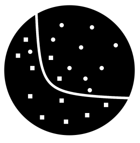
PROGETTO PER SISTEMI INTELLIGENTI

Prof. Nunzio Alberto Borghese
6 CFU

Luca Cappelletti

Project Documentation
Year 2017/2018



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Indice

1 Introduction **2**
1.1 Why is the Zipf interesting? 2
1.2 What is attempted in this project? 2

2 The Zipf **3**

3 The classifier **4**
3.1 Training the classifier 4
3.1.1 Convert documents to vector representation 4
3.1.2 Choosing representative points 4
3.1.3 Completing the classifier 5
3.2 Classifying a document 5

4 Results **6**
4.1 Reproducing the results 6
4.2 Authors 7
4.2.1 Confusion matrix 7
4.2.2 Truncated SVD reduction 7
4.3 Literary periods 8
4.3.1 Confusion matrix 8
4.3.2 Truncated SVD reduction 8
4.4 Recipes websites 9
4.4.1 Confusion matrix 9
4.4.2 Truncated SVD reduction 9
4.5 Newspaper websites 10
4.5.1 Confusion matrix 10
4.5.2 Truncated SVD reduction 10
4.6 Recipes websites or non recipes websites 11
4.6.1 Confusion matrix 11
4.6.2 Truncated SVD reduction 11

1 Introduction

1.1 Why is the Zipf interesting?

The Zipf law is an empirical law that refers to the fact that in nature, many data can be approximated by a Zipfian distribution, for example texts, some images[1], even sounds in spoken languages[2]. It is therefore of interest to identify ways to exploit this relatively simple way to convert documents into representative vectors in problems such as classifications.

(a) Books follow a zipf distribution

(b) Image formats such as jpeg follows a zipf distribution

(c) Sounds in spoken language follow a zipf distribution

Figura 1.1: Examples of things in nature that follows the zipf distribution

1.2 What is attempted in this project?

In this project was attempted to classify textual documents using the bag of words model, ignoring any semantic structure, to their class using a general clustering approach with algorithms such as KMeans and CURE. No heuristics relative to the nature of the texts was used.

[1] https://www.dcs.warwick.ac.uk/bmvc2007/proceedings/CD-ROM/papers/paper-288.pdf

[2] https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0033993

2 The Zipf

The zipf function z converts any document $d \subseteq \mathbb{D}^m$ comprised of elements into a representative vector $\underline{\boldsymbol{v}} \subseteq [0,1]^n, n \leqslant m$ based on the frequency of said elements in the given document. Taken in consideration the set of elements $d \subseteq \mathbb{D}$ that comprise the document and $d_{\neq} \subseteq d$ the set of distinct elements of the set d, for any given element $d_{\neq_i} \in d_{\neq}$, the value assigned by the zipf function is:

$$z(d_{\neq_i}) : \mathbb{D} \to \mathbb{R} = \frac{\#\left\{\forall d_i \in d : d_{\neq_i} = d_i\right\}}{\#d}$$

3
The classifier

3.1 Training the classifier

3.1.1 Convert documents to vector representation

Given a set of training class-labeled elements T, we convert the documents, treated as *bag of elements*, to enumeration-sorted frequency vectors.

Given a document composed of $n = \#d$ elements $d = \{e_1, e_2, \dots, e_n\}$, first we define $d_{\neq} \subseteq d$ as the set of distinct elements in d. Then, we map to every distinct element its normalized cardinality in the set d:

$$z(e_i) = \frac{\#\left\{e_j \in d : e_j = e_i\right\}}{n}$$

Then, we proceed to map to a common enumeration the elements, using as full-set of elements the entire training set elements, so that $\forall e_i, e_j \in T, \exists! i, j \in \mathbb{N} : i = j \Leftrightarrow e_i = e_j$.

3.1.2 Choosing representative points

Given an arbitrary percentage of points $p \in [0,1]$ and an arbitrary distance in percentage $\alpha \in [0,1]$, for each class of points $C_j \in T$ we choose using k-Means:

$$k = \lceil \#C_j \cdot p^2 \rceil$$

This way the centroids surely distribute among the different points, following their density. If the points are, in truth, a unique cluster, the centroids will distribute themselves in an uniform fashion.

