

Detecting Footnotes in 32 million pages of ECCO

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In "An Answer to the Question: What is Enlightenment?", the eighteenth-century German philosopher Immanuel Kant responded to a big question buried in a little footnote. But you wouldn't know it, because contemporary editions of Kant's famous essay no longer reproduce the parenthetical directive that Kant's original essay printed right under the essay's title in the December issue of the *Berlinische Monatsschrift* in 1784: "S. Decemb. 1783. S. 516." (See December 1783, p. 516). And, in fact, page 516 in the December volume of the *Berlinische Monatsschrift* 1783 has a footnote: "What is Enlightenment? This question is nearly as important as: what is truth? And should certainly

be answered before one starts to enlighten! But I have yet to find it answered anywhere.”

Kant’s attempt to define enlightenment, then, was a reply to a specific question. The footnote to which Kant’s essay refers was published in an essay written by the Berlin pastor Johann Friedrich Zöllner, who had published several sermons in the *Berlinische Monatsschrift*. Zöllner’s essay, “Is it wise to no longer sanction marriage through religion?”, discussed whether it would be “enlightened” to no longer require clergy to officiate weddings.¹ Kant’s essay was addressed to a larger philosophical question, but also a particular question posed on a particular page in a particular periodical by a particular contemporary. And yet we tend to read Kant’s essay, and, thus, the Enlightenment, apart from these relationships and particular moments of printed address and response.

Footnotes like the one on the bottom of page 516 in Zöllner’s essay are visible traces of these mediated relationships, markers of conversations, references, connections, and the sociability of knowledge. They are also visible markers of legitimacy and authority. They demonstrate familiarity, identity, and knowledge. As Anthony Grafton writes with respect to the eighteenth-century origins of the footnote within the nascent discipline of history: “The footnote is bound up in modern life with the ideology and the technical practices of a profession.”² It is an element of the history of disciplinarity and scientific credibility.

The footnote is also one of several visual typographic practices that have shaped modern knowledge. Our effort to understand better the footnote’s place within the eighteenth century is part of a larger, on-going project that seeks to understand a range of visual practices of scientific notation in the past: whether it be footnotes that communicate authority and the relationality of sources; tables that bring together disparate forms of information into geometric relations; diagrams that provide abstract representations of intellectual procedures or natural phenomena; or illustrations that provide mimetic representations of objects in the world. In each of these cases, authors, editors, and publishers used a graphic process to convey information and make truth claims, often in a way that sought to reduce complexity. And contemporary scholars continue to use these processes in order to communicate well and more efficiently with one another. Instead of reproducing the entirety of another text, we cite it. Instead of reproducing all of the underlying data of a process, we transform it into a table of relations. Diagrams abstract more detailed processes into more formal essence. Even illus-

¹ Pasanek, Brad and Chad Wellmon. “Enlightenment, Some Assembly Required.” In *The Eighteenth Centuries: Global Networks of Enlightenment*, eds. David T. Gies and Cynthia Wall (University of Virginia Press, 2018).

² Anthony Grafton, *The Footnote: A Curious History* (Cambridge: Harvard UP, 1999).

trations have an indexical relationship to the larger real-world phenomena they are meant to represent.

As we explain in greater detail elsewhere, our larger project is about bringing together the intersecting strands of research from the fields of book history, the history of science, and document image analysis to better understand the analytical unit called “the page image” and its role in the history of scientific knowledge. Our aim is to take seriously the page image in a double sense: first, as an image of a page, that is, to see the digitized page first and foremost as an image rather than a flawed mediation of text; and second to see the page itself as an image, as a visual unit rather than a primarily textual one. What have been the ways that the graphic practices of pages have underpinned the epistemic claims of scientific knowledge?

In this essay, we recount our process of using machine learning and classification algorithms to detect footnotes within the Eighteenth-Century Collections Online dataset (ECCO). ECCO represents one of the most complete digitized collections of a national publishing context within a specific historical period, consisting of over 100,000 volumes and 32 million pages published in Britain between 1700 and 1800. It has become a staple of research in the history of ideas, not just in Britain but for scholars of the Enlightenment more generally. We see the enrichment of collections like ECCO as a primary research goal for furthering historical understanding.

We discuss here the samples of training data that were collected and manually annotated, the different types of page-features that were used in the detection process, and the estimated accuracy of our predictions. The net result is metadata on the presence of footnotes within approximately thirty-two million pages of historical documents, which we share along with metadata regarding the initial training data used so that others can work with the same data. As we detail in Table 1, overall we are able to recall pages with footnotes with 67.87% accuracy and of those we achieve a precision of 96.2%. This suggests that there are a considerable number of footnotes we may be missing but that when we do detect them we do so with a very high degree of confidence. In addition to these summary statistics, we also provide users with an estimated percentage of footnoted pages per document, a table of all page IDs that have predicted footnotes on them, and finally the estimated probability of a footnote being present for all pages in ECCO. We see this as a first step in fully annotating ECCO according to our four visual categories of footnotes, tables, diagrams, and illustrations.

We want to emphasize from the outset just how challenging this process has been. “At first glance, all footnotes look very much alike,” writes Grafton, “[but] even

a brief exercise in comparison reveals a staggering range of divergent practices.” As we quickly learned, discerning what constitutes a footnote in the eighteenth-century is by no means a straightforward process. Training machines to identify such visual ambiguity is even more difficult. One of the issues that will need further reflection are the trade-offs between the gains of acquiring knowledge at larger scale and the challenges introduced by a fundamental uncertainty surrounding historical evidence.

