Hierarchical structuring of Cultural Heritage objects within large aggregations

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Abstract. Huge amounts of cultural content have been digitised and are available through digital libraries and aggregators like Europeana.eu. However, it is not easy for a user to have an overall picture of what is available nor to find related objects. We propose a method for hierarchically structuring cultural objects at different similarity levels. We describe a fast, scalable clustering algorithm with an automated field selection method for finding semantic clusters. We report a qualitative evaluation on the cluster categories based on records from the UK and a quantitative one on the results from the complete Europeana dataset.

1 Introduction

More and more Cultural Heritage (CH) content is being digitised and made available through digital libraries and aggregators such as Europeana.eu and the new Digital Public Library of America (dp.la). These aggregators provide access to large numbers of heterogeneous Cultural Heritage objects (CHOs), e.g., Europeana gathers 26 million objects (books, paintings, sound recordings, movies...) contributed by over 2,200 CH institutions from all over Europe.

Metadata plays a crucial role for these aggregations, which are largely relying on mappings from the original metadata, created by providers in many different formats and vocabularies, to a shared vocabulary like the Europeana Semantic Elements (ESE). However, aggregating metadata from heterogeneous collections raises quality issues such as uneven granularity of the descriptions, ambiguity between original and derivative versions of the same object, even duplication if different providers give access to a same object. Also, simple, common-denominator vocabularies like ESE, are inappropriate for capturing internal semantic links between objects (e.g., parts of an object, adaptations of a work, objects representing others) or external links to contextual entities (e.g., places or persons related to an object). Both types of link could benefit services like Europeana by enabling a wider range of search and browsing options [10].

There are many efforts in the cultural domain to enable and encourage the provision of richer and interoperable metadata, e.g., CIDOC-CRM³ and the

³ http://www.cidoc-crm.org/
new Europeana Data Model (EDM). And yet, many providers do not have the resources to enhance their metadata in the way envisioned by these approaches, especially for links spanning across different collections. Data enrichment in aggregations such as Europeana is therefore valuable.

Meanwhile, keyword-based search is still the main access and navigation mechanism for such aggregations. Recommendations for similar object browsing are often provided, e.g., one can “Explore further” in Europeana. Still, in such facilities it is difficult for a user to have an overall picture of what is available or to find objects with different levels of relatedness. Researchers have started looking at automatically identifying related CH objects [2, 3, 7]. However, the existing work has mostly focused on one dimension of similarity despite the multidimensional characteristics of the cultural domain. Moreover, it often stayed at a small scale and could not process datasets as large as Europeana’s.

This paper presents a feasibility experiment on semantic linking for a general, large cultural aggregation. We focus on “internal” links between objects from the aggregated collections, with a specific eye on enabling better-quality “similar object” browsing. The issue bears similarity with “FRBRization” in the library domain [9]. However, given the variety of collections, as well as the simplicity of the current metadata, it is deemed more realistic to consider a wider range of object relations: duplication (recognizing records that describe a same object), depiction/representation, derivation (an object has been created by reworking another), succession (an object continues another one), etc.

In this paper, we try to answer the following research questions: (1) can we apply clustering to find semantic groups at different similarity levels? (2) what types of useful relationships can we extract with this technique?

To this end, we propose a framework for hierarchically structuring objects at different similarity levels in Section 2, including a fast and scalable clustering algorithm and an automated field selection method for finding focal clusters. In Section 3, we report a qualitative evaluation on the cluster categories based on records from the United Kingdom and a quantitative evaluation on the results from the complete Europeana dataset.

