Dataset of Pages from Early Printed Books with Multiple Font Groups

Mathias Seuret*
Pattern Recognition Lab,
Friedrich-Alexander-Universität
Erlangen-Nürnberg
Erlangen, Germany
mathias.seuret@fau.de

Saskia Limbach*
Gutenberg-Institut für
Weltliteratur und schriftorientierte
Medien Abteilung
Buchwissenschaft
Mainz, Germany
limbach@uni-mainz.de

Nikolaus Weichselbaumer*
Gutenberg-Institut für
Weltliteratur und schriftorientierte
Medien Abteilung
Buchwissenschaft
Mainz, Germany
weichsel@uni-mainz.de

Andreas Maier
Pattern Recognition Lab,
Friedrich-Alexander-Universität
Erlangen-Nürnberg
Erlangen, Germany
andreas.maier@fau.de

Vincent Christlein
Pattern Recognition Lab,
Friedrich-Alexander-Universität
Erlangen-Nürnberg
Erlangen, Germany
vincent.christlein@fau.de

ABSTRACT

Based on contemporary scripts, early printers developed a large variety of different fonts. While fonts may slightly differ from one printer to another, they can be divided into font groups, such as Textura, Antiqua, or Fraktur. The recognition of font groups is important for computer scientists to select adequate OCR models, and of high interest to humanities scholars studying early printed books and the history of fonts. In this paper, we introduce a new, public dataset for the recognition of font groups in early printed books, and evaluate several state-of-the-art CNNs for the font group recognition task. The dataset consists of more than 35 600 page images, each page showing up to five different font groups, of which ten are considered in this dataset.

CCS CONCEPTS

• **Information systems** → **Clustering and classification**; *Document filtering*; *Presentation of retrieval results*; • **Computing methodologies** → **Information extraction**; **Computer vision**; **Neural networks**.

KEYWORDS

dataset, neural network, digital humanities, historical documents, document analysis, incunabula, book history, type, typography, fonts, Antiqua, Italic, Textura, Rotunda, Gotico-Antiqua, Bastarda, Schwabacher, Fraktur, Greek, Hebrew

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1 INTRODUCTION

The dataset presented in this paper[1] is meant to aid the automatic recognition of font groups in scans of early modern[2] books (see Sec. 3). The primary purpose is to train and apply font-specific OCR-models in order to improve the quality of OCR for historical documents that currently suffers greatly from the almost unmanageable variance of early modern fonts.[3] Training font group detection methods requires a lot of data, and the dataset presented in this paper is, to the authors' knowledge, the very first for early modern font groups.

Automatic font group recognition also helps historians by enabling them to analyse how font groups were used over time and how other factors like genre, language and printing place played a role in this development. This will help to answer long-standing research questions about phenomena like the rapid establishment of Fraktur as the font for German texts from the 16$^{\text{th}}$ century onwards.

2 EXISTING DATASETS

As for modern fonts, there are some datasets available, such as the Adobe VFR Dataset [19], and it is also possible to generate images on the fly. However, for early modern printed documents, there is, to our best knowledge, no font group dataset comparable to ours. The most related is the one used

*Equal contribution
[1]https://doi.org/10.5281/zenodo.3366685
[2]From the middle of the 15$^{\text{th}}$ century to the end of the 18$^{\text{th}}$ century.
[3]For more information about this approach see http://ocr-d.de.

for the ICFHR'16 and ICDAR'17 competitions in the classification of Latin medieval manuscripts (CLAMM) [2, 3] – script type classification is an important aspect of paleographic research [9, 17, 18], and has recently gained more attention. The CLAMM dataset consists of 5 500 images containing handwritten text, labeled with 12 different scripts.

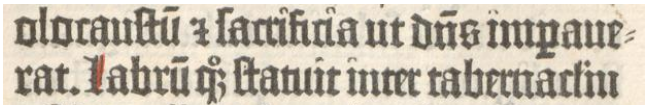
3 FONT GROUPS

"Type is something you can pick up and hold in your hand" [1, p. 5]. A piece of type is a rectangular block of metal that bears the raised, mirrored image of a glyph. Type can be arranged into lines, columns and printing forms. It is the fundamental building block of typography. The metal type of the hand-press period from Gutenberg to about 1820 is made by cutting and hardening a steel punch, driving it into a piece of copper, which is then cleaned and filed down to the final width of the type. This so-called matrix is inserted into a hand mould and used for type casting.

