

Machine Learning for Ancient Languages: A Survey

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Ancient languages preserve the cultures and histories of the past. However, their study is fraught with difficulties, and experts must tackle a range of challenging text-based tasks, from deciphering lost languages to restoring damaged inscriptions, to determining the authorship of works of literature. Technological aids have long supported the study of ancient texts, but in recent years advances in artificial intelligence and machine learning have enabled analyses on a scale and in a detail that are reshaping the field of humanities, similarly to how microscopes and telescopes have contributed to the realm of science. This article aims to provide a comprehensive survey of published research using machine learning for the study of ancient texts written in any language, script, and medium, spanning over three and a half millennia of civilizations around the ancient world. To analyze the relevant literature, we introduce a taxonomy of tasks inspired by the steps involved in the study of ancient documents: digitization, restoration, attribution, linguistic analysis, textual criticism, translation, and decipherment. This work offers three major contributions: first, mapping the interdisciplinary field carved out by the synergy between the humanities and machine learning; second, highlighting how active collaboration between specialists from both fields is key to producing impactful and compelling scholarship; third, highlighting promising directions for future work in this field. Thus, this work promotes and supports the continued collaborative impetus between the humanities and machine learning.

1. Introduction

Ancient languages are key conveyors and repositories of ancient civilizations, as they encode the thought, cultures, and histories of the past. The texts that preserve these languages were written over the centuries on a variety of media (bone, metal, palm leaf, paper, papyri, parchment, potsherds, stone) and in different scripts (Brahmi, Old Chinese, Egyptian hieroglyphs, ancient Greek, Indus, Latin, Mayan, and others). Over the last twenty years, the introduction of advanced technologies has spurred transformational advances in the study of ancient languages and texts, with the rise of machine learning leaving a particular mark. Machine learning models can discover and harness intricate statistical patterns in vast quantities of data. Recent increases in computational power and advances in deep neural network models, a sub-area of machine learning known as deep learning, have enabled these models to tackle challenges of growing sophistication in several fields (LeCun, Bengio, and Hinton 2015) (see Section 2), including the study of ancient languages (Parker et al. 2019; Kang et al. 2021; Assael et al. 2022; Yoo et al. 2022). The patterns discovered by these models can be leveraged to advance the state-of-the-art in tasks ranging from character recognition to stylometrics, from author attribution

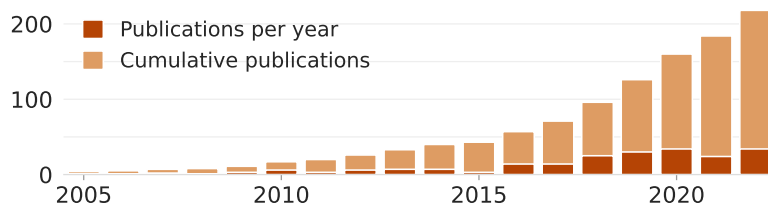


Figure 1

Bar chart depicting the number of articles published on the topic of machine learning for ancient languages per year. As can be seen, the last 5 years have seen a substantial increase in the number of publications.

to textual restoration. Similarly to how microscopes and telescopes have contributed to the realm of science, the humanities can now be assisted by machine learning methods and techniques.

The steep increase in scholarly efforts in this field can be connected to the wider availability of digitized datasets, comprising publicly accessible high-quality photographs or transcriptions of ancient texts. In parallel, the field of machine learning is constantly being advanced by novel learning methods and architectures, deep learning being one of the most recent examples. This fecund situation has engendered a “virtuous circle” of sorts, whereby greater availability of data and fast-paced scientific progress have inspired more people to both digitize ancient texts and explore novel machine learning methods to study them, fuelling a dynamic feedback loop (competitions are a clear example of this trend). As a direct consequence, new interdisciplinary research questions are being posed—the growing number of publications per year as surveyed below and seen in Figure 1 demonstrates this momentum.

In a machine learning setting, ancient languages exhibit several differences from their modern counterparts. For ancient languages, often very limited data is available today, owing to low survival record, damaged state of material preservation, or complex transmission traditions. Moreover, only a small fraction of the extant ancient data has been digitized in a standardized, open-access and metadata-rich format, which is crucial to machine learning tasks. Ancient languages were written in a variety of writings systems, some of which are now extinct (e.g., Mayan hieroglyphs) or still undeciphered (e.g., the Indus script). What is more, a single script might encode several languages, but the relationship between these languages might be unclear. Even within the same script or language, variations between genres, written supports, and text types (e.g., epigraphic and literary texts) and geographically or chronologically specific variants (e.g., local dialects) make the generalization of machine learning methods complex. Language-specific idiosyncrasies (e.g., Latin abbreviations), complex textual transmission histories (e.g., disputed authorship), and semantic shifts between ancient and modern languages also add a layer of sophistication to an already complex endeavour. Finally, the lack of “ground truths” concerning, for instance, the restoration of textual lacunae or the dating of a text also makes evaluating a model’s performance extremely difficult. But it is this very complexity that makes the study of machine learning for ancient languages a worthwhile research topic and an interesting benchmark.

In this survey, we offer a detailed review of scholarly contributions to this field. We have chosen to discuss scholarship focusing on *ancient texts written in ancient languages*. More specifically, with “ancient languages” we consider all languages in use across the world, written on any medium and in any script, between the birth of writing systems

in ancient Mesopotamia (3400 BCE) up until the conventional end of “ancient history” in the late first millennium CE. Owing to space limitations, this article exclusively considers those works dealing with interdisciplinary machine learning research for ancient languages: works that did not use machine learning models, as well as those published before the 2000s, were excluded. Compared to previous literature reviews (Stamatatos 2009; Dexter et al. 2017; Papantoniou and Tzitzikas 2020; Mantovan and Nanni 2020; Fiorucci et al. 2020; Bhurke et al. 2020; Narang, Jindal, and Kumar 2020; Sahala 2021; Bogacz and Mara 2022; Faigenbaum-Golovin, Shaus, and Sober 2022), which are either task- or language-specific (e.g., artificial intelligence [AI] for the Greek language, digital Assyriology, handwritten text recognition, AI for archaeology), this work strives to encompass all tasks and all ancient languages benefiting from the synergistic collaboration between machine learning and the humanities.

