Integration of heterogeneous datasets

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1 Summary

2 Introduction

2.1 Heterogeneous data, producers and value

Nowadays, the production of data has considerably grown. Each organization exploits and issues data, using its own schema. Most of the time, these files are produced for specific purpose, taking into account some internal rules or constraints. That leads to a vast amount of data available online, often sharing the same file formats, but still deeply heterogeneous by their structure. Indeed, this heterogeneity complicates the integration of different files.

By the same time, the current enthusiasm around data science and its predictive models shows a high potential for crossing data.

2.2 A theoritical framework

Related problems

Our strategy

3 An application to Open Data

3.1 Open and heterogeneous data

In order to collect a vast amount of heterogeneous data we exploit the Open Data available online.

A French platform exists, gathering all the information needed to use the files issued by the French public organizations: data.gouv.fr. This website hosts and indexes multiple sources

3.2 How can we reuse the data

3.3 An academic angle

3.4 Internship's goal

4 From a bunch of heterogeneous data to a recommendation system

Before any analyze, we build our dataset. From the platform data.gouv.fr, we collect quantities of metadata. It generally includes an URL address where the file is stored. We then directly download as many files as possible. For each file downloaded, we try to clean it such as we can display its content in a tabular form.

At that point, we start the analysis. Firstly by preprocessing files' textual content. The result consists in a Term Frequency - Inverse Document Frequency (TFIDF) matrix. It allows us to weight word occurrences within our corpus according to their importance for each file. Secondly by building a vectorial topic space to represent

every files (a file embedding) and based on the TFIDF matrix. This also includes an optimization step where we compare two topic extraction algorithms - Non-negative Matrix Factorization (NMF) and Singular Value Decomposition (SVD) - along with different configurations. Thirdly by looking for closest neighbors in this "topic space", in order to interpret distances within the embedding. Using a pretext task (the prediction of a reuse between pairs of files) and a metric learning algorithm, Least Square-residual Metric Learning (LSML), we also try to strengthen our file embedding and the interpretation of its clusters.

4.1 Build a database

The first step is to store a sufficient amount of dirty data in order to keep a statistically significant volume of data throughout all our process.

Collect metadata As described above, the platform data.gouv.fr offers us the opportunity to easily collect a numerous files from different French public organizations. A RESTful API exists in the website. It allows us to get, from a HTTP request, several metadata about more than 25000 pages. These include producer's identity, a description of the page's content, some related tags, the different files belonging to the page and, the most important, an URL for each file[1].

Some URL lead us to another website which host files, some directly launch the download of file. We only focus on the latters. It already represents around 60000 URL.

Download data We use DRAGO, an INRIA's server, and a parallelized process to efficiently download as many files as possible. We use DRAGOSTORAGE, another server, to store the results of our downloads. By the end it represents around 350 Gb of data for more than 55000 files.

4.2 Clean and filter data

Among these files, there are several format: text, JSON, XML, spreadsheet, zip... Indeed, the second step consists in inferring the nature of files in order to filter them. The right process could then be applied in a attempt to clean files and reshape their content in a tabular form.

Filter the formats According to the supposed format of the file, we apply a different strategy to clean it. That involves to avoid the empty files and detect its MIME type (using *magic* library). If we meet a zip file, we repeat the procedure for every zipped items. We mainly focus on three types of documents:

- Text files, from which we try to detect a potential tabular form like in a CSV file.
- Spreadsheets, generally with an obvious tabular form that could make the inference of irregularities more difficult.
- Semi-structured files, generally containing geographical data like in a GEOJSON, easy to read, but difficult to flatten within a table.

CSV files For every file detected as text file, the very first operation executed is a test to determine if it could be a semi-structured file (JSON or GEOJSON). This test simply consists in reading the file, using the loaders from *json* and *geopandas* libraries. If an error occurs, the test fails and we process the file as a proper text file and a potential CSV or TSV file.

