Improving text relationship modelling with artificial data

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Abstract
Data augmentation uses artificially created examples to support supervised machine learning, adding robustness to the resulting models and helping to account for limited availability of labelled data. We apply and evaluate a synthetic data approach to relationship classification in digital libraries, generating artificial books with relationships that are common in digital libraries but not easier inferred from existing metadata. Artificial books are generated by remixing existing texts into synthetically constructed formats. We find that for classification on whole–part relationships between books, synthetic data improves a deep neural network classifier by 91%. Furthermore, we consider the ability of synthetic data to learn a useful new text relationship class from fully artificial training data.

Keywords
Data augmentation; digital libraries; machine learning

1. Introduction
Identifying whole/part relationships between books in digital libraries can be a valuable tool for better understanding and cataloguing the works found in bibliographic collections, irrespective of the form in which they were printed. However, this relationship is difficult to learn computationally because of limited ground truth availability. In this article, we present an approach for data augmentation of whole/part training data through the use of artificially generated books. Artificial data are found to be a robust approach to training deep neural network classifiers on books with limited real ground truth, working to prevent over-fitting and improving classification by 91.0%.

Modern cataloguing standards support encoding complex work-level relationships, opening the possibility for bibliographic collections that better represent the complex ways that works are changed, iterated and collated in library books. Traditionally in bibliography, cataloguing has controlled for work relationships only at the level of exact, so-called manifestation-level duplicates, where the same work is represented identically in its physical form, and cataloguing at higher levels of sameness — such as reprints or new editions — is a challenging manual process. Recent work has begun looking at computer-assisted ways of learning more about work relationships and properties [1,2], capitalising on computational access to books afforded by large digital libraries.

Learning to tag work relationships from scanned digital library volumes relies on existing ground truth to learn from. Since granular relationships have not been historically catalogued, ground truth needs to be inferred from metadata using a mix of heuristics [3] or additional authoritative sources, such as OCLC. However, the value of metadata is limited in certain instances, due to uneven cataloguing of information such as enumeration, chronology and tables of contents. Subsequently, there are training imbalances to data for supervised learning, challenging efforts to tag complex book relationships.

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In this work, we address imbalanced training data for text document relationships through the use of synthetically created training examples. Specifically, each artificial book is created to complement a real book, extracting and rearranging texts to create a fake book in the style of a complex relationship. We focus on a relationship that is difficult to infer from metadata alone: whole–part relationships, where two books do not have the identical content, but overlap partially or one is subsumed by the other. Figure 1 visualises the pairwise similarity between books that hold this type of relationship, where the dark red diagonal of identical or near-identical content fully spans one axis (i.e. one book) but not the other. Examples of this relationship include

- Anthologies and the individual works held within them, where a number of smaller works are contained within a larger one.
- Anthologies and other anthologies, where there may be overlap between sub-works within them.
- Abridgments and unabridged books, where the abridged version removes or shortens the full text.
- Multi-volume sets vs a single-volume printing, where in one instance a full work is published in three books, where in another, it is published in just one.

A proper tagging of whole–part relationships in digital libraries presents promise for improving information access in our digital libraries, making it more clear which materials are within a multi-work book or for completing collections that are spread across multiple volumes. It also is immensely valuable for scholarship that tries to learn about language or culture by applying text mining to digital libraries, allowing text models to better avoid repeating texts and works, which may otherwise confound an accurate analysis of a collection [4].

We demonstrate that, even with a small number of training examples for whole–part relationships, it is possible to improve classification results through the use of artificially generated book data to support training. Successfully generating training examples requires a case where an expert can effectively describe the structure of the synthetic data, and may not apply for all instances. Yet, our strong results suggest that for cases where the characteristics of a class can be sufficiently described, synthetic data can be feasible way to communicate those properties to a text-based neural network classifier. We briefly consider that possibility in practice: after observing synthetic data greatly improve classification on low-support training labels, we train a classifier on a fully artificial – but useful – class of partially overlapping books. On manual review, we see that our artificial ‘overlaps’ class surfaces metadata and cataloguing errors from a test set of

Figure 1. What the classifier sees: examples of book-to-book similarity matrices on PARTOF and CONTAINS. Darker squares denote greater similarity between sub-units of the two books, and alignments of identical or extremely similar content are generally recognisable through a prominent diagonal pattern.
labelled examples. Leveraging synthetic data on such low- or no-support classes have the potential to help identify more scanning, printing or metadata errors in digital libraries.