Our goal is twofold: First, we seek to map this interdisciplinary field to aid future research; second, we aim to highlight how the joint, collaborative effort of specialists in both the sciences and the humanities is key to producing relevant, robust, and cogent scholarship. Our target audience therefore comprises humanities researchers (historians, classicists, linguists, philologists), reviewing the plethora of machine learning methods available to tackle ancient textual challenges; and computer scientists, examining the many idiosyncrasies of ancient writing systems. Our final aim is to promote and support an increased collaborative impetus between the humanities and AI (Palaniappan and Adhikari 2017; Popović, Dhali, and Schomaker 2021; Assael et al. 2022).

To best undertake our review work, we designed a taxonomy (Figure 2) following the different, but not necessarily sequential, steps involved in the study of ancient documents:

- **Digitization:** bringing textual sources to a high-quality machine-readable format, for example, through optical character recognition and handwritten text recognition.
- **Restoration:** the process of recovery of missing text and reassembly of fragmented written artifacts.
- **Attribution:** contextualizing a document within its original geographical, chronological, and authorial setting (i.e., who wrote the text, when, and where).
- **Linguistic analysis:** involving linguistic tasks such as semantic analysis, part of speech (POS) tagging, text parsing, and segmentation.



Figure 2

Proposed taxonomy to study machine learning for ancient languages, inspired by the different steps involved in the study of ancient documents.

- **Textual criticism:** the process of reconstructing a text's philological tradition of textual transmission.
- **Translation and decipherment:** which aim to make a text's language comprehensible and interpretable to modern-day researchers.

The majority of the surveyed works operate on text, apart from those focusing on quality enhancement (*digitization*), fragment reassembly (*restoration*), palaeographic analysis, and writer identification (*attribution*), which instead operate mainly on visual inputs; whereas works focusing on recognition (*digitization*) harness both modalities.

The arrangement of our taxonomy into separate sections is intended to enhance readability. Each section's content dictates the underlying paper review order, be it chronological, by language, or by model type. By assigning a logical structure to each section, the reader will be able to follow related works in a more straightforward manner.

2. Background

Before commencing the discussion of each step in our pipeline, we will spare a few words to the history of machine learning over the last two decades, for the benefit of historians and non-experts. Before the advent of deep learning, scientists developed hand-crafted features to describe the input data and better address different tasks. These features ranged from image descriptors (e.g., Histogram of Oriented Gradients [HoG] and Scale Invariant Feature Transform [SIFT] for object recognition and image classification [Forsyth and Ponce 2011, p. 155]), to frequency-based or categorical text features (e.g., term frequency-inverse document frequency [TF-IDF] [Manning and Schütze 1999, p. 543], grammatical features). These features were then used as inputs to clustering algorithms (e.g., *k*-means, Gaussian mixture models, which automatically discover groups of similar texts), statistical models (e.g., hidden Markov models [HMMs] and conditional random fields [CRFs], which learn to tag sequences by assigning POS tags to word sequences), and classification algorithms (e.g., support vector machines [SVMs], random forests, and boosting algorithms, which learn to classify texts by author, historical period).

However, the capabilities of these hand-crafted feature representations were limited and tailored to tackle only specific tasks, and as such were gradually superseded starting in 2012 with the advent of deep learning and neural network (NN) models. NN models have the ability to process raw data and automatically learn the representations needed for the task. This representation learning in a supervised setting relies on labeled data, where the model is trained to learn the optimal features of the inputs to predict specific labels. In contrast, unsupervised representation learning focuses on identifying patterns and structures within the data without explicit guidance, allowing the model to capture intrinsic characteristics and form meaningful features. In NNs this process is implemented hierarchically by using non-linear layer modules that transform data from one layer of representation to the next, gradually increasing the abstraction level. Complex functions can be learned by the composition of enough layers (LeCun, Bengio, and Hinton 2015).

Massive increases in computing power engendered by the parallel processing capabilities of Graphics Processing Units (GPUs), the growing availability of large datasets, and continued methodological advances could now enable the NN models to learn better and more generalizable feature representations from the data itself as part of

their training process. The initial focus was on convolutional neural networks (CNNs) working on images. The mechanisms behind CNNs were inspired by visual neuroscience: simple cells that are sensitive to specific orientations of edges, and complex cells that respond to patterns of edges with a particular orientation and spatial frequency (Hubel and Wiesel 1962). CNNs were soon extended from images to learning word representations, for example, word2vec (Mikolov et al. 2013): In this setting, words are represented by means of embeddings, a learned representation for text where words with the same meaning will also have a similar representation. At the same time, recurrent neural networks (RNNs) (Goodfellow, Bengio, and Courville 2016) started to show enormous potential for modeling text sequences, for example, long short-term memory (Hochreiter and Schmidhuber 1997) and gated recurrent units (Chung et al. 2014). NN models continued to evolve, classifying inputs, mapping textual sequences to sequences (seq2seq) (Sutskever, Vinyals, and Le 2014), featuring attention mechanisms for RNNs, introducing novel generative models (e.g., variational autoencoders and generative adversarial networks [GANs] for text and image generation [Goodfellow, Bengio, and Courville 2016; Goodfellow et al. 2020]). One of the most important breakthroughs was the Transformer (Vaswani et al. 2017) in 2017—a deep learning model that relied extensively on attention mechanisms to better capture contextual information, and which could process sequences in parallel, unlike RNNs. Soon, Transformer-based models became the standard for extracting features from texts (e.g., BERT; Devlin et al. 2019), while other larger Transformer models—for example, GPT-3 (Brown et al. 2020), PaLM (Chowdhery et al. 2022), and ChatGPT—trained on even larger corpora demonstrated emergent capabilities on a wide range of tasks. Today, such large-scale models are routinely applied to protein folding, video generation and translation, image captioning, as well as the study of ancient languages. The works surveyed in this research retrace the above-mentioned chronological progression.

