng20 corpus

This recent method confirms the surprising observation above: ACM and Ng20 yield good performances in Okapi space, whereas Re8 does in Salton's space.

2.3 - LDA

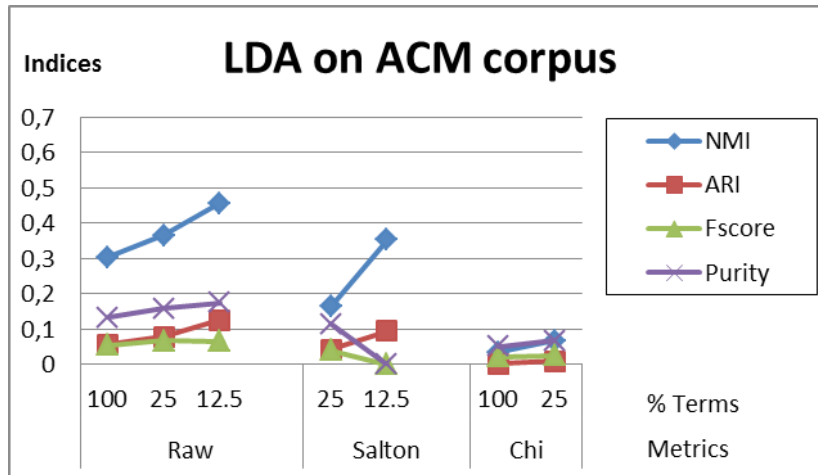


Figure 7: LDA on ACM corpus

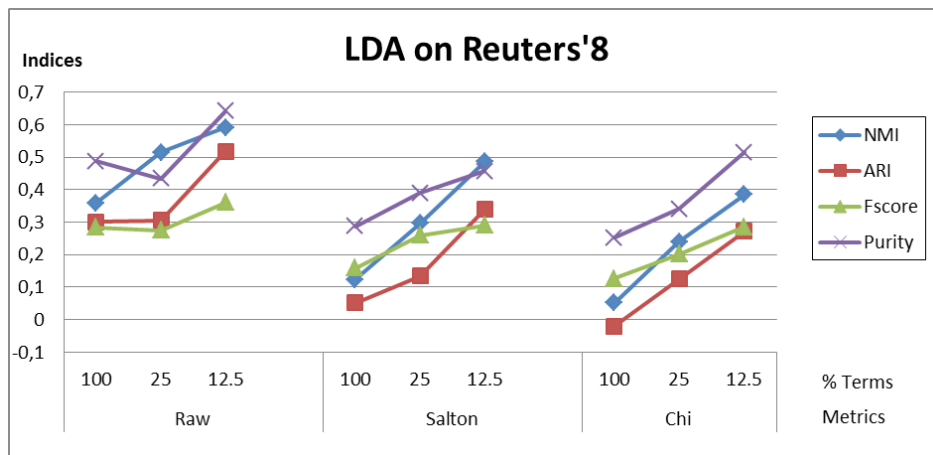


Figure 8: LDA on Re8 corpus

The somehow chaotic performances and the unpredictable computing time (10 to 40 minutes) led us to not process the 3-times bigger Ng20 corpus.

However it seems that LDA is more fit to the raw euclidean dataspace, perhaps more in line with its underlying statistical hypotheses. Another observation: the more vocabulary truncation, the better.