Overall, we see this project contributing to a larger effort of enriching digitized collections of historical documents with more information about the documents (what is traditionally called “metadata” or data about data). We see this particular effort as contributing to knowledge about the visual qualities of page images, with a specific attention to what we are calling the history of “scientific notation.” One of the major obstacles for historical understanding is the minimal amount of knowledge we have about individual documents within large document collections. We might think of this as a second-wave of digital history: the first—which is still on-going—involves the act of digitization itself. This effort is about making physical copies, which are geographically limited in their accessibility, more widely accessible to a broader reading public. The second wave, to which we see our work contributing, can be seen as the attempt to provide more knowledge about the composition of the collections to facilitate large-scale study of cultural history. ECCO metadata currently consists of features like publication date, author, title, publisher, and in some cases subject headings. There is much more that we can do to annotate collections. But to do so at large-scale requires developing algorithmic procedures for expertly labeling documents, which in turn necessitates greater collaboration between the humanities and the sciences.

However, it is important not to mistake these labels for what computer scientists call “ground truth.” All knowledge is situated. This project represents the coordinated efforts of a team of 14 researchers split between the humanities and computer science, including both students and faculty, ranging in levels from BA to Masters to Phd to Professor. It entailed a lengthy collaboration to create mutual understanding and shared goals as well as a clear understanding of the cultural object of study (in this case historical practices of footnotes). The training data assembled thus represents the understanding and prior knowledge of the humanities cohort, while the detection algorithms represent the understanding and prior knowledge of the computer science cohort. Any machine learning process inevitably encodes, explicitly and implicitly, these biases into its outputs and are thus not value free. While this may seem less controversial with a more straightforward visual object like footnotes, it is important that we continue to foreground the human learning behind machine learning. We now proceed to

describe the process we used to annotate thirty-two million pages of ECCO.

What is a footnote? (Training Data)

We began our research by defining a footnote and then identifying positive and negative examples within ECCO. For our purposes we defined a footnote as:

Footnotes need to be distinct, marked text at the bottom (foot) of the page that are referenced in the main part of the text.

Each of these components is important: footnotes have a distinct location; they are marked (i.e. have a distinct marker); and refer directly to a location within the main body of the text through a matching mark (Fig. 1). Such a definition rules out side-notations (Fig. 2) or unmarked commentary that may be located at the bottom of the page (Fig. 3). Footnotes require some rule-based distinction of being “off-set”. Despite these clarifications, we encountered numerous examples of pages that looked deceptively like footnotes (Fig. 4, Fig. 5). Because footnote marks are both highly varied in the eighteenth century and also highly indistinct as images (what is the difference between a poorly printed asterisk and an ink blot from the reproduction process?) (Fig. 6), the footnote mark, as we quickly learned, is only weakly significant in discriminating between footnotes and commentary. For this reason, we encountered a serious limitation in our analysis that is important to signal at the outset: given the heterogeneity of footnote markers as well as their printed ambiguity (footnotes can be designated by numerous different shapes which are very hard to distinguish from other marks or blemishes on the reproduced page), our analysis does not indicate where in the body of the text the footnote is anchored. In other words, we cannot provide analysis of the footnoted word, but only an estimation of the presence of the footnote itself at the bottom of the page. Further research would be needed to reliably capture the location of the footnote mark as indicated in Figure 1.

Based on the above definition and limitations, and with extensive discussions between students and faculty responsible for collecting training data, we manually annotated 21,939 page images for training (6,028 pages with footnotes and 15,911 pages without), and another 5,520 pages for testing (522 with and 4,998 without). All pages were randomly generated from ECCO I and II and then reviewed by a single student. Ambiguous cases were reviewed by the project investigators. As we will demonstrate, our models do not appear to show biases towards different

historical timeframes within the overall dataset or between ECCO I and II, which are collected separately by Gale.

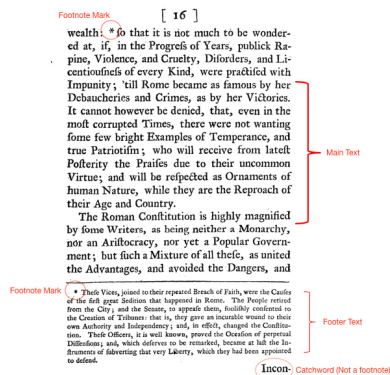


Figure 1. Example of a footnote. From *Reflections on ancient and modern history* (1742).

1800.
Nov. 14th.

DON EX DEM. BARNFIELD AND OTHERS v. WYTON.

At the trial of this action before Lord Eldon Ch. J. at the sitting after last Trinity term, a verdict was found for the Plaintiff, subject to the opinion of the Court, upon a case which stated in substance as follows:

G. Taylor being seized in fee of the premises in question, which were copyhold, and having previously surrendered the same to the uses of his will, on the 18th of May 1751 devised as follows: "I give devise and bequeath unto my wife Phoebe Taylor all my freehold copyhold and leasehold messuages tenements hereditaments and premises with their appurtenances whereofsoever situate for and during her natural life", after several bequests of personal property, and charging the said premises with an annuity secured by bond he proceeded as follows: "And from and after the decease of my said wife I give devise and bequeath all my said freehold premises together with my said leasehold premises (charged and chargeable nevertheless as aforesaid) unto my friend Francis Barnfield his heirs executors and administrators, upon trust nevertheless from and after payment and satisfaction of the said bond debt to permit and suffer my said son John Taylor to have receive and take the rents issues and profits thereof to and for his own use and benefit for and during his natural life, and from and immediately after his decease then upon trust to and for all and every the sons and daughters of the body of my said son John Taylor lawfully issuing and their heirs and from and after the decease of my said wife as aforesaid I give devise and bequeath all my said copyhold messuages and premises (charged and chargeable nevertheless as aforesaid) unto my Daughter Susannah Saunders her heirs and assigns for ever but if my said daughter shall happen to die leaving no child or children lawful issue of her body living at the time of her death then I give devise and bequeath all the said copyhold premises chargeable as aforesaid unto the said Francis Barnfield and his heirs upon trust nevertheless by and out of the rents and profits thereof to keep the said premises in good and substantial repair as occasion shall be required and to pay or permit and suffer my said son John Taylor to have receive and take the rent and residue of the rents issues and profits of the said copyhold premises to and for his own use and benefit for and during his natural life, and from and after his decease then upon

Fig. 2 Figure 2. Example of side notation.