To conclude this preamble, we must stress that progress in machine learning relies not only on powerful models, but also on the quality and quantity of datasets, evaluation metrics, and experimental protocols. For this reason, we emphasize: (a) the direct correlation between the choice of dataset and a model's performance; (b) the importance of robust hypothesis testing, with data partitioning (into train, validation, and test sets) or resampling to train different models and measure their effectiveness and stability in generalizing results (e.g., with cross-validation); and (c) the value of statistical significance tests, which ensure that observed differences in performance across models are not merely random artefacts.

3. Digitization

3.1 Recognition

The first steps in the study of ancient texts using machine learning are digitization and recognition. The task of automated transcription of a text from the image of a written support (e.g., a photograph, drawing, or scan of an inscription, manuscript, or papyrus fragment) to its digitized form is a central task in the conservation of ancient documents, making them digitally accessible for downstream tasks. Optical Character Recognition (OCR) and its sub-field Handwritten Text Recognition (HTR) are indeed well-studied areas of research.

The tasks of OCR/HTR have been attracting interest of early traditional machine learning approaches since the 1980s. These early works were followed by efforts

to use self-adapting software to digitize the Latin writing tablets from Vindolanda (Terras and Robertson 2005) and open and closed cavity character detection on early Christian manuscripts in Greek (Gatos et al. 2006; Ntzios et al. 2007). In more recent years, research focused on training new models or on adapting existing OCR engines to Latin and ancient Greek text recognition. Indeed, the impact of open-source OCR engines such as Abbyy FineReader, Gamera, Tesseract, OCRopus¹ has been essential to this field, granting free access to off-the-shelf OCR solutions to humanities researchers. For the purpose of this review, we will focus exclusively on the *ex novo* development of models and tools for OCR/HTR. Firmani et al. (2018) used a word to character segmentation algorithm followed by a CNN to classify characters in Latin historical documents, and then used language modeling to yield their word transcriptions. More recently, Swindall et al. (2021) introduced two “Ancient Lives” datasets consisting of more than 490k labeled character images of ancient Greek manuscripts manually annotated by volunteers. The authors evaluated multiple CNN models, and the highest accuracy was obtained using a residual neural network (ResNet) model (He et al. 2016a). The importance of such manually annotated datasets cannot be underestimated, an observation which applies throughout this review.

Multiple efforts have focused on cuneiform sign recognition. Early works (Edan 2013; Mostofi and Khashman 2014) used *k*-nearest neighbors (*k*-NN, classifying each test instance to the majority class of its most similar training instances) or NNs with very few layers, to classify small subsets of cuneiform signs. Further work has attempted to build an automated pipeline for transliterating entire lines of text (Bogacz, Klingmann, and Mara 2017). Working on a small number of tablets, the pipeline segments the lines, extracts image features, and aligns them to their transliteration. The best performing model was an HMM, but the accuracy was low, leading the authors to conclude that transliteration is tractable, but requires significantly cleaner data. A fully automated approach for automatic transliteration was proposed by Dencker et al. (2020). The authors began by weakly aligning sign transliterations to their corresponding tablet images, using a CNN and a CRF, and then trained a CNN sign detector. Combining these steps in an iterative process enabled the training of a better aligner and, as a result, a better sign detector. The model was evaluated on tablets from the Oracc and CDLI datasets. Several other ancient writing systems have been the focus of HTR/OCR efforts, including: Devanagari (Narang, Jindal, and Kumar 2019; Narang et al. 2020; Narang, Kumar, and Jindal 2021; Jindal and Ghosh 2022), Egyptian hieroglyphs (Franken and van Gemert 2013; Haliassos et al. 2020; Barucci et al. 2021; Moustafa et al. 2022), Old Tamil (Suganya and Murugavalli 2017; Subramani and Murugavalli 2019; Devi et al. 2022), ancient Ge’ez (Demilew and Sekeroglu 2019), Brahmi (Wijerathna et al. 2019), Grantha (Raj, Jyothi, and Anilkumar 2017), Indus script (Palaniappan and Adhikari 2017), Maya glyphs (Can, Odoñez, and Gatica-Perez 2016), Oracle bone (jiāgǔwén) script (Zhang et al. 2019), Phoenician (Rizk et al. 2021), and Tibetan script (Liu et al. 2022).

HTR remains among the most challenging tasks in machine learning for ancient writing systems. The implementation of recognition pipelines relies upon the existence of digital images, and a successful pipeline requires high quality and quantity of digitizations; for example, compare the rich datasets of cuneiform tablet images to their paucity for Greek inscriptions. A standard recognition pipeline comprises: image

1 Abbyy FineReader: <https://www.abbyy.com>, Gamera: <https://gamera.informatik.hsnr.de>, Tesseract: <https://github.com/tesseract-ocr/tesseract>, OCRopus: <https://github.com/ocropus>.

pre-processing, text segmentation, feature extraction and classification, and post-processing. Segmentation can work at a line-, word- or character-level, and is a crucial phase of an OCR/HTR system, as it can directly affect the overall accuracy of transliterations (Narang, Jindal, and Kumar 2020). Several studies propose HTR as a classification problem of pre-segmented character images (Terras and Robertson 2005; Edan 2013; Franken and van Gemert 2013; Mostofi and Khashman 2014; Can, Odobez, and Gatica-Perez 2016; Raj, Jyothi, and Anilkumar 2017; Firmani et al. 2018; Zhang et al. 2019; Subramani and Murugavalli 2019; Narang, Jindal, and Kumar 2019; Narang et al. 2020; Haliassos et al. 2020; Swindall et al. 2021; Barucci et al. 2021; Rizk et al. 2021).