2 Hierarchical structuring based on levels of similarity

We aim at finding related Europeana objects at different levels of similarity, which potentially reflect different semantic relations between them. As depicted in Fig. 1, we provide clusters at five similarity levels. A user can explore the collections to find CH objects with different levels of relatedness. We now describe our framework in three parts: (1) fast clustering based on minhashes and compression similarity (Section 2.1), (2) hierarchically structuring records at different similarity levels (Section 2.2) and (3) automatically selecting important fields based on genetic algorithm to generate focal semantic clusters (Section 2.3)

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4 http://pro.europeana.eu/edm-documentation
Field selection 3
Provider 3

Fig. 1. Hierarchical structuring of CHOs at different similarity levels. White squares indicate original records which are clustered at level 100. Based on genetic metadata field selection, the original records are represented by selected fields and clustered at level 80. Then clusters at a level (circles) are summarised into new artificial records (rounded squares at the level below). These are then clustered at the lower level, together with the objects that were not yet clustered.

2.1 Clustering based on minhashes and compression similarity

Grouping records using combined minhashes Records should be clustered based on certain kinds of similarity. Because of the sheer amount of records in the dataset, calculating the pair-wise similarity between all records is practically impossible and also unnecessary. Therefore we first group records which could potentially be further clustered based on a bag-of-bits approach.

For each record, the metadata from all fields is combined and divided into words, with numbers removed. Each word is transformed into 8-shinglings [13]. A set of minhashes [4] from these shinglings are calculated and randomly put into 4 groups. The logical operation exclusive disjunction (XOR) is applied to each minhash group, producing 4 combined minhashes. Thus, every Europeana record is represented by four combined minhashes. Records with the same combined minhashes are grouped together, as they are the ones that are most likely to be clustered further on.

Iterative parallel clustering based on compression similarity The clustering process is iterative as follows:

Step 1 Choose a similarity level and set the maximum iteration.6

The size of these groups depends on the desired similarity level. If clustering at level 100, 16 minhashes are randomly chosen for each group, while if at level 20, only 2 minhashes are selected. In this way, clusters at higher similarity levels have higher probability to be precise than those at lower levels.

In our experiments, the maximum iteration is set at 5.
Step 2. Group records based on combined minhashes, as described above, and put the groups on a stack.

Step 3. Get a group of records from the stack if the stack is not empty, otherwise, go to Step 7.

Step 4. From the group, randomly select up to 10 records as *cluster heads* that are not closer than the required similarity.

Step 5. Assign each record within this group to its closest cluster head, which, after all records are assigned, creates candidate clusters.

Step 6. For each candidate cluster, if the average similarity between the cluster head and the rest of the records is lower than the required similarity, put this group of records on the group stack to be further divided. Otherwise, this cluster is considered to be a real cluster. All the records are considered as *clustered* to the cluster head and will not join the next iteration.

Step 7. Collect all the records which are not clustered, together with the current cluster heads, repeat Step 3 to 6, until no more records can be clustered or the maximum iteration has been reached.

The similarity between records is calculated using a formula adapted from the Normalised Compression Distance (NCD) [5]. Let \( x \) and \( y \) be two records, \( C(xy) \) the compressed size of the concatenation of \( x \) and \( y \), \( C(x) \) and \( C(y) \) the compressed size of \( x \) and \( y \). Then the similarity between \( x \) and \( y \) is defined as

\[
\text{sim}(x,y) = 1.0 - \frac{C(xy) - \text{min}(C(x),C(y))}{\text{max}(C(x),C(y))}
\]

Note, a large part of the clustering process (steps 3 to 6) is implemented as multi-thread computing, making it very fast and scalable to all Europeana data.

2.2 Hierarchically structuring records based on similarity

We assume that the clustered records represent a cultural entity. This is obvious when the similarity level is high. Clusters at level 100 often contain duplicates (same object provided twice with the same digital representation) or near-duplicates (three digitised versions of the same book page). A cluster at level 80 is often a focal semantic cluster (see Section 2.3). These clusters could be clustered at a lower similarity level too. For instance, pictures of different buildings are clustered at a lower similarity level, and these pictures could be clustered with census data about the same area at an even lower level.

Therefore, after each round of clustering at one similarity level, we generate an artificial record from each cluster, summarising the information of all the clustered records. These artificial records, together with all the records which could not be clustered at this similarity level, will join the clustering process at a lower similarity level. In this way, hierarchies of records are generated, so that one can have some structural information about these records, instead of quickly getting drowned in the sheer amount of data.

