Explorations in Economic History 87 (2023) 101475

Contents lists available at ScienceDirect

Explorations in Economic History

journal homepage: www.elsevier.com/locate/eeh

Digitizing historical balance sheet data: A practitioner's guide☆

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ARTICLE INFO

JEL classification:
C81
C88
N80

Keywords:
OCR
Data extraction
Balance sheets

ABSTRACT

This paper discusses how to successfully digitize large-scale historical micro-data by augmenting optical character recognition (OCR) engines with pre- and post-processing methods. Although OCR software has improved dramatically in recent years due to improvements in machine learning, off-the-shelf OCR applications still present high error rates which limit their applications for accurate extraction of structured information. Complementing OCR with additional methods can however dramatically increase its success rate, making it a powerful and cost-efficient tool for economic historians. This paper showcases these methods and explains why they are useful. We apply them against two large balance sheet datasets and introduce quipucamayoc, a Python package containing these methods in a unified framework.

1. Introduction

Optical character recognition (OCR) is a powerful tool that allows researchers to unlock historical data. OCR quality has improved dramatically in recent years thanks to advances in machine learning (ML) techniques, creating opportunities to access previously unavailable historical large-scale datasets. However, off-the-shelf OCR software still exhibit error rates high enough to limit its application for accurate extraction of structured information as recognition errors can easily get compounded. For instance, applying an OCR engine with a 95 percent character accuracy rate on a table with ten six-digit numbers will result in an output *with errors* in 95.4 percent of cases.[1]

In this paper, we discuss how to successfully digitize large-scale historical micro-data by augmenting OCR engines with pre- and post-processing methods. We argue that when applying OCR, *the researcher is the practitioner*. The success of digitizing in most cases does not depend on developing OCR engines themselves. Rather, successful data digitization results from complementing commercial OCR software with additional tools that can dramatically increase its success rate, making it a powerful and cost-efficient tool for economic historians. We illustrate why these methods are useful by applying them to two large balance sheet datasets. Further, we introduce `quipucamayoc` (Correia and Luck, 2022), an open-source Python package containing our methods in a unified framework.

Section 2 discusses the general trade-offs faced by researchers when considering using OCR to digitize data. A key takeaway is that returns to scale make OCR more practical as the underlying data sources become larger and more standardized. In turn, the improvements discussed in this paper, while not always cost-effective for small or unstructured datasets, become particularly valuable

☆ Our code is available as the https://pypi.org/project/quipucamayoc package on the Python Package index (PyPI) as well as on Github at https://github.com/sergiocorreia/quipucamayoc/. This paper expresses the views of the authors and not necessarily those of the Board of Governors of the Federal Reserve. We benefited from discussions with Eugene White and Tom Zimmermann, as well as conference participants at the 2021 Methodological Advances in the Extraction and Analysis of Historical Data conference.

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[1] As a first approximation, this can be modeled as a binomial distribution with $10 \times 6 = 60$ trials, each with a 0.95 success probability.

https://doi.org/10.1016/j.eeh.2022.101475
Received 31 March 2022; Received in revised form 9 September 2022; Accepted 14 September 2022
Available online 21 September 2022
0014-4983/Published by Elsevier Inc.

REPORT OF THE COMPTROLLER OF THE CURRENCY. 297

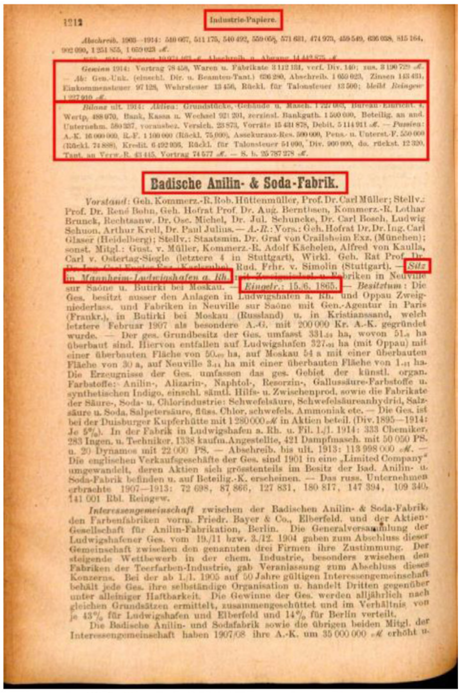
NEW JERSEY.

National State Bank, Camden.

First National Bank, Clinton.

Clinton National Bank, Clinton.

(a) *OCC Annual Report*



Industrie-Papiere.

Badische Anilin- & Soda-Fabrik.

(b) Saling's Börsen-Papiere

Fig. 1. Case studies. These figures show examples of the two datasets showcased in this paper. Panel (a) shows page 297 of the *1882 OCC Annual Report to Congress*. Panel (b) shows page 1212 of "Teil 2" of the 1915 edition of Saling's Börsen–Papiere, with the items to be extracted highlighted in red. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

for large-scale data such as structured balance sheets. If the researcher concludes that OCR is the most promising route to obtain her data, we thus provide a classification and description of the general methods we recommend using. We argue that commercial products should be integrated and combined in a way that serves the researcher's purpose. We suggest following a "data extraction pipeline" that has the following steps: First, the original image files are pre-processed (de-warped, contrast adjustments, etc.). Second, the commercially available OCR and layout recognition techniques are applied. Third, the data are extracted and validated by leveraging relationships that must hold in the data such as accounting identities. A crucial step is a human review in which the researcher herself validates some of the data creating a "ground truth." Such validated data allows researchers to then test and improve the accuracy of the digitization pipeline by serving as a benchmark against which the digitization output can be compared to construct accuracy metrics. In turn, these metrics allow for more advanced optimization of the parameters used throughout the digitization process.

Section 3 discusses each step of the data extraction pipeline in depth. We accompany this discussion with illustrations of how these methods were used to improve the performance of two large-scale balance sheet digitization projects:

1. The Office of the Comptroller of the Currency's (OCC) Annual Reports between 1867 and 1904, containing more than 100,000 national bank balance sheets in tabular format (Fig. 1(a)). These data are used, e.g., in Carlson et al. (2022).
2. 30,000 balance sheets of German financial and non-financial firms from 1915 through 1933, published by *Saling's Börsen–Papiere* as text paragraphs (Fig. 1(b)). These data are used in ongoing research, Brunnermeier et al. (2022).

Although both sets of documents represent firm-level balance sheet data, they do so in diametrically opposed layouts; the OCC dataset is in a more standard tabular form, and the *Saling's* dataset is in free-form paragraphs. Further, these sets of documents differ in their language, the quality of the scanned documents, the fonts used, and even the century when they were published. This increases the likelihood that the methods discussed here are general enough and not specific to a certain document or type of document.

Section 4 describes the `quipucamayoc` Python package, showcase how to use its different components, and illustrate how it can be used to obtain high-quality digitized data. Section 5 concludes.

2. Extracting balance sheet data at scale

We start by discussing the general choices and trade-offs a researcher faces when considering using OCR to digitize data. Depending on the size of the historical records that will be digitized, practitioners can generally opt for three different approaches. As shown in Fig. 2, these approaches differ in the initial setup cost, as well as in the variable cost-per-page.

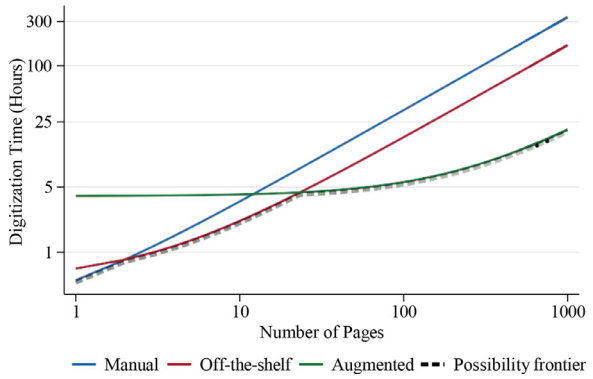


Fig. 2. Digitization time by type of approach. *Note:* axes in log-scale.

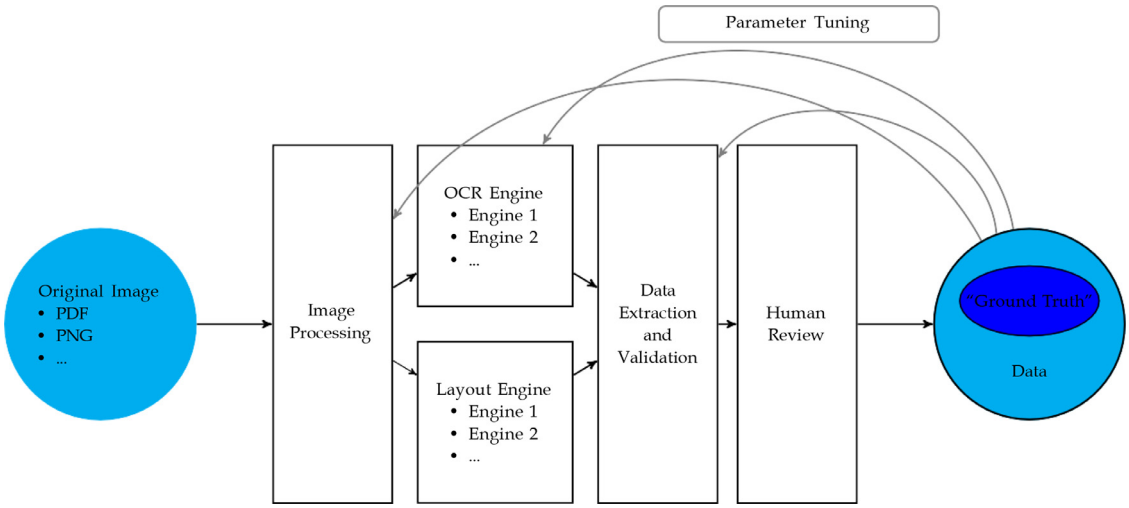


Fig. 3. Data extraction pipeline. This figure shows the six steps of the augmented digitization approach that is the focus of this paper.