From Reports of cases argued and determined in the Courts of Common Pleas (1802).

in simili modi, & perfereretur. Reghe mi pare il più sile, & convenientemente ricordo, che per la prima vi posso dare.

Cometo, che andando voi a Roma, che è festina de tanti i mali, entrate in maggior difficoltà di fare quanto vi dico di sopra, perché non solamente gli offensi mancavano, ma non vi mancheranno particolari incitatori & contrattori: per che come voi potete intendere, la promissione vostra al Cardinalato, per l'età vostra, & per l'altre condizioni sopradette, arriva l'età grande invidia, & quelli, che non hanno potuto impedire la perfettion di questa vostra dignità, s'ingegneranno fittamente diminuirla, con domgere l'opinion della città vostra, & farvi adrecciarle in questa stessa foglia, dove essi sono caduti, copolandosi molto, che debbo lor rinfiere per l'età vostra. Voi dovete tanto più apperci a queste difficoltà, quanto nel collegio loro si vede meno

"I never in the frequent use of such means. This seems to me the most feasible and beneficial counsel that I can at first recommend to you."

"I know, that as you are going to Rome, that ink of all corruption, it will be the more difficult to conform to what I have said above, as, besides the contagion of bad example, you will not want bad counsellors and seducers; for, as you may well think, your promotion to the cardinalate will, both on account of your age and the circumstances above mentioned, bring much envy on you; and they who have not been able to hinder your acquisition of this dignity, will have no more success in being a flatterer to, by suggesting the opinion concerned of your life, and causing you to slip into the same snare into which they themselves are fallen; and this, to your prejudice themselves, they shall bring about by reason of your age. Against these difficulties you must make head with the greatest vigour, as I shall advise."

"It now to be found in the college; though I remember to

Figure 3. Example of commentary at the bottom of the page. From New observations on Italy and its inhabitants (1769).

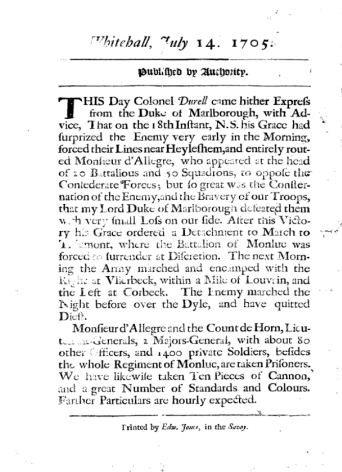


Figure 4. Example of footnote-like text in an early newspaper (1702).

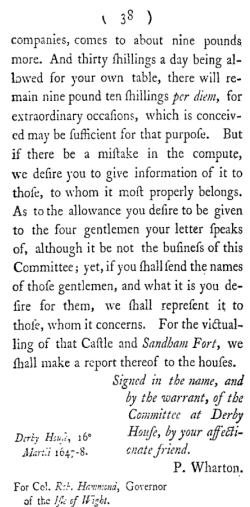


Figure 5. Example of footnote-like text. From Letters between Col. Robert Hammond (1764)

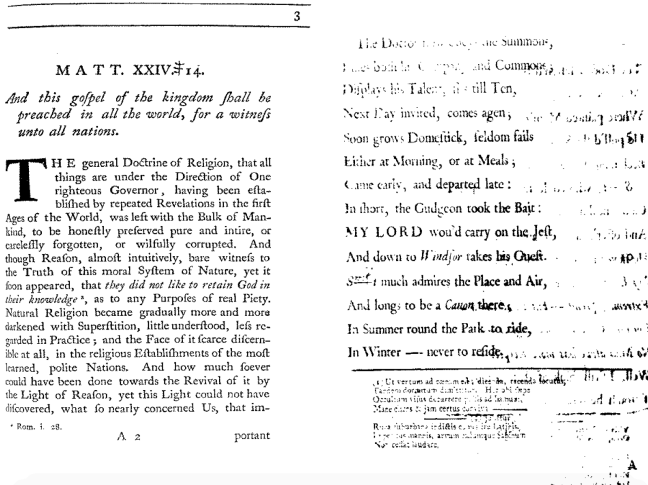


Figure 6. Examples of degraded or hard to capture footnote-marks. Part of the seventh epistle of the First book of Horace (1713) (left) and A sermon by Joseph Lord Bishop of Bristol (1739) (right).

Detecting Footnotes at Large Scale (Machine Learning)

After collecting our positive and negative examples of footnoted pages, we then set out to design features and learning algorithms that could best predict the presence of footnotes on a page. We chose to use four models which we describe here. The performance of the models is reported in Table 1. The designed models cover a range of machine learning approaches, beginning with a conventional model based only on hand-designed features and moving to a learning-based model that utilizes deep learning.

Our first approach is a “rule-based” model that tries to capture three overarching visual features related to the differential line-size and line-spacing of pages (thus “rule-based”). Our hypotheses for this model are that footnotes will: 1) have a smaller font size than the main text; 2) be located at the bottom of the page; and 3) be indicated by significant spacing between the footnote and the main text. The advantage of this kind of approach is that the creation of custom features can target our prior knowledge of the problem (i.e. what is a footnote) and increase precision. The drawback is that the delimitation of features may not be able to capture the broader diversity of footnote behaviors in our data and thus may lower recall. This can be compensated for by more learning-based approaches where features are not pre-defined but learned from the training examples. However, as we show in Table 1, we see how overall in our results we do achieve higher precision (finding true positives) and lower recall (producing false negatives, i.e. overlooking footnotes).