In our experiments we activate this hierarchical grouping only below level 80 because we want to apply a specific field selection process for this level, which requires all objects.
2.3 Field selection at level 80 for focal semantic clusters

Checking a set of clusters at a high similarity level (e.g., level 80), one can easily find out that some clusters are of specific interest, for example, pages of the same book, parts of a same building, etc. These are often found within a collection from one data provider. They are more loosely connected than clusters of (near-)duplicates, because they gather different cultural objects. Yet records from these clusters collectively represent a small cultural entity. We name these clusters focal semantic clusters (FSC). These FSCs can be further clustered at lower similarity levels as described in Section 2.2.

However, detecting such FSCs is not easy. The Europeana data is obtained from a wide range of providers. The information associated with each record is not uniform, since providers use different metadata schemes originally and enrich their records with different amounts of textual information. Take the example of digitised book pages. One provider may assign exactly the same metadata to all the pages of the same book while another may give a detailed description of each page of an illuminated manuscript. For the latter, if all the metadata fields were used for clustering, the large body of descriptive texts could falsely separate pages of the same book into different smaller clusters. It is therefore important to select the most important metadata fields for clustering these FSCs. As shown in Fig. 1, such selection is done on a data provider basis.

For each data provider, we aim at the selection of metadata fields which gives the best FSCs. We apply a genetic algorithm (GA) to automatically select important fields, that is, taking an evolutionary approach to select the optimal solution based on a fitness function [15]. This algorithm handles candidate solutions as binary sequences, “1” when a metadata field is selected and “0” otherwise. For example, if a given institute provides metadata records with dc:title, dc:contributor, dc:subject and dc:source, then a candidate solution 1010 indicates clustering on dc:title and dc:subject only. In the Europeana dataset, dc:title is the most used and often the only descriptive field. Given its importance, we therefore decided to set it as compulsory for each data provider’s solutions.\footnote{Note, either dc:title or dc:description are mandatory for data input in Europeana; when dc:title is not available, we take dc:description as the compulsory field.}

The fitness function is to evaluate how good a solution, i.e., a selection of metadata fields, is to produce reasonable clusters. We adapted a measure of variance ratio clusterability [1] as our fitness function: Let $X$ be a dataset, and $C$ a set of clusters over $X$. The fitness function is defined as following:

$$f(C, X) = \log(Avg(C)) \times \frac{B_C(X)}{W_C(X)}$$

where $B_C(X)$ is the between-cluster distance, $W_C(X)$ is the within-cluster distances and $Avg(C)$ is the average size of the set of clusters. This function gives higher fitness (and thus a higher chance to be selected for the next generation) to tightly connected clusters that are relatively big and far apart.

For the genetic evolution, clustering is set at level 80: first qualitative insights (see Section 3.1) hinted that this was the “sensitive level” for finding such FSCs.
The original records are represented by the metadata from the fields selected in the GA best solution, and clustered again at level 80.

When clustering at level 60 and lower, other fields are all taken into account, as this invites broadly linked records to be clustered and potentially corrects the bias towards links within individual providers at level 80. Note, at level 100 also, all the metadata is used to find (near-)duplicates.

3 Results and evaluation

3.1 Qualitative evaluation and categorisation of clusters

To guide future evaluation efforts while tuning the method above, we started a qualitative analysis of intermediate results generated from 1.1M records from UK. The analysis started by looking at the visual representation and metadata of the clustered records on the Europeana portal. We also browsed the “hierarchy” of clusters produced, giving specific attention to how smaller clusters combine into bigger clusters and allowing us to find meaningful clusters for a given (set of) object(s), independently from their level in the hierarchy.

At that stage, clusters were still sometimes rough and our evaluation not wide enough for obtaining a clear insight on their respective representativity. However, this semi-principled analysis offered us precious insight on the typology of groupings—a typology that looked both useful and relatively complete, i.e., covering a broad extent of the relations that EDM covers.