Then, we select following a random uniform distribution for each cluster $Q_i \in \left\{Q_1, \dots, Q_k\right\}$ a number $\left\lfloor \#\left\{p \in C_j : p \in Q_i\right\} \cdot p \right\rfloor$ points. We move each point p of an amount proportional to the distance from the point to its centroid c_i:$\alpha \cdot L^2\left(p, c_i\right)$ towards its centroid.

Using a metric to choose k

For the high dimensionality and number of the vectors, iterating multiple times *KMeans* searching for an optimal k following any given metric has an high time cost. For this reason, an attempt using **PCA** to reduce the dimensionality and predict the number of clusters in high dimensionality space using a density metric was made.

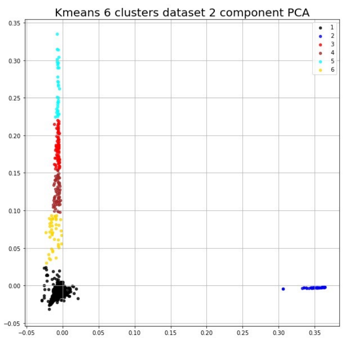
The density was defined as follows:

$$\overline{\rho}_{jk} = \frac{1}{k}\sum_{i=1}^{k} \rho_{jk_i} = \frac{1}{k}\sum_{i=1}^{k}\left(\frac{\#\left\{\underline{\boldsymbol{v}} \in C_{r_j} : \underline{\boldsymbol{v}} \in Q_i\right\}}{\#C_{r_j}}\right)^k \cdot \frac{1}{r_{Q_i}^2} \qquad r_{Q_i}^2 = \begin{cases} \frac{1}{n}\sum_{h=1}^{n}\left(\underline{\boldsymbol{c}}_i - \underline{\boldsymbol{p}}_h\right)^2 & \text{if } n \neq 0 \\ 1 & \text{else} \end{cases}$$

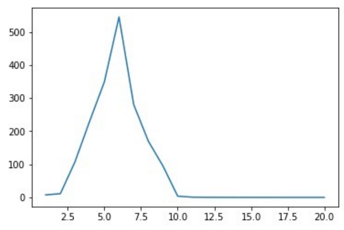
Where r_{Q_i} is the approximated radius of the cluster Qk_i, using the farthest n frontier points p_f.

Does the prediction hold? While the metric on two dimensions reduction seemed to work, when iterated on increasingly larger number of dimensions, with the exception of strongly clustered data, it did not much better than a random selection.

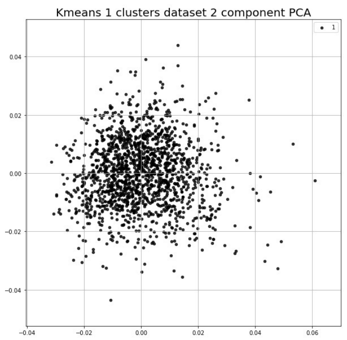
As follows, with 2D PCA density metrics the heuristic seems to be successful to identify the number of clusters k necessary to describe the given classes.



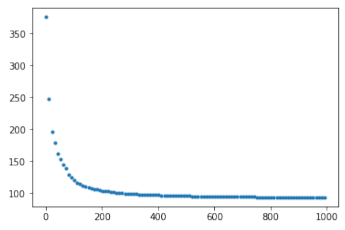
(a) Data with multi-clusters, 2D PCA, $k = 6$