In order to estimate font size (hypothesis 1), we use two methods drawn from the field of document image analysis: the bounding box method (BBox) and the horizontal projection method (Proj) (Fig. 7).³ Bounding boxes are determined for each line by finding the rectangles containing the connected components. A connected component is defined as the continuous connection of black pixels. In theory, a connected component should correspond to individual letters, but given the imperfect reproductions of pages along with typographic irregularities

³Rodolfo P. dos Santos, et al., “Text line segmentation based on morphology and histogram projection,” *Document Analysis and Recognition*, 2009. ICDAR’09. 10th International Conference on. IEEE, 2009 and Laurence Likforman-Sulem, Abderrazak Zahour, and Bruno Taconet, “Text line segmentation of historical documents: a survey,” *International Journal of Document Analysis and Recognition (IJDAR)* 9.2-4 (2007): 123-138.

introduced in historical printing practices, errors can be introduced (Fig. 8). These bounding boxes are then used to estimate the lower case letters' font sizes by finding the distance between the lower and the upper base-lines, as shown in Fig. 7(a). For the horizontal projection method, the horizontal intensity for each line is calculated (i.e., the pixels in the horizontal direction are summed such that there will be fewer pixels at the upper and lower levels of the line where extenders and descenders are located (capital letters or d's or y's for example)). As demonstrated in Fig. 7(b), the font size of a textline is estimated by calculating the distance of the inner intersected line between the derived projection and a threshold line of a value equal to 0.55.

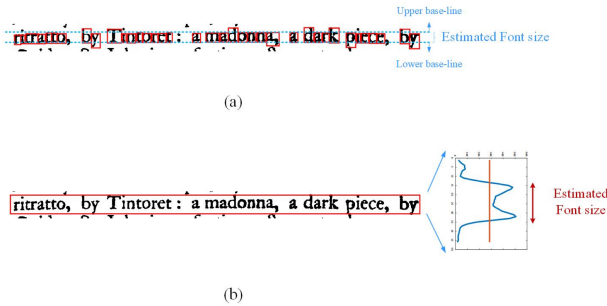


Figure 7. The estimated font size of (a) the bounding box based method and (b) the horizontal projection based method.



Figure 8. We can see in this example of the word “slender” from Hogarth’s Analysis of Beauty a connected component that spans more than one letter due to the typeface used and the potential for bleeding between letters. Each red box represents a connected component.

According to our initial hypothesis, we expect that any line with a footnote would correspond to a decrease in font size when compared to the previous line. Although this would be an ideal case, such a decrease could be attributable to something other than the presence of a footnote, such as the presence of a title, figure,

or tables, etc. We therefore define additional rules in order to improve the accuracy of our footnote detection. We convert these rules into specific features described in Appendix A.⁴

In order to identify the footnote location (our second assumption), we define a series of further rules based on the page layout for each method (BBox and Proj). The relative position of the estimated footnote line to all other lines on the document image is then used as a basis of further features. The third and final technique determines the spaces between the lines and uses them as a feature. More specifically, the textline below the large white space closest to the bottom of the page is considered to be a footnote candidate. The location of a possible footnote is compared to the locations estimated in the first two methods in order to partially form the final feature vector of the image. We illustrate how the three primary features of line height, line spacing, and page location perform with respect to two sample pages, one with a footnote, one without (Fig. 9).

Using these three primary features we develop a total of 72 features related to rule-based qualities of the page (18 BBox + 24 Proj + 30 Location and space as described in Appendix A) which are then fed into a support vector machine (SVM) classifier to detect pages with footnotes.

⁴Sara Zhalehpour, Andrew Piper, Chad Wellmon, and Mohamed Cheriet, "Footnote-based document image classification," In *International Conference Image Analysis and Recognition* (Cham: Springer, 2017): 634-642.



Figure 9. Examples of two document pages, with footnote (a) and without footnote (b), and their related results after applying the BBox-based method (b, f), the projection-based method (c, h) and estimating the lines spacing (d, i).

Our second model is a “layout-based” model that combines hand-designed and learned features, although it weighs the former more heavily. This and the next model might be considered to be hybrid models that combine custom features defined by expert knowledge and learned features defined by the machine’s exposure to the training data. The layout approach primarily depends on understanding the layout of textlines on a page (Fig. 10). Once again, it rests on the hypothesis that footnotes will exhibit distinctive visual behavior with respect to their size and position on the page. Similar to the rule-based approach, we develop 22 custom measures for each textline based on the variables shown in Fig. 10 (see Appendix B for a full description of all features). Because the number of textlines varies between document images, it is necessary to extract features with a fixed length for all of the images. In order to do this, we use Discrete Cosine

Transform (DCT),⁵ where we consider the concatenation of each textline’s 22 measures as a signal. This signal exhibits a repetitive behavior and thus contains frequency information such that DCT can be used to capture this information. Specifically, since most of the signal’s energy (i.e., information) is concentrated in lower frequencies, and assuming that document images have at least 5 textlines, we kept only the first 300 coefficients of the DCT transform for each image.

The final step of the “layout-based” model is classification. We use a combination of an Autoencoder overlaid with a softmax layer.⁶ The Autoencoder creates lower dimensional representation of the provided input data in its hidden layer and then reconstructs this data at its output layer. This representation is then fed to a softmax layer with the labels of the document images to learn the model for classifying new samples.

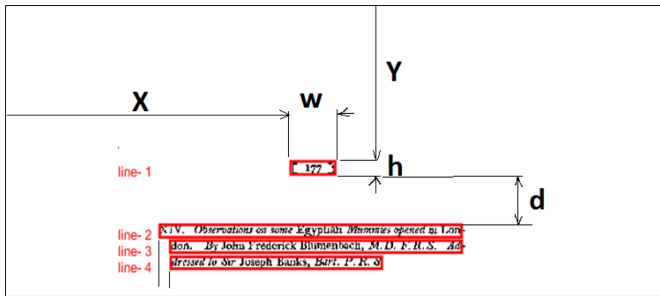


Figure 10. A bounding box of a textline with features X , w , Y , h , and d defined as relative positions on the page.