**Same objects/duplicate records** This is the strongest similarity relationship found in clusters. Europeana datasets come via different channels: individual institutions, European projects, thematic portals. It is possible to receive multiple records for the same object from the same institution. A quality control failure during the data ingestion process can let duplicates be published in the Europeana portal. Clustering allows us to identify these duplicates with a high degree of accuracy; often the exact same metadata appears in many fields.

**Views of the same object** Digitisation practices often lead providers to create different views of the same CHO. These views happen to be provided as different CHOs but they are actually different views on the same “real object,” see Fig. 2. Such clusters usually share exactly the same descriptive metadata.

**Parts of an object** CHOs provided to Europeana can have a hierarchical structure: they are composed of other objects or parts. However, digitisation and description choices by providers, or the barrier of a simplified data format can result in the data describing this structure not being provided to Europeana. The clustering process allows us to find clusters of objects linked by such relationships. In principle relations between different parts of a CHO or between CHOs should be expressed in relation fields (dc:relation) but the clusters indicate that providers often use dc:title, see Table. 1. In the latter case, an automatic procedure would have difficulty making the distinction with other types of relations.

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8 For example, see http://www.europeana.eu/resolve/record/09307/2FDFD07620AFC6600C005D4C1D0AFC6A31778A88 and http://www.europeana.eu/resolve/record/09307/772B1D83F4727C4DEEEFF763C300D5315FC1EBEAA
Fig. 2. Different views on the same CHO—a portrait of Mary of Teck

| Shared metadata                  | Record                                   |
|----------------------------------|------------------------------------------|
| dcterm:s:spatial : City of London | The Oil Shop part 01                     |
| dcterm:medium : Lithograph       | The Oil Shop part 03                     |
| dc:creator : Composer: Dallas, John | The Oil Shop part 04                   |
| dc:date : [1873]                 | The Oil Shop part 05                     |
| dcterm:isPartOf : Victorian popular music. Collect Britain | The Oil Shop part 06                  |
| dc:format : jpeg                 | The Oil Shop part 07                     |
| dc:type : Cover Illustrated Music Printed StillImage | The Oil Shop part 08                  |

Table 1. Parts of a CHO—a music piece made of different individual music scores

Derivative works These are objects which are derived from another one, such as reprint. Fig. 3 shows two different prints created from the same master. Some cases can be analysed in terms of FRBR relationships, where an original work leads to a range of expressions, manifestations and/or items. The metadata of the concerned records are often the same, except the dc:description field, which usually indicates that the object is a copy or other type of derivative.

Fig. 3. Example of derivative works

Collections Clusters can represent coherent collections. They group objects of a specific type, gathered by one individual, for a specific goal. For example, the letters shown in Fig. 4 were written by one specific WWI soldier and contributed by a family member to the Europeana1914-1918 project. Object metadata is often similar, with the dc:relation field expressing membership in a specific collection.

Thematic groupings These clusters gather objects about a similar topic, location or event, which link them to the other collections above. However, they often lack the size or an explicit unity criterion such as common provenance (e.g., a collector) that would allow them to be assessed as complete collections. In fact we have found such individual clusters included in bigger ones, which have been

9 http://www.europeana.eu/resolve/record/09405a1/49EAD0C41C49A4C5F14C626EB067EBD3F9131632 and http://www.europeana.eu/resolve/record/09405a1/1A3460CB8BFE76A1CD4433F7FFA052C34A9B295
classified as collections in the sense above. These clusters have in common some metadata fields that are related to a similar theme, most often dc:subject.

**Conclusion** During our qualitative evaluation, we observed that clusters of “closely related” objects, such as duplicates or parts of a CHO are easier to assess. Recognising clusters describing broader links, such as topical relationships, seems a more difficult, error-prone process, both for human evaluators and the machine. In order to check our finished clustering method, we proceeded further with a more complete, quantitative evaluation over the entire dataset.