1.1. Background

This work grapples with a dilemma of computationally aided cataloguing: while algorithmic approaches have the potential to assist in identifying historically under-catalogued bibliographic properties, that same lack of existing information complicates the ability to teach those algorithms. Specifically, we focus on work relationships, a relatively recent affordance [5] in cataloguing standards that makes it easier to control for when two books are different printings or editions of the same conceptual story, or even when two books are parts of a larger work. This article looks at work relationship classification in the HathiTrust Digital Library, a digital library of more than 17 million scanned books from a worldwide consortium of library and memory institutions. Given that the majority of these materials are professionally catalogued, it also means that the collection is a very rich source for supervised learning. At the scale of the HathiTrust, even metadata that are spotty or inconsistent can usually still offer plenty of support for training and evaluating classifiers. However, this availability does not apply over all important work relationship labels, so that, we evaluate whether artificially generated books can fill the gap.

The most common contemporary way of thinking of different levels of sameness in collections is the four-part hierarchy of relationships for class one entities outlined by the Functional Requirements for Bibliographic Records (FRBR): work, expression, manifestation and item [6]. A work is described as a distinct intellectual or artistic creation. An expression is the specific intellectual or artistic form that a work takes each time it is realised. Two different expressions of a work may be different editions or tellings of the story. The manifestation is the physical embodiment of an expression of a work. As an entity, manifestation represents all the physical objects that bear the same characteristics, in respect to both intellectual content and physical form. Finally, an item is the single exemplar of a manifestation. This is the concrete entity; the physical item you can hold in your hand. These relationships allow for cursory identification of related works and fail to address the abstractions between expressions, manifestations, and items to support modern cataloguing standards. Bibliographic materials are usually controlled at the manifestation level, such as through ISBNs. However, the current Resource Description and Access (RDA) cataloguing standard implements the entities from FRBR, allowing for this form of granularity to be catalogued.

Improving bibliographic records opens up the possibility for information professionals to improve or correct metadata based on its relationship to other works, improve access and discovery within collections, develop a semantic relationship between collections and resources, and allows for the identification of the most representative, or cleanest, copy of a specific work within a collection. In addition, the identification of stylistic similarities can provide valuable information for identifying contextually related but different works, assisting the process of discovery of materials and impact collection development by identifying gaps or overages of information within a collection.

In this article, we have five working relationships to assist in identifying relationships between works: SW, same works, regardless of whether they are the same or a different manifestation, DV, different volumes of the same overarching work; CONTAINS, where one book contains the work of the second book within it; PARTOF, where a book is fully contained within another book’s work and DIFF, referring to works that are not directly related. This is a streamlining of various possible same- or related-work relationship classes. A more detailed definition might differentiate between different expressions or manifestations of the same work, or include more detailed different work relationships, such as works by the same author.

Our focus is on the PARTOF and CONTAINS classes. These labels represent a ‘whole –part’ relationship between works, where two distinct works are related in that one subsumes the other. For example, an anthology of The Works of Charles Dickens is considered a work in its own right, but it may be comprised other works, like Oliver Twist. Identifying such relationships can better inventory all the works seen in a digital library, in the service of improved information access and retrieval. Scholars applying text analysis to study such collections may benefit from a better ability to avoid duplicated – and potentially misleading – text. Understanding the composite parts of anthologies and collections may even be valuable for finding works that inversely are not published alone.

Some relationships can be learned from metadata. Publishers and libraries use control numbers, such as ISBN and OCLC numbers, to describe exact duplicates, and a mix of title, author and publication date information can provide a strong hint towards sameness between books. Sometimes these metadata are insufficient, particularly for less-than-exact similarities, so metadata alone cannot help tag large collections [2]. However, despite its blind spots, metadata can provide enough reliable examples to train content-based classifiers.