2.4 - Linkage methods

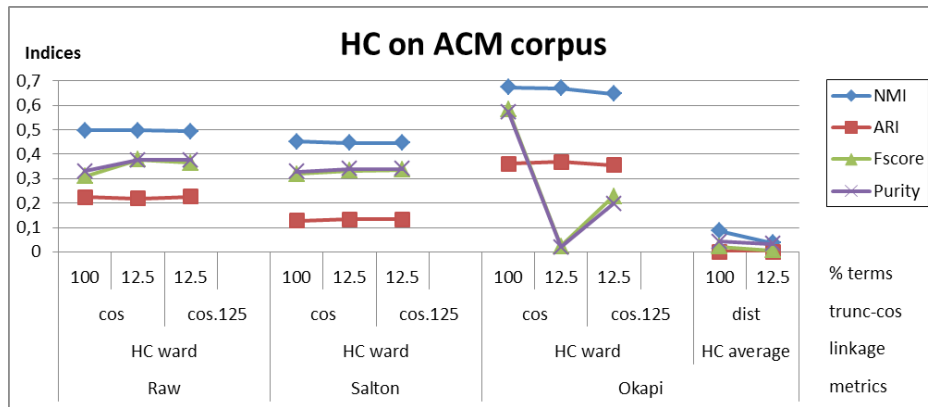


Figure 9: Hierarchical Clustering on ACM corpus

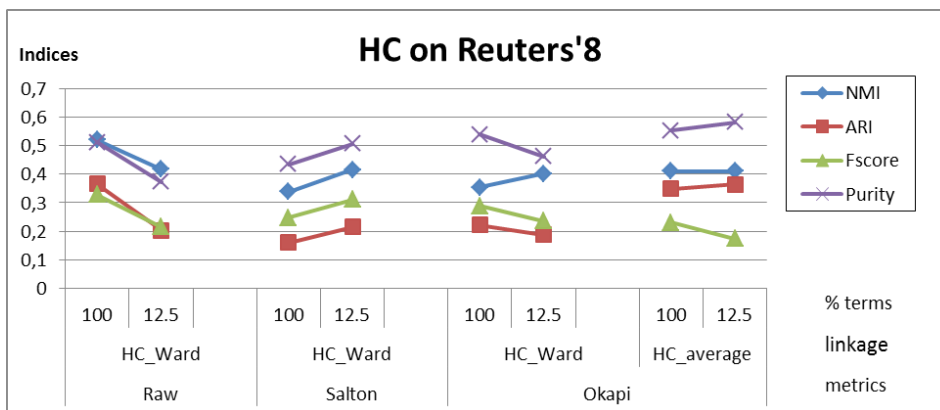


Figure 10: Hierarchical Clustering on Re8 corpus

At first glance, it seems that the average link variant performs correctly with Reuters'8, but not with ACM - another intriguing fact. As linkage option is far more time-consuming, we will not use it for Ng20. Ward linkage variant seems also a clear winner.

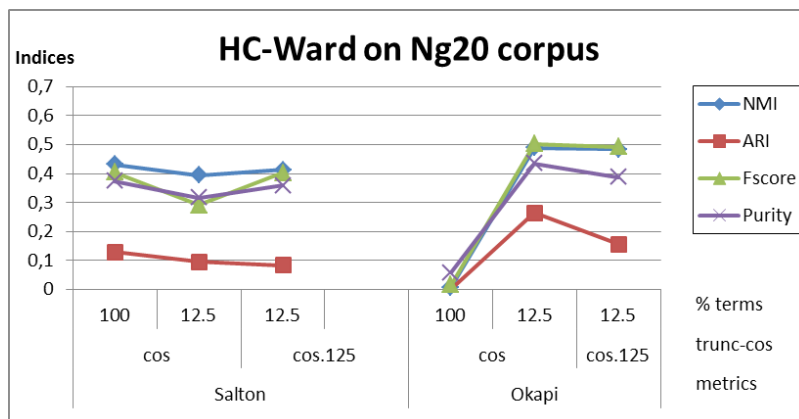


Figure11 - Hierarchical Clustering on Ng20 corpus

Using Okapi dataspace outperforms using Salton's and Raw dataspaces for ACM and Ng20 corpora, in line with the observations above.

2.5 - Spectral clustering

Results for ACM corpus

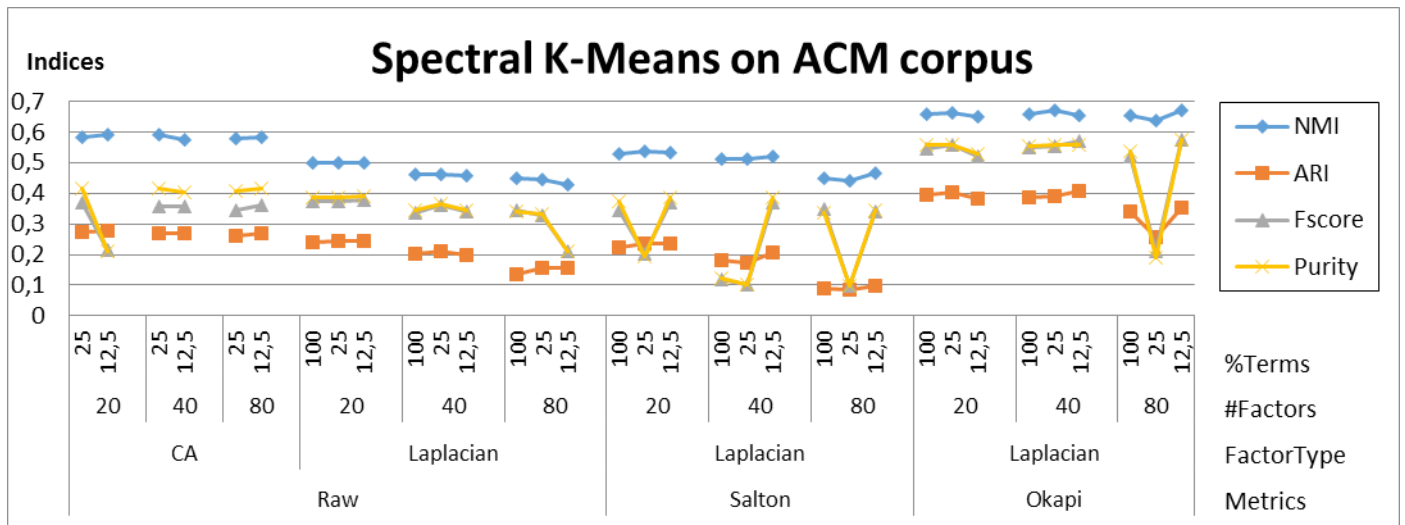


Figure 12: Spectral K-means Clustering on ACM corpus

Note the excellent performance of this method in Okapi-transformed dataset with Laplacian spectral extraction, whatever the number of factors and term percentage, and the good performance of Correspondence Analysis factor space.