Several operations are executed in order to extract some data in a tabular form. Using *chardet* library, the encoding is inferred. If the latter is still undetermined, we read the file by default with an "utf-8" encoding. If the file is long enough, a sample of rows is randomly extracted to speed up the next steps. Using *Sniffer* class from *csv* library, we try to detect a column delimiter. For example, in a CSV file, it's a comma. This is a character which should occur the same number of times on each row. *Sniffer* doesn't use a "all or nothing" approach and then allows some irregularities in the data. Once we have a delimiter, the number of columns can be easily computed. In order to avoid rows with commentary or titles, we only keep those with the right number of columns (or delimiter occurrences). The last step, and the more difficult, before saving data within a *pandas* Dataframe, consists in inferring a pertinent header row. We test the consistency of data types for each row,

[1] A more detailed description of metadata is given in annexes

excepted the targeted one (which should be a string). If every columns nearly keep the same data type along file, we consider the targeted row as a potential header. The operation is repeated for the first rows until a proper header row is found. If nothing return, values by default are assigned as column names.

Excel files When a file is detected as a spreadsheet, it is read and edited using *xlrd* and *xlutils* libraries, respectively. The main difficulty is to skip the wrong rows (title, commentaries) and clearly delimited the pertinent data. Contrary to the previous cases, we can't infer this information based on a wrong number of delimiter: in a spreadsheet, the tabular format is already given. Rows have the same number of columns. But sometimes a row has too many empty cells or the latter are merged. So, before parsing the data through a dataframe and looking for the header, we need to preprocess the cells.

Cell by cell, we first replace characters that could mistake us while reading the document as a text file (for example "\n" and "\r"). Then, we fill merged cells by simply duplicating the information. We collect the potential name of its different sheets. For each sheet, we avoid the rows with an unexpected number of empty cells. The sheet is then parsed within a *pandas* Dataframe and saved as a text file. That allows us to apply the same operation executed with the CSV files in order to infer a header row. By the end, a single spreadsheet should return one cleaned table per sheet.

JSON, GEOJSON and XML files When a text file is detected, as previously explained, we try to read it as a JSON, then as a GEOJSON. The same process is then applied for both of them. Concerning the XML files, we just load it as a JSON file before, using the *xmljson* library.

All these files can be read as a tree. The idea is to recursively explore the tree structure of the file in order to find a pertinent branch to flatten in a dataframe. The pattern we are looking for is a list of dictionaries, where each item of the list is an observation and the dictionaries' keys are features. For performance reasons we just explore the first layers of the tree. By the end, we flatten the part of the tree with the largest number of items and a consistent number of features. This involves *json_normalize* function from *pandas* library. Generally, the header automatically inferred is pertinent.

Errors and extradata Through our cleaning process, numerous files are skipped because of their detected MIME type (PDF, images, etc.) or due to an error. For those which return a cleaned table, we also collect extradata. This are parts of the original file we don't include in the final table. While cleaning the text and Excel files, we still save separately rows with the wrong number of columns. It often represents a commentary, a source or the title. With the semi-structured files, we keep the part of the tree we don't flatten as extradata.

4.3 Build a file embedding

Once we have enough tables, with extradata for some of them, the third step consist in building a file embedding. That means we want to represent our files within a vectorial space in order to easily compute distances between files, and group them by cluster. We define a pretext task, predict a reuse between two files, to validate our process and determine if our embedding represent the corpus efficiently: two files reused together should be close in our space.

Text data preprocessing We mainly use the textual content of the files to determine if it worths to reused them together or not. Thus a preprocessing step is decisive. As every cleaned table is saved as a text file, the goal is to adequately count and weight words occurrences.

We distinguish three parts for a cleaned file: the content of table, its header row and some extradata (in a separate file). Thus, the first time-consuming task includes creating three different $N_{files} \times N_{words}$ occurrence count matrices with N_{files} the number of files and N_{words} the number of different words. This tokenization process is executed with *CountVectorizer* function of *sklearn* library. For each matrix, we normalize its rows, so that the sum of each row returns the same value. This penalizes large files with a lot of textual content. Normalizing the three matrices separately also emphasizes header and extradata, two parts with generally a lower but nonetheless quite pertinent textual content. Ultimately we mix the three matrices such that,

$$D = 0.5 * Content + 0.25 * Header + 0.25 * Extradata \tag{1}$$

The next task is a stemming algorithm from *nltk* library. During this process, we reduce inflected words to their root form (or stem). For example, such cuts could happen,

$$different \rightarrow differ$$
$$differ \rightarrow differ$$
$$differently \rightarrow differ$$

That makes our occurrence count matrix D more consistent with spelling mistakes, grammatical changes and conjugation. During the stemming process we keep an history of changes in order to determine, for each stem, the most frequent inflected word. We can then substitute the stem by its most frequent origin in order to have a list of existing words as a result. In the previous example, our matrix D could have a columns $different$ instead of $differ$. This is called a lemmatization process.