Given the recent advances in the field of deep learning, particularly with architectures such as Convolutional Neural Networks (CNN), we used two CNN-based models for our final two approaches.⁷ We also used two different techniques in an effort to compensate for the limited amount of labeled data available to us, because CNNs generally require large amounts of data during the training process in order to perform efficiently.

In the third approach, “CNN-based,” the model is based primarily on learning the document image’s features throughout the various layers of the neural network. But the model also depends on hand-designed features in order to overcome the limited amount of labeled data. Based on our hypothesis that the foot-

⁵Edmund Y. Lam, “Analysis of the DCT coefficient distributions for document coding,” *IEEE Signal Processing Letters* 11.2 (2004): 97-100.

⁶See Pierre Baldi, “Autoencoders, unsupervised learning, and deep architectures,” In *Proceedings of ICML Workshop on Unsupervised and Transfer Learning*, 2012.

⁷Ian Goodfellow, et al., *Deep learning*. Vol. 1. (Cambridge: MIT press, 2016).

note's text and the main body's text differ in both style and font, each document image is represented using the two top textlines and the three bottom ones. (We use a projection-based segmentation method described above to detect those textlines.) Each of these textlines is represented, more precisely, as a vertical histogram (Fig. 11). As in the previous examples, the performance of this model will be hindered by the reliance on layout assumptions that may not always apply to our object of study. In order to capture changes in font size, here we use vertical projections of the lines, meaning the bars of the histogram represent vertical slices of the red-bounded lines. The lower height of the histogram bars represents a lower average line-height. A concatenated version of the vertical histograms of these textlines is then used as an input to a 1-dimensional CNN (i.e., a 5000x1 histogram).⁸

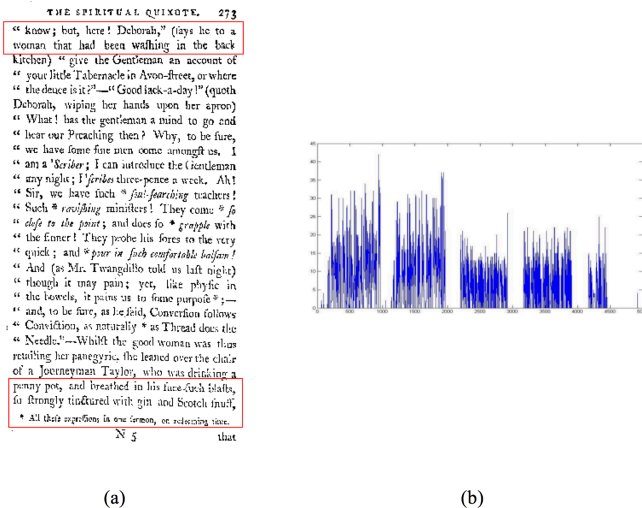


Figure 11. A representation of a document page (a) with its related vertical histograms (b).

Our fourth and final approach is based on transfer learning and CNN (“Transfer Learning”).⁹ According to this approach, the model automatically learns the features without using any hand-designed features. Transfer learning can be par-

⁸Mohamed Mhiri, Sherif Abuelwafa, Christian Desrosiers, and Mohamed Cheriet, “Footnote-based Document Image Classification using 1D Convolutional Neural Networks and Histograms,” In *International Conference on Image Processing Theory, Tools and Applications*, 2017.

⁹Yoshua Bengio, Aaron Courville, and Pascal Vincent, “Representation learning: A review and new perspectives,” *IEEE transactions on pattern analysis and machine intelligence* 35.8 (2013): 1798-1828.

ticularly useful given the scarcity of labeled training data in our case. The model consists of two supervised learning stages, a pre-training stage and a fine-tuning stage. In the first stage (pre-training), an AlexNet is trained on a large dataset of natural images and the resultant learned parameters (e.g., network's weights) are saved. In the second stage (fine-tuning), instead of initializing the CNN's parameters randomly, the model uses learned parameters from stage one. Then, we use the ECCO dataset to train the model to classify document images with footnotes. The novelty of this approach is important to emphasize footnotes are being learned first by learning features of "images" more generally and then being trained on page images more specifically. To prepare the data, we perform two pre-processing steps on the raw document images—resizing and normalization—before using them as inputs to our model. Each document image is resized to 227x227, and its pixel values are normalized to be in the range [0 1] (Fig. 12). Unlike the first three approaches, this model does not require any textline segmentation process; therefore, it avoids the segmentation errors that may result from it.

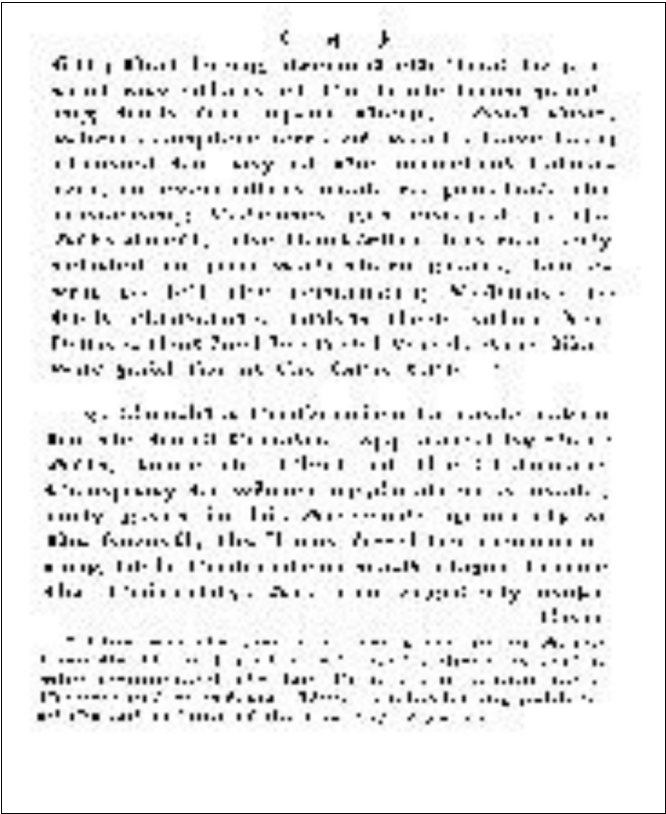


Figure 12. In this example, pages are binarized and then reduced in size to 227x227 pixels (or 51,529 dimensions) rendering them illegible, but ideally capturing the unique visual signature of footnotes.