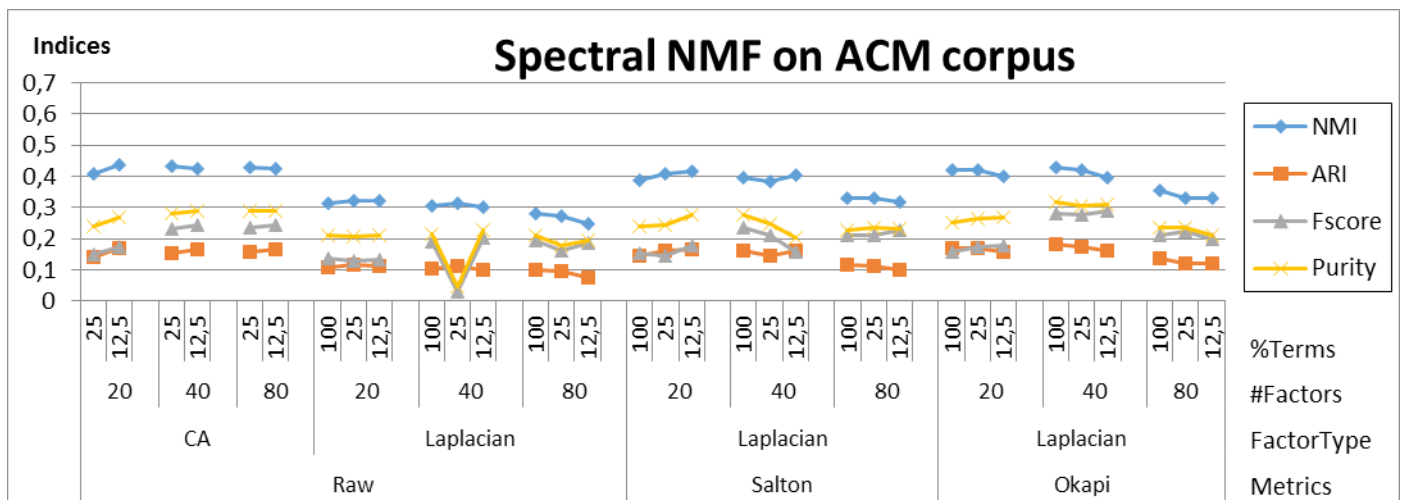


Figure 13: Spectral NMF Clustering on ACM corpus

NMF is not as competitive as KMeans in the same context.

Results for Re8 corpus

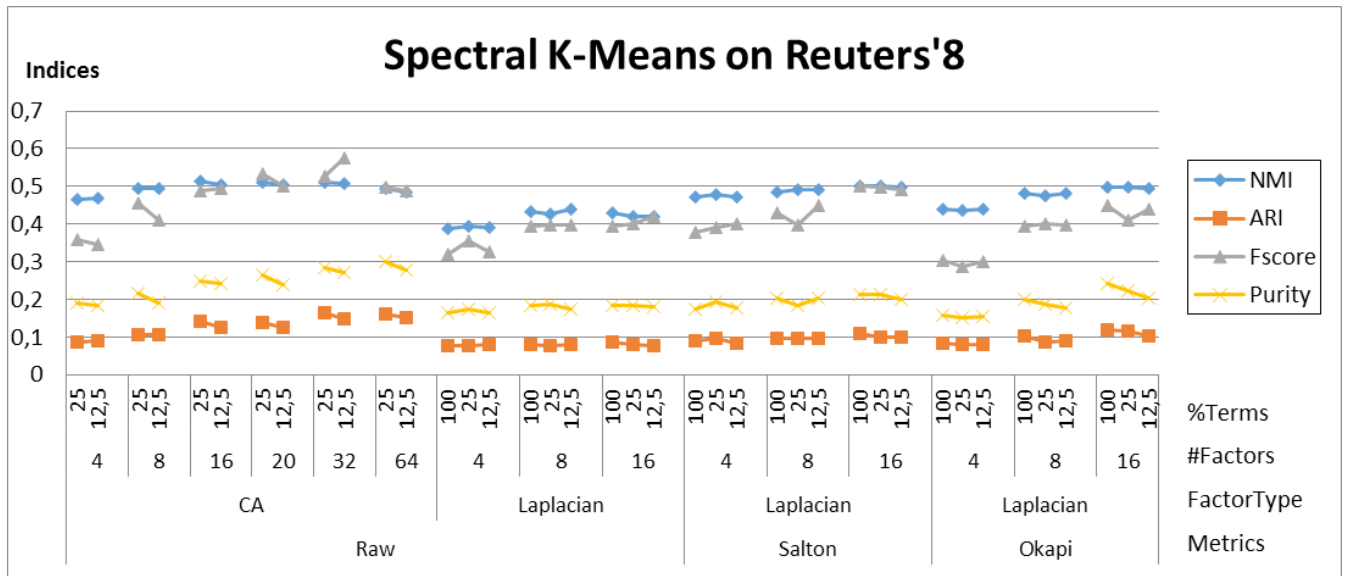


Figure 14: Spectral K-means Clustering on Reuters'8 corpus

"Attraction" of Reuters'8 corpus towards Raw and Salton's dataspace is confirmed, as well as insensitiveness to term truncation and size of the factor space.