The least technically demanding approach is to manually input every value into a spreadsheet. This approach does not require any coding, but inputting each page is a slow process with roughly no returns to scale involved: the first page takes the same amount of work as the last, and one is not taking advantage of patterns or structures common to all the pages to speed up the digitization process. For instance, digitizing a single page of the OCC bank balance sheet dataset takes roughly 20 min per page. At this rate, digitizing the 37,000 pages comprising the 1867–1904 OCC annual reports requires around 12,300 h of work.

A second approach, suitable for small, well-formatted datasets—properly scanned, with standard fonts and simple tables—consists of directly applying off-the-shelf commercial OCR software and then manually correcting and reshaping the resulting data. For the OCC bank balance sheet dataset, this reduced the manual review time by roughly 60%, to eight minutes per page. Yet such an approach is not desirable for a large-scale digitization project; for instance digitizing all the pages in the OCC Annual Report would require roughly 4900 h of manual work.

The third approach, which we recommend for large-scale datasets, involves augmenting the OCR step with pre- and post-processing steps that improve the quality of the resulting data and thus reduce the time required for human review. In particular, this approach reduced the review time of the OCC bank balance sheet to about a minute per page—with some pages requiring extensive corrections but most requiring minimal review. Thus, the total time required to digitize the OCC bank balance sheet dataset becomes a much more manageable 600 h or roughly 15 weeks of full-time work.

Together, these three approaches form the digitization possibility frontier, shown as the gray dashed line in Fig. 2. Note that because the graph is scaled in logarithms, the vast majority of documents—with 25 pages of data or more—are best suited for the large-scale "augmented" digitization approach seen in the green line.

To explain how this augmented digitization approach works, we have classified its different elements into six broad components, illustrated in Fig. 3. Depending on the complexity and scale of the input documents, researchers might want to apply only some of these components and omit others.

The starting point of this pipeline is a scanned document, either as a PDF or as a set of images. Its endpoint is a dataset, either in tabular form (CSV files or Excel tables) or in hierarchical form (such as a JSON file).[2] The first step of the pipeline consists of transforming the scanned images to improve the accuracy of the subsequent OCR steps. It consists of a sequence of transformations known as image filters or image kernels, where each filter has a specific purpose, such as fixing the image alignment or increasing its contrast.

The second step consists of applying one *or more* OCR engines to the transformed images. As discussed in more detail in Section 3.2, there are two reasons for using more than one engine. First, there might not be an OCR engine uniformly better than another, even within a single document. Rather, an engine might perform better on some pages due to page and scanning idiosyncrasies. Thus, assuming we can compute a page-level measure of data quality—such as the count of numbers recognized—running multiple engines might allow us to choose the engine best suited for a given page. Second, at an even deeper level, we could combine multiple OCR outputs through "ensemble methods" that allow us to recover a correct datum—a word or a number—even in cases where all OCR engines outputted incorrect values. This is feasible because most modern engines—such as Amazon's Textract and Google's Vision AI—output not only text but its coordinates, hierarchy—e.g. the line, paragraph, and block where they belong—and even confidence values of each word.

The third step of the pipeline is the layout engine, where we identify the different layout elements of each page, such as tables, columns, paragraphs, and headers. This step, though not often required, provides us with two advantages. First, by knowing the section of a page where a datum is located, we can assign it correctly within a dataset. For instance, in the OCC example, the header of each balance sheet table contains the name, location, and charter number of each bank. Similarly, in the *Saling's* example, the different balance sheets and profit and loss statements are separated by paragraph breaks. The second advantage, particularly useful for poorly scanned datasets with one or more tables, is that by knowing where a table is located, we can crop the image to the area corresponding to a table, and use this selection as an input to the OCR engine, which will likely perform much better than when inputted the entire page.

The fourth and arguably most important step for the researcher is data extraction and validation. This step transforms the mostly unstructured data generated by the OCR and layout recognition engines into structured data suitable to be loaded and processed by statistical software. Further, once the document is transformed into a structured dataset we can evaluate the quality of its data and validate it against a set of invariants, i.e., conditions that must always hold. For instance, the set of labels in a balance sheet might be predefined, and its values might be constrained to certain patterns, where "123,456.00" is a valid number but "023,456.00" (leading zero) and "123,4.56" (only one digit between comma and dot) are not.

Step five is the human validation step, which serves two purposes: The first and most obvious is to fix incorrectly transcribed data. Depending on the situation, researchers might want to either review all data or data flagged as problematic if it fails sanity checks or invariants. The second and more ancillary purpose is to construct ground truth—data that has been reviewed and is assessed to be correct with high confidence.

The sixth and last step is parameter tuning, which consists of adjusting the parameters used in all the previous steps to reduce the error rate against the ground truth available. For example, it is often not clear what thresholds we should select when processing the images, or whether we should apply a spell-checker. Ground truth data allows us to construct metrics of accuracy which we can in turn use to improve the performance of the parameters.

As we will show in the next section, OCR and data extraction and validation are the only required steps, while the others are more context-dependent and might be omitted depending on the quality and scale of the documents at hand.

3. Data extraction methods

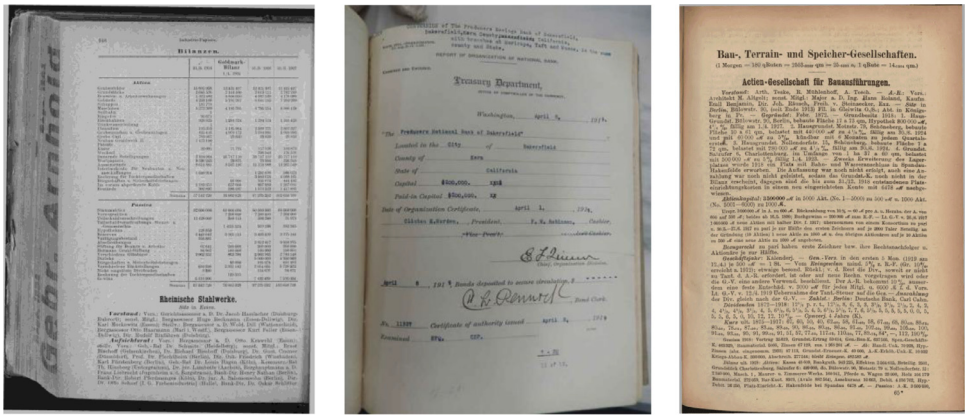
This section discusses in detail the different steps of the data extraction pipeline outlined in Section 2. For each step, we first discuss its rationale and the issues it addresses and then provide an overview of some of the solutions, using as examples the two digitization projects introduced in Section 1.

3.1. Image processing

The main goal of this step is to undo any distortions in the digitized images created by the scanning process. These distortions can alter the size, shape, color, and brightness of the documents, which in turn adversely affect the performance of the subsequent OCR step. They are particularly problematic for historical documents, which often have discolored pages and might suffer from artifacts such as foxing (Choi, 2007), oxidation and fungal action stain parts of the paper, and bleed-through (Gupta et al., 2015), where the ink of the reverse page is visible in the scan of the current page. Further, sheet-feed scanners minimize the curvature and skew of the scanned images but are often unfeasible for historical documents as they require removing the book spines, permanently damaging them.