For the last preprocessing task we compute a TFIDF matrix from D. On the one hand, some words are frequent in every file (for example "the", "a", "is"). They usually appear to be less informative. Some of these words could even be regarded as noise and directly removed from the matrix D, using a predefined *stop words* list. On the other hand, rarer terms may often be more interesting and would deserve a bigger weight. In order to emphasize them, we use *TfidfTransformer* function from *sklearn* library. This transformation weights each word frequency by its inverse document frequency. We have

$$TFIDF(t,d) = TF(t,d) \times IDF(t) \tag{2}$$

with

$$IDF(t) = log(\frac{N_{files}}{1 + DF(t)}) \tag{3}$$

where term-frequency $TF(t,d)$ is the number of occurrences of term t in document d and document-frequency $DF(t)$ is the number of documents that contain term t. Each row is then normalize with a L_2 norm. Ultimately, the most discriminant words for a specific file (or row) have a higher floating score.

Topic modeling At that point, with TFIDF matrix we already have a representation of files within a very high-dimensional vectorial space. Topic modeling can be defined as a dimensionality reduction technique. We use it to reveal a hidden semantic structure in our corpus. We then expect that the topics produced are clusters of similar words. After dimensionality reduction, a file should be interpreted as a mixture of topics. Our aim is to compute a $N_{files} \times N_{topics}$ matrix W, with N_{topics} the number of topics (in our case, an integer to choose between 5 and 100). During the internship we used two different topic modeling algorithms: NMF and SVD. They basically factorize the TFIDF matrix into the product of W, which represents files within topic space, and a $N_{topics} \times N_{words}$ matrix H, which represents topics within word space.

Non-negative Matrix Factorization (NMF) NMF can be used if data matrix doesn't contain negative values. Indeed, it perfectly fit with textual data and more precisely occurrence count. It's also widely used in document clustering, recommender systems or computer vision.

Let V be our TFIDF matrix. The algorithm minimizing a distance between V and the matrix product $W.H$, with W and H containing non-negative elements. We use *sklearn*'s implementation where the distance minimized is a squared Frobenius norm, such as

$$d_{\text{Fro}}(A,B) = \frac{1}{2}||A - B||^2_{\text{Fro}} = \frac{1}{2}\sum_{i,j}(A_{ij} - B_{ij})^2 \tag{4}$$

The objective function to minimize is

$$\frac{1}{2}||V - WH||^2_{\text{Fro}} + \alpha\lambda||W||_1 + \alpha\lambda||H||_1 + \frac{1}{2}\alpha(1-\lambda)||W||^2_{\text{Fro}} + \frac{1}{2}\alpha(1-\lambda)||H||^2_{\text{Fro}} \tag{5}$$

with α a constant that multiplies the regularization terms, and so controls the sparsity of W and H, and λ a constant to balance L_1 and L_2 elementwise penalizations. Ultimately, we have

$$V \approx W.H \tag{6}$$

under the constraints $W \succeq 0$ and $H \succeq 0$.

Singular Value Decomposition (SVD) It approaches a spectral decomposition. We use *sklearn*'s implementation which is a truncated version (called Truncated SVD). We approximate V such as

$$V \approx V_k = U_k \Sigma_k P_k^\top \tag{7}$$

The diagonal entries σ_i of Σ are M's singular values. The columns of U and V are called the left-singular vectors and right-singular vectors of M, respectively. This implementation is called "truncated" because we only compute the k column vectors of U and row vectors of P corresponding to the k largest singular values Σ. The topic space is defined by $U_k \Sigma_k^\top$, with k features (or topics). In relation with our framework, we have

$$k = N_{topics}$$

$$W = U_k.\Sigma_k$$

$$H = P_k^\top$$

Finally, as this algorithm doesn't center the data before computing the singular value decomposition, it's still efficient with sparse matrix from *scipy* library. That perfectly fits with our TFIDF matrix.