Whole–part relationships are more difficult to infer from metadata. This is because they usually are not directly catalogued. There are a few potential sources which may suggest the relationship, with limited coverage. First is volume
enumeration information, which is held in the 995v field of MARC metadata records. When used, this field describes the part, issue, or volume of a larger set that the given book is. For example, a printed or scanned book may be ‘v.6’ of a seven-part set. Sometimes multiple volumes are bound together, so that, a book that contains ‘v.6-9’ can be assumed to contain multiple volumes of a larger work.

Another potential bibliographic metadata source looks inward, enumerating the contents with a printed or scanned book. The MARC 500 field provides general notes, which may contain content information, and the 505 field provides formatted contents notes such as table of contents. Unfortunately, use of the 5xx fields is inconsistently applied so we cannot rely on this field alone to provide contents information for materials. In the HathiTrust, just over 2% of all volumes have 505 information.

With the 995 field offering few examples of whole–part relationships and 505 fields difficult to parse and align, it is difficult to find sufficient training examples for training a content-based classifier to recognise this relationship. In our data, real labels for whole–part data comprise only 0.63% of training data. To enhance the reliability of our ground truth, we incorporate synthetic data, generating books that are artificially stitched together, applying an approach that has shown value in other domains.

2. Related work

The past decade has seen an emergence of digital libraries at unprecedented scale, such as the Google Books project [7], Internet Archive and the HathiTrust [8]. These collections, primarily comprised scanned books and other materials, are notable among text corpora for a number of reasons. These corpora span decades or centuries, at scales that have previously only been seen with contemporary text collections. In addition, many texts originate in libraries, particularly academic libraries, and are accompanied by professionally catalogued metadata.

Emerging areas of study make use of the historical breadth and depth of large bibliographic collections to learn from digital library content at scale. The area of culturomics seeks to infer aggregate-level trends about the emergence of history, culture or language [7], such as work into changing meanings of words [9] or the regularisation of irregular verbs [10]. In the digital humanities, scholars work to augment the traditional close reading exercises of literary appreciation with distant reading [11] and cultural analytics [12]. Finally, in library and information science, large bibliographic collections allow us to effectively zoom out from a focus on individual materials, and learn more about those materials by observing their relationships in a larger system. Large digital library analysis can teach us more about bibliography, such as expanding our understanding of subject access, cataloguing practice or the history of the book. For example, collecting duplicate copies of the same work can be a useful resource for determining data of first publication [1], aligned duplicate passages can be used to improve Optical Character Recognition (OCR) [13–15], and algorithmic modelling of books can test and uncover challenges to conceptual modelling of books [2]. Our work is positioned in this area, developing methods to learn about cataloguing practice and, in turn, supplement it.

This article presents an approach grounded in artificially created data. Artificial data are training data that have not been directly measured. It can be fully generated, synthetic data [16], or it can be created through perturbation of existing data, sometimes called data augmentation [17,18]. It is used for regularisation in machine learning; that is, as a strategy for preventing over-fitting when training a model. In the case of artificial data, it is particularly valuable for overcoming supervised learning problems where it is difficult to collect enough labels.

Artificial data are particularly common in computer vision, where perturbing real data into a synthetic but realistic form is generally tractable. For example, a basic technique to make an image classifier more robust is to take each single labelled example, and use it to make new examples by flipping, cropping, blurring or noising the example [17,19,20]. More novel techniques include changing hairstyles of people or artificially reposing them to add robustness to face recognition [18]. Fully synthetic data are also common in computer vision [16], including for creating images from 3D models [21] or even from imagery in games like Grand Theft Auto [22].

In text-based domains, data augmentation is usually used to perturb existing data, such as by swapping words with synonyms or word embedding nearest neighbours [23], and randomly inserting or deleting words or adding noise [23,24]. Our approach can be considered a perturbation of text structure, using existing text remixed into novel formats resembling classes with very little training data. Modifying the underlying text to swap in synonyms or similar words could be valuable for classification of digital library texts. However, it is of less value to the use presented in this article, since the architecture used already accounts for synonymous language by projecting words to a higher-level word embedding space.

