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# Lifelong learning for text retrieval and recognition in historical handwritten document collections

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#### Lifelong learning for text retrieval and recognition in historical handwritten document collections Lambert Schomaker

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#### Chapter 10

# Lifelong learning for text retrieval and recognition in historical handwritten document collections

#### (Lambert Schomaker)

#### 10.1 Introduction

Current developments in deep learning neural networks show remarkable progress, also in document-analysis systems for historical manuscript collections (Sudholt and Fink, 2018; Gurjar et al., 2018; Sudholt and Fink, 2016; Bluche, 2016). However, there are still many stumbling blocks and recognition performances are still not at a level which matches the expectations in user communities. For scholars in the humanities, these expectations are indeed high, as evidenced from the criticism that large-scale digitization endeavors such as the Google Books  $project^1$  drew (Chalmers and Edwards,  $2017)^2$ . This state of affairs is noteworthy, because optical character recognition of machine-printed text - as opposed to handwritten manuscripts - yields performances that are already incredibly high from the point of view of current handwriting-recognition research. Practical tests reveal character recognition rates from 68% on early 20th century printed newspapers to 99.8% on modern material (Klijn, 2008). Lower rates from 71% to 98% character recognition are mentioned for newspapers from the period 1803-1954 (Holley, 2009) who also reports that any performance below 90% recognition accuracy would be considered 'poor'.

If complaints on the accuracy of recognized text and its OCR-based metadata are already so strong in the recognition of machine-printed text, what can we expect from the user's reactions on current handwriting recognition algorithms? It is clear that some reflection is necessary in order to promote computer-based reading systems for opening access to historical

<sup>&</sup>lt;sup>1</sup>https://en.wikipedia.org/wiki/Google\_Books

 $<sup>^2 \</sup>rm Such$  opinions were raised quite vocally, e.g., during plenary discussions at the Annual Seminar of the Consortium of European Research Libraries (CERL), Oslo, Norway, October 28th, 2014

collections. In this chapter a number of considerations and experiences will be presented concerning the development of the Monk [van der Zant *et al.* (2008, 2009); van Oosten and Schomaker (2014); Schomaker (2016)] e-Science service for historical documents at the University of Groningen in the period 2008-2019. This system aims at supporting researchers in machine learning and scholars in the humanities in doing research concerning the What, When & Who questions:

- 'What has been written?' (text recognition);
- 'When was it written?' (style-based dating of manuscripts); and
- 'Who wrote the document?' (writer identification).

By adding labels at the page-description level, adding line transcriptions at the level of line-strip images and adding zone labels for words and characters, the scholars create a growing index to documents. At the same time, machine-learning researchers can use the harvested  $\{image, label\}$  tuples for training their methods. Table 10.1 gives an overview of a number of relevant statistics.

present within the Monk system	(July 2018)
Number of:	(qty.)
Institutions	30
Page scans	567 152k
Line strips Zone (ROI) candidate images	273k 700M
Lexical and shape classes	147k

 $\begin{array}{c} 120 \ \mathrm{TB} \\ 1.3 \times 10^9 \end{array}$ 

900k

Disk storage .....

Human-labeled zones

Files .....

words, characters, visual elements

Table 10.1 Key statistics representing the data present within the Monk system (July 2018).

In the context of the Monk system *Human labeled* means: 'an image zone, manually labeled as an original individual text item, possibly new to the system', or, alternatively, it may imply: 'recognizer-based labels that are confirmed by a human user on the basis of a ranked hit list provided by the system'. Figure 10.1 gives an overview of the document styles, scripts, and image quality varieties in the current collection on Monk.

During the development of this system, the following issues were encoun-



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Fig. 10.1 Random samples from the collections currently on the Monk system. Apart from handwritten manuscripts also some machine printed material is on the system. In the philosophy of big-data methods, the classification algorithms should not be trained or designed specifically for a particular style. While this is possible to a large extent, the wide range of image quality and layout particularities remains challenging.

tered, concerning the questions of the users and concerning the machinelearning approach to choose:

- Expectation management How is a reading system positioned as a technological tool in terms of the promised functionality and the benefits to be expected for users, i.e., librarians, archivists and end users?
- Usage scenarios Does the institution basically desire an e-Book reader with a key-word search enhancement, is the goal to support users in creating edited digital books from handwritten manuscripts or is the goal to just convert images of paper documents to encoded

text for further processing?