(b) Density for data multi-clusters, 2D PCA, density/k



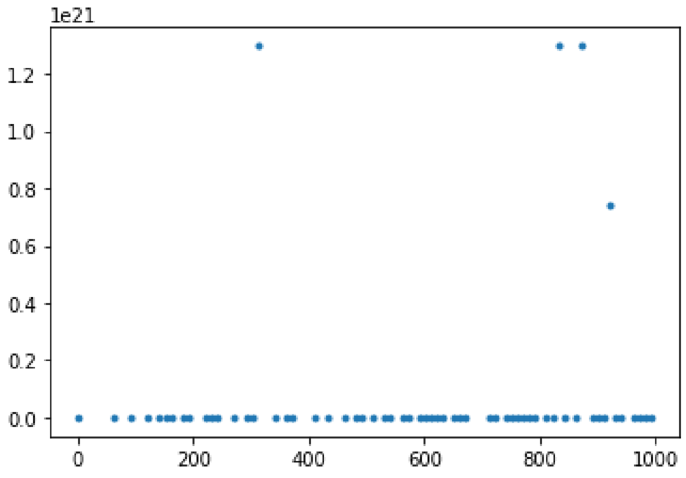
(c) Data with single-cluster, 2D PCA, $k = 1$



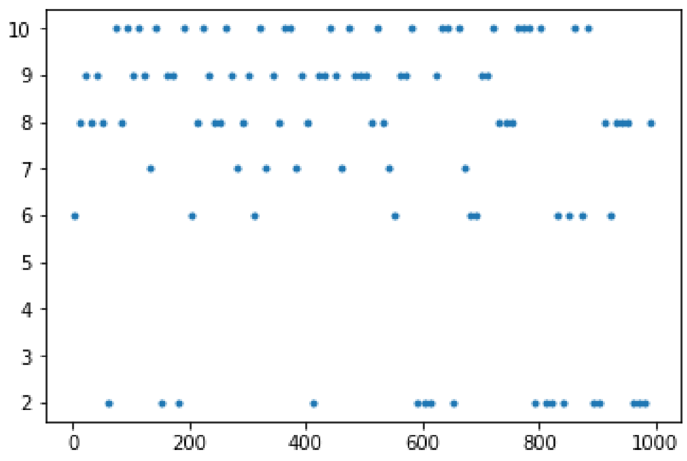
(d) Density for data single-cluster, 2D PCA, density/k

The prediction on any given PCA reduction however is not valid for different dimension numbers, on multi-clusters classes.

Any number of clusters k high enough ($k > 5$) is no more precise than a density metric. With increasing number of clusters, as shown below, it becomes increasingly unreliable.



(a) Best value of k for increasing dimensions in PCA reduction, one-clusters data.



(b) Best value of k for increasing dimensions in PCA reduction, multi-clusters data.

3.1.3 Completing the classifier

The classifier model is now finished, comprised of every class-labeled representative point.

3.2 Classifying a document

To classify a given a document d we proceed as follows:

1. Convert the document d to a zipf representative vector, using the common enumeration: $\underline{\boldsymbol{v}} = z(d)$.
2. The document is then classified with the same label as the closest representative point in the classifier model.

4 Results

4.1 Reproducing the results

Test were run on multiple datasets, all containing non-structured textual documents. All tests were run via the test.py file, available in the github repository, with the following parameters:

Seed The random uniform generator used to split files, run kmeans etc... were initialized to 1242.

Training percentage Of every dataset, 70% of the documents were used for training the classifier. The remaining 30% were used for testing. The split of the training and testing datasets was done selecting documents following an uniform random distribution initialized with the seed above.

Kmeans clusters k For every test, 10 clusters were used.

Kmeans iterations For every test 100 iterations were run before assuming convergence. Better results may be obtained with more iterations.

CURE representatives percentage For every test 10% of the training points were used as representative points.

CURE distance percentage For every test chosen representative points were moved 20% towards their respective centroids.

The complete dataset is available at the following url:

`https://mega.nz/#!XCI3iCiZ!EpBtedozqBivPcWYi8oAj6jx38LAJnUaNDfjvgzJi3I`.