But character segmentation is not a solved task, especially in scripts where character boundaries overlap (e.g., cursive handwriting). Such challenges are made even more taxing by the state of preservation of ancient written media (damaged supports, low quality images, etc.). As a direct consequence, other studies have chosen to approach the task more holistically by introducing pipelines that include handcrafted or trained alignment and segmentation models (Gatos et al. 2006; Ntzios et al. 2007; Palaniappan and Adhikari 2017; Bogacz, Klingmann, and Mara 2017; Suganya and Murugavalli 2017; Demilew and Sekeroglu 2019; Wijerathna et al. 2019; Dencker et al. 2020; Gordin et al. 2020; Narang, Kumar, and Jindal 2021; Devi et al. 2022; Moustafa et al. 2022; Liu et al. 2022; Jindal and Ghosh 2022). Both approaches saw substantial improvements when using CNNs. For further details on recognition and digitization, we refer the reader to the recent subject-specific surveys by Bhurke et al. (2020) and Narang, Jindal, and Kumar (2020).

3.2 Quality Enhancement

When faced with a lack of high-quality image datasets or of significant variability in the data (owing to the paucity of digitized documents), *enhancing or restoring the quality of existing datasets* can yield better results in downstream tasks.

In 2003, Molton et al. (2003) focused on the visual enhancement of Roman stylus tablets using edge detection methods. In 2016, Faigenbaum-Golovin et al. (2016) analyzed ancient Hebrew inscriptions as parallel evidence for dating early biblical texts. However, because of the damaged state of the inscriptions, visual restoration was required to compare different handwriting styles and determine the inscriptions' author. The authors approached the problem of restoring characters on the basis of their composing strokes and representing them as spline-based structures, estimated using optimization.

More recent studies have resorted to NN models. Parker et al. (2019) presented a non-invasive digital recovery method for the carbonized texts of Herculaneum, showing that X-ray-based micro-computed tomography data can capture the presence of carbon ink. The authors used a 3D CNN to detect the volumetric presence of ink using reference papyrus rolls that had been already opened and inspected for writing. Then, using a virtual "unwrapping" pipeline, they were able to align these labels with the tomography volume and reveal the presence of letters in unopened scrolls. In 2020, Zhao et al. (2020) introduced a Laplacian pyramid GAN to enhance low-resolution inputs for ancient Shui handwriting recognition. Subsequently, the authors used an unsupervised clustering algorithm based on information entropy for automatically annotating the manuscript's character images. Similarly, Brandenbusch, Rusakov, and Fink (2021) used a conditional GAN for cuneiform sign inpainting in existing images of tablets. The model was trained on hundreds of photographs of tablets with 45k signs

annotated by bounding boxes, where random patches would be cropped around the signs to be infilled. Further encoder-decoder architectures were evaluated by Yu et al. (2022) for the visual restoration of the Mogao caves findings in Dunhuang.

But small datasets may be imbalanced, thereby introducing bias in the results: One must then seek to improve not just the quality but also augment the quantity of existing datasets. Swindall et al. (2022) used a GAN to generate synthetic characters of ancient Greek letters to balance a dataset of 400k papyri images (Swindall et al. 2021). The synthetic dataset resulted in a 12% recognition accuracy increase. Huang et al. (2022) also introduced a GAN architecture for Oracle bone and cuneiform glyph generation to address the data scarcity problem. The proposed model architecture cascaded a glyph transformation and a texture-transfer GAN. Finally, Nguyen et al. (2021) proposed an encoder-decoder NN architecture for de-noising the images of inscriptions in ancient Cham script. The architecture used attention over multiple scales to enhance the de-noised images. In an artificial noise-generation setting, the proposed model outperformed component analysis methods and other NN models.

4. Restoration

4.1 Textual Restoration

Over the centuries and millennia, ancient texts can be fragmented or become illegible owing to the deterioration or destruction of writing supports. Historians must then reconstruct the lost or illegible parts of the text, a process known as **textual restoration** (Matsumoto 2022). This is a complex and time-consuming task (Woodhead 1959): Specialists typically rely on textual and contextual “parallels” (recurring expressions or linguistic peculiarities) to reconstruct missing parts in similar texts.

Early modeling attempts to automate textual restoration used n -gram Markov chains for texts in the Indus script (Rao et al. 2009b; Yadav et al. 2010). Assael, Sommerschild, and Prag (2019) were the first to address the problem of text restoration using deep learning. Their work focused on Greek inscriptions and introduced an autoregressive sequence-to-sequence RNN model called Pythia. Pythia operated at both word- and character-level, the intuition being that words convey context, but parts of words may be damaged. On a purpose-made dataset based on the Packard Humanities’ Institute (PHI) dataset of ancient Greek inscriptions, Pythia achieved a 30% character error rate, compared with the 57% of two evaluated human specialists. Moreover, in three out of four cases, the ground-truth sequence was among the model’s Top-20 restorations. Fetaya et al. (2020) presented an RNN language model for token prediction and missing word completion in fragmentary Akkadian tablets. The RNN model was far more accurate than traditional n -gram baselines. Similar trends were observed in the work of Papavassileiou, Kosmopoulos, and Owens (2022), who used a bidirectional RNN trained on original and augmented data of Linear B inscriptions (Papavassiliou, Owens, and Kosmopoulos 2020), which exhibited a higher accuracy compared with n -gram baselines.

The introduction of Transformer-based models has led to significant advances in this field. Shen et al. (2020) introduced a Transformer-based architecture capable of generating sequences by dynamically creating and filling in blanks. The architecture was evaluated on the dataset introduced by Assael, Sommerschild, and Prag (2019) and performed on-par with Pythia, but it could also generate arbitrary sequences without the need of experts specifying the target length. Bamman and Burns (2020)