- Technical realization Is the reading system offered as a stand-alone computer tool, running on the the PC of the end user, or running on the infrastructure of a library institution under local supervision, or is it constructed as a 'cloud'-based service, somewhere on Internet, with support from remote, possibly anonymous but expert-level staff?
- Work-flow concept Does the archive intend to perform a singleshot conversion of a given collection (from pixels to encoded text) or do the users realize that continuous efforts in quality control will be required, including labeling by experts or volunteers over a prolonged period of time?
- Quality and quantity of the material Will there be a preselection of materials and what are the criteria? What types of material are present: books, diaries/journals, shoe boxes with letters in their original envelope, written by diverse writers?
- Industrialization and scalability Who is responsible for image preprocessing and layout analysis? A folder with 2000 scanned raw unlabeled images of papyrus texts is not well comparable to an academic benchmark test for machine learning that is preprocessed, packaged, labeled and prepared for k-fold evaluation experiments (LeCun *et al.*, 1998; Marti and Bunke, 2002; Fischer *et al.*, 2012). In real-world applications, collections have a wide variety of document and layout formats. How to handle the consequences of success: "If it works, can we process several hundreds of such collections within a year?"
- Human effort Who will be responsible for quality control of the meta-data input, and the linguistic quality of the labeling process? If users perform an inconsistent labeling, they may blame the system if recognition performances are lower than expected.
- Algorithms Finally, after having listened to signals from user communities, there is the last consideration, which mostly is the starting point for many in our research domain: The selection of the machine-learning methodology used. How to choose between wordspotting (Rath and Manmatha, 2007), word-based recognition (van der Zant *et al.*, 2008) and character-stream based handwritten-text

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recognition (HTR) (Sánchez *et al.*, 2013)? Even here, realistic and pragmatic considerations need to be taken into account, that are insufficiently addressed by designers of machine-learning methods. Will it be possible to enjoy improvements in algorithms, over time? How to select such methods? Are current methods in deep learning usable in practical application settings?

The answer to such questions is not easy. When maintaining a largescale e-Science repository of handwritten document collections, it quickly becomes apparent that at least 'four Vs of Big Data' play a role here: Volume, Velocity, Variety and Veracity. The volume is indeed large and may be in the hundreds of thousands of page scans. This has consequences for storage but also for computation: (re)training efforts will pose a significant load on the infrastructure. Data sets can be much too large to fit in memory, especially considering the fact that training processes for multiple collections will run in parallel. Velocity pertains to the rate at which new scanned pages are entering the system as well as the rate at which labels are being produced by the users. New labeling may refute existing labeling. Since neural networks cannot unlearn individual input/output pairs, new insights or corrections by users usually necessitates a new training from start. Variety plays a role in image-quality preprocessing. Although an 'end-to-end' training is advocated these days, the generalization from, e.g., a parchment training set to a papyrus-based test set will be highly limited. A proper preprocessing increases the reusability of samples that are homogenized in their visual appearance over multiple diverse training contexts. Variety also plays a dominant role at a level where current deep learning does not provide solutions as yet: Layout structure diversity. Curvilinear line shapes, tabular text objects and marginal notes often require collection-specific layout analysis. Finally, writing style variety and linguistic variations need to be handled. As regards **Veracity**, it should be noted that the machine-learning assumption that 'ground truth is a rock solid factum' cannot be held in a live system. In many cases, a coherent labeling systematics needs to be invented by humanities researchers, on the spot: This goal may have been the whole purpose of the digitization effort for the manuscript, in the first place.

In this chapter, the evolution of the trainable search engine for handwritten historical collection, Monk will be used to illustrate the manner in which these considerations were addressed. In this process, a number

of phenomena in machine learning were encountered that are hitherto not handled in great detail in the common benchmark-oriented literature but which will become apparent under large-scale, open domain conditions.

#### 10.2 Expectation management

Both in the Google Books <sup>3</sup> project and in projects aimed at digitizing vast amounts of handwritten material from a wide range of international scripts and historical periods, it is essential to create realistic expectations in end users. The end users can be archivists and librarians, for whom correctness of metadata and core text data is very important. End users have their own expectations, which are concentrated in the areas of legibility and the reading experience, i.e., usability aspects, as well as accuracy of text recognition (van der Zant *et al.*, 2009). Increasingly, there are expectations as regards multimodality, the recognition of the pictorial information next to the handwriting, and the possibility of (semi-automatic) creation of hyperlinks to semantic databases (Weber *et al.*, 2018).

Inspection of the handwriting-recognition literature will lead to unrealistic expectations. From a fundamental-science perspective, standard benchmark tests are clearly necessary. However, they also introduce a bias as well as a reduction in the diversity of data that are handled in literature, in comparison to real-world applications. The standard data sets, especially MNIST (LeCun et al., 1998), but also the George Washington (GW) data set (Fischer *et al.*, 2012) have been introduced quite a number of years ago, with generations of PhD students trying to improve the recognition rate of the previous cohort, which is possible due to the vast accumulation of knowledge and skills concerning precisely these data sets (but not other unseen data sets). Even the IAM data set (Marti and Bunke, 2002), which is very realistic and challenging due to the presence of multiple writers, is of limited use as a predictor for the performance of an algorithm on historical material. The handwriting style and image quality concerns contemporary mixed-cursive and cursive handwriting. Recognition results obtained for such data sets are meaningless for an archivist with a medieval collection, a collection hieratic script on papyrus (Figure 10.2), or a collection of Russian 17th century pamphlets in an exuberant cursive style with large ascenders and descenders (Figure 10.3).

The goal of performing tests under acceptable theoretic conditions of independently sampled and identically distributed statistical properties is

<sup>&</sup>lt;sup>3</sup>https://en.wikipedia.org/wiki/Google\_Books



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Fig. 10.2 An example of hieratic script with papyrus in two types of aging within the same text column and weak contrast differences between ink trace and papyrus fibers.