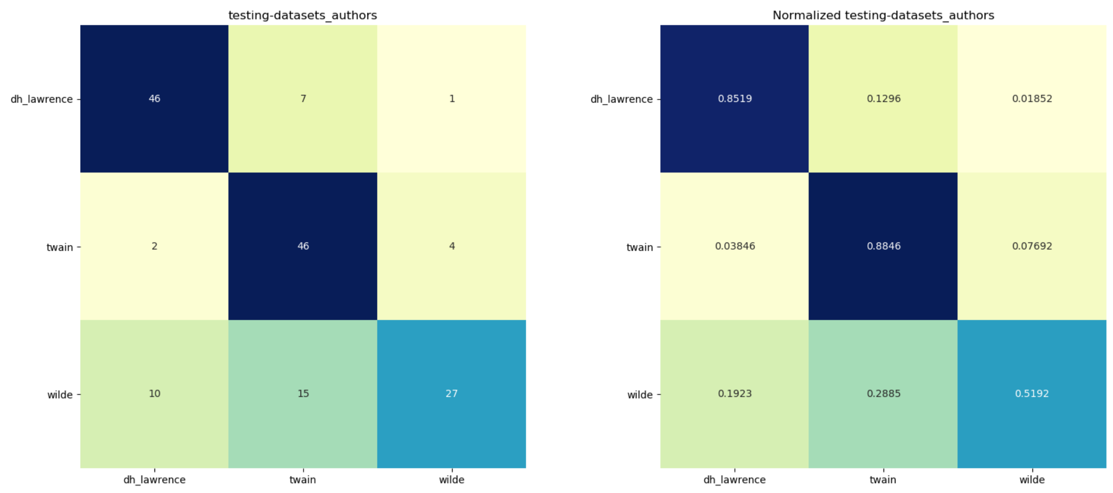
The already trained classifiers are available at the following url:

`https://mega.nz/#!yLAR0CSI!4g6jNfTeTpoEbss3P4jmuJyvTvv0Wmtw1sZQydQS1Qs`.

4.2 Authors

The “authors” dataset contains 315 texts from 3 authors: D. H. Lawrence, Mark Twain and Oscar Wilde. Each author has 105 documents.

4.2.1 Confusion matrix



(a) Confusion matrix for dataset “authors” (b) Confusion matrix for dataset “authors”

Figura 4.1: Ctrix for datascest “authors”

4.2.2 Truncated SVD reduction

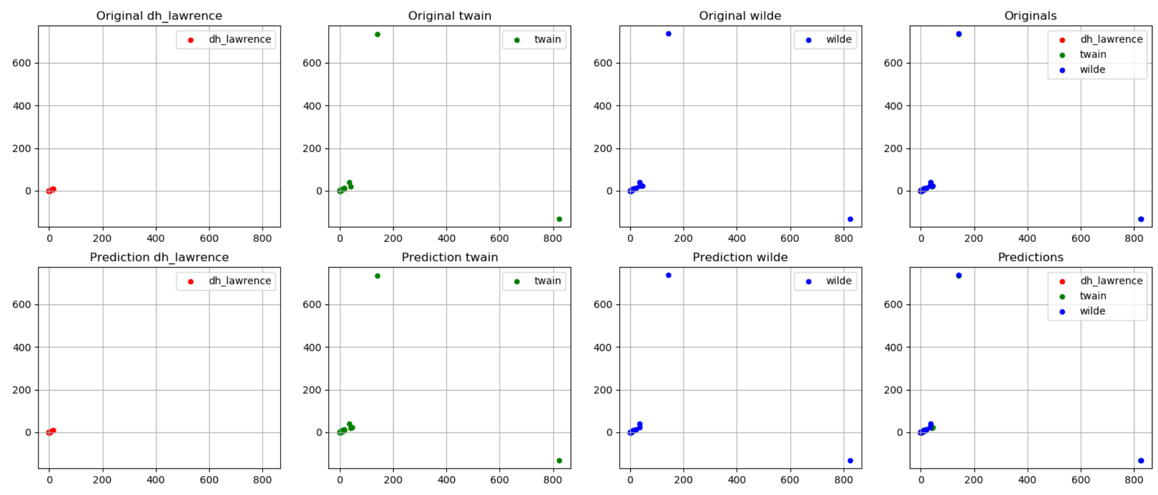
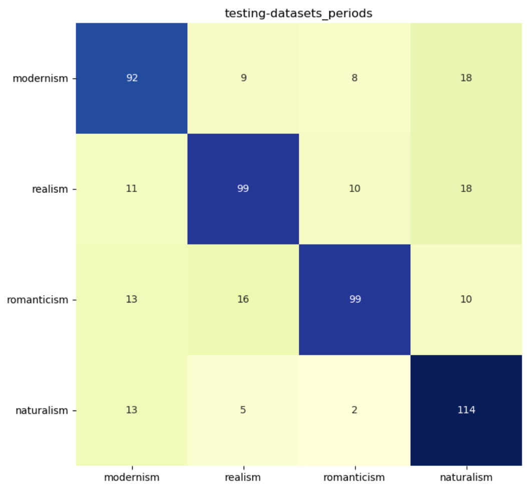