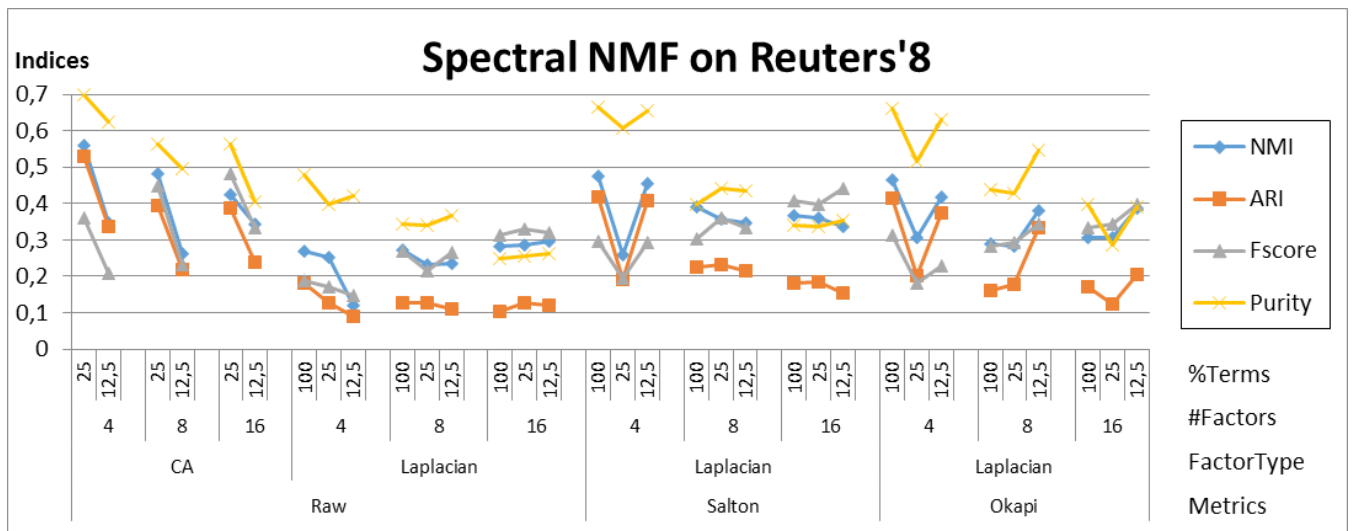


Figure 15: Spectral NMF Clustering on Reuters'8 corpus

Not so good, purity is privileged.

Results for Ng20 corpus

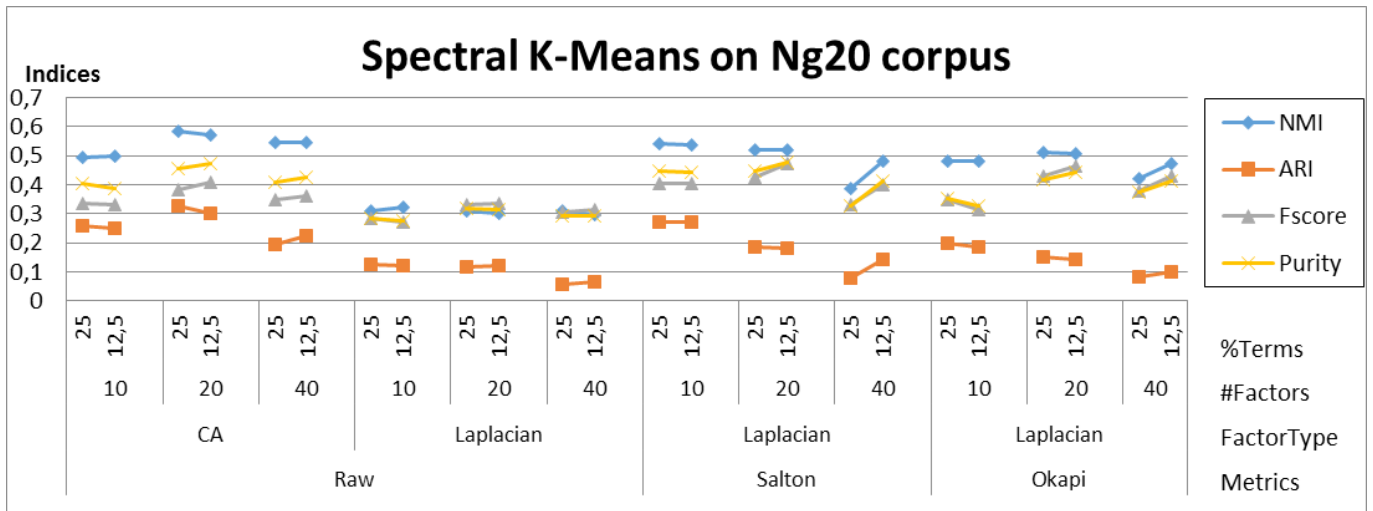


Figure 16: Spectral K-means Clustering on Ng20 corpus

Excellent performance in "k-factor" Correspondence Analysis dataspace, slightly better than in Laplacian ones.