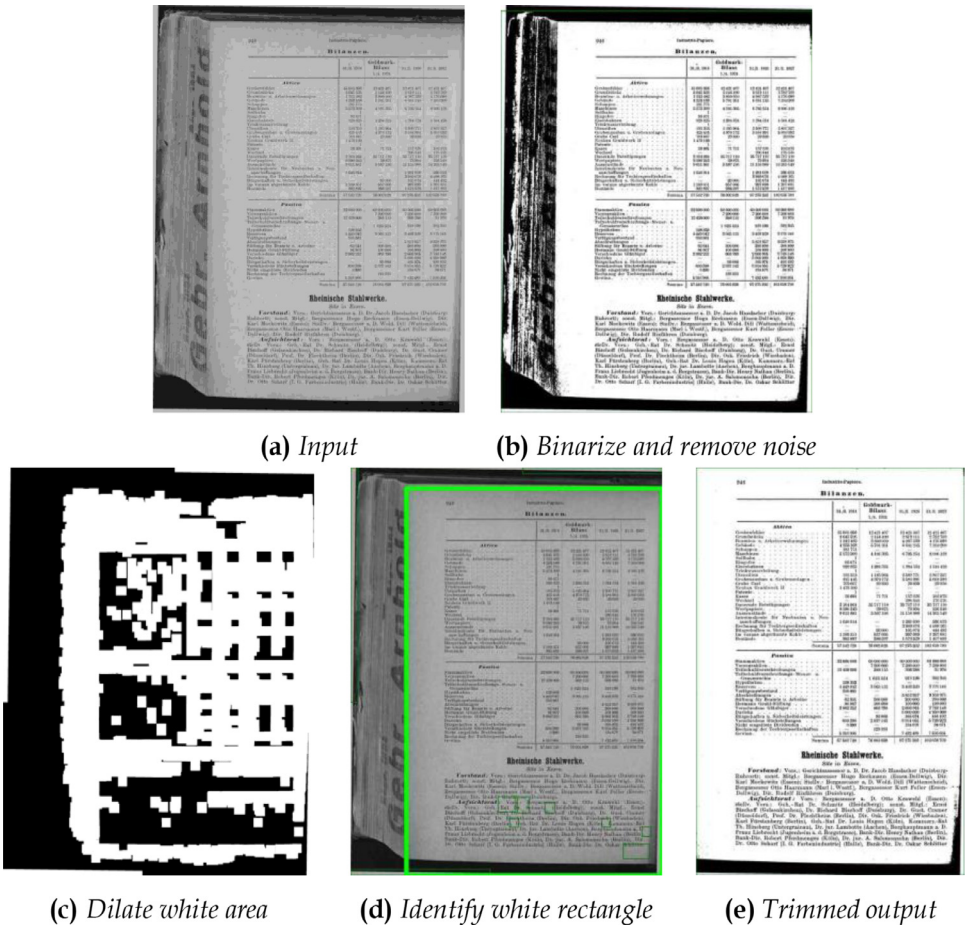
Fig. 4 shows examples of the three most common types of distortions, which we discuss in more detail below.

[2] Note that the resulting datasets might not just be mere digitization of the documents, but instead require further transformations to make the data useful for researchers. For instance, items in the *Saling's* dataset are listed as free-form labels, so a given balance sheet might contain items such as "Inventory of Portland cement at the Berlin warehouse," which then needs to be aggregated into a broader "Inventory" category in order to be comparable across firms and industries. Similarly, even the more standardized OCC dataset lists items as specific as "Gold dust on hand," which we aggregate into the "Specie" category.



(a) *Distorted image size* **(b)** *Distorted image shape* **(c)** *Distorted image color*

Fig. 4. Image distortions. This figure shows examples of the three main types of image distortions in scanned documents. Panel (a) shows size distortions in a *Saling's* page due to the fore-edge of the book and the scanner background. Panel (b) shows geometry or shape distortions in a national bank organization report. Panel (c) shows a *Saling's* page with yellowed background and bleed-through of the text on the reverse page.



(a) *Input* **(b)** *Binarize and remove noise*

(c) *Dilate white area* **(d)** *Identify white rectangle* **(e)** *Trimmed output*

Fig. 5. Removing fore-edges on *Saling's* balance sheets. Panel (a) contains the input image. Note the black background and the fore-edge with the words "Gebr. Arnhold." Panel (b) shows the output of the binarization and denoise step. Panel (c) further reduces noise by expanding the white space. Lastly, in panel (d) we select the largest white rectangle in the text, corresponding to the page itself, and crop the image to this rectangle in panel (e).

3.1.1. Size distortions

Due to the inability to use sheet-feed scanners, most document scanning efforts involve either flatbed scanners or overhead cameras. These often fail to restrict the image to the document itself, and instead produce a scanned image that is too large and also contains part of the scanner bed or the book edge, as shown in Fig. 5(a). For the *Saling's* project, these two extraneous image elements significantly reduced the accuracy of all OCR engines considered in this paper.

To trim the image to correspond to the page itself, we follow a three-part approach that proved quite robust while only requiring minimal tuning, and is illustrated in Fig. 5. This approach exploits the fact that the page itself is in a lighter color than the often-black scanner background and the often-gray book edge. Then, it identifies the largest white rectangle in the image and interprets that this rectangle corresponds to the page itself.

In more detail, the three steps are as follows:

1. Binarize the image, converting it into a black-white version. This is implemented by converting all the pixels lighter than a certain threshold to white color and all others into black. Then we remove the noise in the image. This is implemented by sequentially applying the `erosion` and `dilation` OpenCV image filters available in Python (Kaehler and Bradski, 2016). The output of this step can be seen in Fig. 5(b).
2. Expand the white area to further remove noise and ensure that all margins of the page are white. This is implemented by using the OpenCV *dilate* filter. Its results are seen in Fig. 5(c).
3. Identify the largest white rectangle in the image. For this, we first detect all rectangles with the *findContours* filter, which implements Suzuki et al. (1985). Then, we combine all large rectangles into a single one that in most cases exactly encompasses the page itself.[3] The selected area is shown as a green rectangle in Fig. 5(d), and it is this area that we use to crop the original document into Fig. 5(e).

3.1.2. Geometric distortions

Geometric distortions are a particularly pernicious scanning artifact that OCR engines often fail to solve, although modern OCR engines such as the one powering Google Books do at least partially address them with solutions such as page dewarping (Lefevere and Saric, 2009). These distortions can be classified into two types.

The first, simplest case involves 2D distortions, which occur when the scanner or camera is at an angle relative to a flat page. This is solved by a process known as *2D page dewarping and deskewing*, implemented via OpenCV's *getPerspectiveTransform* filter, which corrects the perspective of the camera as if the document was scanned with the camera directly on top.[4]

The second type of distortion occurs when pages are curved while being scanned, so not only the camera perspective has to be adjusted but the page representation must be rectified to a flat one. Also, as discussed in the next subsection, geometric distortions often lead to scanned pages with non-uniform shadows, as camera lights reflect differently on the paper depending on its curvature. Traditional approaches to flattening curved pages involve exploiting geometric properties of surfaces to model the curvature of a given page (Fu et al., 2007; Tian and Narasimhan, 2011; You et al., 2018). They typically model the entire page as a single object and assume that the curvature of the page is smooth. Although these approaches work well for most curved pages, they are less successful at flattening pages with folds and creases, as the curvature is not smooth at the folds. Moreover, they often fail to adequately remove the shadows caused by the geometric distortions.

Recent approaches address these two limitations via machine learning techniques. *DocProj* by Li et al. (2019) use a convolutional neural network to first identify distortions on segments of a page, instead of the entire page, producing output more robust to folds and creases. The flattened segments are then stitched, and an additional network is used to correct the illumination of the page. *PiecewiseUnwarp* by Das et al. (2021) improve on this work by using an additional network to obtain more robust stitching. Alternatively, *DewarpNet* by Das et al. (2019) exploits the fact that variations in a page illumination are likely to be caused by geometry distortions, and thus jointly models and corrects both types of distortions simultaneously.

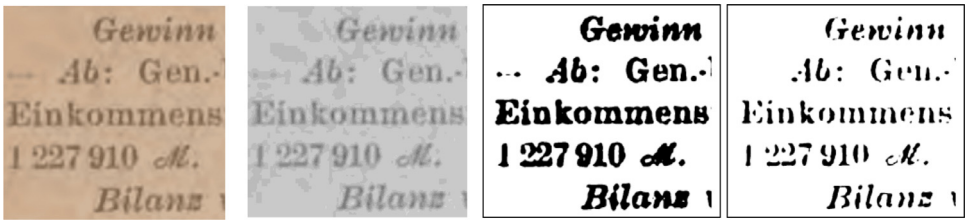
3.1.3. Color distortions

Scanned historical documents often have color distortions caused by the scanning process and age of the document. Backgrounds might be yellow and stained due to foxing. The ink of the text on the reverse page might be bleeding through to the current page. The illumination of the page might not be uniform, due to poor lighting or the curvature of the pages, particularly at the gutter shadows, which connect page edges to the book spine.

To address this issue, the user must first decide the type of the output image, which in most cases is either a grayscale image or a black-and-white monochrome image. On principle, monochrome images are preferable because the underlying document is also monochrome—black for text and white for the background. Further, monochrome images occupy a much smaller size and are faster to upload and process. However, binarization, the process of converting images to black and white, often produces poor results with low-quality scans. This is because forcing each pixel to take binary values eliminates information that both OCR engines and human reviewers might be able to use otherwise to better recognize the images. Thus, the choice of grayscale or monochrome outputs is a practical matter that depends on the characteristics of the documents at hand. Such a phenomenon is illustrated in Fig. 6. Panel (b)