Figura 4.2: Dimensionality reduction using truncated SVD in dataset “authors”

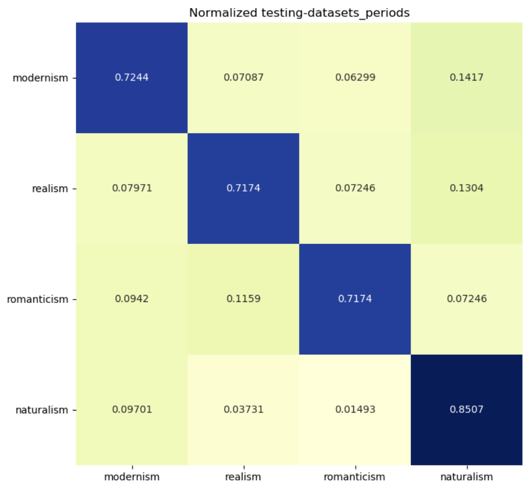
4.3 Literary periods

The "literary periods" dataset contains 1060 texts from 4 literary periods: Modernism, Realism, Romanticism and Naturalism. Each period has 265 documents.

4.3.1 Confusion matrix



(a) Confusion matrix for dataset "literary periods"



(b) Normalized confusion matrix for dataset "literary periods"

Figura 4.3: Confusion matrices for dataset "literary periods"

4.3.2 Truncated SVD reduction

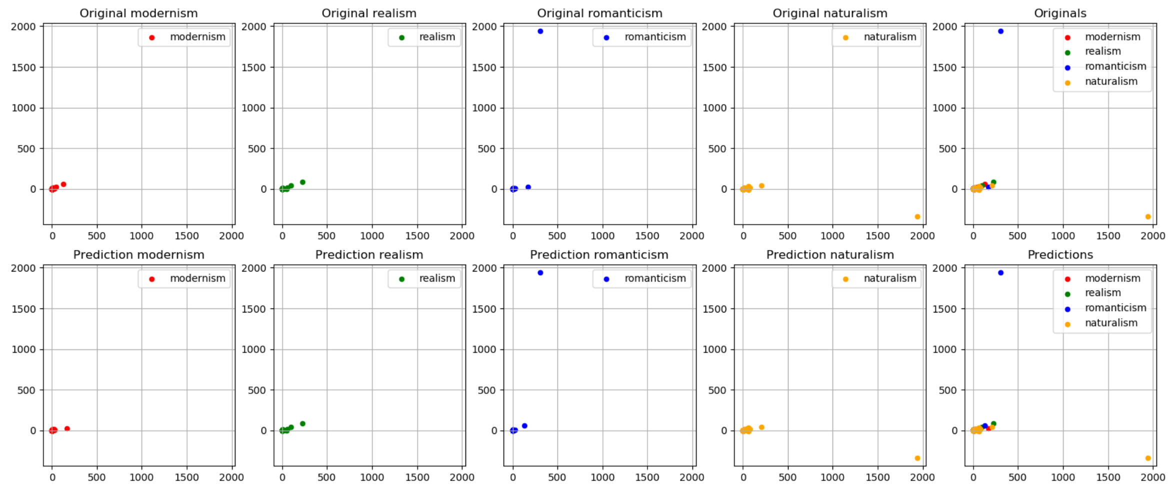
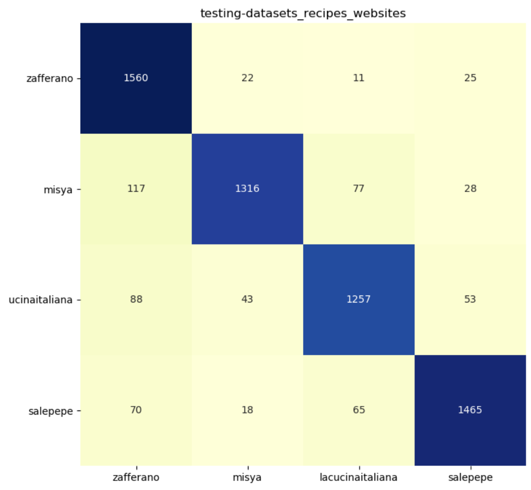