Metric learning In practice, the previous unsupervised step is enough to build an efficient file embedding. For a certain N_{topics}, words clusters could form homogeneous topics which are even interpretable. Any Euclidean distance between two files would be synonymous of similarity. Two files close in W would have the same semantic structure, the same textual content. This is a first step toward reuse prediction. Indeed, it's pertinent to reuse similar files in order to increase data volume. Our goal is to go further in the analysis, to see if metric learning could yet improve the way we interpret distances. We want to base reuse prediction on more than just similarity. With a supervised metric learning algorithm, the idea is to learn from the existing reuses the potential of crossing two files weighted in two strictly different, but yet complementary, topics.

Let's consider two files represented in a topic space by two vectors x and y. A distance can be computed between them, using for example the quadratic norm

$$\begin{aligned} ||x-y||_2^2 &= \sum_{i=1}^{N_{topics}} (x_i - y_i)^2 \\ &= (x-y)^T (x-y) \end{aligned} \tag{8}$$

However, we can assign a different weight for each dimension, such that

$$\begin{aligned} ||x-y||_w^2 &= \sum_{i=1}^{N_{topics}} w_i \times (x_i - y_i)^2, \quad w_i \geq 0 \, \forall i \\ &= (x-y)^T diag(w)(x-y) \end{aligned} \tag{9}$$

With a more generally form we have

$$||x-y||^2 = (x-y)^T M (x-y), \quad M \succeq 0 \tag{10}$$

For $z = x - y$ and we define $\tilde{z} = M^{\frac{1}{2}} z$, so

$$\begin{aligned} ||\tilde{z}||_2^2 &= z^T (M^{\frac{1}{2}})^T M^{\frac{1}{2}} z \\ &= z^T M z \\ &= ||z||^2 \end{aligned} \tag{11}$$

The matrix M is called Mahalanobis matrix, such that $M = L^T L$ with $L = M^{\frac{1}{2}}$. The aim of a metric learning algorithm is to compute M and its factor L. Thus we can apply the latter as a transformation matrix

to convert any multidimensional difference between two files $(x - y)$. Standard Euclidean distances can then be easily computed from the new transformed vector $L(x - y)$. It amounts to weight each feature (or dimension) and combination of features.

One big advantage of this method is the possibility to use a supervised framework. Thus, the Mahalanobis matrix is computed such that the transformation matrix L moves reused files closer within our learned metric space. To do that, we use a LSML algorithm from the *metric_learn* library.

Least Square-residual Metric Learning (LSML) This algorithm uses pairs' label to learned the Mahalanobis matrix M from constraints. The latters are defined as relative comparisons. For example, the distance between two reused files A and B is supposed to be smaller than the distance between two non reused files C and D. Contrary to a usual classification problem, we don't want to class a pair as reusable or not, as this objective seems meaningless. The results we are looking for are only relative.

Let $x_i \in \mathcal{R}^{N_{topics}}$, $\forall i$, we define a set of relative comparison as

$$\mathcal{C} = \{(x_a, x_b, x_c, x_d) : d(x_a, x_b) < d(x_c, x_d)\} \tag{12}$$

and the distance function as a M-transformed quadratic norm

$$d_M(x_i, x_j) = \sqrt{(x_i - x_j)^T M (x_i - x_j)} \tag{13}$$

with M the Mahalanobis matrix we want to learn. We also define a Hinge loss

$$L(d(x_a, x_b) < d(x_c, x_d)) = H(d_M(x_a, x_b) - d_M(x_c, x_d)) \tag{14}$$

where a Hinge function is defined as

$$H(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ x^2 & \text{if } x > 0 \end{cases} \tag{15}$$

The loss function is zero when the constraint $\mathcal{C}$ is satisfied, otherwise it's the difference of the new learned distance (the Euclidean distance in the L-transformed space). This loss penalizes any learned metric which moves reused pairs away within the vectorial space (and breaks the relative constraint). We also note that the shape of the Hinge function doesn't penalize the matrix M for moving reused pairs too close. Thus the closeness between reused files may be excessive sometimes.

Once a proper Mahalanobis matrix is learned from a set of pairs file (reused and not reused), we can directly transform the file embedding W with the transformation matrix L. It modifies the weigh of each file through the topics and so its vectorial representation within the topic space.