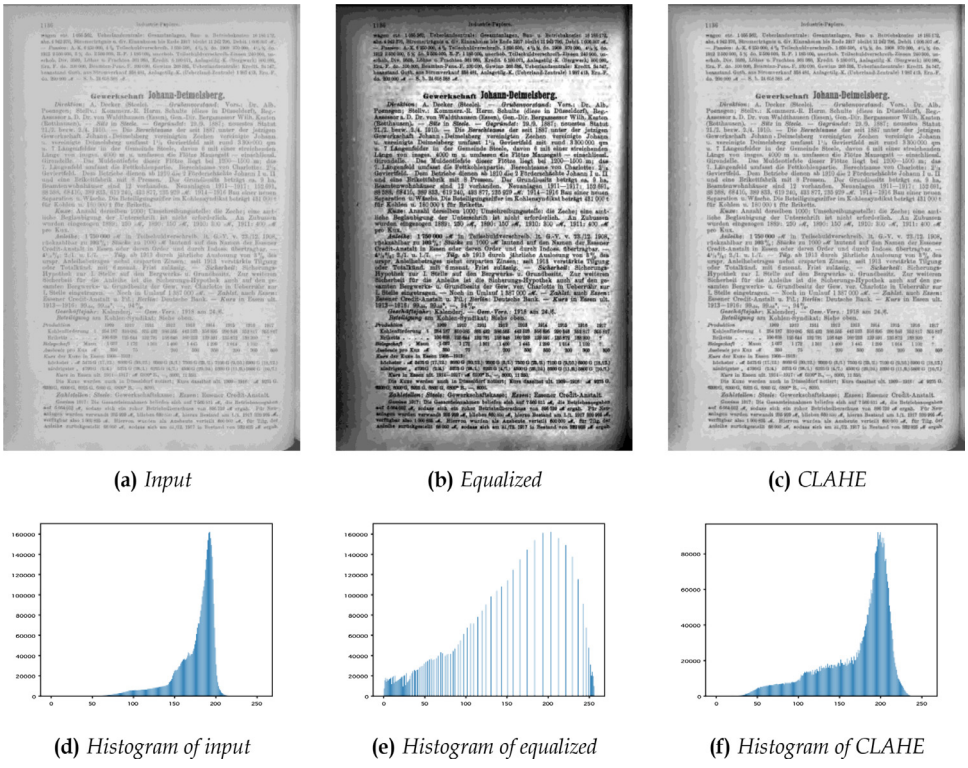
[3] Note that if the resulting rectangle has a proportion too different from that of the initial document, we abort and avoid trimming the image at all. This is done because it is better not to crop an image than to crop too much of it.

[4] An even simpler issue is image rotation, which can be treated as a special case of a 2D perspective transform.



(a) *Input image* **(b)** *Grayscale* **(c)** *Binarized* ($\tau = 160$) **(d)** *Binarized* ($\tau = 140$)

Fig. 6. Grayscale and monochrome conversion of color images. Panel (a) shows a zoomed-in snippet of Fig. 1(b). Panel (b) shows its grayscale version, where all text is still easily readable. Panel (c) shows a binarized version where all pixels with values above 160 are converted to white and all below to black (note: 0 = black and 255 = white). In this panel, most letters are clearer, but some, such as the number "9" or the letter "z" at the end of *Bilanz*, have become harder to distinguish as their font is too thick. Lastly, panel (d) shows how reducing the binarization parameter from 160 to 140 can produce thinner fonts, but at the cost of other values becoming harder to distinguish.



(a) *Input* **(b)** *Equalized* **(c)** *CLAHE*

(d) *Histogram of input* **(e)** *Histogram of equalized* **(f)** *Histogram of CLAHE*

Fig. 7. Improving contrast of grayscale *Saling's* image. Panel (a) contains the input image. Note the poor contrast between the text and the page background, evidenced by the narrow intensity histogram of Panel (d). Panels (b) and (e) show the results of the "image equalization" method, where the intensity histogram is stretched to span the entire black-to-white gamut. This method ignores differences across different parts of the page, which in this case leads to extremely dark areas close to page borders. Lastly, panels (c) and (e) show the result of the CLAHE method, which works locally on different areas of the page, and thus works best in cases such as where different parts of the page had different levels of illumination, as in this example.

shows how converting a snippet of the *Saling's* dataset to grayscale maintains the readability of the text, while panels (c) and (d) show that although binarization improves the clarity of most characters, some become unreadable.

Color corrections with grayscale output

The main methods used to create color-corrected grayscale images revolve around *histogram equalization*. The starting point of these methods is an "intensity histogram" characterizing all the pixels in an image according to their intensity, from black (0) to white (255). If an image has poor contrast, then its intensity will have a narrow distribution which will be reflected in a histogram that is also narrow. This can be seen in panels (a) and (d) of Fig. 7, which shows an image from the *Saling's* dataset exhibiting poor contrast between the page background and the text, as well as its corresponding intensity histogram, which shows most of the figure intensity is located at the 150–200 range.

A simple solution to the lack of contrast in this image involves "stretching" the intensity histogram, so it resembles more that of a uniform distribution. This is achieved through a process known as image equalization, showcased in Fig. 7(b) and (d). There are two common problems with this process. First, because the histogram only takes values from 0 to 255, equalizing the image will create gaps in the support, as evidenced by looking at the large gaps between intensity values in the 100–200 range in Fig. 7(d). Second, the equalization is performed uniformly across the document, so documents that were not perfectly flat and uniformly lit when scanned will have areas darker than others, such as the page margins, leading to distortions in the output. This is made starkly evident in the page margins of Fig. 7(b).

To overcome these issues, we recommend instead implementing an *adaptive* histogram equalization, which creates multiple histograms in different regions of the page. These histograms are stretched locally, allowing these methods to better deal with differences in lighting across the page. In particular, we recommend using the Contrast-Limited Adaptive Histogram Equalization method, or CLAHE (Pizer et al., 1990), which adds further optimizations. For a review of using CLAHE with historical documents, see Koistinen et al. (2017), which evaluates its performance on Finnish historical newspapers.[5]

Color corrections with monochrome output Depending on the quality and characteristics of the scanned documents, binarization might achieve better OCR engine performance than grayscale conversion. Further, other methods discussed in this paper, such as line detection, rely on a monochrome image as its input, so achieving high-quality binarization is an essential part of the digitization pipeline.

Nonetheless, the degradation of the paper and ink in old documents often causes severe challenges that make binarization difficult. For instance, page foxing and ink bleed-through can lead to white regions classified as black after being binarized. These and other challenges are discussed in quite extensive detail in Sulaiman et al. (2019), to which we will defer.

We explore five types of binarization methods, shown in Fig. 8. The first method, illustrated in Fig. 8(b), simply converts all pixels above a predetermined threshold to white and those below to black. However, the choice of this threshold parameter is problematic because it depends on the characteristics of each page, and choosing the wrong threshold will result in an illegible image. For instance, in this example, we chose as the threshold the value 127, the midpoint between 0 and 255. This value appears to be too low, as many font elements have been converted into white regions.

The second method, known as Otsu's binarization, avoids this problem by automatically choosing the threshold that minimizes the intra-class variance of the pixel intensity. However, it performs poorly if the document brightness is not uniform. For instance, curved documents might be darker in the margins. That is in fact what we observe in Fig. 8(c), where we see that, although most of the text was binarized correctly, there are nonetheless black regions in the margins of the page.

To address brightness differences, the next set of methods are known as local or adaptive methods, which compute thresholds at multiple areas of the page, similarly to the adaptive histogram equalization discussed above. In particular, Fig. 8(c) implements a mean-based adaptive binarization, Fig. 8(e) implements the method by Sauvola and Pietikinen (2000), and Fig. 8(f) implements the one by Wolf and Jolion (2004). Across these five methods, we have found the last two to be the most robust across different types of historical documents. This finding is similar to that of Michalak and Okarma (2019), who compare the performance of these and other binarization methods across documents with different font faces, font sizes, and illumination artifacts.[6]

3.1.4. End-to-end methods

Recently, advances in machine learning have allowed for integrated methods that simultaneously correct multiple types of image distortions, often known as *end-to-end* methods in the ML literature. For instance, Feng et al. (2021), implement *DocTr*, a transformer model that simultaneously deskews scanned documents ("geometric unwarping") and removes their shadows ("illumination correction").[7] Similarly, Souibgui et al. (2022) build an auto-encoder transformer model that can address multiple sources of document degradation and recover high-quality images from distorted sources. Beyond transformers, other ML architectures are also able to address multiple types of distortions under a single model. Thus, Souibgui and Kessentini (2022) implement a generative adversarial network (GAN) that can efficiently binarize documents while applying corrections for blurred documents, watermarks, ink blobs, and ink bleed-through.