Figura 4.4: Dimensionality reduction using truncated SVD in dataset "literary periods"

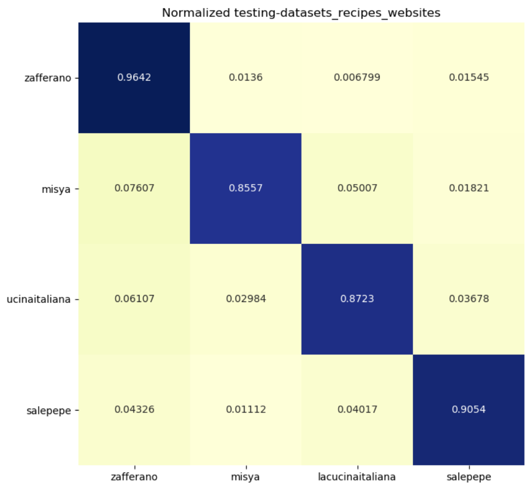
4.4 Recipes websites

The “recipes websites” dataset contains 12768 texts from 4 italian websites dedicated to recipes: Misya, Salepepe, Zafferano and Lacucinaitaliana. Every website in the dataset has 3192 texts.

4.4.1 Confusion matrix



(a) Confusion matrix for dataset “recipes websites”



(b) Normalized confusion matrix for dataset “recipes websites”

Figura 4.5: Confusion matrices for dataset “recipes websites”

4.4.2 Truncated SVD reduction

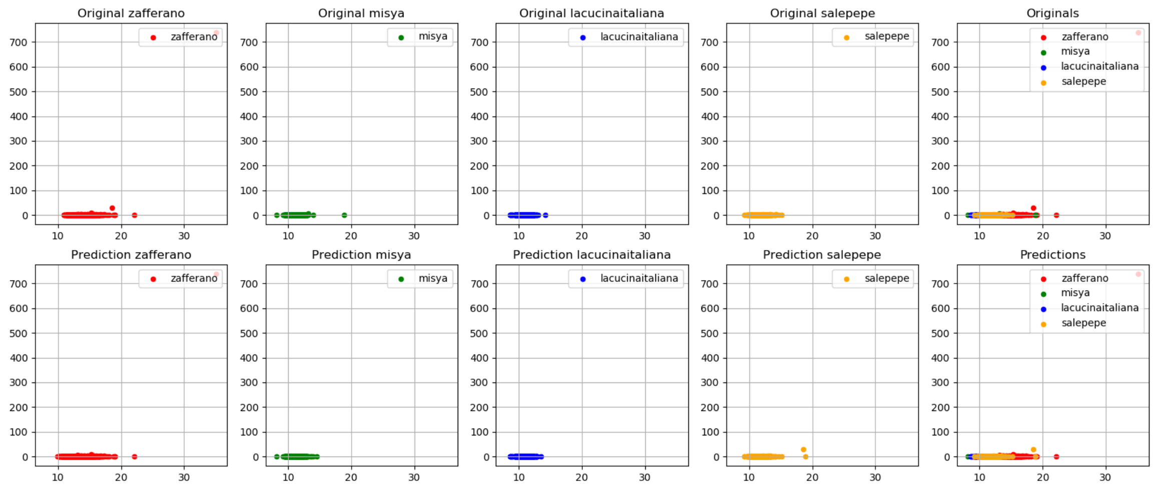
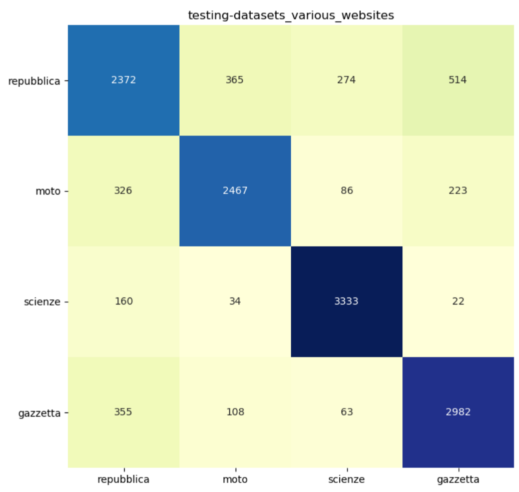