Lau That

Fig. 10.3 A 17th century Russian example of an exuberant style with isolated and connected-cursive elements as well as overlap of ascenders and descenders between successive lines.

laudable and necessary, but it is not enough. Real collections violate both the conditions of stationarity and ergodicity which are needed for successful machine learning. A writer of a journal (diary) will usually start out with high ambitions and a clean style, in eloquent full sentences. However, as time progresses, this may evolve into sloppily produced entries containing more and more abbreviations, marginal notes in all orientations, and other idiosyncrasies (doodles) that were not present in the first pages. Both at the level of shape and at the level of language, the source processes are not stationary. Ergodicity, the requirement for a stochastic process that its statistical distribution can be estimated (read: because there is a sin-

gle, underlying signal source) is also often questionable. A single document may be produced by multiple scribes (read: different writing-style signal sources) and the linguistic content may vary from chapter to chapter to such a degree that one cannot consider the overall process ergodic: it is based on a diverse set of stochastic language generators. Such considerations seem to point to the use of machine-learning models that are trained and applied, *conditional* to a known aspect of the signal source, e.g., "we are in a Chinese section of the series of page scans", which indicates that a deep-learning model trained on Chinese characters may be considered as more appropriate than other style models. More formally, if p(x|M1, S1) > p(x|M2, S2), then p(C|x, M1) > p(C|x, M2), for samples x, a sample class C, two styles  $S_i$  and corresponding trained models  $M_i$ , i = 1, 2. In words, if the data are likely to be generated by model M1 if the source is in style S1, the probability is higher that a correct class label C is computed by model M1 rather than by model M2. An alternative approach would, e.g., require the assumption that there is enough training data for all possible scripts and classes such that a true 'omniscript' neural network can be trained. In this second, ambitious approach it is assumed, unrealistically, that a) enough data are present to bypass the problems of non-stationarity and non-ergodicity and that b) the resulting model would not suffer from the competition between all the classes, i.e., the complete set of international scripts. Please note that the Chinese language alone has a dictionary set (Ytizi Zydian) of 106.203 character shapes. Although other languages have smaller character sets, the mutual competition is bound to create risks. If whole-word classification is performed, the number of classes will be equal to the sum of the word lexicon sizes of all involved styles. For the case of Chinese alone, a convolutional neural network with a 'normal' dimensionality of a thousand units in pre-final layer N-1 and 100k output units in 'one-hot' configuration would require a fully connected layer with more than 100 million weights (Figure 10.4). At this number of coefficients it is unlikely that the 'dropout trick' (Hinton et al., 2012) will alleviate this situation.

With such a large number of incoming weights to a neuron, the collinearity problem entails that there are too many equipotential solutions for realizing a target (output) activation value, turning training into an ill-posed problem, i.e., a problem for which not one or, alternatively many solutions exist. It this example, the estimation problem is so massive that it can be argued that even in the absence of a collinearity problem, the underlying densities (the shapes of the underlying manifolds) need to be covered in





Fig. 10.4 In case of a very large number of output classes, the notion of a one-hot target output vector representing the classes becomes untenable. Handcrafted attribute representations need to be designed for the final layer, reducing its dimensionality (He and Schomaker, 2018).

sufficient detail by giving the neural network a sufficient number of training examples. Considering a lenient rule-of-thumb to have 5 samples (I/O pairs) per coefficient this would require half a billion training samples, disregarding the number of weights in the earlier layers in that network. If one would argue, that with a dropout probability of, say 0.8, the net number of coefficients is 20 million weights, this still implies that 100 million labeled samples would be needed according to the rule-of-thumb, a quantity that few research groups have at their disposal. With some additional (human) thinking, other representations than 100k-dimensional one-hot vectors can be used to solve the large set classification problem. We have proposed a solution based on attribute learning for the case of very large character sets (He and Schomaker, 2018). Within the Chinese character set, convenient attribute representations concerning the presence of radicals but also the order of strokes (e.g., the Wubi Xing method  $^{4}$ ). Similarly, for Western texts, an attribute method was introduced, PHOCNet (Sudholt and Fink, 2016). While very useful, such useful methods are highly script and/or language specific, thereby blocking the ambition of an 'omniscript'

<sup>&</sup>lt;sup>4</sup>https://en.wikipedia.org/wiki/Wubi\_method

approach. If it is necessary to improve the recognition rates by using linguistic statistics, this introduces yet another condition that needs to be determined for processing a given image region. An e-Science service for handwriting recognition will need to be able to handle a wide variety of scripts and languages. Sometimes, it will not even be possible to flag individual pages with a code for script style and language condition. The 17th century Cuper-Braun <sup>5</sup> collection in Monk, concerns a series of European scholarly letters by different writers. They write in a multitude of languages, switching from Latin to French, interjecting the text with phrases in Greek and Hebrew (Figure 10.5).

Therefore, in any case, some form of modular classification approach appears to be more practical when it comes to historical manuscripts. As a consequence, dedicated training will be necessary on most of the ingested digital documents. In some cases, it will even mean that separate models are necessary for papyrus-based and for parchment-based documents of a particular writing style, due to the clear differences in the ink deposition and absorption process for the two materials. See Figure 10.2 for an example of problematic pre-processing requirements for hieratic script on papyrus.