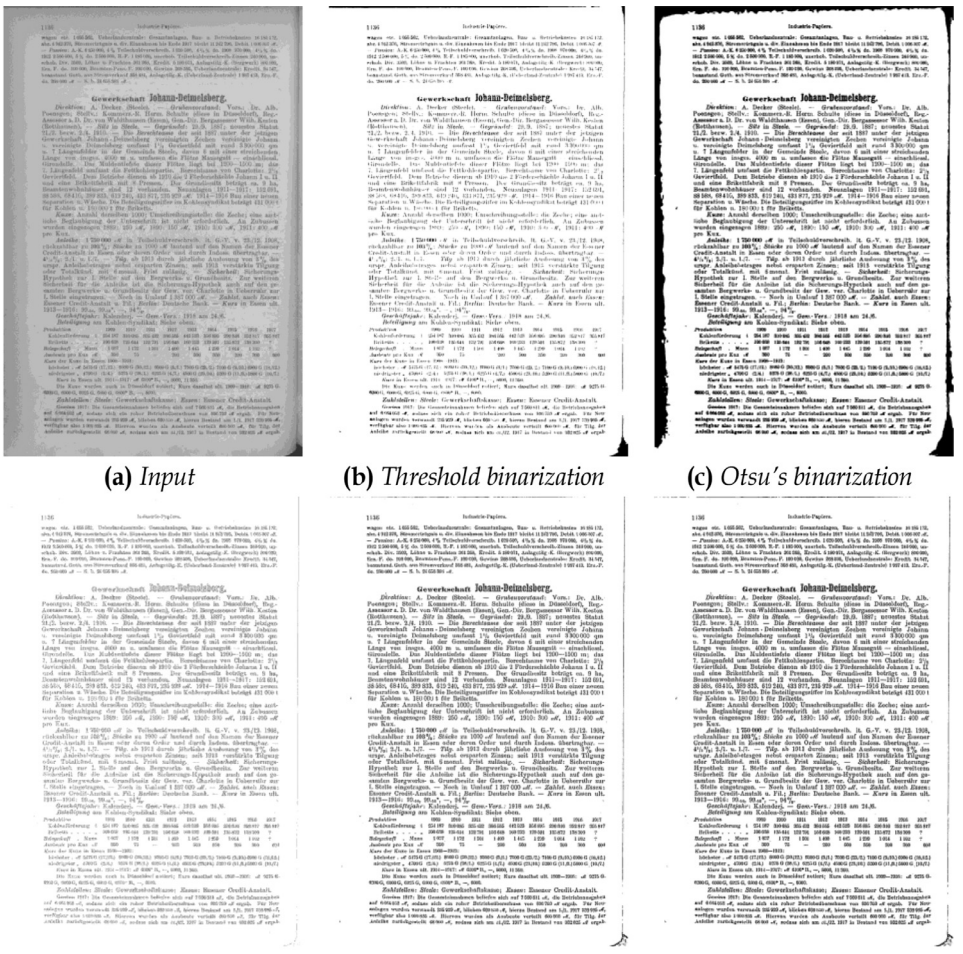
3.2. Optical character recognition

By its nature, OCR is at the core of the entire digitization process. However, most OCR engines act as a black box and offer poor customization, so, for practical purposes, this step is the simplest one for the user; the only key decision is the choice of the OCR engine to use. Although there are a large number of OCR solutions, in this section we will focus on four widely-used OCR engines. The first three are cloud-based commercial products from Google, Amazon, and Microsoft. The last one, Tesseract, is an open-source engine.

[5] Beyond equalization methods, there are other approaches aimed at solving particular the existence of shadows in a document. For instance, Bako et al. (2017) implemented a novel method based on explicitly identifying shades and increasing their brightness.

[6] For a broader comparison of binarization methods, see Pratikakis et al. (2019), who use a standardized benchmark to compare the performance of the 24 methods submitted to the 2019 Competition on Document Image Binarization.

[7] See this Github repository for a Python implementation.



(a) *Input* **(b)** *Threshold binarization* **(c)** *Otsu's binarization*

(d) *Adaptive mean binarization* **(e)** *Sauvola binarization* **(f)** *Wolf binarization*

Fig. 8. Comparison of binarization algorithms. Panel (a) contains the input image. Panels (b) and (c) show global binarization methods, which fail to account for brightness differences across different page regions. Panels (d)–(f) show the performance of three adaptive binarization methods, with methods (e) and (f) leading to the clearest documents.

Table 1
Comparison of OCR engines.

Provider	Product	Coordinates	Confidence	Hierarchy	Lang. hints
Google	Vision AI	Yes	Yes	Symbol, word, paragraph, block	Yes
Amazon	Textract	Yes	Yes	Word, line, table, cell	No
Microsoft	Computer Vision	Yes	Yes	Word, line	No
N/A	Tesseract	Yes	Yes	Word, line, paragraph, block	Yes

As documented by Hegghammer (2022), the commercial engines vastly outperform the open-source engines, particularly with noisy documents likely to be found when working with historical data. Thus, our suggestion for most users is to select a cloud-based solution, which is likely to be both faster[8] and cheaper once the reduced time spent in the human review process is accounted for.

Table 1 compares four of the most widely-used OCR engines. Strikingly, they have mostly converged in terms of their features and the characteristics of the data they return. For instance, for each word all offerings will return its coordinates, its confidence (likelihood of a correct transcription), and even a hierarchy of blocks to which the word belongs.[9] Moreover, because they are very

[8] Cloud providers can parallelize OCR tasks across many servers, while users running their own servers would need to either wait very large amounts of time for large-scale documents or manage digitization tasks across many of their own servers, a costly and cumbersome endeavor.

[9] See also the ALTO and hOCR (Breuel and Kaiserslautern, 2007) standards, which provide XML and HTML representations of digitized material hierarchy and metadata.

similar in terms of their output, `quipucamayoc` has built a wrapper around them so they are relatively interchangeable. This allows users to compare the performance of alternative engines and thus choose those which perform better on their input documents.

Lastly, note that beyond plain text recognition, some of the commercial engines have begun to offer more advanced products, such as table and form detection, as well as recognition of handwritten text. Note, however, that these products are usually trained with modern documents, so they often fail to perform well on historical records.

3.2.1. Ensemble methods

An implicit assumption in the paragraphs above was that users had to choose one and only one OCR engine—the best engine—for this step. This is not necessarily the case; it is possible to combine the output of multiple OCR engines into an *ensemble* that performs better than any one engine by itself.

Ensemble methods go beyond looking at each page and choosing which OCR engine performed better with the page. Instead, they go deeper into the word level and compare the words and numbers produced by the different OCR engines. For instance, suppose we use three engines, which identify a given number as 123, 120, and again 123. If we interpret the engine outputs as votes for a given candidate, then 123 would have received two votes, 120 one vote, and thus the ensemble would have chosen 123 as its output. Moreover, it could also be the case that the true value is 123 but the engines instead identify it as 23, 120, and 153. Here, no single value wins the vote, so we can right-align the values and have the engines vote at the character level, voting among blank, 1, and 1 for the first digit, among 2, 2, and 5 for the second digit, and among 3, 0, and 3 for the third digit. In this case, even though no single OCR engine correctly identified the number 123, the ensemble of the three engines still voted for the correct number.[10]

There are two practical assumptions behind the use of ensemble methods on OCR engines, without which ensembles are unlikely to provide an advantage over single-engine approaches:

1. The OCR engines are good enough to correctly identify the words, even though they fail to identify all their characters. If some engines completely fail to identify a piece of text, the accuracy of the method becomes limited as fewer engines would be voting on the results.
2. The errors made by the OCR engines are idiosyncratic. Otherwise, if all errors are systematic and common across all engines, there would be no advantage to using more than a single one. From experience, this seems to be the case, perhaps due to each product using different training datasets, ML models, or even different tuning parameters within the same model.[11]

More in-depth discussions of ensemble methods are contained in Lund (2014) and in Section 3.2.1 of Nguyen et al. (2021). Further, an illustrative Stata implementation is available online here.

3.3. Layout recognition

The main purpose of the layout recognition step is to help researchers assign a given word or number to specific categories or groups. For instance, in a two-column table, identifying the location of the line delimiting the columns would allow users to identify to which column each word belongs. In the case of our examples, we rely mostly on two types of layout recognition methods; one focusing on detecting lines that delimit columns and rows and another focusing on detecting the empty spaces that surround different sections of the text.

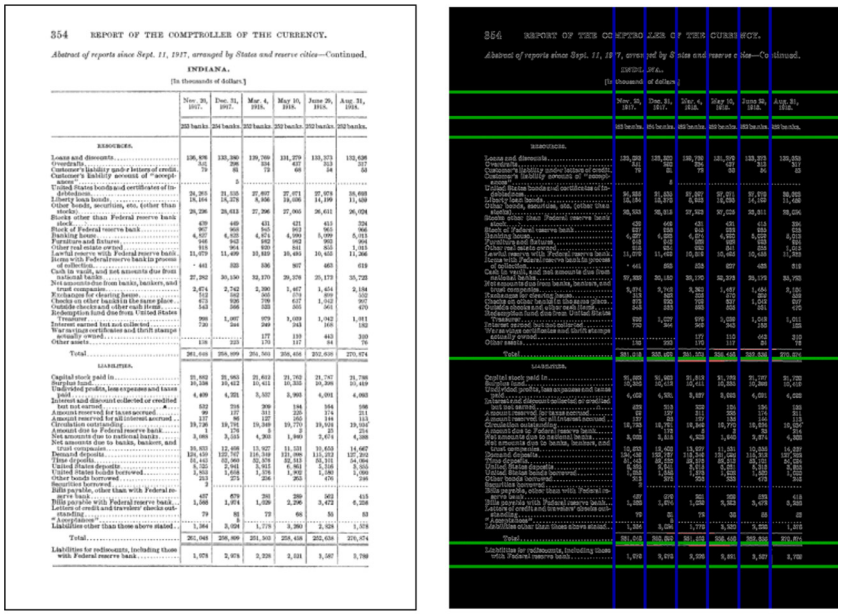
We illustrate the first method with the OCC dataset, where we identify the boundaries of the three tables present on every page in order to assign the recognized pieces of data to the correct balance sheet. As illustrated in Fig. 9, this method has three steps. We first apply a Canny Edge Detector (Canny, 1986) to identify boundaries between regions or objects. Then, we apply a probabilistic Hough transform (Hough, 1959; Kiryati et al., 1991) to the pixels highlighted as boundary regions and identify possible lines in the text. Lastly, we apply a custom algorithm to reduce the number of lines and avoid false positives, and we end up with the lines identified in Fig. 9(a). With this information and the coordinates of each word produced by the OCR engines, we are thus able to assign each word to a given column of a table.