pre-trained a BERT (Devlin et al. 2019) model on Latin texts from Perseus, PROIEL, and Index Thomisticus Treebank, targeting restoration and several other downstream tasks. The effectiveness of Latin BERT's restoration accuracy was evaluated against the emendations made by experts with an accuracy of 33%, and many of its restorations were within its Top-10 predictions. Another masked language modeling Transformer architecture was proposed by Lazar et al. (2021) for the restoration of cuneiform tablets (in Akkadian). The model achieved an 83% accuracy on the Oracc dataset. The authors also evaluated two human annotators, who reviewed the model's Top-5 predictions. In the majority of cases, they accepted the model's restorations when up to 2 characters were missing, whereas when 3 characters were missing they accepted only half of the restorations generated by the model. Kang et al. (2021) used a Transformer-based model to restore and translate Korean historical records dating to the Joseon Dynasty. The model's Top-10 restoration accuracy was 89%. Finally, Assael et al. (2022) introduced Ithaca, a sparse-attention Transformer-based architecture for restoring, dating, and attributing ancient Greek inscriptions. Like its predecessor Pythia, Ithaca operates at both a character- and a word-level. To train Ithaca, the authors created a processed version of the PHI dataset of Greek inscriptions. While Ithaca alone achieved 62% accuracy when restoring damaged texts, as soon as evaluated historians used Ithaca, their accuracy leaped from 25% to 72%, thus effectively demonstrating the impact of this synergistic research aid. Finally, Ithaca uses saliency maps as a visual aid to highlight and inform the historians about which inputs were most important for the model's predictions.

Several studies relied on human baselines to measure effectiveness: Assael, Sommerschild, and Prag (2019), Lazar et al. (2021), Assael et al. (2022), but only Assael et al. (2022) sought to augment the interpretability of predictions using tools such as saliency maps and distributional outputs for human experts to evaluate in a real-world setting. The inclusion of humans in the training loop could result in more effective research.

4.2 Fragment Reassembly

Written supports may be broken into several pieces, which must be *reassembled* or visually restored to make the text legible again.

In 2012, Tyndall (2012) proposed naive Bayes and maximum entropy classifiers for rejoining the texts of fragmentary Hittite cuneiform tablets. Collins et al. (2014) introduced a matching algorithm for 3D scans of cuneiform tablets. In 2019, Pirrone, Aimar, and Journet (2019) used a Siamese-network architecture to reassemble papyrus fragments. By extracting "patches" of papyrus fragment images, they deployed a NN to score each matching pair. The model achieved a high accuracy on a synthetic dataset comprising gapless fragments in Coptic, Greek, Arabic, Hebrew, Hieratic, Latin, and Demotic from the APIS UM Papyrology Database. In 2021, Abitbol, Shimshoni, and Ben-Dov (2021) introduced a more complex system for the reassembly of the Dead Sea Scrolls. They first identified continuous natural fibre thread patterns in the papyrus fragments by processing square patches of different fragments through a CNN. The resulting local matching scores were then fed into a voting mechanism enhanced by geometric alignment techniques and a random forest classifier. The system produced a list of candidates for expert evaluation. In 2022, Zhang et al. (2022a) proposed a self-supervised network to rejoin bone fragments (inscribed in Oracle Bone script) based on shape similarity between joining fragments. The model consisted of a GAN for augmenting positive pairs of re-joinable fragments and a Siamese network trained on

the augmented data to retrieve the matching Oracle Bone fragments from a fragment gallery. The network could reassemble half of the previously disjoined fragments.

Fragment reassembly is a challenging problem, as the lack of real-world datasets poses significant obstacles. To overcome this hurdle, the development of real-world datasets and establishment of benchmark challenges could facilitate future research in this field.

5. Attribution

5.1 Language Identification

Ancient languages evolve over time and vary in space: Words fall in and out of use, grammar changes, regional dialects develop. Thus, *attributing* ancient texts to their place and time of writing is key to grounding them within their original historical and cultural context.

Identifying what language a text might be written in is a task that has received particular attention in machine learning competitions. An influential effort in language identification was initiated by Jauhiainen et al. (2019), who introduced a corpus of texts from Oracc for the Cuneiform Language Identification shared task, part of the 2019 VarDial Evaluation Campaign (Zampieri et al. 2019). The authors evaluated multiple statistical frequency methods to classify different languages in cuneiform script, and the product of relative uni- to four-gram frequencies exhibited the best performance. On the same challenge, Bernier-Colborne, Goutte, and Léger (2019) proposed a modified version of the BERT model taking characters as input, which led to substantial performance improvements. A similar performance was exhibited by an SVM classifier used by Wu et al. (2019), which used character and word weighted n -grams. The authors utilized test-time adaptation to label the validation set, and then retrained the model on the whole dataset. Several other teams also proposed SVM-based models (Benites de Azevedo e Souza, von Däniken, and Cieliebak 2019; Paetzold and Zampieri 2019; Doostmohammadi and Nassajian 2019) on the same task. Meloni, Ravfogel, and Goldberg (2021) introduced a seq2seq RNN model to identify phonetic alterations between words in Latin and in “daughter” Romance languages. The authors constructed a dataset of 8k comparative entries, and showed that NN models outperform non-NN models in detecting historic language change.

5.2 Chronological Attribution

When *dating* ancient documents, specialists often rely on internal (paleographical, prosopographical) and external (archaeological) contextual clues. Modern techniques (e.g., C-14 radiocarbon dating) are unviable when the writing supports are made of inorganic materials (stone), and are often prohibitively expensive.

In 2003, Kashyap and Koushik (2003) were the first to build a probabilistic NN for dating texts in Kannada script. In 2014, Soumya and Kumar (2014) used binarized image features and random forests to date the images of 110 Kannada inscriptions to 6 historical periods. To increase the amount of data available for the dating task, Adam et al. (2018) created KERTAS, a dataset of 2k high-resolution images of Arabic manuscripts dating between the 8th and 14th century CE. The authors used k-NN to predict each image’s century with 86% accuracy. In 2019, Yu and Huangfu (2019) proposed an RNN for dating ancient Chinese documents. The authors extracted 800K characters from several ancient documents and then dated to three different