In light of the problems lined out thus far, it may be clear that the concept of an *AI black box* that will produce a perfect Microsoft Word text file when given a scanned image of historical text is utterly unrealistic. Consequently, the conclusion was to inform potential Monk system users according to the following notes:

- Don't promise perfection
- Don't promise exhaustive coverage
- Don't promise that it is a single conversion step
- Make clear that labeling will be necessary along the digital life cycle of the collection

#### 10.3 Deep learning

The successes of deep learning are based on a number of favorable conditions that are lacking in the context of historical document analysis. The problem of the archivist consists of a pile of scanned images, with an image quality that is not guaranteed to be amenable to optical character recognition or handwritten text recognition beforehand. The language may be known, but that does not mean that an appropriate lexicon exists. The

<sup>&</sup>lt;sup>5</sup>The Cuper-Braun collection was kindly provided by dr. J. Touber

Liber seundus Continet Co Sita XXVI. I De USON Brachis Sacerdohum. 11. De TROS Cunica. III. De UJIS Balteo. IV. De MYZER Pileo minorum faces V. De Grup Pallio P VI. De 71 32 Enhodo VII. De TUTT Dector De V//1. la milibul petion 1X. De TUE Tomario. X. De 7777 Smaragdo ed et facit de Captiro, Chryfolitho, Chryfoleutro, et aus loquens jubintelligi cettes isoro vel inpur vel fimilem. April Autorem de Fluminious in Alpheo finistar vulgo; יש טחל הסוגינישי לאמטיטוגייסד באחרי בשידט בול הסדבאנטי אטאדוגנטי בו Tonbus abactus feinfum in flurum Myctimum conject - fallor aut his legi debetnowar we a Furys, que promie itauveur, et agitare facinerofes, mai parricidas, ut vel drefes, pott, licuntur; et fimilia exempla gabes april in descriptione Inachi, et aliotum. + pus eundem in INDo Atijtoteles for Khir opin lapidem no puou xopin Toud ex xuplour green en tois 010, omatus gratia geftare in Sokeriis-Maufacus Eurifer explicated rete m felta ad Indos? med pe-Hanc correctionem is, gas frunt poltacieptam falutem, jed quid Grace The Reinesium 1.3. C. 13 the Indos in confesso the si Toto wrapionon i.e. in auticulus, find f Var. Lect. menje lanuari ing ner monere oblivifier Custius lib vin c. 1x. Lapilli'ex antibus 1690. primum pnimaduesti.

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Fig. 10.5 Examples of mixed Latin, Greek and Hebrew text within 17th century European scholarly letters. In the same collection, also correspondence letters containing French and other languages can be found next to fragments of classical language and script.

same holds for other linguistic resources. The character shapes, allographs are usually unknown, or a variant of a known style and no labeled data for machine learning is present. In fact, the whole purpose of the digitization is to get at encoded text, given the pixels in the image. What can be done to enjoy the benefits of current machine-learning technology? One possible approach is proposed with the Transkribus (Kahle *et al.*, 2017) platform within the READ project. Scholars are required to label a sufficient amount of pages, by transcribing them at the line level. Typically 70 to 100 transcribed pages are considered to be necessary. This approach has limitations. For instance, what is the optimal set of pages to be used as the

training set for a larger collection? Will it concern a single run of human transcription activity? As discussed above, starting with the first pages of a handwritten document is risky due to the intrinsic non stationarity. Secondly, the benefits of the labeling will only become apparent after the investment of human labeling has been done. In the design of the Monk system, an alternative approach is proposed, where pattern recognition starts upon the input of the first word label. From an over-segmented data set, hit lists are generated of 'mined' word zones and presented to the user, for confirmation. The user may choose to label words on the basis of a given line of text, thereby enlarging the covered lexicon. This type of process was dubbed 'widening'. Alternatively, the user may choose to confirm labels in the hit list for a pattern, thereby improving the training set for that particular class: 'deepening'. In labeling the hit lists, also additional catches of well-segmented words can be labeled, adding to the lexicon of known patterns. In this framework, useful computations are applied at the earliest moment in time. However, not all machine-learning methods are suitable in such an approach, as will be detailed in the next section.

#### 10.4 The ball-park principle

In fact, while a label-agglomeration process is evolving over time, the system passes different ball parks, each with its own most suitable machine-learning approaches.

No labels (zero labels). - In case no labels are available, it may be possible to rely on a pre-trained recognizer from the nearest handwriting style and a comparable lexicon. Additional training can then be applied for transfer learning. A particularly interesting solution is provided by machine-learning approaches based on attributes. Attributes are symbolic tokens that can be used to provide a text hypothesis in what basically constitutes are rule-based computation (Sudholt and Fink, 2016; He and Schomaker, 2018) known as zero-shot learning (Larochelle *et al.*, 2008). Please note that in a system such as Monk, which immediately exploits the arrival of new labels, the underlying class of patterns can directly be trained. In this manner, a secondary classification method, B, is kickstarted by the earlier applied primary method, A, which may be not optimal but still able to handle the zero-labels condition.