### 3.2 Quantitative manual evaluation on the full Europeana dataset

**Working dataset** The entire Europeana data was made available as a dump on February 2013. It contains 23,595,555 records from 2428 data providers (defined by europeana:dataProvider field, or europeana:provider when it is not present).

**Field selection for FSCs** 1198 individual data providers provided more than 100 records and cover 99.9% of the entire dataset. We applied the genetic algorithm to select the important fields over these providers.

We used a python package Pyevolve,\(^{10}\) setting the number of individuals at each generation to 50 and the maximum number of generations to 100. The time taken by field selection depends on the number of records one provider has. For the 10 providers with most records, it takes 161 minutes in average, while datasets with 200-250 records require 21 minutes in average. Table 2 lists the top 5 most selected metadata fields and the most selected field combinations. For an overwhelming majority of data providers, dc:title carries the most distinguishing information. In the end, we use the the metadata from the selected fields for each provider to generate the FSCs at level 80. For the rest of the data providers, we select dc:title directly. This leads to 1,476,089 clusters in total.

\(^{10}\) [http://pyevolve.sourceforge.net/](http://pyevolve.sourceforge.net/)
Hierarchical structuring of records  The clustering was carried out on a server with two Intel XEON E5-2670 processors and 256G memory. Table 3 gives the clustering time per level. As described in Section 2.2, clusters generated at higher levels lead to artificial records replacing the clustered records for the lower levels. This greatly reduced the amount of items to be clustered at lower levels.

| Similarity level | #Records to be clustered | #Clusters | Time     |
|------------------|--------------------------|-----------|----------|
| 100              | 23,595,555                | 200,245   | 6m2.82s  |
| 80               | 23,595,555                | 1,476,089 | *        |
| 60               | 6,407,615                 | 382,268   | 3m35.26s |
| 40               | 2,431,753                 | 212,389   | 2m28.79s |
| 20               | 1,068,188                 | 84,554    | 1m20.99s |

Table 3. Clustering performance (* Level 80 is clustered differently due to the field selection based on GA, see Section 2.3 for more detail.)

Clusters can be hierarchically ordered across similarity levels. In Fig. 5, at the record level (the bottom grey boxes), one can see the sibling records. These can be closely clustered at level 80 (in pink), or more vaguely connected (at level 40 in blue). These clusters can again be clustered at level 20 (brown). When more records are involved (the size of level 20 clusters ranges from 2 to 456,155, with an average size of 190), such structural information is crucial to make sense out of a large amount of records.

Manual evaluation  To evaluate our method on the full Europeana dataset and further validate the categories discovered in Sec. 3.1, we randomly chose 100 clusters at each level and asked 7 evaluators to categorise them. Clusters were assigned to evaluators so that each cluster is checked at least by two evaluators. For each cluster, the evaluators assigned one of the six categories from Sec. 3.1 or indicated if it did not make any sense.

The evaluators can leave comments and propose new categories if necessary. We found that evaluators gave many comments without proposing any new categories. We measured for each level the average number of clusters which are assessed as belonging to each category.

As shown in Table 4, duplicate records and views or parts of the same CHO are mostly clustered at levels 100 and 80. At these levels we also found different editions of the same work, different volumes of the same book, pictures of the same event, etc. Note that the latter illustrates how thematic groupings also appear as clusters at the highest level. Derivative works are rare and only occur at high levels. Lower levels lead to bigger, more heterogeneous clusters, many of which fall into the categories of collections or thematic groupings while many...
of which do not make much sense any more. These big clusters could contain views of different buildings, issues of the same journal, different books by the same author, pictures taken at the same place but at different time, pictures of different sarcophagi and ships, collections of religious or folk music, thesis of the same university, specimen of birds, posters about movies or Communist movements, or more vaguely, collections of furniture or Spanish books, etc.

The general impression from the evaluators is that most clusters make sense. At level 60, it is often clear that the records form a “collection” according to some implicit logic; but in most cases the original provider sites did not present them as explicit collections. So the clustering was being creative and yet correct.