Type cast from the same matrices can usually not be distinguished from one another. In contrast, fonts (sharing the same punches but different matrices) may vary in spacing or alignment. There are thousands of these structurally and stylistically similar fonts which historians can divide into font groups.

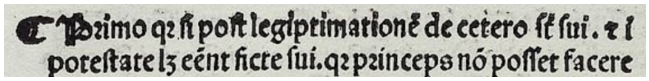
Most font groups appear in the first decades of print, with only Italic and Fraktur being introduced in the early 16$^{\text{th}}$ century. The first fundamentally new font group in the Latin West was sans serif fonts in the 19$^{\text{th}}$ century. Until then, new fonts rarely developed outside the stylistic boundaries of established font groups. In order to keep the font readable and recognizable, any changes were fairly subtle and concern aspects like the shape of single characters, their relative dimensions, the stroke width contrast, or the design of serifs. In early modern books, font groups are regularly mixed to emphasise words, lines or abstracts, such as with Italic lines in a Schwabacher text. The mix also occurs to emphasise other languages. Thus, a German text from the 17$^{\text{th}}$ century is usually printed in Fraktur, with words derived from Latin printed in Antiqua, the font group most often used for this ancient language.

3.1 Textura



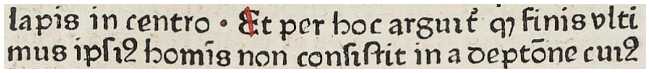
Textura fonts are based on Gothic "textualis" scripts, which were the dominant form in late medieval manuscripts in England, France, Germany and the Low countries from the 12$^{\text{th}}$ century onwards. The letters are tall and narrow and have short ascenders and descenders. Bows are "broken" into straight, angled lines. Characters with bows that face one another like "be", "po" etc., form a ligature where the bows overlap (a phenomenon called "biting"). Minims (short vertical strokes) often do not or barely connect, which makes it difficult to differentiate the letters i, n, u and m. These features serve the aesthetic ideal of making a page of text even and regular. In the 15$^{\text{th}}$ century, Gothic script reached its most extreme form in "textus quadratus", a perfectly even and stylized form that was commonly used, i. e., for liturgical texts [4]. Johannes Gutenberg used this style when he developed his first fonts. The square and very upright shapes were ideal for printing; yet it proved difficult to produce the many ligatures and abbreviations. By the beginning of the 16$^{\text{th}}$ century, Textura was mostly replaced and remained in use just as a headline font [11, p. 37–64]. We also chose to classify Dutch and English "old style" Blackletter as Textura, as they are closer in appearance to it than to any other font group.

3.2 Rotunda



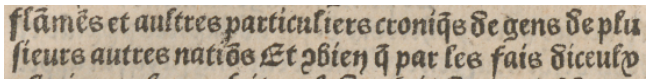
Rotunda emerged as a script in Italy in the 12$^{\text{th}}$ century, where it served the role that Textura had north of the Alps. It is a gothic font and shares the "biting"-phenomenon of Textura, but shows hardly any broken bows. In general Rotunda is wider and rounder. It was adopted into a font in the 1460s and made popular by the interpretation of Nicolas Jenson in Venice whose "litterae venetae" were imitated all over Europe. Rotunda was a very widely used in the 15$^{\text{th}}$ and early 16$^{\text{th}}$ century, after which it was replaced mainly by Antiqua (Sec. 3.7). In Italian liturgical books, Rotunda remained in use until the early 17$^{\text{th}}$ century [14, pp. 262–266][16, pp. 229–232].

3.3 Gotico-Antiqua



Gotico-Antiqua is an in-between phenomenon. In this font group we find features from Rotunda and Antiqua. Lower-case b, f, h, k, l and f have longer ascenders than in Rotunda, the g has a double-belly-shape, but the r-rotunda and the uncial d still come from Rotunda [11, p. 181]. Upper-case characters range from pure Rotunda to Antiqua. It was however not designed as a hybrid of existing font groups, but was adopted from a manuscript template, called "fere humanistica", a script that developed out of the desire of Italian humanists to clarify and declutter scripts. Gotico-Antiqua was a popular font in the incunabula period, but it fell out of fashion by the 1480s and was no longer relevant by the beginning of the 16$^{\text{th}}$ century [14, p. 270].