**One label**. - In case a single label is present, we enter the ball park of nearest-neighbor (1NN) classification. The labeled instance can be used

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for a data mining process, as in word spotting. Some appropriate distance measure is needed for comparing feature vectors. Such feature vectors can be dedicated (designed) or be trained, as is the case for embedded features tapped from some layer in an existing pre-trained neural network (Chanda *et al.*, 2018a). The resulting hit list can be presented to human users for confirmation. Upon entering a few labels, the system enters the next ball park.

**One to five labels**. With a few labels, some methods are able to produce rudimentary models. It becomes possible to compute standard deviations of features, enabling the use of Bayesian modeling. Instead of 1NN, kNN can be applied but it is much more attractive to use nearest-mean (nearest centroid) classification, because this reduces the computation load. After all, in a data mining context, if the reference set is large and the pool of patterns to be mined is huge, computational costs are too high. Taking, again, the extremal example of the Chinese dictionary set of 106k characters, the presence of 5 examples per class would require 530k times N comparisons, N being the huge number of candidate patterns in the data-mining pool.

**Twenty to hundred labels**. - As the number of labeled instances increases, more powerful classification methods can be used. For instance, with 50 positive examples of a class and an appropriate number of counter examples, support-vector machines (SVMs) can be trained for a more advanced form of targeted (specialized) pattern mining in the pool of unknown objects.

More than one hundred labels. - Here, finally, a level of coverage is obtained which allows training of contemporary deep-learning methods. However, this is only sensible if there are enough classes, such that the total number of patterns is in balance with the number of weights (model coefficients) in the classifier. This amount of labeling is just a starting point. As is long known in professional OCR classifiers for machine print, each class requires thousands of examples. Similarly, for handwritten digits large data sets are currently being collected with 830k samples (Uchida *et al.*, 2016).

As Figure 10.6 shows (upper left), the word (or pattern) accuracy performance of single classes may approach 100% recognition with thousands of examples, but not in all classes. Such scatter plots provide a deeper insight in where the friction towards a higher performance resides. Consider, for instance, the case were a class is performing suboptimally. Following 'old-school' precision thinking, the tendency would be to use, e.g.,



Fig. 10.6 Distribution of recognition accuracy as a function of labels, for a wide range of documents, script types and languages. Word classes will be moving towards the right and up over time, until a performance asymptote is reached. Some classes already have a decent performance with less than one hundred labels. On the other hand, some difficult shape classes remain just below 100% accuracy. The color of a circle denotes the manuscript group. The radius of the circle represents the size of the test set and is an indicator of the harvest.

k-means clustering to separate style variants in the training set for that class, thereby zooming in to a more precise modeling of allographs and increasing the number of shape classes. However, as Figure 10.6 shows, this would entail an approximate halving of the number of examples from n to  $\approx n/2$  corresponding to a large jump to the left on the horizontal axis, towards a point where the estimated expected accuracy (vertical axis) will be much lower. Indeed, we found that the performance will usually decrease after such an 'increased model-precision operation'. It is much easier to increase the performance by adding labels than to improve a given classifier on the basis of a reduced set of examples. There is no data like more data! Apparently, if the recognizer method is powerful enough, it is better to have mixed densities for style variants in one classification model, than have, e.g., two specialized models where each is trained on half the size of the original set of examples (Figure 10.7). We will only know whether the specalisation in modeling was worthwhile after our lifelong-learning engine has been able to harvest the original large number of labeled samples for

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each of the subclasses  $C_1$  and  $C_2$  that was present in the lumped set C at the onset, i.e., n examples.



N training examples for a class

Fig. 10.7 Schematic representation of the effects of 'precise' modeling by splitting the training set for a class in style-based subclasses. (a) a class C shows suboptimal performance. (b) The idea is to use, e.g., k-means clustering with k=2 to zoom in on the shape differences and have two specialized models  $C_1$  and  $C_2$ . (c) As a result of the smaller training sets, there will be a considerable drop in expected performance for the specialized models. On the basis of the large set of reference experiments, it is statistically questionable whether the supposed exactness of the models can counteract the large drop in accuracy due to the loss of examples.

In any case, by the time the final ball park of abundant labeling has been reached, a solid ground is present for constructing an index of a document. If linguistic models are present, an attempt can be made towards fullpage transcription. Infrequent shapes and classes still pose a risk at this stage. It may be desirable to replace uncertain recognition results with an ellipsis ... instead of presenting uncertain text hypotheses. Presenting postprocessed results introduce a new type of problem, especially if a recognized text is fluently legible, but unfortunately not what has been written. The user interface needs to allow the users to compare recognized results and handwriting one on one. If this particular risk is not communicated to users, their disappointement with the system if they detect such output may be larger than necessary.

#### 10.5 Technical realization

Is the reading system offered as a stand-alone computer tool, running on the infrastructure of a library institution under local supervision, or is it constructed as a 'cloud'-based service, somewhere on Internet, with support from remote, possibly anonymous but expert-level staff?

#### 10.5.1 Work flow

Does the archive intend to perform a single-shot conversion of a given collection (from pixels to encoded text) or do they realize that continuous efforts in quality control will be required?

#### 10.5.2 Quality and quantity of material

Will the be a preselection of materials and what are the criteria? What types of material are present: books, diaries/journals, shoe boxes with letters in their original envelope, written by diverse writers?