One text domain where synthetic data show promise is in the development of OCR error detection and correction algorithms. In this space, it is common to align sequences of OCR with ground truth, a challenging task which underlies its own area of study [14,25–27]. To augment alignment data, some have proposed using generated errors [28]. Other
works have aimed to improve text recognition itself [29]. This approach is especially interesting for Handwriting Text Recognition, where there is scarce ground truth available to accompany handwriting [30,31].

Data augmentation is also used for balancing label representations in a dataset. For example, using complex language models to generate synthetic training examples for question and answer tasks provides a slight improvement over using solely real examples [32]. For generating examples to balance labels, generative adversarial networks (GANs) are increasingly used [33–35]. A GAN is a two-part generative process, which simultaneously trains a generator to create data examples and a discriminator that aims to differentiate generated examples from real examples. This approach to synthetic data still needs sufficient data to train the GAN, but it provides an opportunity to inspect those training examples with a specificity that a classifier might not have. GANs are notoriously unstable, and are difficult to apply in text contexts. Our work follows in the tradition of synthetic data for label balancing. While it does not use GANs, it approaches the generation process as one akin to images: sidestepping complex considerations of syntax in text use and instead focuses on the structure of pages and books while remixing real examples of text.

3. Data

For this study, we focus on the HathiTrust Digital Library, a massive, 17 million work digital library. The HathiTrust is a non-profit consortium of institutions collecting their scanned bibliographic works for preservation and access [8]. It is appropriate for our goals because, due to the distributed way in which its collection was build, it offers a great deal of overlapping or duplicate works in various forms. Where a single library may not acquire tens or hundreds of different versions of a work, this type of bifurcation is more probable in the HathiTrust given that it is sourced from independently built collections.

The HathiTrust, through the HathiTrust Research Centre, also provides various tools, services and datasets to aid scholarship over the collection. For access to the content of the books in the HathiTrust Digital Library, we used their extracted features (EF) dataset [36]. The EF dataset provides token count information for each page of each book in the corpus, including in-copyright works. The trade-off for such deep access is that it does include the order of words on each page. To prepare them as input for classification, books from the EF dataset were parsed from their original JSON format and their words were projected to a word embedding space, summed into approximately 5000 word book chunks, and compared pairwise with cosine similarity. This processing is detailed in the ‘Methods’ section.

Ground truth and training labels were derived from the cataloguing metadata using parsing heuristics. Primarily, the volume enumeration field was used, which libraries contributing to the HathiTrust take from the MARC 995v field or a number of other possible locations. This information lists which volume of a multi-volume work the given scan is. For pre-processing and information extraction, we first cleaned and normalised the field for 9 million English-language HathiTrust texts, standardising atypical values, such as volume 1 or v1 instead of v.1.

Subsequently, a basic parsing strategy was used to identify when the chronology information listed a series for the given scan, extracted the individual parts of that series, and looked for corresponding volumes that only held those individual parts. For example, when a HathiTrust scan was listed as containing volumes 2 and 3, just volume 2 of the same book was searched for as well as only volume 3. When there was an alignment, the relationship was saved as CONTAINS and the inverse relationship was tagged as PARTOF. As discussed in the ‘Background’ section, these metadata are limited in coverage. This work seeks to better classify the known examples of these two classes, with the understanding that there are many more examples in the corpus that cannot be inferred from cataloguing metadata.

4. Methods

To evaluate the efficacy of artificial data for whole/part relationships, we incorporate it into identically instantiated deep neural network relationship classifiers, in various mixes alongside known relationships. The three conditions evaluated are

- **Baseline** (nofake). A classification model trained without any artificial data,
- **Mixed train** (mixed). A model trained with a mix of artificial data and ground truth,
- **Artificial-only** (allfake). A model trained with only artificial data representing the PARTOF and CONTAINS classes.