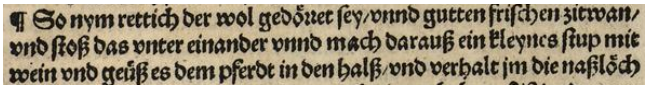
3.4 Bastarda



In the late Middle Ages a new kind of script emerged between highly stylized book scripts and cursive scripts that were mainly used for everyday writing: Bastardas were more easily readable and less abbreviated than cursive, but still showed some remnants, like looped ascenders. There are

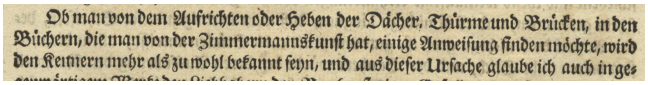
many regional variants that were often adapted into fonts for vernacular texts [14, p. 266–270]. While other Bastardas were less used by the end of the 16th century, Fraktur (Sec. 3.6) and Schwabacher Sec. 3.5 – formally also Bastardas – formed very rigid styles and remained relevant into the 20th century.

3.5 Schwabacher



Schwabacher is a form of Bastarda (Sec. 3.4) from southern Germany that found wide application, especially as a font for German language printing. Schwabacher can be clearly differentiated from other Bastardas by its lens-shaped lower-case o and its very distinctive upper-case letters like the closed S and the hook-shaped H. In some cases, other Bastardas can look very similar and we have encountered several fonts that showed mixed features. In general, Schwabacher often looks fairly rough and dark, especially when compared to Fraktur. It was first printed in 1472 by Johann Bämler in Augsburg and became widely used, primarily for German vernacular printing [14, pp. 269–270]. In the 16th century it was gradually replaced by Fraktur. However, Schwabacher remained in use for typographic emphasis in combination with Fraktur until the middle of the 20th century.

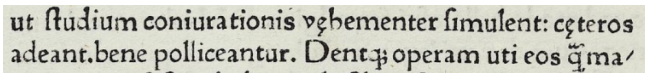
3.6 Fraktur



Fraktur is a Bastarda (Sec. 3.4) that has a very stable form and that was used so widely that it forms a font group of its own. It can be easily identified by the so-called elephant-trunks, characteristic swashes that are part of some upper-case letters, like A, B, M, N and P. The first Fraktur was designed in the early 16th century by men close to the imperial court of Maximilian I. and can be seen as the first font originally designed for print, although many features can already be found in manuscript Bastardas of the time [5].

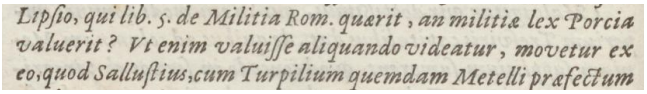
The first Fraktur designs were seminal for the emergence of Fraktur, but very delicate and too fragile for the rigors of commercial use. Instead, German printing centres of the 16th century adopted more robust Fraktur designs. Particularly during the Reformation, Fraktur became widely used for vernacular texts in the German-speaking lands and Scandinavia, and remained in that role until into the 20th century [13].

3.7 Antiqua



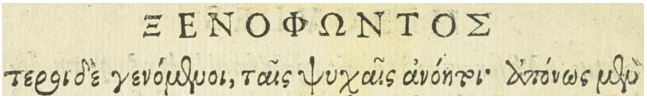
Antiqua first appeared in Italy as a humanist script. It was a combination of "Capitalis quadrata" – a majuscle script used since antiquity – and medieval Carolingian minuscule, used in the oldest copies of classical texts that the humanists found in their search for original sources. It was first made into fonts in the 1460s and quickly gained popularity with Nicolas Jenson's interpretation from 1470. In the 16th century, Antiqua became the predominant font for Latin and other texts in romanic language.

3.8 Italic



Italic is derived from a humanistic chancery script first used by Niccolò Niccoli around the turn of the 15th century. The first Italic type was cut by Francesco Griffo for Aldus Manutius, who started to use it in 1501[10]. Initially Italic consisted only of lower-case letters. If upper-case letters were needed, they were borrowed from Antiqua. Later Italic fonts include upper-case letters which were redesigned to fit better with the rest of the font. Particularly the lower-case shows its origins in cursive script with a preference for letter forms that can be written in one stroke, like *a* instead of a, and descenders for *f* and *ſ*. The font was very popular, not least because its narrow style allowed printers to save valuable paper. Already during the 16th century, Italic was used in Antiqua texts to emphasize certain words or phrases. This practice persisted although Italic as a font for main texts declined and was in the later centuries almost only used for prefaces.