#### 10.5.3 Industrialization and scalability

Who is responsible for image preprocessing and layout analysis? A folder with 2300 scanned raw unlabeled images of papyrus texts is not well comparable to an academic benchmark test for machine learning that is preprocessed, packaged and prepared for k-fold evaluation experiments. How to handle the bad luck of success: "It works, now we need to process several hundreds of such collections within a year."

#### 10.5.4 Human effort

Who will be responsible for meta-data input, labeling, linguistic quality evaluation?

#### 10.5.5 Algorithms

As the last consideration, the machine-learning methodology used: Will it be possible to enjoy improvements in algorithms, over time? How to select such method? Are current methods in deep learning usable in practical application settings?  $\label{eq:lifelong} \textit{Lifelong learning for text retrieval and recognition in historical handwritten document collections 19}$ 

#### 10.5.6 *Object of recognition: Whole-word approaches*

For an e-Science service in historical document analysis, it is important to strive for generic solutions wherever possible, given the large scale and huge diversity. Traditional speech and handwriting recognition usually rely strongly on linguistic resources. These are usually not present for unique documents that just enter the digital stage of their life cycle. The assumptions for 'optical character recognition' as 'classification of sequences of character classes' are not valid for a wide range of documents. At the same time it was clear in the period 2000-2008 that general image classification was making large leaps forward (Rath and Manmatha, 2007). In the document-analysis community, word-spotting techniques were being proposed. We found that biologically inspired neural networks provided very high word-classification rates on connected-cursive script (van der Zant *et al.*, 2008). As a consequence, a word-based classification approach was opted for in Monk.

#### 10.5.7 Processing pipeline

Ingest. - The processing pipeline starts with the *ingest* stage of a collection. It is verified that the users will have a long-term interest in the document, there is a responsible local 'editor' who instructs a group of volunteering labelers. The material needs to be sufficiently homogeneous, sufficiently large: much more than a hundred page scans, and of a manageable image quality. A choice is made for the basic text object on the scans that will be the target of recognition. This often requires a split in separate recto/verso images and a subsequent layout analysis to identify the major text columns in the document. Over time, a growing library of software scripts is collected such that new collections require just a variation on a known preprocessing scheme. This stage usually requires some additional programming using image processing tools. For instance, for a multi-spectral collection, a flattened image version that is optimal for ink/paper separation should be produced. The initial data transfer is realized using ftp,transfer web sites or hard disks sent via surface mail. We have experimented with allowing an upload of individual unorganized raw scans but this does not bring much to either party. Such isolated small projects do not benefit from the large scale of data-science approaches and the isolated material gives little chances to act as a multiplier for the solid coverage of a hitherto unseen script style.

**Line segmentation**. - Using horizontal ink-density estimates which are low-pass filtered, an automatic segmentation into lines is attempted. This is first done on a random subset of the scans, in order to find a proper parameter setting. Perfection is difficult to realize with a considerable portion of submitted collections. For difficult cases, curvilinear segmentation methods such as seam carving are applied (Surinta et al., 2014; Chanda et al., 2018b). Current approaches in machine learning favor end-to-end classification that starts with the original color image. However, the curvilinearly cropped text line requires an artificial background. Replacement by pure white pixels is not desirable, because it will introduce sharp nontext edges along the curvilinear cut. In Chanda et al. (2018b) an attempt is realized to construct an artificial background with the texture and color properties of the original image, replacing undesirable ascenders and descenders of the surrounding text lines. Even such an advanced method will not solve all possible problems. Collections with marginal notes and posthoc corrections will be intrinsically unsolvable without some form of human intervention such as providing manual segmentations for deviant objects in the image. If the goal is a mere indexing (as opposed to full transcription) the attribution of a word to a particular line is less important. In many applications it will already be a great benefit if a target key word can be found and marked on the page, disregarding its membership to a line.

Word-zone candidates by over segmentation. - Using vertical inkdensity estimates, candidate word zones are segmented which are of variable overlapping size. Widely spaced connected-cursive text is ideal: The number of word zones will be limited and wide white spaces prevent the occurrence of multi-word image crops. At the other end of the spectrum would be a faded typewritten text where even a single letter may consist of multiple connected components. Also here, some experimentation with a random subset of page columns is required. The segmentation is facultative. If at a later stage other word-zones are added by another word-segmentation algorithm, the resulting candidates are just added to the pool of word-zone candidates.

**Word recognition**. - At this stage, the document will enter the autonomous continuous learning cycle. Word classification tools will be applied to it, generating word-hypothesis lists for each word-zone candidate. The text hypotheses are added to a large raw Index. In the training of the word classifiers, data augmentation is performed using random elastic morphing [Bulacu *et al.* (2009)], which is necessary for all classes that have

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less than about 20 examples.

Word ranking: Hit list generation. As described elsewhere (van Oosten and Schomaker, 2014) we found that using the likelihood estimates generated by recognition engines, for instance the maximum a posterior likelihood p(C|x) does not by necessity yield believable, intuitive hit lists. The task of separating an instance class from competing candidate classes, i.e., recognition, is another function than ranking, where one wants instances to appear sorted at the top of a hit list, with a strong similarity to a canonical model, i.e., optimizing the reverse probability, p(x|C). Therefore, a method is used that is optimal for ranking, yielding hit lists with understandable positive results and even understandable errors.