In each condition, the classifiers are trained on the following classes: The classes used for this article are the two whole/part classes of interest to this article — PARTOF and CONTAINS — as well as same work, different volumes of the work and different works. The additional classes are used to help understand classification errors. The model’s
performance for all conditions was evaluated against the same split of held-out ground truth data \((n = 12,358 \text{ for } \text{PARTOF, } n = 12,386 \text{ for } \text{CONTAINS})\). These classes are reciprocal and, including training and cross-validation splits, each had \(n = 20,238\) examples overall.

The nofake condition presents a baseline condition, representing a situation without artificial data. After withholding texts for testing, we have a total of 11,903 training relationships for the two whole-part classes, PARTOF and CONTAINS. For all other classes, we have 1.85 million labels, so that, the whole–part classes comprise 0.63% of all training data (Table 1).

The mix condition adds 272,475 artificially generated documents to the training set. This is an ideal parameterisation, using artificial data to augment a class with disproportionately few training examples for supervised learning. With the synthetic data included, the whole–part examples comprise 12.74% of all training labels.

Finally, the allfake condition serves to provide an impression of how successfully the artificial data represent the class. While it is not a realistic practical approach to actively remove the real training examples, even if they are under-represented, it offers us a glimpse into how successfully the generated anthologies ‘pretend’ to be real ones. In this condition, we still evaluate on the same known relationships as in the other conditions, even if we are not training with them.

### 4.1. Artificial data

Our whole–part artificial data were created by breaking up or patching together existing books. Specifically, we create three types of artificial books:

- Artificial anthologies, comprised multiple short works by the same volume;
- Artificially combined volumes, created by concatenating scans which are different volumes of the same collection (e.g. combining v.1 and v.2 of Jane Austen’s *Emma*);
- Smaller volumes artificially split from a longer book.

The short books used for anthologies were those that are shorter than the 40% percentile of book lengths in the English-language HathiTrust. After de-duplication by author and title, this pool contained 757k books. During concatenation for anthologies and combined volumes, front matter and back matter were roughly separated by removing a randomly selected number of pages, up to 10, from the front and back of each book. The front and back of one of the sub-unit books was kept as the front and back matter of the subsequent larger book, with the centre content of all the books included in the middle.

The classification setting here is relationship classification, which compares the relationship between two books. Thus, for each training example with synthetic data, the input is actually a comparison between a real book and the synthetic book that was constructed to contain or excerpt the real book.

### 4.2. Deep neural network classification

The robustness of artificial data in training relationship classes is evaluated in situ, by including it in the context of a larger relationship classification pipeline. For training, we duplicated an architecture that worked well internally for other relationship classification. While this article does not provide a deep treatment of the architecture, the details are described below and in the supplemental code. Importantly, the same parameters and maintains in all experimental conditions.
For each left/right book pair, the classifier is provided two inputs. The first input is a pairwise similarity matrix based on chunked sub-units of the book. Each book was collected into 5000 word chunks. Chunking allows books to be represented as smaller sub-units, allowing for more sensitivity to book similarities. Furthermore, controlling for size makes them more easily comparable. The chunk size was motivated by computational performance considerations, as smaller chunks allow more expressiveness but too many chunks per book cannot be tractable represented in the downstream classification architecture. The choice of 5000 presented here aimed to balance those considerations and was not compared formally. Chunks were projected to a dense vector space, using a pre-trained 300-dimensional GloVe model [37], by converting each word to a vector and summing all the words for the chunk. With a single-summed word vector for each chunk, pairwise cosine similarity was performed between the chunks of both works, and the resulting similarity matrix was zero-padded or truncated to a size of 150 × 150. The texts that were truncated — those more than 750k words — were not included in this study. These amount to the 2.98% of corpus.

The use of a similarity matrix for input was motivated by the scale of the primary texts: the classifier looks at full-document relationships for materials that are particularly long and highly variable in length, two or three orders of magnitude longer than a document can be represented using a standard contextual or transformer-based language model. In turn, the use of cosine similarity was the motivation for applying GloVe: while more recent models tend to outperform static embeddings like GloVe in most applications, they do not preserve linearity in their representations and are generally ill-suited for distance metrics over their raw embeddings.