historical periods with very high accuracy. The same year, Goler et al. (2019) used Raman spectrography to date the carbon ink in Egyptian papyri dating between the 4th century BCE and the 10th century CE. They trained a Gaussian mixture model on a dataset of 17 papyri to model the distribution of a particular set of Raman spectral parameters, and their discoveries had important implications for the authenticity of two controversial papyri, the “Gospel of Jesus’ Wife” and a fragment of the Coptic Gospel of John. In 2020, Bogacz and Mara (2020) used a CNN to classify cuneiform tablets among four historical periods. The model exhibited high accuracy on the Heidelberg Cuneiform Benchmark dataset, but half of the samples were attributed to a single historical period. Further research operating on per century classification of ancient Greek papyri images was conducted by Paparigopoulou, Pavlopoulos, and Konstantinidou (2022) and the best results were obtained using a multilayer perceptron (MLP) trained on CNN-derived features. Harnessing recent advances in large-scale language models, Assael et al. (2022) introduced Ithaca, a sparse-attention Transformer-based architecture for the chronological attribution of ancient Greek inscriptions. On the I.PHI dataset, Ithaca could date texts to less than 30 years of their ground-truth ranges, outperforming the evaluated human baseline four times over. The authors also used Ithaca to re-date some of the most important decrees of classical Athens whose dating is controversial. Using a similar large-scale architecture inspired by BERT, Yoo et al. (2022) presented a dataset, HUE, and a model for dating, topic classification, named entity recognition, and summary retrieval tasks of ancient Korean Hanja documents. The model was pre-trained on two large textual datasets and fine-tuned on two smaller datasets containing historical annotations. The model could attribute texts to the different kings of the Joseon dynasty with very high accuracy. Finally, Chang et al. (2022) modeled the historical evolution of characters in the Oracle Bone script using a GAN architecture.

An issue shared by all these efforts is data circularity. The dates recorded in the models’ training datasets are the product of accumulated scholarly knowledge, which may imply circularity in results. Emphasis on dataset analysis could avoid pinning misleading objectivity to dating predictions.

5.3 Geographical Attribution

Written monuments or supports may have been moved in ancient or modern times for a multitude of reasons, and experts must then establish their *geographical attribution* (Tsirogiannis 2020).

Materials analysis offers one possibility (Harper et al. 2020), but Assael et al. (2022) was the first to use a deep NN architecture to attribute Greek inscriptions among 84 ancient regions (among other tasks) with an accuracy three times higher than the evaluated human baseline. Yamshchikov et al. (2022) fine-tuned existing BERT language models trained on ancient Greek to attribute texts among different authors and four regions. Focusing on pseudo-Plutarchian works, they demonstrated that the texts could have originated from an Alexandrian context.

Further work on language identification and geographical-chronological attribution should attempt to shed light upon the possible reasons underlying a model’s hypotheses: Although historians know that linguistic variation and regional-thematic practices contribute to the distinctiveness of writing habits, expanding the interpretability of models’ results (e.g., saliency maps, retrieval) could illuminate previously unknown patterns, habits, and regionalities.

5.4 Topic Modeling, Genre Detection

Texts can be grouped within the system of literature on the basis of their shared features of form, style, and contents. Automatic genre detection has been approached through **topic modeling**, a machine learning technique for clustering and classifying document topics.

Early works on topic modeling focused on text clustering. In 2013, Bracco et al. (2013) used the k -means clustering algorithm to group transliterated cuneiform texts sharing stylistic features. The authors computed the frequency features for ancient Babylonian letters and experimented with different clusters. In 2017, Wishart and Prokopidis (2017) adapted a POS tagger and a lemmatizer to Hellenistic Greek. The processed texts from a dataset comprising the Greek New Testament, the ancient Greek Dependency Treebank, and the O'Donnell corpus were used as inputs to a Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003) statistical model for topic modeling, determining the most significant words per topic. Similarly, in 2020 Köntges (2020) used an LDA model on ancient Greek philosophical texts from the First1kGreek and Perseus corpora. Using the topics discovered, the author distilled three numeric scores for philosophical text in Ancient Greek: One score measured “good and virtue,” the second score measured “scientific inquiry,” and a third combined the two to measure the “philosophicalness” of a given text. Kaše, Heřmánková, and Sobotková (2021) extracted frequency features from Latin inscriptions and compared extremely randomized trees, random forests, and SVM classifiers in predicting different inscription categories (honorific, epitaph, curse, etc.). The categories originated from the Epigraphic Database Heidelberg (EDH) and were used to label inscriptions from the Epigraphic Database Claus-Slaby (EDCS) with high accuracy, significantly enriching the original dataset's inconsistent metadata. Finally, in 2022 Yoo et al. (2022) introduced a dataset and a Transformer-based model for modeling historical documents written in Hanja, ancient Korean. Among other tasks, the model was able to classify the documents among hundreds of major and minor topics.

5.5 Authorship Attribution

Authorship attribution is the task of determining the author(s) of a text, often based on salient stylistic markers and characteristics (Koppel, Schler, and Argamon 2009). This task has been supported by statistical or computational methods since the 19th century (Stamatatos 2009). Today, “quantitative authorship attribution” (Grieve 2007) can be essentially envisaged as a classification task, building upon a background training dataset of multiple authors, from which textual features can be extracted and compared in order to classify text(s) to author(s).

Following this approach, Koentges (2020) paired the analysis of word and character n -grams with philological arguments concerning the authorship of the “Menexenus,” a contested Platonic dialogue in ancient Greek. He extracted a feature set from a background corpus of literary works in ancient Greek, and computed the similarities to conclude that the “Menexenus” is in all likelihood not Platonic. Tang, Liang, and Liu (2019) selected a small set of linguistic features to classify the novel “The Golden Lotus” (in vernacular Chinese) among four authors, using a background dataset of poems. Their experiments concluded that Wei Xu's writing style was closest to that of the “The Golden Lotus.” The k -NN approach of Martins et al. (2021) was unable to offer definitive results for the multi-author classification task of the contested “Historia

Augusta" (in Latin). Corbara, Moreo, and Sebastiani (2022) used syllabic quantity to derive an additional set of stylistic features for attributing texts by Latin authors using an SVM, based on the fact that certain authors show a preference for specific rhythmic patterns obtained by specific sequences of long and short syllables. Yamshchikov et al. (2022) fine-tuned existing BERT language models trained on ancient Greek. The model focused on pseudo-Plutarchian works, and could attribute texts to different authors active in different regions of the ancient world.