These then were the four models we developed to detect footnotes. As a final step, we use an ensemble detection method that combines all four classifiers. Applying this ensemble method on the test set of ECCO, we achieve 96.2% precision and 67.87% recall in our footnote detection results (Table 1).

Approaches	Precision (%)	Recall (%)	F1 score
Rule-based	68.24%	60.8%	0.643
Layout-based	60.8%	69.4%	0.6482
CNN-based	90.35%	48.37%	0.63
Transfer learning-based	74.31%	41.49%	0.5325
The final detection approach	96.2%	67.87%	0.7959

Table 1. The individual performance of each detection approach, in addition to

the final approach performance.

Applying our detection methods on the full ECCO dataset, we discovered 1,319,000 footnoted images from approximately 26,000,000 document image in ECCO I and 239,754 footnoted images from approximately 6,000,000 document image in ECCO II. We therefore estimate that roughly 4.9% of all pages in the eighteenth contained footnotes. The figures below (Figs. 13-15) provide more detailed results, including the number of document images with detected footnotes over time (publication years) as well as document images with detected footnotes according to subject classifications in both ECCO I and II. We expect in a separate piece to explore this data in more detail. We share the underlying metadata of footnote annotation to allow others to do the same.

We also provide detailed information in Tables 2-3 that demonstrate the consistency of our final model's performance across different time periods and subjects in both ECCO I and II. As we show, the values of the average footnote probability per page are stable (i.e., around 0.68) regardless of the year or subject of the examined document image. These tables give us confidence that our predicted levels of footnotes are not dependent on either document type or the year of publication. All of our derived data has been shared as supplementary data to this article.

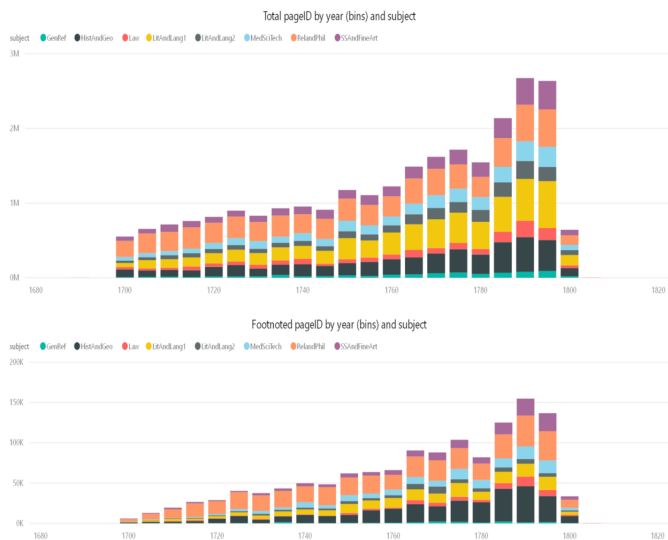


Figure 13. Distribution of document images (all and footnoted) in ECCO I by year using Gale's eight subject classes.

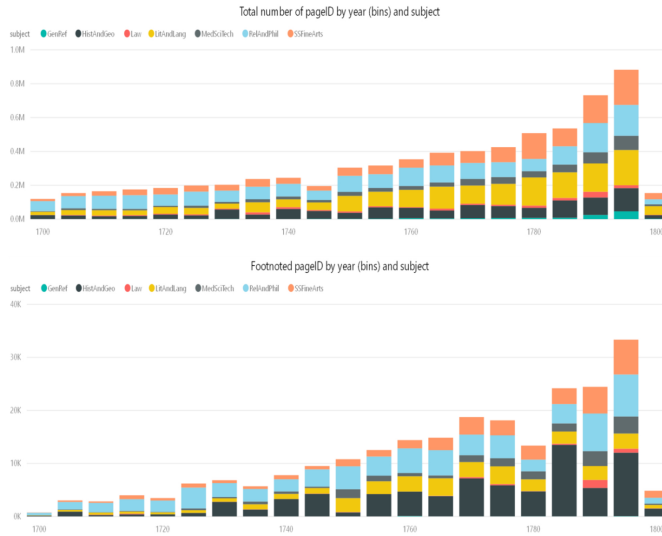


Figure 14. Distribution of document images (all and footnoted) in ECCO II by year using Gale's eight subject classes.

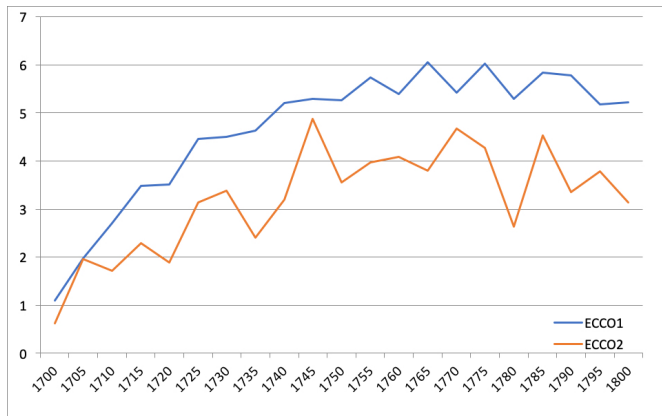


Figure 15. The percentage (%) of the detected footnote document images to the total document images at both ECCO I and ECCO II.