Figura 4.6: Dimensionality reduction using truncated SVD in dataset “recipes websites”

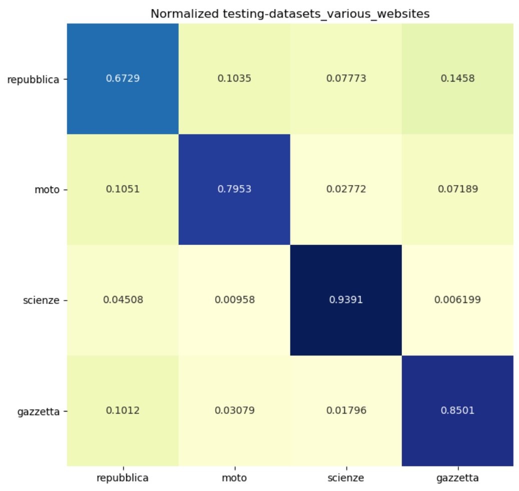
4.5 Newspaper websites

The "newspaper websites" dataset contains 28000 texts from 4 italian news websites: Repubblica.it, Moto.it, Scienze.it and Gazzetta.it. Every website in the dataset has 7000 texts.

4.5.1 Confusion matrix



(a) Confusion matrix for dataset "newspaper websites"



(b) Normalized confusion matrix for dataset "newspaper websites"

Figura 4.7: Confusion matrices for dataset "newspaper websites"

4.5.2 Truncated SVD reduction

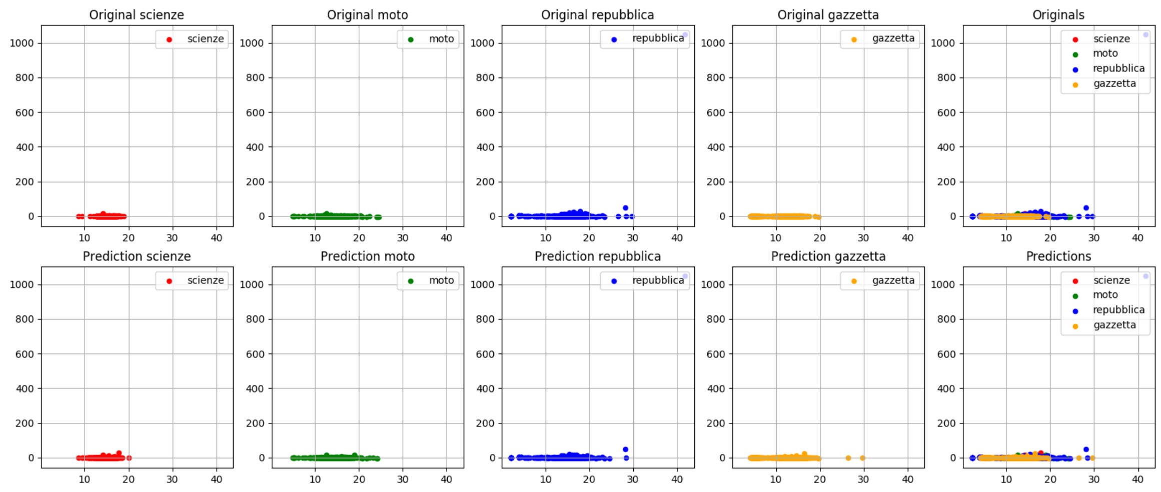
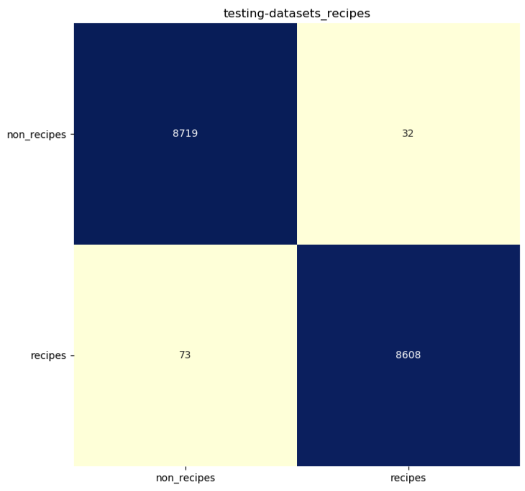