3.9 Greek



The first attempts to produce Greek type were neither numerous nor satisfactory. Incunabula with the main text in Greek exist only in small numbers and only from Italy. In 1495, Aldus Manutius managed to establish a Greek font – cut by Francesco Griffo – that proved immensely influential [14, p. 281]. Stylistically this design followed a contemporary cursive which many scholars at the time were used to read. The design also created many ligatures and abbreviations that caused these fonts to swell to almost 1 000 characters. The situation became even more challenging with Claude Garamont's font named "Grecs du Roi" from 1540/1550, which tripled that number. In due course the amount of special characters was significantly reduced, but the general style of Greek text fonts remained cursive. In addition to cursive fonts, there are also upper-case fonts that closely resemble Antiqua and often share homoglyph characters like A, B, E etc. with corresponding Antiqua fonts. This font group comprises pages printed in Greek fonts, including those in all-caps Greek.

3.10 Hebrew

This group contains all fonts that use the Hebrew alphabet. Our dataset contains mainly Hebrew and Jiddish. Hebrew has

been used in print since around 1470 and became more and more popular from the 16$^{\text{th}}$ century onwards [14, pp. 289–292][12]. Hebrew could be differentiated further into, i. e., Block, Rashi and Semicursive, but we decided not to do so for two reasons: firstly, we had a very limited amount of images available compared to other font groups and secondly, because our experiments showed that Hebrew is already very clearly recognized despite its variety.

3.11 Other Font

This catch-all label comprises other fonts and scripts, such as handwritten annotations, corrections and additions as well as non-Latin alphabets beyond Greek and Hebrew and astrological signs, etc.

3.12 Not a Font

This group contains artefacts that frequently appear in scans of early printed books but that are neither font nor script. It includes blank pages, book covers, woodcuts, etchings, paintings, printers marks, ornaments and remnants of the digitization process like color charts, scanner beds and accidentally reproduced hands.

4 DATASET DESCRIPTION

The dataset is composed of a total of 35 623 page images of various resolutions and comes from a variety of libraries.[4] The libraries in Berlin, Erlangen, Göttingen, München and Stuttgart gave us a large proportion of their digitized material from the 15-18th century. We then asked the libraries in London, Köln and Heidelberg specifically for their books from the 15th century as we tried to counterbalance the high number of books from the 17th and 18th century. On top of that, we asked the Herzog August Bibliothek Wolfenbüttel to provide us with material on specific font groups that were so far underrepresented in our sample (especially Greek and Hebrew) The side length of the images range from 79 to 13 997 pixels, and their median surface is $5.3 \cdot 10^6$ pixels.

Each page has up to five class labels. If a font group is used for the majority of the text, it is the main font group. So, for example, if a page has two columns of text, each in a different font group, we did not specify a main font group. The frequency of font group co-occurrences is given in Tab. 3.

We only included pages with a main font group in the test data. We recommend using the evaluation approach presented in Sec. 5, which allows to compute a simple single-class accuracy. For each font, we selected randomly 30% for the test data and payed special attention to Gotico-Antiqua to avoid having pages from the same book in both test and training data.

[4] We would like to thank the British Library (London), Bayerische Staatsbibliothek München, Staatsbibliothek zu Berlin, Universitätsbibliothek Erlangen, Universitätsbibliothek Heidelberg, Staats- und Universitätsbibliothek Göttingen, Stadt- und Universitätsbibliothek Köln, Württembergische Landesbibliothek Stuttgart and Herzog August Bibliothek Wolfenbüttel.

Table 1: Label statistics of font groups and pages.

Number of font groups	Number of pages
1	30855
2	3732
3	891
4	136
5	9

4.1 Labeling Procedure

We labeled data using two separate approaches: First, we used labelbox (https://labelbox.com) and uploaded a selection of images from our partner libraries. Then we asked a number of participants to assign the correct label(s) and specify the main font if there was more than one. Second, we used the rest of the material our partners supplied to select pages manually with only a single font group. For this we prepared a batch of images from multiple libraries in one folder and extracted the 'not a font' images in thumbnail view. We examined the remaining images and deleted every page with more than one font group. Finally, we transferred each image in the right single class folder. This second method proved to be much more efficient since we could reduce loading times considerably and got significantly more data for underrepresented font groups, such as Textura and Rotunda. As a result our dataset consists mostly of pages with only one font group.