The second method is illustrated with the *Saling's* dataset. Here, the goal is to detect individual paragraphs, which in turn might correspond to separate balance sheets and income tables, as well as headers that indicate when the information for a specific firm starts. For paragraphs, they are already pre-identified by the OCR engine, so there is no need to implement a custom algorithm. For titles, they can be easily identified by the coordinates of the lines (which can tell if a line is centered), by the font size of each word, and by the empty space above and below each line.

Beyond the two examples outlined above, recent advances in neural networks have led to an almost exponential growth in the document layout analysis literature. While these models have some disadvantages, such as a large size due to parameters in the order of millions or billions, they work well enough for a wide variety of layouts without requiring ad-hoc tuning. Some of the most widely-used models include *EDD* by Zhong et al. (2020), an attention-based encoder-dual-decoder network that accurately converts table images into tabular representations, and *LGPMA* by Qiao et al. (2021), a deep network aimed at segmenting complex

[10] All major engines provide confidence estimates on the quality of each element of a page. These confidences can be used to provide word- or character-specific weights to each vote to further improve the accuracy of the ensemble.

[11] Book aging, as well as the scanning process, provides another source of idiosyncratic errors that can be exploited by ensemble methods. In particular, the artifacts present in old books, such as discoloration or ink blobs, are often uncorrelated across different digital versions of the book. This is particularly useful with large digital libraries, such as Google Books and HathiTrust, which often provide multiple digital versions of a given book, obtained from different libraries and scanned independently.



(a) *Preprocessed image* **(b)** *Image edges and detected lines*

Fig. 9. Detecting table delimiters on OCC balance sheets. We combine two computer vision techniques to identify the lines that separate the different sections of a table. First, we apply a Canny edge detector to identify discontinuities in the brightness of the page. Then, we apply a probabilistic Hough transform to identify likely lines within the text. From this set, we extract horizontal lines (green) which detect table sections and vertical lines (blue) which detect column delimiters. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

tables by using both local information about segments of a table likely to be table cells, and global information about the overall table layout. Similarly, *CascadeTabNet* by Prasad et al. (2020) implement a convolutional neural network model that simultaneously detects tables in documents and identifies their layout. However, as emphasized by Shen et al. (2021), note that these models are usually pre-trained on modern document datasets, so their performance on historical documents—which often used obsolete fonts and design conventions such as drop caps—might not be as good. For a comprehensive review of the performance of different machine learning and deep neural network approaches to this topic, including discussions on benchmarks and publicly available datasets, see Hashmi et al. (2021).

3.4. Data extraction and validation

An additional aspect of data digitization is that even if one were able to perfectly digitize scanned data, the obtained representation most likely would not correspond to the one required to conduct a statistical analysis. For instance, the *Saling's* balance sheets are contained within paragraphs, so we need to identify which words correspond to balance sheet items, which correspond to values, and which correspond to notes or other extraneous information. A string such as *"A.-K. 7 300 000, 4% Anleihe 600 096 4 1/2% do. 7 795200"* would need to first be unabbreviated (*A.-K.* into *Aktienkapital*), interpreted according to the context (*do.* indicating a repeat of the previous label, i.e. *Anleihe*), and matched to a consistent category (so both *Anleihe* items would be assigned into the *Long-term debt* liability category).

More generally, the words and numbers recognized by the OCR step need to be mapped into key-value pairs that will then be assigned to specific cells in the final datasets. Except for very simple cases, practitioners will inevitably have to rely on some programming to assign or reshape the data to their needs. We believe that Python is an ideal language for this step, as its accessible, widely known, and comes with top-of-the-line libraries.

Given that practitioners are thus likely to be using a programming language for the data transformation step, one might as well use this step to reduce error rates and more generally correct mistakes caused by the scanning and OCR processes. Otherwise, they would have to be corrected manually, which is particularly costly and slow. Below we describe two types of improvements that we have used in the OCC and *Saling's* digitization efforts, and which we believe might be generally useful for practitioners.[12]

[12] A novel field, known as visually-rich Document Understanding (VrDU), combines the layout recognition and data extraction steps, directly producing information from scanned structured documents, such as forms or receipts. For instance, *LayoutLMv2* by Xu et al. (2020) is a multimodal transformer model that combines textual, layout, and image information to extract data from scanned documents, such as entities or names. Note

3.4.1. Correction of words and numbers

There are often restrictions on the possible values that each key or value can have. For instance, numbers representing dollar values cannot contain letters. Thus, if the letter "O" was found between two digits ("1O9"), it would be prudent to replace it with the number zero. Similar patterns apply to other letters, so "1GB" could be replaced with "168." Note, however, that there is a cost to these replacements in that they might introduce false positives, so users should avoid being too aggressive with them and always try to benchmark how the addition of each replacement affects the quality of the final dataset.

Labels often only take a small set of possible values. For instance, in most years, the OCC balance sheets contained only a few dozen possible asset and liability categories. Similarly, the city where each bank was located—written at the top of each table—could be validated against the list of all existing and ghost towns in the US maintained by the U.S. Geological Survey. As a last resort, one could validate a free-form word against the set of valid words in a given language—its dictionary—to assert whether the word is valid or not.

Once a word has been diagnosed as invalid, it can be fixed by applying a spellchecker to it. For instance, Peter Norvig's famous spellchecker (see Jurafsky and Martin, 2009; Kemighan et al., 1990) can be easily implemented in a few lines of code as long as there is a dictionary with the list of all valid values.

The improvements we have discussed are mostly specific to our specific datasets, but can be expanded into more general approaches. Schulz and Kuhn (2017) propose an automatic post-OCR correction process that works in two stages. First, independent modules propose corrections to the OCR output. These corrections can be at the word level, such as spell checkers and word splitters, at the sentence or word pair level, such as word mergers, and even at the text level, where probabilistic spellcheckers suggest corrections based on the internal frequency of words within the text. In the second stage, a decision model chooses the most likely correction among the proposed candidates.

Some approaches combine this step with ensemble methods discussed earlier, particularly for OCR engines also produce confidence estimates of their result. An example of such an approach is Boschetti et al. (2009), who implement an ensemble through a technique called "progressive multiple alignment," where OCR output from multiple engines are aligned, and then the most likely character across the aligned datasets is chosen. This is then followed by a spellchecker based on a naive Bayes classifier, or with a regular expression in case the spellchecker fails to find a match.

For a broader discussion of the post-OCR processing problem, see Nguyen et al. (2021), who provide an in-depth discussion of the post-OCR processing problem, illustrate typical pipelines, and compare several existing approaches, ranging from manual approaches such as ReCAPTCHA to state-of-the-art neural network language models. For a survey tailored towards historical texts, see Bollmann (2019) does, who surveys the particular difficulties of normalizing historical documents, where for instance word spellings change as time passes (e.g. "their" was once "theyr", "thar", or "per"). The paper then compares solutions involving rule-based methods, statistical models, and neural network approaches. Interestingly, and in contrast to other steps where neural networks have proven substantially more effective, the author finds that statistical models and even rule-based methods might have similar performance, which makes them preferred given the high computing costs required by deep neural networks, particularly at the training stage.

3.4.2. Correction of document hierarchy

As discussed in the previous subsection, most OCR engines provide incredibly useful information on the hierarchy to which each word belongs—its line and paragraph. However, in the same way as words might be misrecognized, this hierarchy can also be detected incorrectly. This is illustrated in Fig. 10. There, Fig. 10(a) shows all the words and paragraphs identified by Google's Vision AI. Because the page represents a table, the paragraphs are not recognized correctly although the words are.

To solve this, the first step, shown in Fig. 10(b), involves grouping words together into lines, which will represent the balance sheet labels. For this, we simply pair up words in the same column as long as they have enough overlap in the y-axis. However, several labels are long enough to overflow the column width and thus occupy multiple labels. To solve this, we exploit the fact that the second line in each label is always indented, which allows us to arrive at the corrected output in Fig. 10(c).

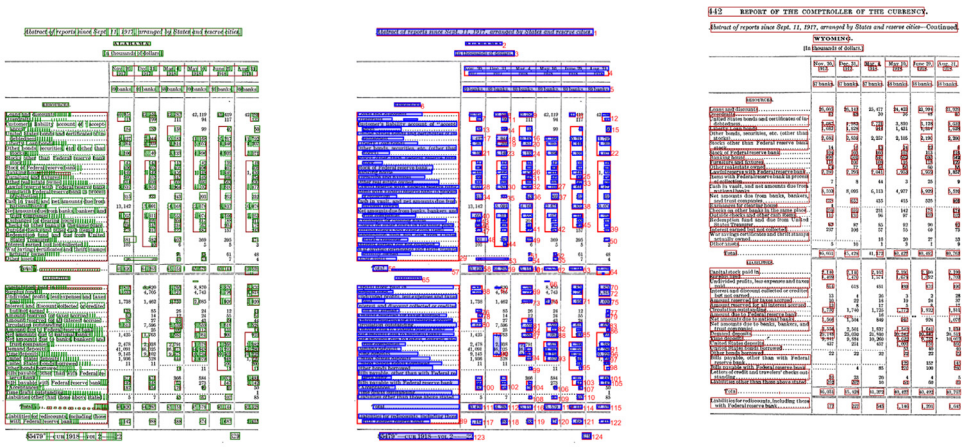
3.4.3. Data invariants and sanity checks

Another important way of improving the digitization process is to flag potential errors, which can be then reviewed and corrected by hand. Without such flags, even a detailed human reviewer may overlook potentially problematic mistakes in the data.