Figura 4.8: Dimensionality reduction using truncated SVD in dataset "newspaper websites"

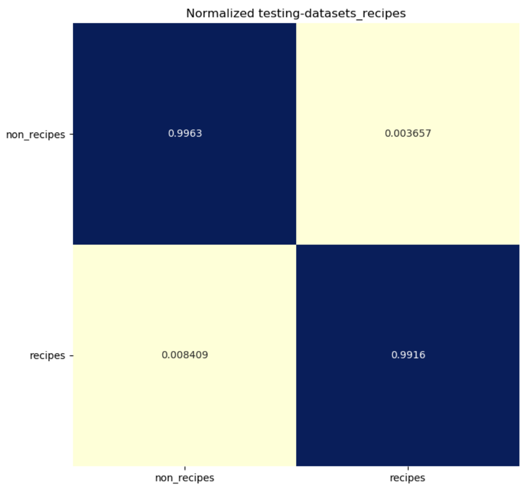
4.6 Recipes websites or non recipes websites

This dataset contains 36000 texts, with two classes: recipes and non-recipes. Each class has 18000 texts.

4.6.1 Confusion matrix



(a) Confusion matrix for dataset "recipes"



(b) Normalized confusion matrix for dataset "recipes"

Figura 4.9: Confusion matrices for dataset "recipes"

4.6.2 Truncated SVD reduction

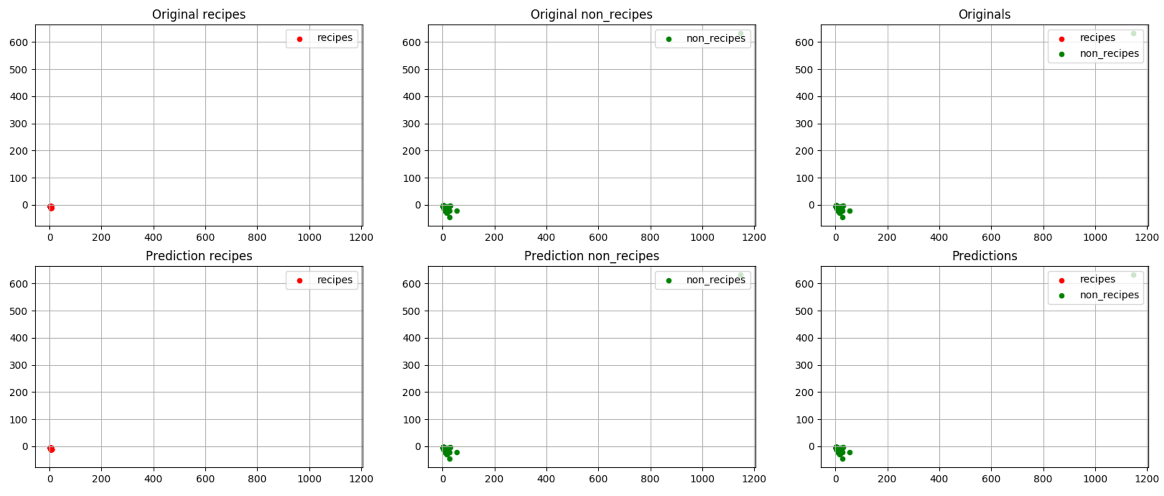


Figura 4.10: Dimensionality reduction using truncated SVD in dataset "recipes"