We attempted to include pages from all editions of Gotico-Antiqua[5] that were digitally available under free licenses in order to compensate for the form variety within this font group.

4.2 Data Statistics

Each image of the dataset has up to five labels, as shown in Tab. 1. In our dataset, there are 159 different label combinations (regardless of the order of the labels). For example, 32 pages contain Antiqua, Fraktur, Italic, and Schwabacher. The combination of Antiqua, Fraktur, and Italic is found in 111 pages.

Some combinations appear only once. For example, this is the case for Antiqua, Fraktur, Greek, Italic, and Schwabacher. Thus, the classification of the pages of this dataset has to be considered as a multi-class problem, as unique combinations of labels appearing in the test data would not appear in the training set.

5 EVALUATION METRICS

Due to its nature, our dataset can be considered as highly unbalanced. As shown in Tab. 2, some font groups, such as Textura or Bastarda, are present only in a few hundred pages, while others are in more than 2 000 pages. The test set could

[5] As a result of the large variety of Gotico-Antiqua (Sec. 3.3), there is more than one definition of what should be included in this class. For this dataset we followed Johnson [8, 360–361], resulting in a fairly conservative selection without many outliers.

Table 2: Numbers of pages for each font group. As a single page can contain multiple font groups, the sum of the fractions is higher than 100%.

Font group	Number of pages	Percentage of pages
Antiqua	8018	22.5 %
Bastarda	974	2.7 %
Fraktur	7333	20.6 %
Gotico-Antiqua	2589	7.3 %
Greek	507	1.4 %
Hebrew	1046	2.9 %
Italic	2887	8.1 %
Rotunda	5088	14.3 %
Schwabacher	2640	7.4 %
Textura	1293	3.6 %
Other font	1470	4.1 %
Not a font	7734	21.7 %

only be balanced by greatly diminishing the amount of test pages for the most represented font groups, and therefore decreasing the reliability of the test.

Also, the data was cherry-picked, thus it is not statistically representative of what can be found in libraries. For example, as we had a small amount of Textura at the start, we specifically looked for more pages containing this font group, so we can expect that less than 3.6 % of randomly selected pages from libraries would contain Textura.

Additionally, computing weighted scores would add a bias to the methods, giving more importance to font groups more frequent in our page selection. We can note that there is no reason to believe that these font groups are of a higher or lower importance to scholars in the humanities.

For these reasons, we propose to average evaluation results for subsets of pages defined by their main font group. We recommend to use the class-wise mean Intersection over Union (IoU), which is defined for N classes as

$$\mathrm{IoU} = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{|\mathcal{T}_i \cap \mathcal{Y}_i|}{|\mathcal{T}_i \cup \mathcal{Y}_i|} \,, \tag{1}$$

where $\mathcal{T}_i$ is the set of images containing font group i acc. to the ground truth, and $\mathcal{Y}_i$ the set of images estimated by the method as containing this font group.

Beside its simplicity to implement, it has several advantages. It is easy to explain to non-computer scientists. The same weight is given to all classes so that normalization is not necessary. Thus, for rare font groups, such as Textura, false negatives are avoided, since they could have a great influence on the IoU, while a lack of true positive has a significant influence on the IoU.

6 BASELINE METHODOLOGY

To highlight the difficulty of the proposed dataset, we evaluate the performance of several different artificial neural network architectures and data augmentation methods. As an exemplary task, we classify the main font group of the pages, ignoring the secondary font groups. This implies that the highest mean IoU which can be obtained is 88.46 % – with the main font group given in the ground truth. Thus, to obtain results higher than this threshold, a method must be able to accurately produce several labels per page.

For our experiments, we selected randomly 20 % of the training images as validation set. From the remaining training images, we extracted roughly 15 000 random crops of 320×320 pixels for each main font group. As the network architectures usually take inputs of 224×224 pixels, this size allows for rotations, shearing and some rescaling with minimal border effect. The training and validation data is kept identical across all experiments.