4.4 Find neighborhood

Once we have a file embedding where distances can be interpreted as a similarity score between files and potential reuse, the fourth step consists in implementing neighbor searches. We look for pertinent groups of files in order to validate the distances between actual reused files. Yet, it would allow us to find files which belong to a cluster of reused files, but no one reused yet.

We use the *NearestNeighbors* function from the *sklearn* library to implement neighbor searches. We don't specify the number of neighbors we want. It relies on the local density of points. It's a radius-based neighborhood. Every file within a fixed radius from the targeted file is counted as neighbor. We choose a basic L2 distance, since we already transform our topic space with our transformation matrix L. The critical parameter of this step is the radius. Too small, very few neighbors would be assigned to our target. Too big, the algorithm would class noisy files as neighbors. The choice of a pertinent radius is detailed in the next section, along with the optimization of several other parameters.

5 Results and validation

We first present here the dataset built at the end of downloading and cleaning steps. Then, we explain how several actions can influence our final results and our file embedding. Our pipeline includes different parameters we need to set up. From the TFIDF matrix, a topic extraction model and the number of topics extracted have

to be specified to perform a dimensionality reduction. The metric learning process has to be evaluated too, along with the way we compute an affinity score between two files. Hence, we define a cross-validation framework to test different settings and evaluate their pertinence regarding our objective: predict potential reuses. Once we find our optimal parametrization, the best embedding is computed and its related results can be displayed and interpreted.

5.1 Downloaded and cleaned files

5.2 Metrics and cross-validation framework

The cross-validation framework starts once we compute the TFIDF matrix. It allows us to validate the settings of both the topic extraction and the metric learning processes.

For each setting we define a random permutation cross-validation to generate 50 independent train/test datasets. We randomly permute our list of pages before splitting it in two equal parts (a train and a test datasets). Therefore, to be consistent with our reuse information (we collected at the page level), we don't have the same page present both in train and test datasets. Performing it 50 times per setting allows us get a better understanding of the setting consistency through samples variations and randomness.

We start with a TFIDF matrix. In order to optimize our file embedding, we first test the parameters relative to dimensionality reduction: the model for topic extraction (NMF or SVD algorithm) and the number of topics (20 different levels from 5 to 100). From the random permutation cross-validation result, we split the TFIDF matrix in two. We use the train matrix to fit a topic extraction model. We obtain a topic space W_{train}, with a lower dimension, and a fitted dictionary we can apply to any other TFIDF matrix to reduce its dimension. This is what we do on the TFIDF test matrix to get a topic space W_{test}.

The second step consists in building X and y vectors from both topic spaces. We don't want to train a supervised classifier model, but only compute an Area Under Curve (AUC) with the Precision Recall Curve. This is achieved using *precision_recall_curve* and *average_precision_score* functions from *sklearn* library. Considering two files, we need to feed the functions with a probability to reuse them together (X) and a 0-1 label reporting if they have actually been reused together or not (y). From the topic space, we randomly choose pairs of files and compute the multidimensional difference of their vectors. Finally, we use a specific norm (among L1, L2 and infinite norms) to get our score. Usually, a probability close to one predicts a label 1 (in our case the reuse), so to be consistent we take the opposite score. Two distant files in the topic space give a vector with large differences and thus a large score. Considering two distant files, the opposite score allows us to associate a very low (and negative) score to a probable label 0 and conversely. A negative score fits with *sklearn* functions and can replace the probability in this case. We just need it to be increasing. To build X_{train}, y_{train}, X_{test} and y_{test}, we randomly select pairs of files among train and test datasets. We control the ratio of reused pairs and arbitrarily fix it to 30%. We also set a maximum vector length to $90,000$ pairs in order to save computation time.

Those vectors are used to compare settings to each other by computing an AUC. Even if we don't specifically train a model on our pairs, because of our framework, we can validate our settings and compare our association score-label in the same way we would do in a classic binary classification task. The Precision-Recall curve shows precision-recall pairs for different probability thresholds, supposedly returned from a fitted classifier. In our case we replaced the probability by an increasing score. So it's equivalent to decide if two files have been reused based on their affinity score. If it is greater than the threshold, as with a simple binary classifier we *predict* a reuse, otherwise no. By varying the decision threshold, several precision-recall pairs can be estimated such that

$$precision = \frac{TP}{TP + FP}$$
$$recall = \frac{TP}{TP + FN}$$

with TP the number of True Positives (reused pairs correctly predicted), FP the number of False Positives (non reused pairs predicted as reused) and FN the number of False Negatives (reused pairs badly predicted). In our case, the precision describes the ability of a supposed simple binary classifier not to falsely label as reused a pair that haven't been reused together. On the other hand, the recall intuitively measures the ability of this supposed classifier to correctly predict all the reused pairs. Thus, the Precision-recall curve shows a trade-off between our propensity to predict relevant pairs as reused and our capacity to return all the truly reused pairs.