Presentation of recognition results to the user: per line, or per hit list for lexical words. At this stage, the user will be able to confirm text hypotheses or enter new word labels. This is detected by the event handler of the system, which will add a recomputation request for the class models at hand. This in turn will lead to re-recognition batch jobs, which generates new, improved text hypotheses, usually within 24 hours. At this point, the system will thus return to the Word-recognition stage, closing an iterative loop we have dubbed the 'Fahrkunst' principle. Closing of the loop to realize an autonomously learning system was realized in the summer of 2009. Controlling the feedback loop concerns the manual adjustment of computation policy parameters: Which books to focus the computation on, with which amount of delay time per cycle. A distinction is made between cold and hot books in the collection. Hot books are those where the user community has a great interest and displays a fruitful labeling harvest.

**Construction of alphabetic word lists and provisional transcriptions**. Finally, in this on-going process, there is a periodic selection of confirmed text hypotheses and manual transcriptions that is presented on internet as static files. A mechanism for downloading indices is also present, using download licenses with a limited time validity for end users. Together with end users, a 'work list' is defined for this type of objects. This part of the system is becoming more and more important and a large diversity of export formats is expected to be relevant at this level. For handwriting, the Alto standard is not optimal, but the Page XML format by the Prima group is an example of a usable output format for a range of further applications beyond this stage.

#### 10.6 Performance

Although performance evaluation for recognition are straightforward, the same cannot be said of retrieval engines. The usual performance evaluation in machine learning assumes a train set, validation set and test set, all with labeled raw-data instances. Commonly, k-fold evaluation is performed to obtain reliable performance indicators in terms of accuracy, precision and recall. For the labeled portion of the data in a large document analysis system, a similar periodic evaluation can be applied to select optimal classifiers per script style, and so forth. One might think that the recall performance is a good predictor for the actual recall capability of a classifier in openended data mining. However, this is not straightforward while being in the middle of a continuous learning process. We do not know how many instances of a particular class are out there, in the mining pool? If an asymptote is reached in the accuracy for a particular class, does that mean that the pattern is 'mined out', i.e., that no more instances of that class exist in the pool, or, alternatively, is it the case that there is a particular problem at the level of shape representation and classification that cannot be solved by the current recognition method? In a lifelong learning context, new performance criteria are needed. For instance: where in the class space will additional labeling has the largest beneficial training effects?

An example of a new concept that was developed in this respect is the definition of the EUR, Equal Uncertainty Rate as a replacement for the EER, Equal Error Rate. In case of ranking instances of a single class, the labeled training examples are the basis for the computation of the False Reject Rate (FRR) curve. However, its counterpart, the False Acceptance Rate is less clear, since it is not known whether residual instances in a hit list are of the target class or not. Still, the EUR provides a good insight in the quality of instances as regards the likelihood that they are a member of the target class or not. By attracting the user to those classes where FRR/FAR curves indicate a good separating performance, human efforts are directed to where fruitful harvest are to be expected in the mining process. Figure 10.8 shows the effect of labeling on the False-Reject Rate and False-Accept Rate curves. The Equal Uncertainty rate should go down. In this real example, we see that the FRR rate (green curve, representing the target class) remains about the same, as well as the EUR value, but the False-Acceptance Rate curve (red, non-target samples) is becoming steeper. In lifelong machine learning, it is the goal to find the classes where these improvements are largest. In the Monk architectures,

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dedicated neural networks are trained to predict which classes give the highest improvement upon labeling. The users can then be attracted to these 'prospects', to confirm or disconfirm the label values for those classes. So basically, this constitutes a selective-attention mechanism of the learning system, answering the question: 'Where is the action?' in the learning process.



Fig. 10.8 Schematic overview of the effects of interactive labeling on the False-Reject Rate (FRR) and False-Accept Rate (FAR) curves for a class, in this example a typewritten letter 't'. By labeling a few candidates (light colored) in the hitlist, they become part of the training set and have an effect on the classification performance as indicated by the arrows. The samples and curves are an actual example of the consequences of adding nine new instances for the letter 't'. The Monk collection does not only contain handwriting: methods are also used for other classes of shapes. Equal Uncertainty Rate (EUR) is used instead of EER because the class labels of non-target patterns, i.e., the samples under the FAR curve, are unknown in open-set data mining.

During the writing of this chapter, a large-scale field test was performed, comparing a traditional method and deep convolutional networks (Schomaker, 2019). The goal was to perform unmonitored end-to-end training of word, shape and character images in several hundreds of books with widely differing styles. Computing, using several GPUs, lasted from January 2019 to the end of April 2019. Although deep end-to-end training was able to obtain 95% word accuracy in many books, the training process

failed several times for problems with more than 1000 classes in one-hot encoded classification, even with a fairly small number of hidden units in the pre-final layer (150). Due to the fact that nearest-mean classification using bags of visual words is not limited by the number of (lexical) classes, the average performance over all books was higher for this traditional method (BOVW 87% vs 83% when failed CNN trainings were included). As we have shown (He and Schomaker, 2018), the problem of high numbers of classes can be solved using attribute learning, but this is a form of handcrafting of an output representation that would be required for different scripts and languages. For a system such as Monk, a pragmatic approach is chosen: For each book, the best-performing method can be selected.