year (bins)	GenRef	HistAndGeo	Law	LitAndLang1	LitAndLang2	MedSciTech	RelandPhil	SSAndFineArt	Total
1695				0.57		0.64			0.62
1700	0.64	0.66	0.64	0.66	0.66	0.68	0.68	0.66	0.67
1705	0.68	0.67	0.69	0.68	0.64	0.69	0.69	0.66	0.68
1710	0.66	0.66	0.69	0.67	0.66	0.67	0.68	0.67	0.68
1715	0.68	0.67	0.68	0.67	0.68	0.68	0.68	0.68	0.68
1720	0.68	0.67	0.68	0.66	0.68	0.68	0.69	0.67	0.68
1725	0.66	0.67	0.67	0.68	0.67	0.69	0.69	0.68	0.68
1730	0.68	0.66	0.67	0.68	0.67	0.69	0.69	0.67	0.68
1735	0.67	0.67	0.66	0.67	0.67	0.68	0.69	0.67	0.68
1740	0.68	0.67	0.65	0.67	0.67	0.70	0.69	0.68	0.68
1745	0.66	0.67	0.67	0.68	0.68	0.69	0.69	0.68	0.68
1750	0.67	0.67	0.67	0.67	0.67	0.68	0.69	0.68	0.68
1755	0.67	0.68	0.68	0.68	0.68	0.68	0.69	0.68	0.68
1760	0.65	0.68	0.70	0.68	0.67	0.69	0.69	0.67	0.68
1765	0.67	0.69	0.67	0.67	0.69	0.69	0.69	0.68	0.68
1770	0.67	0.68	0.68	0.68	0.68	0.69	0.69	0.68	0.68
1775	0.66	0.68	0.68	0.68	0.68	0.72	0.68	0.68	0.68
1780	0.67	0.68	0.68	0.68	0.68	0.69	0.69	0.68	0.68
1785	0.70	0.68	0.68	0.68	0.67	0.68	0.69	0.68	0.68
1790	0.68	0.69	0.68	0.67	0.67	0.69	0.69	0.68	0.68
1795	0.66	0.68	0.69	0.67	0.67	0.68	0.69	0.68	0.68
1800	0.67	0.68	0.66	0.67	0.68	0.68	0.69	0.68	0.68
1805		0.66					0.71		0.70
Total	0.67	0.68	0.68	0.68	0.68	0.69	0.69	0.68	0.68

Table 2. The average probability of footnote by years and subjects (where images are detected as footnote) at ECCO I.

year (bins)	GenRef	HistAndGeo	Law	LitAndLang	MedSciTech	RelAndPhil	SSFineArts	Total
1700		0.64	0.55	0.64	0.63	0.66	0.64	0.65
1705	0.65	0.66		0.65	0.69	0.67	0.66	0.66
1710	0.59	0.66	0.68	0.67	0.68	0.67	0.64	0.67
1715		0.64	0.68	0.68	0.67	0.66	0.67	0.66
1720	0.57	0.65	0.57	0.66	0.66	0.67	0.66	0.67
1725	0.56	0.68	0.64	0.65	0.69	0.68	0.67	0.68
1730		0.65	0.67	0.66	0.67	0.66	0.67	0.66
1735		0.65	0.66	0.65	0.67	0.66	0.66	0.66
1740	0.61	0.66	0.62	0.65	0.66	0.67	0.66	0.66
1745	0.61	0.68	0.66	0.65	0.66	0.67	0.66	0.67
1750	0.72	0.67	0.66	0.66	0.68	0.68	0.66	0.67
1755		0.66	0.69	0.65	0.67	0.67	0.67	0.66
1760	0.67	0.66	0.63	0.67	0.67	0.66	0.67	0.67
1765	0.63	0.68	0.63	0.66	0.68	0.68	0.66	0.67
1770	0.67	0.69	0.66	0.66	0.67	0.67	0.68	0.68
1775	0.62	0.67	0.67	0.65	0.68	0.67	0.67	0.67
1780	0.63	0.66	0.64	0.65	0.68	0.67	0.67	0.66
1785	0.63	0.68	0.65	0.66	0.68	0.67	0.67	0.68
1790	0.64	0.67	0.68	0.66	0.67	0.67	0.67	0.67
1795	0.64	0.66	0.66	0.66	0.67	0.67	0.67	0.67
1800	0.66	0.69	0.67	0.66	0.69	0.67	0.67	0.68
Total	0.65	0.67	0.67	0.66	0.67	0.67	0.67	0.67

Table 3. the average probability of footnote by years and subjects at ECCO II.

Appendix A: The Rule-based Footnote Detection Approach Features

The final utilized feature vector at the rule-based footnote detection approach contains 72 features, which is the combination of the features extracted at the following three techniques.

1) The Bounding Box (BBox) based Method:

At this method, 18 features are being utilized based on some initial assumptions; for instance, the assumption that the font size of any footnote line is at least 0.55 smaller than the font size of the main text. More assumptions are considered and demonstrated in details in table A1.

Table A1

Feature	Condition
1	1 if there is no drop more than 0.55
2	1 if there are 1+ drops of more than 0.55
3	1 if the last two lines' heights are less than 0.1
4	1 if the last lines' height is less than 0.1
5	1 if the last two lines' heights are less than 0.1 and there is a footnote
6	1 if the line before last line's height is less than 0.1
7	1 if the footnote is not in the 4th line
8	1 if there are 2+ drops more than 0.55
9	1 if the footnote is not in the 4th, 5th and 6th lines
10	1 if there are 2+ drops less than 0.55 or the footnote is not in the 4th, 5th and 6th lines
11	1 if there is a drop greater than 0.15
12	1 if footnote line is in the 6th line or later
13	1 if the height of the footnote line is 0.55 greater than the line before the last line
14	1 if there is a drop of greater than 0.35 between the lines before and after the footnote line
15	1 if there is a line except the last line selected as the footnote line and there is a drop of greater than 0.35 between the lines before and after it
16	1 if there is a difference less than 0.17 between the lines before and after the footnote line
17	1 if there is a line except the last line selected as the footnote line and there is a difference less than 0.17 between the lines before and after it
18	1 if it the page has more than 3 lines

2) The Horizontal Projection (Proj) based Method:

At this method, 24 features are being utilized. Table A2 demonstrates the extracted features in more details.