As data augmentation approach, we apply the following transforms: three sequential random rotation ($[-5, 5]$ degrees) and shearing transforms ($[-3, 3]$ degrees), random rescaling of a ratio in $[0.25, 1]$ and modification of aspect ratio in $[0.9, 1.11]$, random modification of contrast (70 %), brightness (70 %), saturation (30 %), and hue (2 %), random low-quality JPEG compression to produce artefacts (quality factors between 2–100), and binarization using Otsu's or Sauvola's methods with a probability of 15 %.

We evaluate three kinds of Convolutional Neural Networks (CNNs): residual networks with 18 and 50 layers [6], a 16 layers VGG with batch normalization [15], and a 121 layers dense network [7]. We use the same hyper-parameters for all models: learning rate of 0.001, weight decay of 0.0001, and we decrease the learning rate by 5 % at each epoch.

After each epoch, we evaluate our model on the validation data, and retain the model that has the highest IoU, which is subsequently evaluated on the test data.

The results obtained on the test data over three runs are given in Tab. 4. We can conclude that the architecture choice has little influence on the IoU, thus reaching high IoU values requires to focus more on the methodology than on the network choice. The multi-label nature of our data is made especially challenging by the low surface potentially covered by secondary font groups – it is indeed difficult to distinguish between a false positive and a single word of a secondary font in a text page.

7 CONCLUSION

In this paper, we presented a new, large, and publicly available dataset for font groups recognition. We gave a short overview of the history of font groups as well as additional details on the groups in the dataset. We evaluated several state-of-the-art CNNs for this task, and showed that the multi-label nature of the data cannot be ignored, thus highlighting the challenge offered by this dataset.

ACKNOWLEDGMENTS

We thank all libraries (see footnote 4) for contributing images, as well as Oliver Duntze (Gesamtkatalog der Wiegendrucke, SB-PK Berlin), Christoph Reske (Buchwissenscharft, JGU Mainz) and Jerôme Knebusch (ANRT Nancy) who supported the compilation of this dataset with their expertise. We also

Table 3: Co-occurence matrix showing how frequent it is for a page to contain two font groups, e. g., "10.6 % of pages containing Antiqua also contain Fraktur". Note that cells containing values below 0.05 % are left empty for readability purpose.

	Antiqua	Bastarda	Fraktur	Got. ant.	Greek	Hebrew	Italic	Rotunda	Schwab.	Textura
Antiqua	–	0.1	10.6		3.2	0.5	27.3	0.5	5.3	0.9
Bastarda	0.6	–	0.5				0.1	1.3	1.0	0.8
Fraktur	11.6	0.1	–		0.3	0.1	3.1	0.1	10.2	0.1
Gotico-Antiqua				–				0.2	0.0	
Greek	50.9		4.7		–	1.6	31.0	0.4	2.2	0.2
Hebrew	4.0		0.4		0.8	–	3.1		0.2	
Italic	75.7	0.0	7.8		5.4	1.1	–	0.2	4.2	0.3
Rotunda	0.8	0.3	0.1	0.1	0.0		0.1	–	1.9	0.9
Schwabacher	16.1	0.4	28.2	0.0	0.4	0.1	4.6	3.8	–	1.6
Textura	5.3	0.6	0.3		0.1		0.8	3.6	3.2	–

Table 4: Mean Intersection over Union (IoU) obtained using different CNN architectures.

Network	Mean IoU [%]	Std. Dev. [%]
ResNet-50	82.51	0.15
ResNet-18	83.34	0.19
VGG-16	83.44	0.53
DenseNet-121	84.06	0.23

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IMAGE CREDITS

3.1 UB Frankfurt, Inc. fol. 101. Bd. 1, fol. 49r.; 3.2 UB Heidelberg, I 4584 Folio INC::[5], fol. 2b; 3.3 UB Heidelberg, Q 569-1 D Folio INC. 1, fol. 34v; 3.4 Paris, Bibliothèque Sainte-Geneviève, OEXV 760 RES, fol. [5r]; 3.5 ULB Halle, Inc.II-394, fol. 2r; 3.6 SLUB Dresden, Archit.318, p. [viii]; 3.7 UB Heidelberg, D 5965 Quart INC, fol 13v; 3.8 SBB-PK Berlin, 17 in: Fi 2994, A3b; 3.9 SLUB Dresden, Lit.Graec.B.2312, fol. [12v]; 3.10 HAB Wolfenbüttel, Bibel-S. 529, fol. A2b. All images are hyperlinks to their respective online sources.

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