#### 10.7 Compositionality

The whole-word based approach has as advantage that it exploits the redundance of shapes and has a diminished reliance on the well-formedness of individual character shapes. The disadvantage is that there is a reduced exploitation of the presence of stable pattern fractions corresponding to letters and syllables. In the HMM-era this was addressed by 'state sharing'. In the modern recurrent neural networks (LSTM, BLSTM, MDLSTM), the training process will sort this out, automatically. However, this still requires a sufficient regularity of character shapes to be successful, and many labeled examples are needed, for instance 2000 lines of transcribed text. This allows for compositionality and proper handling of words that were never seen ('out of lexicon' recognition rate. However, not all collections lend themselves to the use of LSTM, because spatial invariance is not its strongest asset and is better dealt with using CNNs. Whole-word based approaches will be able to handle unseen classes, if attribute schemes are used for constructing class vector representations as targets for neural-network output. What is most important for a data-mining framework, is that the harvest of labels keeps the users motivated. Figure 10.9 shows the number of elicited labels evolving over time. same collection are ingested. The growth curves show non-linear speedup at points where labeling is facilitated due to the collaboration between man and machine. A detailed view on the growth curves shows the 'snow-ball' effect at a smaller time scale: thirty labels are added within a minute by a single user. Therefore, labeling of instances in hit lists can be 'faster than linear', i.e., faster than begin-to-end, word-by-word transcription.

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Fig. 10.9 Examples of label harvesting over time. Top: three books of the same collection are ingested. Note non-linear, steep speedups at some points due to hit-list based label confirmation. Bottom: zooming in on the growth curves show this 'snow-ball' effect at a smaller time scale: Twenty to thirty labels are added within a minute by a single user.

#### 10.8 Conclusion

In this chapter, an overview was given of design considerations, practical solutions and problems encountered around a large-scale multi-user e-Science service for text recognition and retrieval in a variety of historical-document collections. The focus was more on text recognition than on document dating and writer identification algorithms, which have been published elsewhere. The major contributions of this chapter concern:

- A message to the machine-learning community that the current habits of algorithm evaluation entail the risk of a narrow view on pattern diversity in and preprocessing problems in real manuscript collections;
- Contrary to a separate laboratory and operational stage, continuus improvement requires lifelong learning, in an integrated manner, also called 'persistent cognition';
- An active label-harvesting engine that is running in autonomous mode needs new predictive algorithms to direct the investment of computational resources and human labeling labour to the data portions where the most attractive harvest prospects are to be expected. Such prospects are located on the fringe of a training front;
- When critical numbers of labels are reached, the label harvesting enters into a cascade of avalanche mode, such that ranked hit lists can be easily labeled, until the next performance asymptote is reached;
- The necessity for massive numbers of labels constitutes an intrinsic limitation of current deep-learning methods. The ball-park principle allows for exploitation of different types of methods which produce good results with a few or no labels, and then progressing to more advanced methods as more labeled instances are collected over time.

At this point, it also becomes important to add critical remarks. As a general method, a whole-word based method is very attractive. The task is very similar to general image retrieval, where a wide spectrum of algorithms is available to process greyscale and color images. In Monk, a single convenient general-purpose classifier is used to this effect. However, if individual characters actually *are present* and sufficiently regular,

#### $\label{eq:lifelong} \textit{Lifelong learning for text retrieval and recognition in historical handwritten document collections 27$

character-based methods and recurrent networks become applicable. In the methods described in this chapter, linguistic post processing did not play a role, because in most cases there is no suitable linguistic corpus. Again, however, if such a corpus actually *does exist*, it would be suboptimal not to use it. Current projects around the Monk system are directed at incorporation of linguistic and semantic resources to improve the classification accuracy. An intrinsic problem in document retrieval concerns the statistical distribution of terms: Many interesting target terms will be located in the long tail of the word distribution. A low frequency of presence implies a limited number of training examples. Also for these cases, letter or character based methods will be very important. An additional solution for this problem is given by the attribute-based methods which allow for zero-shot learning. Finally, a few words need to be spent concerning alternative projects, such as Transkribus (Kahle et al., 2017) and READ. For historical reasons and due to different funding sources, the development of the Monk system took place in relative isolation. Still, a considerable number of users from the humanities are interested in the type of solutions provided by Monk. From their point of view, it would be very desirable if they could benefit from the advances in each of the different approaches. As an example, transcription data collected in Transkribus can be used to train recognizers in the Monk system. Alternatively, text-recognition results on word images could be cross checked by dedicated word classification systems on manuscript-processing e-Science servers, world wide, including those from READ, Monk and other projects. The ultimate goal would be to realize the type label-harvesting avalanches reported here, but over a wide range of document collections. In some areas, such as medieval European script styles, such a critical mass is about to be reached in the coming few years. The costs involved in maintaining large-scale computing and storage infrastructures will force all parties to cooperate. A good example is given by the astronomers, who have a similarly long-term perspective as the archives and humanities scholars, but who also have the tenacity to procure and maintain such long-term e-Science services (Valentijn et al., 2017).

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