This is particularly important for panel balance sheet data, which has two particular properties. First, errors are very costly in such datasets. For instance, suppose a bank has stable total assets of $100, but in one year there is a typo that adds one zero at the end, so the reported value of total assets becomes $1000 for that year. This mistake would lead to an incorrect 1000% increase in total assets in the year where it occurs, plus another incorrect value of the subsequent year, where total assets would be reported to fall by 90%. Second, balance sheets have several constraints or invariants that we could exploit to validate the quality of the data. For instance, the balance sheet identity must hold, so the sum of total assets must equal the "total assets" label, which in turn must equal the "total liabilities and equity" label.

To increase confidence in the quality of the digitized data and to help guide human reviewers, the practitioner must identify as many constraints as possible and incorporate them into the code. For instance, the following are some of the constraints we implemented for the OCC digitization project:

however that these models might not be as practical for historical data extraction; for instance, the list of entities used to train the models might be vastly different than those in historical records.



(a) *OCR-recognized "words"* **(b)** *Lines identified by* `quipucamayoc` **(c)** *Combined lines (correct)*

Fig. 10. Identifying balance sheet labels. To correctly identify rows—and thus balance sheet items—of each table, we apply a three-part process. First, we identify the *words* recognized by an OCR engine such as Google Vision AI. Second, we concatenate words based on their relative horizontal distance. Lastly, we concatenate lines based on their indenting and vertical distance and are thus able to correctly identify row labels.

1. Accounting identity. The sum of all assets must equal the label "total assets"; the sum of all liability and equity labels must equal the label "total liabilities and equity"; the two total fields must be equal to each other.
2. Reserve requirements, bond-holding requirements, and minimum-capital requirements. Whenever such a constraint is violated, the page can be automatically flagged for human review.
3. Constraints across time. It was difficult to change the amount of certified bank capital during the National Banking Era. Hence, a change across time for the same bank can be flagged and reviewed.
4. Label and numeric constraints. Balance sheet labels that are not part of the valid label list, as well as invalid numeric fields, are automatically flagged. For instance, the number "0123" is always flagged because dollar values do not have a leading zero digit.
5. Unique identifiers. Bank charter numbers should uniquely identify banks across time, so a manual review was prompted if they were either missing or duplicated in a given year.

Altogether, these constraints allow us to flag the most prominent errors in the dataset, which then in turn releases more time for a more careful inspection of the documents afterward.

3.5. Human review

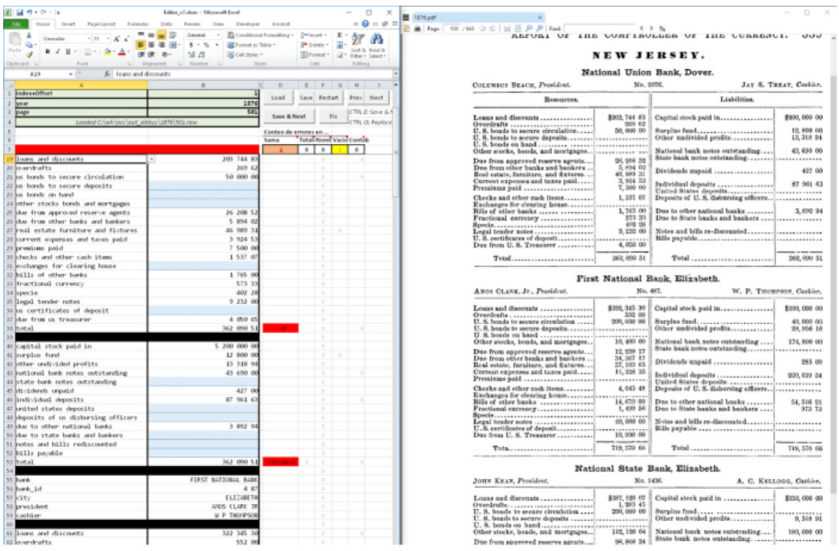
In large-scale digitization projects, the human review step needs special consideration as this is often the most expensive and time-consuming part. In general, user productivity increases with well-designed interfaces, that are comprehensible, predictable, and controllable (Shneiderman et al., 2016). For our goals, we have found that the most important thing is to ensure human reviewers are *on task* for as much time as possible. Any interruptions of the workflow such as having to save corrected files, load and scroll through PDFs, or manually *alt-tab* to review the list of pages pending review will slow down the reviewers beyond just the amount of time used by those interruptions.

Instead, we find that automating the human review process as much as possible increases the attention available to reviewers, leading to faster reviews with fewer errors. In terms of software, for both the OCC and *Saling's* project, we rely on an Excel workbook containing VBA functions automating steps previously done manually by users. We have also used a browser-based solution in an ongoing project digitizing data from St. Louis Fed's FRASER archives. While the Excel approach worked quite well for the authors, the browser solution worked better when delegating review tasks to others, as it reduced setup costs as well as the sharing of input pages and corresponding corrections. Fig. 11 shows screenshots of both of these tools.

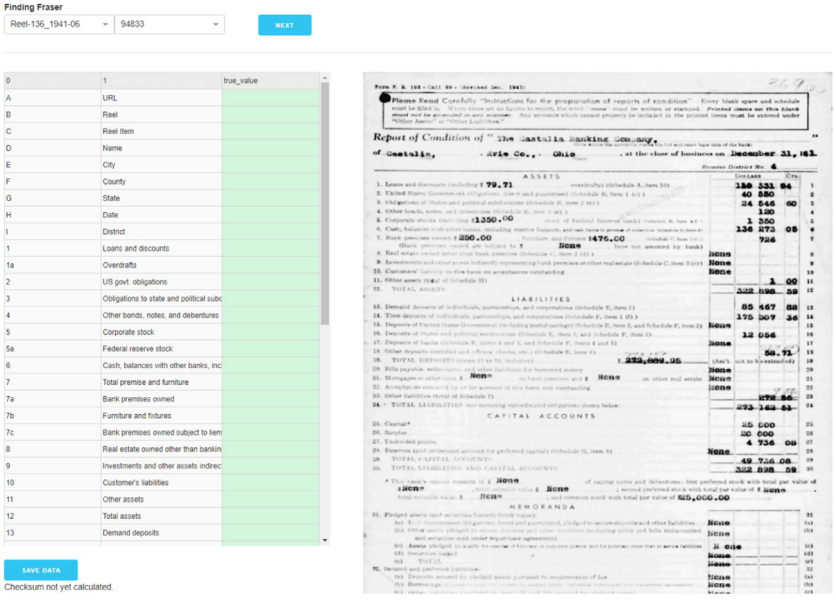
Based on our experiences, below we list some of the steps where we found automating was invaluable:

1. Show data and scanned images side-by-side. Whenever the reviewer loads a new page or table, the corresponding image should be automatically loaded as well.
2. Add shortcuts as much as possible, for loading and saving CSV files, navigating the list of pages that need to be reviewed, etc.
3. Flagging likely errors in red or yellow colors, so the reviewer can monitor those items more closely.
4. Automatically keeping track of the balance sheet identity, so the reviewer can know when errors are remaining.

Once we automated these steps, we found a substantial increase in review speed, leading to a larger amount of ground-truth data, which in turn can be utilized to improve the overall digitization pipeline, as discussed below.



(a) *OCC Dataset*



(b) *FRASER Dataset*

Fig. 11. Interfaces for human review of transcription output. Panel (a) shows a screenshot of the program used to validate the OCC and *Saling's* dataset. It consists of an Excel workbook powered by a set of VBA functions that load and save the data, and display the corresponding images. Panel (b) shows a screenshot of an ongoing program used to validate St. Louis Fed's FRASER archives. It is a self-contained website powered by Python Dash.

3.5.1. Parameter tuning

Parameter tuning—or more appropriately, hyper-parameter tuning, as it is known in the machine learning community—is a method for selecting the optimal values for the parameters employed throughout the digitization process. It involves using ground truth data, known to be correct, to create a measure of the overall quality of the digitization process, and then "tuning the parameters" to maximize the value of this measure.

At its simplest, this tuning could be done manually. That is what we do in Fig. 12, where we implemented a grid search to select the optimal binarization threshold of the fore-edge removal step (Fig. 5).