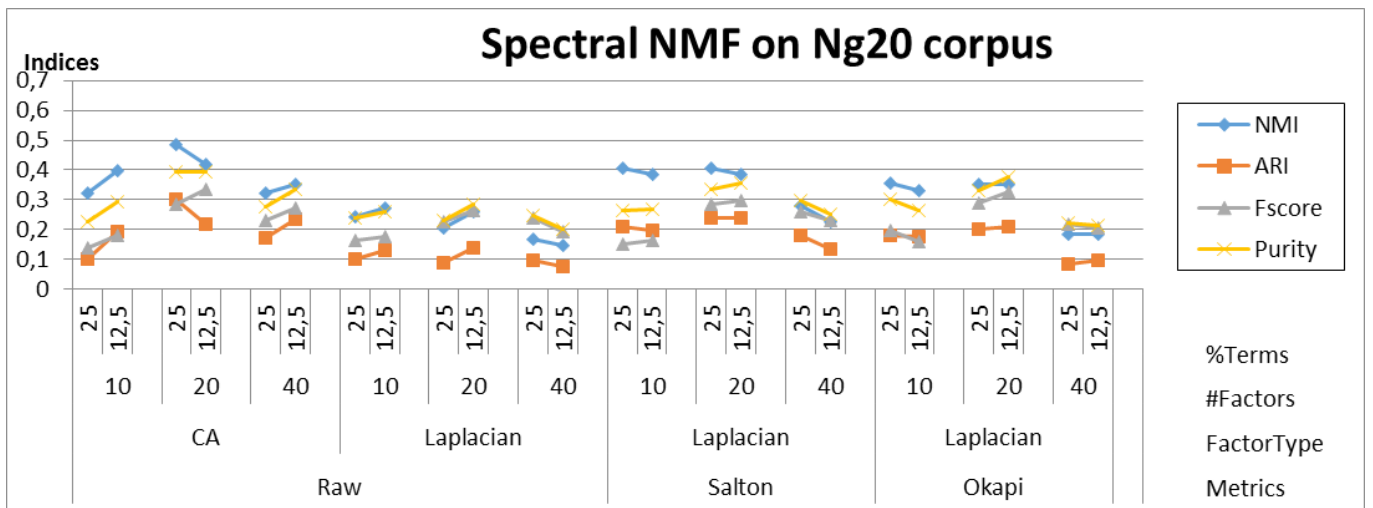


Figure 17: Spectral NMF Clustering on Ng20 corpus

Does not add benefits to other combinations. NMF seems more fit to operate in non-spectral dataspace (Okapi, Salton, Kernel - see below) than in spectral ones: a major difference with KMeans, "comfortable" in all contexts.

2.6 - Kernel clustering

When using a second-order polynomial kernel, this more recent method is not based on term counts, unlike all other methods, but on binary presence/absence vectors, which makes it possible to take into account term 2-itemsets, i.e. supersets of term bigrams. As semantic units seem to be embedded in word bigrams or trigrams more than unigrams, at least in technical texts, this dataspace should result in another meaningful view upon the data.

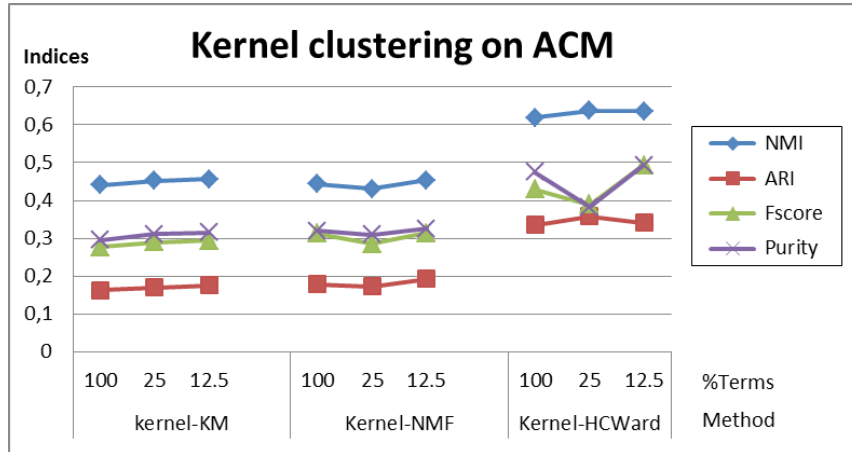


Figure 18: Kernel Clustering on ACM corpus

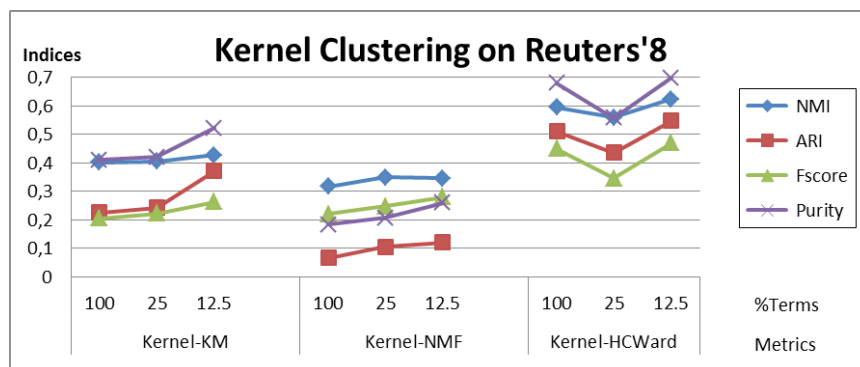


Figure 19: Kernel Clustering on Reuters'8 corpus

It is indeed the case, the surprise being that usual Kernel K-means is clearly outperformed by Ward-linkage clustering in the kernel space. We have not heard of this result elsewhere.

Given the long computation time on Ng20 corpus (3 hours), we performed only two runs with a disappointing outcome: at best, NMI=.404, ARI=.202, Fscore=.313, Purity=.336 on a 25%-truncated vocabulary.