Simply said, if the setting of our file embedding returns high recall but low precision, it doesn't discriminate enough the non reused files and tends to makes too many files close. On the opposite, if it returns high precision but low recall, it makes very few files close, but most of them are actually reused. The *average_precision_score* then compute the AUC, between 0 and 1. A high AUC means a simultaneous high precision and recall: our file embedding presents many clusters which actually gathers reused files. By shuffling the labels we can even simulate random predictions. In this case, the AUC is supposed to return the fraction of reused pairs, namely 0.3 (as we previously fixed it while building X).

With such a framework, we can already test both topic extraction models for different number of topics. We can even switch the norm used to compute the affinity score from X and compare the different AUC returned. A last parameter need to be tested: the choice to learn a new metric or not. We use the multidimensional differences from X_{train} (before we compute a one-dimensional score with it) and y_{train} in order to train a LSML model. It returns a transformation matrix L we can directly apply to W_{test} or X_{test} before computing the affinity score to get X_{test}^{ML}.

In practice, we parallelize this cross-validation framework at the topic extraction level to speed up the computation. We define 40 unique settings (20 different number of topics tested with NMF and SVD models). For each setting, a worker computes 50 times the full cross-validation pipeline. Each run returns 9 different AUC. For the three possible norms (L1, L2 and infinite), the worker compute an regular AUC, one based on random prediction and one with X_{test}^{ML}. With the parametrization related to topic extraction, we finally test 360 different settings using a cross-validation framework. For each of them, we collect 50 AUC value in order to analyze its distribution and evaluate its efficiency.

5.3 Results

After comparing 360 different settings, we can compare them and choose an optimal parametrization to build our file embedding from the full TFIDF matrix. Some results are then presented, in relation to the topics themselves, the topic space and its ability to form pertinent clusters or associations between files.