While the first classifier input includes a sense of internal similarity between books, it does not capture topical differences. To do that, the second classifier input was derived from an overall GloVe vector for each book. The left book and right book vectors were used to calculate a centroid vector between the two, which was concatenated with the difference vector where the right was subtracted from the left.

The classifier used the similarity matrix input in a two-dimensional convolutions neural network (CNN), extracting convolutions in a moving window of the similarity matrix, akin to how adjacent sequences of pixels are looked at for patterns in an image CNN. Two CNN layers are used, with down-sampling through maximum pooling, which drops information to avoid over-fitting and to reduce the parameter count. The parameters from the CNN are flattened, and dropout — a technique that randomly hides nodes on training to encourage more creative models — is applied [38]. For the second input, a typical multi-layer model is used, also leveraging dropout, and the weights are concatenated with the weights of the similarity matrix layer.

For training, the same hyperparameters are used for all reported results. Classifiers are trained with a batch size of 4096 and up to 30 epochs, with early stopping applied based on validation accuracy. Early stopping has a patience of four measurements. Learning is optimised with Adam [39] at a static learning rate of 0.001.

An example of how the classifier sees the book input for whole–part relationships is shown in Figure 1. Here, each book is split into 5000 word chunks, those word chunks are projected to a 300-dimensional vector in a word embedding space, and the figure depicts the cosine similarity between each chunk-to-chunk comparison across two books. Darker squares denote greater similarity, and in each, you can track the darkest diagonal to see pages of overlapping content. For PARTOF and CONTAINS, the diagonal spans the length of one axis but not the other.

5. Results

Tables 2 and 3 show the results of the respective conditions for including synthetic data. Overall, the synthetic data greatly improve the performance on the classes, with the macro-averaged $F_1$-score improving from 0.411 to 0.783, a 37-point improvement (+91%). Across all classes, the micro-averaged $F_1$-score, which equally weighs each class, improved from 0.689 to 0.815.

The improvement to the classification $F_1$-score comes through a massive 50-point gain to recall at a small 16-point cost to precision. In other words, without the synthetic data, the classifier rarely classified whole–part relationships except when it was very confident — missing many in the process. The synthetic data were not perfect representation of what real data look like, but it encouraged the classifier to better trust the general rules that were encoded in the heuristics driving the synthetic data generation.

When trained without any real data, the synthetic-only data still outperformed the regular condition without data, though not to the level of the full, mixed-input. Still, it is notable that the fully synthetic data communicated something about the structural identity of class it was imitated. At the same time, given that the synthetic data outnumbered the real data 22:1, the fact that the mixed class improved over the synthetic-only class — both in precision and recall — shows that it was still using the ground truth to aid in cases that were overlooked by the synthetic generation criteria.

To consider whether too much synthetic data can be detrimental, we trained classifiers with different proportions of the synthetic data: 0%, 5%, 10%, 25%, 50%, 75% and 100%. Figure 2 shows the effect of each on precision, recall and
We observe that $F_1$ keeps improving, with the majority of the improvements early. Underlying the $F_1$-score improvement, there is again a gradual degradation in precision compensated by a larger improvement in recall.

5.1. Overlapping books

These results are promising for considering another class of relationship, for which very little ground truth is available: books that have a partial overlap. In this section, we consider whether synthetic data can be used to surface a fully constructed relationship.

Consider the following two books: The writings of Oscar Wilde (Wm. H. Wise & Co., 1931), and The portable Oscar Wilde (Penguin, 1981). Both volumes contain A Picture of Dorian Gray, but they differ in the other contents published within them.

Table 2. Performance on PARTOF relationships by classifiers trained with varying mixes of artificial data.

| Class               | Precision | Recall | $F_1$ |
|---------------------|-----------|--------|-------|
| NOFAKE (baseline)   | 0.96      | 0.29   | 0.44  |
| ALLFAKE             | 0.75      | 0.66   | 0.70  |
| MIX                 | 0.82      | 0.76   | 0.79  |

Best performance in bold.