2.7 - Graph clustering

- Louvain

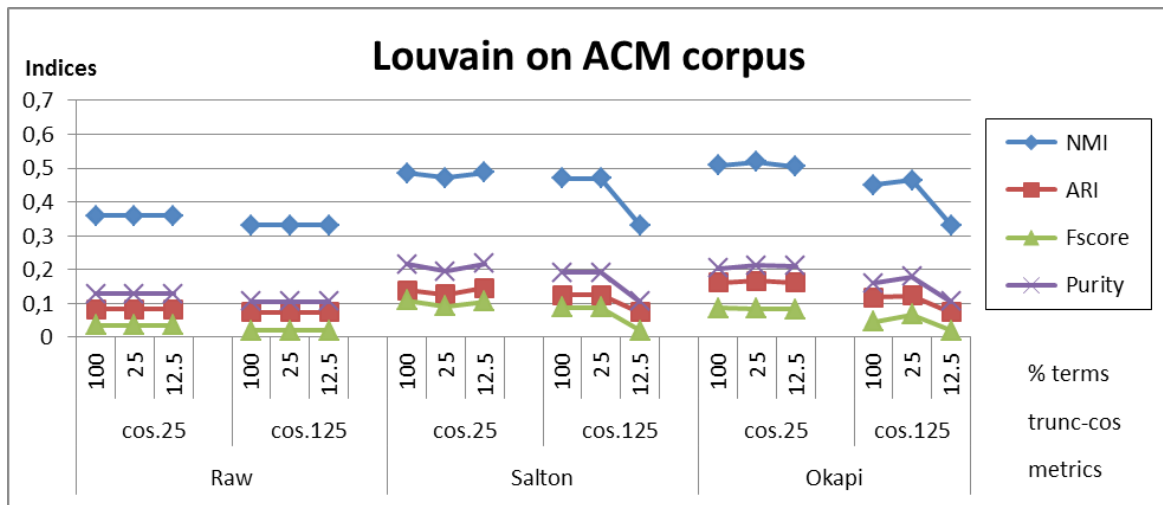


Figure 20: Louvain graph clustering on ACM corpus

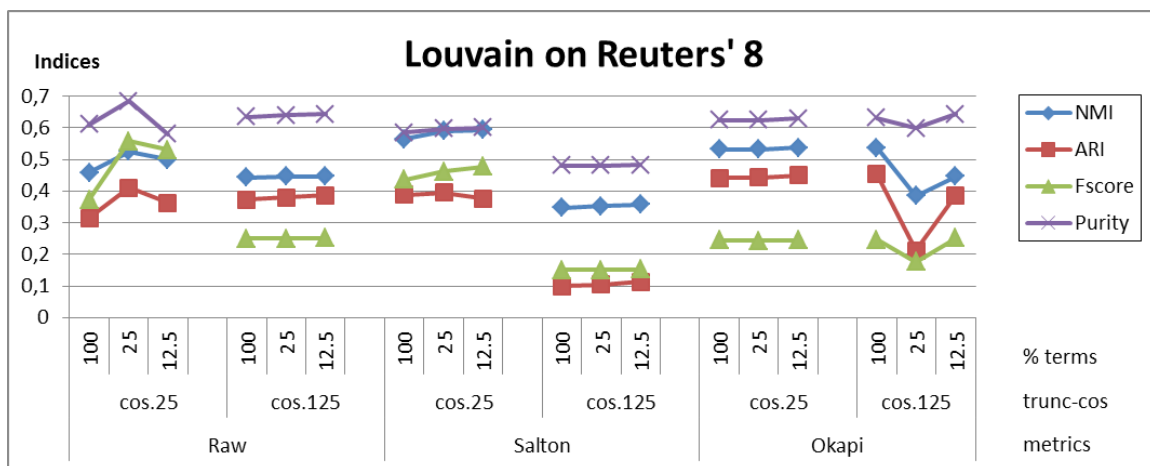


Figure 21: Louvain graph clustering on Reuters'8 corpus

The performance is not so good as HC-Ward, but shows a slight indifference to thresholds, on vocabulary as well as on cosines. Thus a sparse "graph-like" cosine matrix does not seem to be an advantage, contrary to our initial guess.

This guess led us to test a single run of Louvain on a doubly truncated Ng20 space (25% truncated vocabulary, 25% truncated cosines) but the performances were poor: , NMI=.302, ARI=.116, Fscore=.114, Purity=.211, which seems to confirm the above statement.