A background dataset is key to extracting meaningful features, but datasets are often imbalanced. Unless sampling is done robustly, there is the risk of introducing bias in the results. For example, Reisi and Mahboob Farimani (2020) used a CNN with a self-attention mechanism to determine that the "Khān al-Ikhwān" (in ancient Persian) was written with high probability by Nāsir-i Khusraw, but their background dataset of Persian literature comprised only 4k randomly selected sentences from the train and test sets. Others have preferred instead to select a fixed number of texts per author to test their SVM classifier on ten ancient Arabic travel writers (Ouamour and Sayoud 2012, 2013a, b, 2018), while Kestemont et al. (2016) applied approximate randomization to validate the statistical significance of their results on the authorship verification of the Latin "Corpus Caesarianum." Following prior work, Koppel and Winter (2014) and Stover et al. (2016) used repeated feature sub-sampling and a pool of impostor authors to attribute the newly discovered Latin "Compendiosa Expositio" to the author Apuleius, based on the text's similarities to his "De Platone." These results confirmed philological analyses on the new text.

Further works investigated the possibility of authorial variability taking place within the same literary work. Manousakis and Stamatatos (2018) applied an SVM classifier with character n -grams to both full-texts and text segments from their background dataset of ancient Greek plays to capture the authorial variability in the play "Rhesus," whose Euripidean authorship is contested. Finally, variability within the same work might be due to interpolation: Tuccinardi (2017) analyzed Pliny the Younger's Latin correspondence to the Roman emperor Trajan, using profile-based methods on n -grams features to detect a large amount of interpolation in the text of the letters. Pavlopoulos and Konstantinidou (2022) used a statistical language model's perplexity on samples of the ancient Greek epic poems "The Iliad" and "The Odyssey" to identify outlier-passages from other texts of the Homeric canon.

5.6 Palaeographic Analysis and Writer Identification

Machine learning has been successfully used to identify the hand(s) of the people writing ancient texts, based primarily on digitized handwriting images (Davis 2007; Stokes 2015). *Palaeographic analysis* enables, for example, identifying writing hands, joining or grouping segments, dating documents and their writers, and making historical observations concerning ancient scribal cultures.

Palaeography is based on the analysis of letter shapes, and the main difficulty lies in distinguishing between variations in one writer's style, and similarities in different writers' styles (Popović, Dhali, and Schomaker 2021). Significant research has been carried out on distinguishing medieval scribes working on, for example, ancient Greek, Latin, or Hebrew texts, but this time-frame is beyond the remit of the present work, as the transmission of ancient authors' works cannot in most cases be traced back to antiquity. The contribution of conferences such as ICFHR and ICDAR (Fiel et al. 2017; Christlein et al. 2019; Seuret et al. 2020; Lai, Zhu, and Jin 2020; Chammas et al. 2022) to the field is substantial, as they sponsor competitions addressing topical challenges.

Relevant reports, datasets, methodologies, and evaluation metrics are made public after the conclusion of the competitions, increasing accessibility to key resources.

Current approaches to writer identification focus on either global (text-based) or local (grapheme-based) features (De Stefano et al. 2018). Recent studies have shown not only that the former are more effective (He et al. 2016b), but also that joint feature representations can improve the classifier's performance (Dhali et al. 2017). For ancient Greek, Panagopoulos et al. (2008) and Tracy and Papaodysseus (2009) used image segmentation and statistical analysis to isolate the writing styles of different cutters on a small dataset of Athenian inscriptions; follow-up work by Papaodysseus et al. (2010) also operated on a character-level, but also created an ideal prototype of each alphabet character, from which they extracted geometric features using heuristics and maximum likelihood estimation procedures. The same research group (Papaodysseus et al. 2014; Arabadjis et al. 2013) dated Greek inscriptions and Byzantine codices based on analytical comparisons between letter curvatures and "ideal prototype" curvatures. Arabadjis et al. (2019) also identified specific writers across codices recording editions of "The Iliad" based on letter curvature and on the ideal prototype of letter rendition. Considerable work has also been done on ancient Hebrew texts: Faigenbaum-Golovin et al. (2016) and Shaus (2017) worked on a set of Hebrew ostraca (ink on clay fragments) from the Arad fortress in the First Temple period (8th–6th century BCE). They focused (among other tasks) on writer attribution using a combination of features (including binary pixel patterns and Fisher's method) to estimate a minimum of 6 different writers. Dhali et al. (2017) worked on the Dead Sea Scrolls (3rd century BCE to 1st century CE in Hebrew, Greek and Aramaic): They used a feature representation method that relied on the curvature information of the neighboring fragments to detect regions of interest and attribute them to different scribes. Popović, Dhali, and Schomaker (2021) revealed a break in a section of the Great Isaiah Scroll (part of the Dead Sea Scrolls): They observed that the handwritten columns of the first and second halves of the manuscript showed substantially different feature-representations. A further visual inspection concluded that the break was due to the activity of two different scribes working on the scroll. We refer the reader to Faigenbaum-Golovin, Shaus, and Sober (2022) for further details on handwriting analysis and writer identification for Hebrew texts.

As in the case of authorship attribution, imbalanced datasets can penalize a model's performance, especially when training datasets are limited in size. For example, Mohammed, Marthot-Santaniello, and Märgner (2019) created a new dataset of 50 handwriting samples in Greek papyri. The authors used a Naive Bayes Nearest Neighbor classifier with FAST (Features from Accelerated Segment Test) keypoints to identify 10 different hands. Compare this situation with the automated palaeography of post-antique Arabic-language documents, for which there exist far richer image datasets (Asi et al. 2017; Abdelhaleem et al. 2017; Adam et al. 2018). For example, Fecker et al. (2014a, 2014b) attributed a dataset of thousands of images of Arabic manuscripts to different hands using traditional image features (SIFT, HoG) as inputs to a voting procedure and an SVM. Some works have attempted to work around the problems of data availability: for example, Nasir and Siddiqi (2020) evaluated different pre-trained CNNs for the palaeographic analysis of Greek papyri, and compared them with FAST features and a Nearest-Neighbor classifier. The models were first tuned on contemporary handwriting images (relatively larger dataset) and later tuned to the smaller dataset of papyri. Researchers must be aware of this data imbalance: Certain languages or writing methods (ink texts written with a pen or brush vs inscribed texts on stone or metal) are underrepresented in this task owing to the lack of digitized data. Moreover, just as for the chronological attribution task, the risk of data circularity within

palaeographical arguments and the ground truth labels they produce should be taken into serious account.