Table 3. Performance on CONTAINS relationships.

| Class               | Precision | Recall | $F_1$ |
|---------------------|-----------|--------|-------|
| NOFAKE (baseline)   | 0.97      | 0.24   | 0.38  |
| ALLFAKE             | 0.78      | 0.64   | 0.71  |
| MIX                 | 0.80      | 0.77   | 0.78  |

Best performance in bold.

Figure 2. Effect of varying amounts of synthetic data on classification of PARTOF and CONTAINS classes, where $n = 272,475$ with 100% of synthetic data. Also shown are results when training only on 100% of synthetic data, with real labels removed from training. Labelled along the top is the associated synthetic:real ratio.

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The reason that there is little ground truth available for this type of overlapping relationship is that there are simply few use cases for it – it is valuable to know that Dorian Gray is in an anthology, but not necessarily that two different anthologies contain it. However, this relationship is important because it is one that a classifier may encounter, and not understanding the overlaps relationship will cause a misclassification when two such works are compared.

Overlapping work may be partially alignable from tables of contents, such as those sometimes listed in the MARC 505 field. Given its structural similarity to PARTOF and CONTAINS relationships, the results above suggest that a simulated data approach may also be tractable in this case. For a preliminary exploration, we developed synthetic overlapping data in the same manner as the whole–part data. We created fake anthologies, but while they shared material, this time neither fully subsumed the other.

Table 4 shows a selection of books that the resulting classifier considered to highly resemble the artificial OVERLAPS label. These are books from the evaluation performed earlier, meaning that they all already have a (different) ground truth label already. We manually reviewed the scans of the books lists, finding that most were indeed ground truth errors, resembling the intended OVERLAPS class. Associated similarity matrices for each listed example are shown in Figure 3. For illustrative purposes, we consider three examples more in-depth below.

- **The Madras Journal of Literature and Science** (left: nyp.33433081888137, right: umn.31951000747566r). For the ground truth, the metadata suggest that these books are identical: volume 16 of the Madras Journal of Literature and Science (1850), with a similar number of pages. The reality is that both scans are incomplete, structurally resembling an OVERLAPS relationship. They start with no. 38 of volume 16; however, after the first page, the right book continues to page 2 while the left book jumps to page 174. After the truncated issue 38 ends in the left book, issue 37 is included. So, the two scanned books intersect in front matter and the latter half of no. 38, but diverge in that one has the first half also while the other has no. 37.

- **List of the specimens of the British animals ...** (left: nncl.cu04802497, right: ucl.c026291064). For the ground truth, the metadata suggest that the left book is volumes 8 and 9 of List of the specimens of the British animals in the Collection of the British Museum, and the right book is volume 9 – a CONTAINS relationships. In reality,
our classifier gives this relationship a 94% likelihood of being ‘OVERLAPS’. The right book actually contains volume 9 of the listed work and a second work, the Catalogue of the Genera and Subgenera of Birds Contained in the British Museum.

- High school mathematics, first course. In the ground truth, the label is ‘CONTAINS’. The left book is said to be volumes 3 and 4, while the right book is said to be volume 3. The reality, however, is that right book has identical pages as the first half of the left book, but it has additional pages inserted throughout the book, interwoven without page numbers.

This is a small exercise, looking at a small number of high confidence results. However, we also look at books that were already labelled – books with unambiguous metadata that were deemed high confidence enough to including in the evaluation corpus. Given that each was found to either be a misclassification or a printing error, this exercise suggests that there may promise in further pursuit of fully artificial classes.

6. Discussion

6.1. Synthetic data are tractable for improving classification large text corpora

The results reported here show a strong performance increase from the inclusion of synthetically created books. The whole–part work relationships were the greatest source of misclassifications in a larger classifier of work relationships, probably due to low relative representation in the collection. While their precision was high, there were many false negatives which, in a multi-label classifier, in turn lead to more false positives and lower precision for other classes. Through the inclusion of artificially created books, the $F_1$ for the under-represented classes improved significantly.

When comparing different quantities of synthetic data, the results provide insight on how such strategies may be used in future digital library contexts. First, the synthetic data were beneficial even with a small set of training examples. Furthermore, we found that increasing the quantity of examples – which are trivial and computationally inexpensive to generate – continued to improve the quality of results, albeit with gradually diminishing returns.