- InfoMap

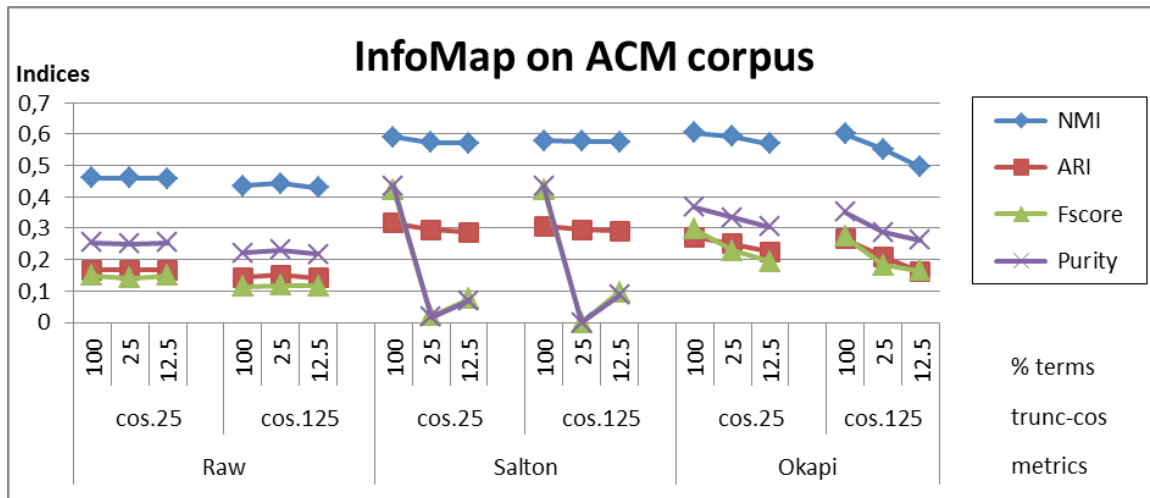


Figure 22: InfoMap graph clustering on ACM corpus

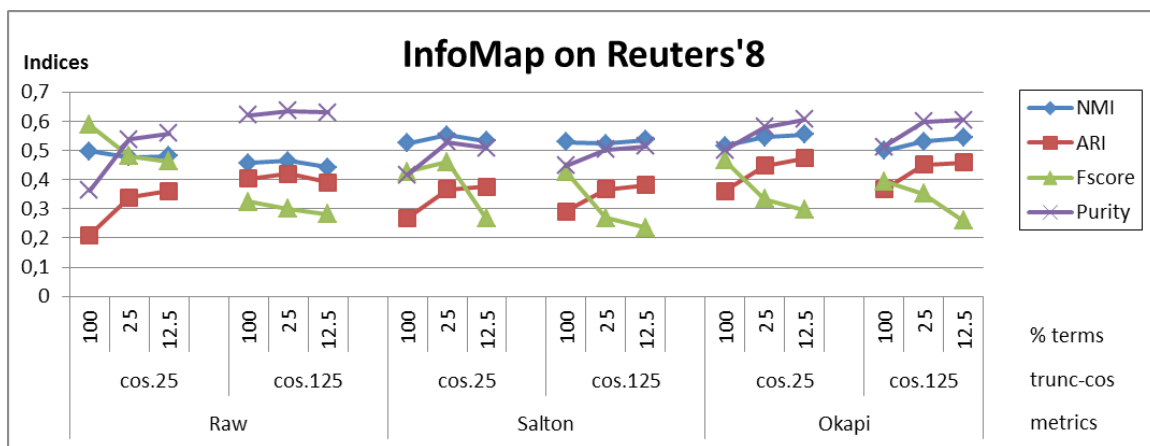


Figure 23: InfoMap graph clustering on Reuters'8 corpus

The performance is good, especially in the Okapi and Salton's dataspace, with no sensible influence of the thresholds.

We tested two InfoMap runs on two Ng20 spaces (3 hours each), both 25% cosine-truncated, the first with 100% vocabulary, the second with 25%, resulting in average scores: maximum NMI=.356, max ARI=.162, max Fscore=.213, max Purity=.290.

3 - Synthesis

Let us first focus on the measurement tools: we can observe that in the case of the two "balanced" corpora, the four evaluation indices behave in a much parallel and orderly manner - see fig. 1, 3, 4, 6, 20. In contrast, this parallelism and regular ranking deteriorate in the Reuters'8 unbalanced corpus, and to a lesser extent when hierarchical methods are used. F-score and Purity indices may (see fig. 15, 22, 23) or may not present (see fig. 14, 16, 17, 20) a somehow contradictory or non-monotonic behavior. A thorough investigation

could perhaps explain these interesting discrepancies, but is clearly out of our present goals. We have thus chosen the more stable NMI index as a reference measure for ranking each corpus' runs (ACM: 184 runs, Re8: 170 runs, Ng20: 103 runs).

3 - 1 - "Top three" runs:

<i>ACM corpus:</i>
1) HC-Ward on integral, non-truncated vocabulary, Okapi dataspace; NMI:.674, ARI:.361, Fscore:.582,Purity: .573; elapsed time: 75"
2) Spectral KMeans on 80 factors Laplacian space over 12.5%-truncated vocabulary, Okapi transformed data; NMI:.671, ARI:.353, Fscore:.575,Purity: .574; elapsed time: 6"
3) HC-Ward on integral, 12.5%-truncated vocabulary, Okapi dataspace; NMI:.670, ARI:.368, Fscore:.023,Purity: .019; elapsed time: 75"
<i>Reuters'8 corpus:</i>
1) Kernel HC-Ward on 12.5%-truncated vocabulary, kernel raw dataspace (no Okapi, etc. transformation); NMI:.625, ARI:.548, Fscore:.469,Purity: .699; elapsed time: 767"
2) Kernel HC-Ward on non-truncated vocabulary, kernel raw dataspace (no Okapi, etc. transformation); NMI:.595, ARI:.516, Fscore:.449,Purity: .680; elapsed time: 753"
3) Louvain on 12.5%-truncated vocabulary, Salton's dataspace with 25%-truncated cosines; NMI:.594, ARI:.376, Fscore:.477,Purity: .600; elapsed time: 2324"
<i>20 NewsGroups corpus:</i>
1) NMF on non-truncated vocabulary, Okapi dataspace; NMI:.625, ARI:.548, Fscore:.469,Purity: .699; elapsed time: 107"
2) KMeans on 12.5%-truncated vocabulary, Salton's dataspace; NMI:.621, ARI:.461, Fscore:.527,Purity: .594; elapsed time: 122"
3) KMeans on non-truncated vocabulary, Salton's dataspace; NMI:.612, ARI:.429, Fscore:.492,Purity: .545; elapsed time: 185"