However, assessing clusters gets more difficult as the similarity level lowers. It is often difficult to recognise any specific logic beyond more general and overarching rules like: “belonging to same data provider”, “being of the same type”, etc. This is especially so at level 20, where the average size of the evaluated clusters is 3442, ranging from 2 to 60,204, with 11 clusters having more than 10,000 records. It is not possible to manually go through them one by one. Many clusters are also in a language which the evaluators are not familiar with, which made them even more difficult to assess. The evaluators only selected as many sub-clusters as possible to explore the rough structure within such big clusters.

Of course, not every cluster at level 20 is too big to judge. For example, one is composed of two (higher-level) sub-clusters that each corresponds to an edition of a multi-volume book. While these are represented as hierarchical objects on the provider’s site this information could not reach Europeana. The out-of-the-box SOLR “MoreLikeThis” function returns the volumes of both editions, but as a flat, mixed list that includes other books—some configurations tested for Europeana even fail to bring all volumes of both editions as related items when one of them is being explored.

In summary, our evaluation shows the clusters are rather relevant. The two highest levels, especially, could directly provide meaningful subsets for users of a “similar items” browsing feature. However, clusters, especially at lower similarity levels, are much more heterogeneous than we initially thought. We need to make more detailed distinction between these clusters. The next step of detecting these different categories automatically is a more challenging task.

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11 See http://www.biodiversitylibrary.org/bibliography/14916#/summary and http://www.biodiversitylibrary.org/bibliography/931#/summary

12 http://wiki.apache.org/solr/MoreLikeThis
4 Related work

Providing similar objects for access to large collections is not novel. Europeana itself uses SOLR’s “MoreLikeThis”. But such standard search engine features are designed for full-text documents and suffer from the heterogeneity and sparseness of the metadata, resulting often in lists that seem random and unidimensional. Amazon.com exploit users’ input to infuse more relevance in similar items. But the necessary user data is not available for cultural aggregators yet. Others have explored using image similarity instead [6] or next to [2] descriptive metadata. However, digitized content is not available consistently in cross-domain aggregations, where media types and quality vary greatly.

Tuning textual similarity to CH metadata is therefore still relevant. [3, 11] have used the standard corpus-based similarity measures of [13]. Recently, researchers started looking at using external knowledge bases such as Wikipedia [7] or WordNet [14] to help measuring similarities between objects. Different similarity measures were compared [8, 3] but most existing work explore a single dimension of similarity, which does not take into account the multidimensionality of CH collections; it also focuses on smaller-scale collections. The extraction of FRBR-like relations, a topic researched for more than a decade [17, 9], has been a clear source for inspiration for us. It requires however collections from well-bounded domains with extensive and consistent metadata, and would need to be completed with techniques with a broader application scope. Our work tries to complement these efforts, further exploring the aspects of scalability and the typing and organizing of clusters of similar objects.

5 Conclusion

Identifying semantic links and groups of CH objects is desirable for data enrichment in large cultural aggregations. Finding similar objects is the first step towards such semantic links. Our approach avoids too much dependence on metadata fields and the multidimensionality they denote. Instead, we try to hierarchically structure Europeana objects at different levels, starting with a rather simple similarity measure. We developed a fast and scalable clustering algorithm and applied a genetic algorithm to select important fields for generating focal semantic clusters. We qualitatively evaluated intermediate results from UK records before carrying out a larger-scale quantitative evaluation of the results obtained from the entire Europeana dataset.

We found that clusters at higher similarity levels are usually accurate and the semantic groups make sense to evaluators, e.g., as duplicates or parts of a CHO. The relevance of lower-level clusters is much more difficult to judge. Even at higher similarity levels, our evaluation shows that based on a single dimension of similarity we generate highly heterogeneous clusters. We need to investigate more multidimensional similarity measures while maintaining the performance levels for clustering large amounts of data. Future work shall of course include the practical evaluation of hierarchical structuring for improving end-user navigation.
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