We expect at some point that the synthetic data might start lowering the classifier accuracy as the real ground truth is overwhelmed, but we did not observe that point, even at a 22:1 ratio of synthetic-to-real data. In this study, then, the exact quantity of synthetic data was found to not be a highly sensitive parameter, and we expect that future use of the strategy would not require careful tuning.

Finally, we observed that while results were lower when real training labels were removed entirely, they still provided a notable improvement over the baseline. The strength of this condition was surprising, and seems to speak to the general strength of artificially concatenated books for our specific case.

6.2. Generated data are appropriate for communicating class properties

Why did the all-synthetic condition with real ground truth removed entirely outperform the baseline? One possibility is that the problem was particularly well-suited for describing a robust generator.

The characteristics of whole/part relationships are plain and uncomplicated enough for an expert-crafted imitation, where other types of labels may be more difficult to infer. A good classifier finds patterns that are too complex or too small for a person to observe. Yet, for all the internal complexity in deep neural network classification, this article’s results points to one way to ‘talk’ the language of the classifier when you do know how to describe a specific class. This is akin to how 3D or video game imagery can help train a computer vision classifier – a screenshot of a 3D-modelled streetlight may be missing some essence of a photograph, but will still convey many of the fundamentals of what a streetlamp looks like. In other words, if we have a label that can be described, writing a generator for synthetic data may allow us to nudge a high complexity classifier without sacrificing that complexity or requiring a re-engineering of the classifier. This promise seems supported by our brief look into teaching a new class label for overlapping data.

In information science, the possibilities for using fully constructed book structures are intriguing. For example, one common type of printing and binding error is a book with runs of pages that have erroneously been included more than once, often in place of other, missing pages [40]. This type of error is imported into scanned book digital libraries, but as a structural issue, could be addressed through a synthetic data method akin to what we employed.
6.3. Future directions

The present study uses synthetic training examples to augment under-represented whole–part relationships in a digital library classifier. This is just one possible application of synthetic data in digital libraries. With data augmentation, the size of the training corpus may be grown in a predictable way.

For relationship tagging, comparing books with artificially perturbed versions of themselves can aid in training same work, same manifestation relationships — scans of books that have the same physical form, but which may have slight variation introduced during the scanning process. Replacing random words in a target text with typographical errors, akin to Wei and Zou [23] may help train downstream classifiers to be more robust to this type of variance. A more drastic type of text perturbation could create examples of different expressions of the same work — the fuzzier type of relationship between different iterations of a text. In the HathiTrust, cataloguing metadata provided enough labels for train those forms of relationships, but the strategy may help built more robust classifiers over corpora without such labels.

Beyond perturbations to the text itself, other remixes to the structure of a document are possible. Akin to the artificial examples of overlapping texts in this study, one can conceivably mimic relationships such as abridgements, excerpts, plagiarism or reprints with different page boundaries by cutting and mixed different known documents.

7. Conclusion

In this article, we employ synthetic data as a means of label-balancing text training data for classification. In the context of scanned book digital libraries, we artificially remix real book through selective splitting or concatenation of real books, towards augmenting whole–part book relationship classes for which there is a disproportionately low amount of real data available. In essence, for a real book we generate a fake relative for that book, and use the relationship between the two in a classifier.

We find that the synthetic data are extremely effective for improving classification for our labels. Growing the size of the synthetic data improves performance, though the process is fairly permissive, and we find that carefully tuning for quantity is generally unnecessary. In addition, relationships derived with artificial data train a surprisingly robust classifier even when the real ground truth is withheld. Encouraged by these results, we train and briefly review a fully constructed class, with encouraging results.

The results of this article hold promise for information access in digital libraries in a number of ways. Directly, they will aid in building better methods for identifying relationships between books in digital libraries. More broadly, they hold promise for progressing bibliographic research. Synthetic data provide us a way to mix described bibliographic properties with known, labelled data in deep neural network classification, offering a way to improve supervised learning problems in contexts with limited or imbalanced training data.

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