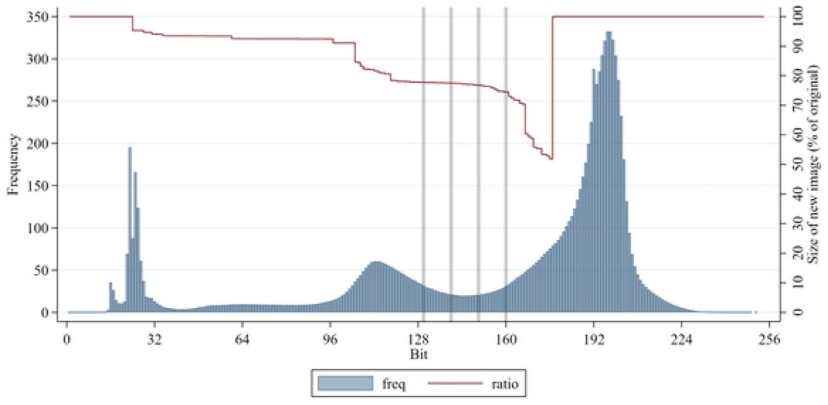


Fig. 12. Fine-tuning pre-processing parameters. This figure shows how the binarization parameter used in Fig. 5(b) affects the performance of the trimming step shown in Fig. 5(a). The histogram in blue shows the distribution of all points in a scanned page, from 0 (black) to 255 (white). The three modes of the histogram correspond to the black background and fonts, the dark gray book edge, and the light gray page background. The red line shows how changing the binarization parameter affects how much of the page is trimmed. Choosing a number between 128 and 160 will correctly separate the page background from the book edges, so the edges can be removed without trimming down the actual page contents. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

```
import quipucamayoc as q          # Import package
doc = q.Document('myfile.pdf')    # Validate that the file is accessible
doc.describe()                    # Display number of pages, metadata, etc.
doc.extract_images()              # Extract all pages of the PDF as images
```

Listing 1. Starting up.

For more advanced uses, grid search can be replaced by more efficient methods such as gradient descent. Moreover, if we expect to perform large amounts of automatic parameter tuning, we also advise users to set aside part of the ground truth data so it can be used for cross-validation, which helps to prevent overfitting the algorithms to set of ground truth data already collected.

4. Software implementation

This section describes the main functionality of the `quipucamayoc` Python package (Correia and Luck, 2022). The goal of this package is to make the methods discussed in Section 3 accessible to researchers and lower the bar for future efforts to digitize structured historical data.

Why quipucamayoc We have found that to make OCR algorithms truly accessible to researchers and practitioners it is not enough to just provide a code implementation of the algorithms themselves. There are significant barriers to using these tools, such as difficult installation processes and lack of compatibility with other OCR tools that researchers might be using already. Thus, we built `quipucamayoc` with two principles in mind:

1. Batteries included. Providing a method that e.g., "removes fore edges from a page" is not particularly useful for a researcher that has no easy way of extracting images from PDFs or passing modified images to OCR engines for further processing. Thus, the first goal of this package is to provide all the tools required for a complete OCR pipeline, so users can get started easily.
2. Modular. For best performance on large datasets, users will likely want to extend the methods provided by `quipucamayoc` or integrate them with other algorithms available in the Python ecosystem. To facilitate this integration and extensibility, `quipucamayoc` is built in a modular way, so the different parts can be modified and extended independently of each other and connected with other machine learning or computer vision Python packages.

Getting started

The package is available on the Python Package Index (PyPI), so it can be installed on the command line via *pip install quipucamayoc*. This step also loads several other packages for numerical analysis, image processing, cloud OCR integration, etc.

The main object in this package is the *Document* class, which encapsulates all pre-processing, OCR, and post-processing tools. It allows for two types of inputs: PDF documents and folders with sequentially numbered images, each representing a page in a scanned document. For instance, when working with a PDF file, a common first step would be (Listings 1 and 2):

Once the images are extracted, each image can be manipulated individually:

```
page = doc.pages[0]  # Select a page to process
page.load()          # Load image from disk into memory
page.view()          # Display current version of the image on screen
```

Listing 2. Working with pages.

```
for page in doc.pages:
    page.load()
    page.remove_black_background()          # Crop black background
    page.remove_fore_edges()                # Remove book fore-edges
    page.dewarp(method='simple')            # Dewarp and deskew image
    page.convert_to_grayscale()             # Convert image to grayscale
    page.equalize(method='clahe')           # Improve contrast with CLAHE
    page.binarize(method='sauvola')         # Apply Sauvola's binarization
    page.save()                             # Save page into disk
    page.unload()                           # Optional; reduces memory use
```

Listing 3. Image processing.

```
page.detect_lines(columns=5, save_annotated_image=True)
page.lines.view() # View image with overlaid lines
```

Listing 4. Layout recognition.

```
# Document-level OCR
doc.run_ocr(engine='google')

# Page-level OCR
page.run_ocr(engine='google')     # Synonyms: gcv, visionai
page.run_ocr(engine='aws')        # Synonyms: amazon, textract
page.run_ocr(engine='microsoft')  # Synonyms: azure
page.run_ocr(engine='tesseract')

# What OCR engines have been applied to a given page?
print(page.engines)
```

Listing 5. OCR.

Image processing

This step is implemented as a set of methods that can be iteratively applied to all pages, as shown in Listing 3. These methods are, for the most part, based on the OpenCV and scikit-image libraries, and are thus computationally efficient (Listing 4).

Layout recognition

Similarly, layout recognition methods are also available at the page level:

OCR

```
# Amazon's OCR engine involves a difficult initial setup that we automate
quipucamayoc.install_aws()

page.run_ocr(engine='aws', extract_tables=True)
```

Listing 6. Table extraction.

```
s = quipucamayoc.load_spellchecker(filename='frequencies.csv')  # Load a
    spellchecker based on a list of valid words
process_data(page, spellchecker=s)  # "process_data" is a user-created function

# Internals are accessible:
page.ocr['aws'].tables[0][0][0]  # View cell A1 of the first table of the page
page.ocr['google'].paragraphs[0]  # View first paragraph of the page
```

Listing 7. Data extraction and validation.

```
$ quipu install aws
(installing quipucamayoc pipeline for aws/textract)
$ quipu extract-tables myfile.pdf
(uploading file)
(waiting for OCR completion)
(downloading output)
(3 CSV files generated and placed on the ./myfile/ folder)
```

Listing 8. Command-line usage.

OCR is available using multiple OCR engines, at both the document and the page level. As shown in Listing 5, these OCR engines are as interchangeable as possible, which allow users to select the engines that work best for their data at hand:

For PDF documents with no pre-processing, the OCR step is available at the document level, while for documents where images have already been extracted and processed, OCR can be applied at the page level:

Further, some OCR engines are also able to extract additional elements such as tables and forms:

Because the target market for the OCR offerings of the commercial cloud providers is certainly not researchers but instead large corporations with dedicated IT *divisions*, setting up these providers to interact with `quipucamayoc` is a complex task. For example, substep 4 of step 6 of the instructions for Amazon's Textract requires carefully giving "IAM users or AWS accounts the appropriate permissions to publish to the Amazon SNS topic and read messages from the Amazon SQS queue." Because knowing the nuances of these steps is of no particular value for economic historians, we have implemented functions that programmatically link `quipucamayoc` with OCR engines. For instance, the *install_aws()* function encapsulates all the steps required to setup Amazon's Textract on a given AWS account and on a given `quipucamayoc` installation (Listings 6–8).

Data extraction and validation

This is the most customizable and user-dependent step, as it involves rearranging the extracted characters or tables into a meaningful dataset, which often requires expert knowledge of the researcher. For instance, a user might write a *process_page()* function that takes as input a given page, with all its associated information (recognized text, tables, etc.) and use it to output a CSV file with validated information:

Command-line tools

Some of the methods provided by `quipucamayoc` are available as command-line tools. This allows practitioners to use these methods and obtain OCR results without needing to write python scripts. This makes this package more practical for small-scale projects, where the researcher might want to run OCR to get to a starting point from which she will correct and validate data by hand:

Future development

`quipucamayoc` is an actively maintained and developed package, and as such, is open to improvements from both the authors as well as future users of the package. We believe potential users will benefit from the existing tools and "batteries included" design; and for large-scale projects, we encourage them to extend the set of pre- and post-processing tools to improve the quality of their output.

5. Summary

Archives and libraries have vast amounts of structured historical data of high value to economic historians, such as balance sheets, logs and records, price lists, and so on. For the most part, these datasets are considered either too expensive or too difficult to digitize for researchers without access to large funds or arrays of research assistants. In this paper, we propose that this is not the case anymore and that even large-scale datasets can be accurately digitized with only modest resources and limited programming knowledge. Although there is no one-size-fits-all solution, we argue for leveraging well-established and battle-tested tools, such as OpenCV and cloud-based OCR software, to construct digitization pipelines that can be tailored to the data sources at hand while requiring the least amount of customized ad-hoc code.

For large-scale datasets, we suggest that researchers' time is more valuable when applied to the elements specific to their datasets, instead of focusing on directly managing the OCR tools and the scaffolding connecting the different parts of the OCR pipeline. By avoiding the more repetitive and cumbersome aspects of the OCR aspects, researchers are more able to devote resources to developing metrics for identifying errors in the data, either by constructing ground truths via human reviews or by exploiting characteristics of the data at hand. In the case of balance sheet records, we can exploit accounting identities to allow for straightforward error detection. In contrast, security price data may be less well suited, as they contain fewer constraints that we can validate against. Moreover, accuracy metrics allow researchers to easily test and tune the different components of the digitization pipeline, so instead of being relegated to the latter stages of the digitization, they can be used from the beginning to build a more accurate pipeline.

Lastly, although the pipeline discussed in this paper can be quite complex depending on the scale and difficulty of the digitization task, we believe that for most use cases even simple pipelines would perform quite accurately while maintaining only very minor programming requirements. Indeed, we recommend starting with simpler pipelines even for large projects, and only adding complexity as needed, which maximizes the likelihood of successful digitization efforts and helps to avoid premature optimization problems.

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