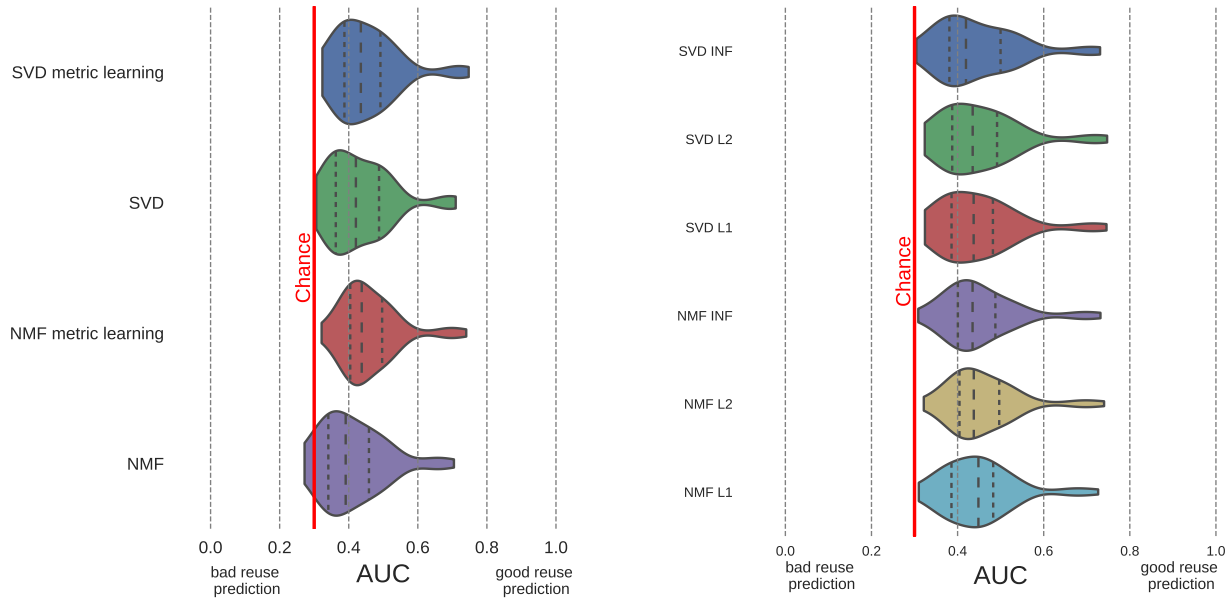
5.3.1 Optimal parametrization

A first information is that almost all settings are performing better than a random prediction. Their lowest percentiles are generally above 0.3, the chance level (confirmed empirically, see annexe). As we can see in the annexe, it seems that the best results in term of AUC value are found for 20 topics or more. We fix the number of topics to 25 at first, in order to compare the models and the norms used. Then we search the optimal number of topics considering the best model and norm.

According to the figure 1 every norm seems to have approximatively the same median AUC around 0.45. This parameter does not impact so much our result. However, L1 and L2 norms clearly have higher minimum values for the AUC around 0.32. We choose to use L2 norm for the rest of the study. Firstly, it presents a higher minimum AUC than L1 norm when it's combined with a NMF model. Secondly, it's consistent with the theoretical presentation of the Mahalanobis matrix section 4 and contrary to infinite and L1 norm, it's a smoother function. We can notice that every AUC computed with the three norms perform at least just above the random prediction level.

Concerning the best topic extraction model to choose, we set a NMF model which present a slightly better 25^{th} percentile than SVD model when then are combined with a learned metric. In this precise configuration, both models don't really differ from each other. However without metric learning, NMF model can even present results worse than the chance. According to the overall distribution of the returned AUC, we can notice the small but clear impact of metric learning as it improves the reuse recognition.

Setting the L2 norm, the use of a NMF model to build a first topic space and then its transformation by a Mahalanobis matrix, we compare the AUC computed for different dimensionality reduction amplitudes. According to the figure 2 results start being interesting from 20 topics. With a smaller number of topics, we loose too much information to do better than chance. The best precision-recall pairs seems to be obtained with 25 topics. It return a median AUC of 0.45 and a 75^{th} percentile just below 0.5. More topics still gives correct results until 100, but with no serious improvement. Moreover, a large number of topics reduces the interest of a dimensionality reduction. Our matrix W is returned so sparse than some topics are quasi null. That is why we keep 25 topics to ensure the simplest, but yet efficient settings to build our file embedding.