Table A2

Feature	Condition
1	1 if there are more than 3 lines in the page
2	1 if there is no possible footnote
3	1 if there is more than one possible footnote (drops with the amount of 0.55 or more)
4	1 if the footnote line is in the first 3 lines or there are more than 3 possible footnotes
5	1 if there are more than 3 possible footnotes or there are lines shorter than 0.13 but not footnote lines
6	1 if the footnote line is in the first 3 lines or there are lines shorter than 0.13 but not footnote lines
7	1 if the footnote line is in the first 3 lines

Feature	Condition
8	1 if there are more than 3 possible footnotes
9	1 if there are lines shorter than 0.13 but not footnote lines
10	1 if the footnote line is in the first 3 lines, there are 3+ possible footnotes or there are lines shorter than 0.13, but not footnote lines
11	1 if the last line or the line before it has a height less than 0.1
12	1 if the last line or the line before it has height less than 0.1 and there is a footnote
13	1 if the last line has a height less than 0.1
14	1 if the line before the last line has a height less than 0.1
15	1 if there still exists a footnote line
16	1 if the height of the last line is less than 0.4
17	1 if the last line has a height less than 0.1 and there exist a footnote line
18	1 if the line before the last line has a height less than 0.1 and there exist a footnote line
19	1 if the height of the last line is less than 0.4 and there is a footnote line and the last line or the line before has a height less than 0.1
20	1 if the greatest height drop is equal or greater than 0.4 and there is at least a 0.25 drop between the line before and after footnote
21	1 if there is at least a 0.25 drop between the line before and after the footnote and the footnote line's height is less than 0.4
22	1 if the greatest height drop is equal or greater than 0.4 and the height of the last line is less than 0.4
23	1 if the height of the last line is less than 0.4 and the greatest height drop is equal or greater than 0.4 and there is at least a 0.25 drop between the line before and after footnote
24	1 if the height of the footnote line is 0.4 below the highest height of all the other lines except the first 3 and last lines

3) Location and Space based Features:

Table A3 demonstrates the 30 extracted features in more details.

Table A3

Feature	Condition
1	1 if there is more than 10 lines in the page
2	1 if there is a space peak in the 2nd 1/4th of the page and there is more than 10 lines in the page
3	1 if there is a space peak in the 3rd 1/4th of the page and there is more than 10 lines in the page
4	1 if there is a space peak in the 4th 1/4th of the page and there is more than 10 lines in the page
5	1 if there is only one peak in the page, select its location: (Peak location/ # of lines) and there is more than 10 lines in the page
6	1 if there is more than one peak in the page, select the last one's location: (Peak location/ # of lines) and there is more than 10 lines in the page
"7-8"	1 if there is a footnote in the last 1/4th of the page: (FN location/ # of lines) and there is more than 10 lines in the page
"9-10"	1 if there is a footnote in the page: (FN location/ # of lines) and there is more than 10 lines in the page
"11-16"	Check if feature 5 appears anywhere around feature 7(Proj) using a threshold from ± 0.02 by a 0.02 step and up to ± 0.14
17-22	Check if feature 6 appears anywhere around feature 8(Proj) using a threshold from ± 0.02 by a 0.02 step and up to ± 0.14
23-26	Check if feature 5 appears anywhere around feature 7(BBox) using a threshold from ± 0.02 by a 0.02 step and up to ± 0.14
27-30	Check if feature 6 appears anywhere around feature 8(BBox) using a threshold from ± 0.02 by a 0.02 step and up to ± 0.14

Appendix B: The Layout-based Footnote Detection Approach Measures

A detailed description of the used measures at the layout-based footnote detection method is demonstrated at Table. B1

Measure	Description
1	<i>Number of objects (characters – connected components) in current textline</i>
2-3	$h_{\text{current textline}} - h_{\text{previous textline}}$, $h_{\text{current textline}} - h_{\text{next textline}}$
4-5	$w_{\text{current textline}} - w_{\text{previous textline}}$, $w_{\text{current textline}} - w_{\text{next textline}}$
6-7	$x_{\text{current textline}} - x_{\text{previous textline}}$, $x_{\text{current textline}} - x_{\text{next textline}}$
8	$(x + w)_{\text{current textline}} - (x + w)_{\text{previous textline}}$
9	$(x + w)_{\text{current textline}} - (x + w)_{\text{next textline}}$
10	$(y + h)_{\text{current textline}} - (y)_{\text{next textline}}$
11	$(y)_{\text{current textline}} - (y + h)_{\text{previous textline}}$
12	$(y)_{\text{current textline}} - (y + h)_{\text{firsttextline}}$
13	$(y + h)_{\text{current textline}} - (y)_{\text{last textline}}$
14-16	$w_{\text{current textline}}$, $h_{\text{current textline}}$, $x_{\text{current textline}}$
17	$(x + w)_{\text{current textline}}$
18	Number of foreground pixel to the number of all of pixels
19	$\text{feature } 18_{\text{current textline}} - \text{feature } 18_{\text{current textline}}$
20	$\text{feature } 18_{\text{current textline}} - \text{feature } 18_{\text{next textline}}$
21	Number of foreground pixel in right half of <u>textline</u> to the number of foreground pixel in left part of <u>textline</u>
22	Average of ratio of black and white pixels for each row of <u>textline</u> image

Table B1



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