These optimal runs clearly depend on the corpora. A large variety of dataspace transformations (truncated or not vocabulary, Salton's, Okapi, or raw dataspace, kernel or Laplacian spectral space, ...) and methods (HC-Ward, KMeans, Louvain, NMF) are present. One remark: it can be noted that one run only may be considered as "classic", i.e. KMeans on Salton's dataspace with a truncated vocabulary, in the sole case of Ng20, the other ones are not.

Now let us investigate what these values mean in the real world, coming back to the data. The correspondence table between classes and best cluster partition for Ng20 corpus (see figure 23) shows off a "snake", more than a diagonal structure: some clusters totally or partially correspond to several classes, and conversely. The N°3 and 9 classes are dispersed among many clusters. The global 0.62 NMI and 0.57 Purity are not so good, after all, and this is confirmed by the 0.53 mean F-score. The reasons of the divergence between human categories and clusters should be thoroughly investigated in relation to experts of the application field, by examining for example the case of classes 3 and 9. This process may perhaps converge to a consensual "ground truth", or diverge, showing off the limits of the sole textual information - or the limits of a weakly linguistic term extraction, in the present case ?

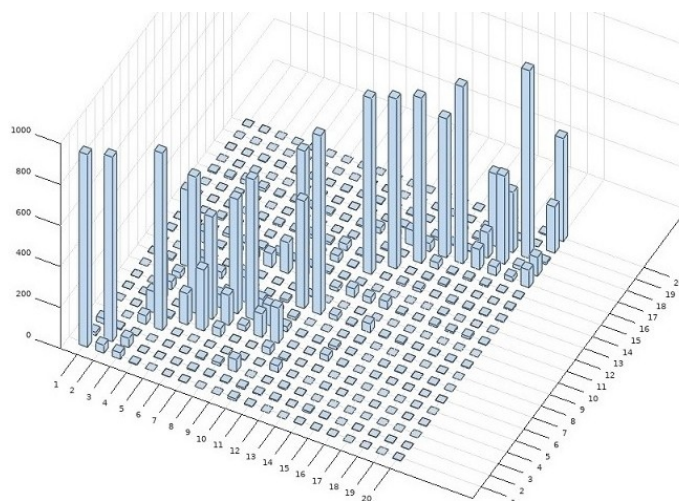


Figure 24 - Cross tabulation of clusters vs. classes on best-NMI run of 20 NewsGroups corpus. At left hand: classes; at right: clusters

The evenness of many above-mentioned weird observations shows that non-clearly elucidated phenomena and interactions are at work: e.g. the role that could be played by the size unevenness and number of the clusters, by the size of the vocabulary, by the type and style of texts, by density contrasts in dataspace, and so on. This opens up a whole unexplored research field.

Now let us search for commonalities. Examining the "Top-30" runs of each corpus, a few common behaviors emerge.

- Partial commonalities: the combination NMF + Okapi dataspace with non-truncated vocabulary is clearly a good option for the two balance-sized corpora, but not for Re8. Spectral NMF in Correspondence Analysis space, limited to "k" factors (8 for Re8, 20 for Ng20) and issued from a 25% truncating of the vocabulary performs well in Re8 and Ng20 context, but not in ACM's. In our present state of knowledge, it is too early for issuing subtle recommendations on the optimal use of this or that algorithm.

- Global commonalities: the best compromise we find is to combine Spectral KMeans with the above-mentioned Correspondence Analysis dataspace, with a number of factors possibly exceeding k or 2k, which is an advantage when the "real" number of clusters is unknown. In this case, the mean ratio to the best-performing run in terms of NMI is around 87%.

This combination is fast (12" with the 19 000 Ng20 documents) as it costs $O(\#documents \times \#variables)$ computation time; it saves storage resources e.g. keeping 25% of the original vocabulary. The main problem being building the spectral space: in many computer languages, efficient sparse Singular Value Decomposition procedures exist, when the problem is just to draw a limited number of eigenvalues and eigenvectors from huge datatables. Parallel graphics co-processors may be dedicated to this task, too. We are not aware of any use of CA factor space for spectral Kmeans yet, and this original combination will be the only cautious recommendation we could issue by now.

4 - Conclusions and perspectives

We hope we have brought some clarification to the problem of evaluating text clustering procedures, by considering separately the algorithms and the dataspace in which they operate. We have achieved some 450

runs of a dozen algorithms and variants, in a few tens various dataspace, on three prototypical and public access test corpora. We have brought to light an unexpected variety of optimal combinations of methods and dataspace, from which we have derived a cautious recommendation for those who do not know the "true" number of clusters to draw from an unknown corpus. This variety requires a considerable continuation effort, in the goal of improving our understanding and mastery of natural and artificial categorization processes. We hope that this empirical survey will contribute to such an issue. In a modest first step, we will explore the influence of the linguistic pre-processing: choice or elimination of word categories, comparison between taking into account multi-word expressions and kernel expansion of uniterms.

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