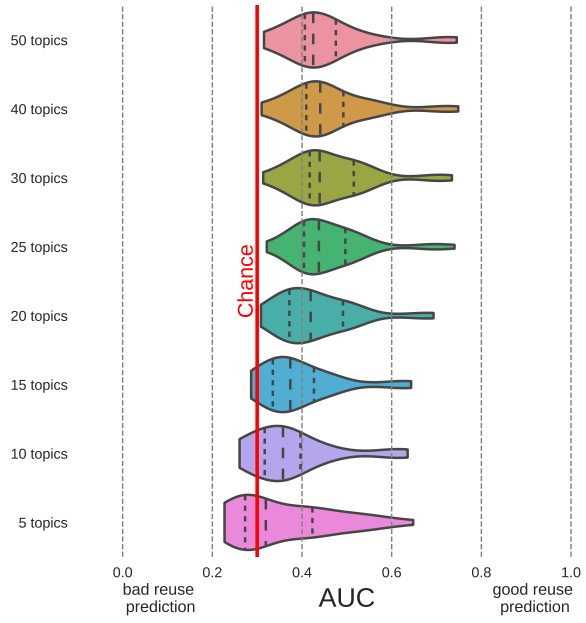


(a) Models comparison **(b) Norms comparison**

1

Figure 1: AUC computed for norms and models comparison

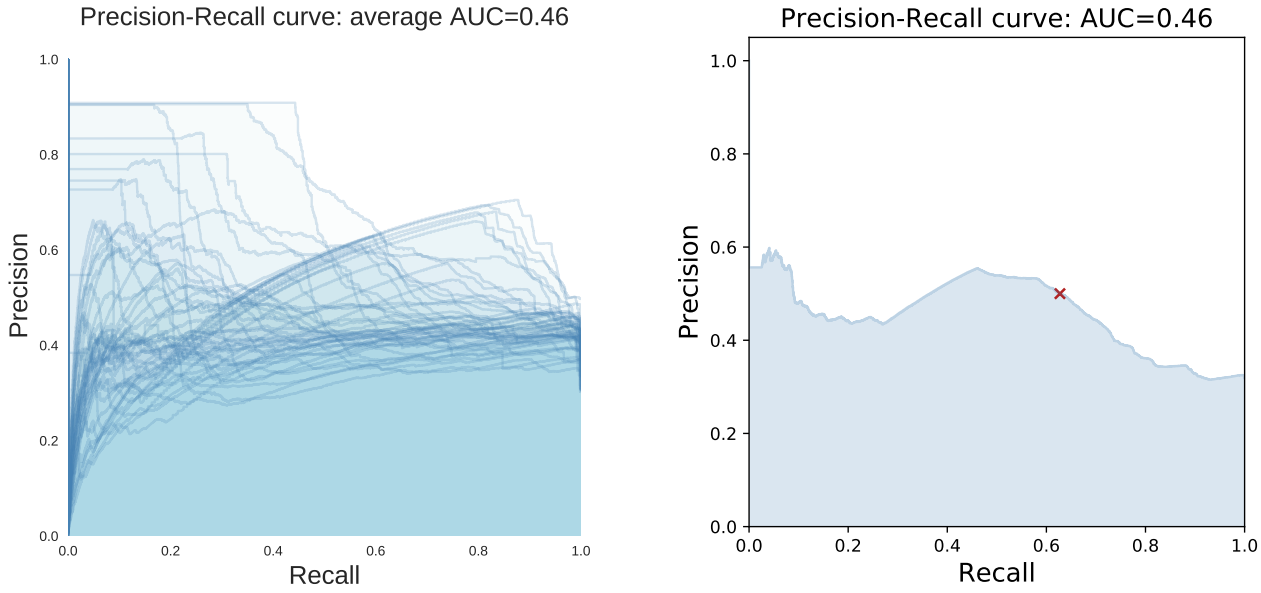
Note: Both figures are computed with 25 topics. On the left, figure a used a L2 norm. On the right, figure b shows result with a metric learned.



2

Figure 2: AUC computed for different number of topics

Note: The L2 norm is used, along with NMF model and a learned metric.



(a) 50 curves from the cross-validation step **(b) Best file embedding**

3

Figure 3: Precision-recall curve

Note: The red dot cross represents the balance chosen between precision and recall.

5.3.2 Topics and Wordclouds

We now compute our file embedding with 25 topics through a NMF algorithm. We also trained a Mahalanobis matrix to learn a metric and transform the topic space.

5.3.3 Reuse prediction

6 Discussion

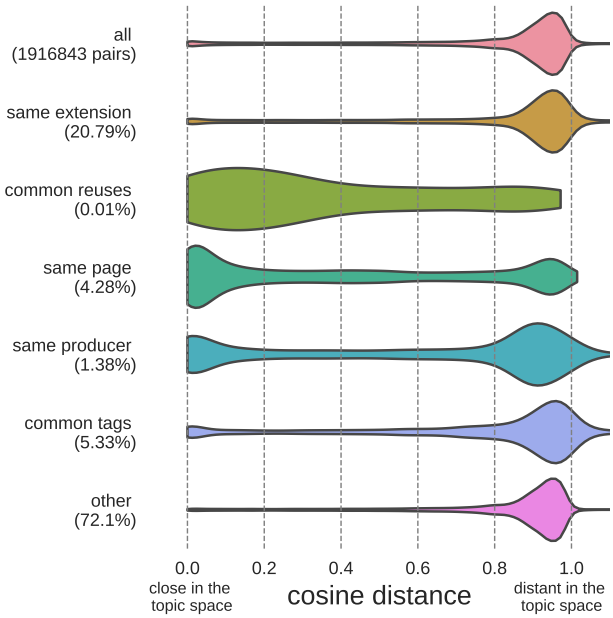
6.1 Limitations

6.2 Problems

6.3 Future work

7 Conclusion

8 Annexes



4

Figure 4: Cosine distance distribution in the best file embedding