6. Linguistic Analysis

6.1 Representation Learning

The success of machine learning algorithms depends on *data representation*, as different representations can either reveal or obscure explanatory factors in the data (Bengio, Courville, and Vincent 2013). Although domain-specific knowledge may help manual feature engineering, learning automated generic representations has been shown to be especially helpful in downstream tasks.

A large body of literature tackling learning representations for ancient languages has focused on Latin. Bjerva and Praet (2015, 2016) used word2vec (Mikolov et al. 2013) to investigate the relationships between persons and themes of interest emerging in the works of the 6th century CE scholar Cassiodorus. Based on the extracted representations, they analyzed the text embedding associations between Cassiodorus, Liberius, Symmachus, and Boethius, and a selection of abstract concepts such as “liberty,” “antiquity,” “modern,” “Greekness,” “Romanness,” and “Gothness.” In 2019, Sprugnoli, Passarotti, and Moretti (2019) compared word2vec embeddings with fastText word embeddings (Grave et al. 2018) by using cosine similarity to fetch similar lemmas. FastText’s skip-gram embeddings exhibited a higher success rate in the task.

Bamman and Burns (2020) trained a BERT model on Latin corpora (Perseus, PROIEL, Index Thomisticus Treebank) and used the learned embeddings for word sense disambiguation and to identify words occurring in similar context, for POS tagging and language modeling. Finally, Burns et al. (2021) assembled a new benchmark and dataset for Latin synonym detection based on Valerius Flaccus’ “Argonautica.” The authors compared different implementations of BERT, word2vec, and fastText embeddings: Using a newly lemmatized Latin corpus, they showed that their embeddings could enhance intertextual search.

The work of Svärd et al. (2018) used word2vec embeddings and Pointwise Mutual Information to find collocations and associations between words in Akkadian. The model was trained on transliterated and lemmatized Akkadian cuneiform texts from the Oracc dataset. More recently, Karajgikar, Al-Khulaidy, and Berea (2021) used word2vec embeddings for Linear A glyphs, as part of an extended analysis of the Minoan writing system, which is yet to be deciphered.

6.2 Word Segmentation and Boundary Detection

Tokenization, the process of locating word or character boundaries in a text, and *sentence segmentation*, the task of identifying sentence boundaries, can aid the automation of linguistic analysis of an ancient text (Palmer 2000). However, the ambiguities and varieties in human languages and writing systems (e.g., logographic such as cuneiform and classical Chinese vs. logosyllabic such as ancient Japanese) must be taken into account.

In 2010, Huang, Sun, and Chen (2010) presented a CRF model for segmenting classical Chinese texts into sentences and clauses. The model used n -gram features, word class, and phonetic information. Similarly, Wang et al. (2016) introduced an RNN for the same task in ancient Chinese. The performance was comparable to that of traditional CRF-based models, and the authors improved the model’s effectiveness by introducing a length-based penalty term. A bidirectional RNN model was presented by Hellwig

(2016) for Sanskrit sentence boundary detection, using a combination of morphological and lexical features as inputs. The model clearly outperformed the CRF baseline, but its accuracy was insufficient for real-world segmentation without human supervision. Li et al. (2018a) were the first to introduce a capsule-based model for word segmentation, which had high accuracy on a dataset of ancient Chinese medicine books developed by the authors. More recently, Zhang et al. (2021) presented a bidirectional RNN with attention and a CRF for identifying the boundaries of historical figures' first names. To generate training labels, the authors matched personal names from the ancient Chinese corpus of "Song History" with a dictionary of historical names.

In 2012, Yoshimura, Kimura, and Maeda (2012) presented a method for segmenting sentences in the ancient Japanese manuscript "Genji Monogatari" into words, by calculating the likelihood of character 2- to 10-grams being words. In 2016, Homburg and Chiarcos (2016) benchmarked rule-based, dictionary-based, and machine learning methods for the word segmentation of cuneiform tablets in Akkadian. The authors evaluated CRF, HMM, SVM, and NN models, but the dictionary-based approaches produced the best-performing classification. More recently, Yu et al. (2020) proposed a word segmentation model for ancient Chinese based on a non-parametric Bayesian model and BERT. Both models were repeatedly trained on large-scale unlabeled data. An and Long (2021) used a bidirectional RNN with a CRF for ancient Tibetan word segmentation, which achieved a high accuracy and outperformed the HMM and other baselines. Tupman, Kangin, and Christmas (2021) and Paolanti et al. (2022) also worked on word segmentation in Roman inscriptions and Medieval notary documents, respectively. Finally, recent work on ancient Chinese has combined the problem of word segmentation with POS tagging, and are presented jointly in the following section.

6.3 POS Tagging and Parsing

Part-of-speech (POS) tagging involves the grammatical mark up of a word in a text as corresponding to a particular part of speech, while syntax *parsing* generates parse trees, showing how words and phrases combine to form larger syntactic constituents. In our context, interest in both tasks has been spurred by conference challenges, especially with regard to the *writer identification* task.

In 2017, the Computational Natural Language Learning (CoNLL) conference featured a challenge (Zeman et al. 2017) that involved training dependency parsers on several languages, including ancient ones, and a real-world setting with noisy annotated labels. The goal was to detect syntactic dependencies and classify the dependency relation type. In 2018, the challenge expanded to morphological feature extraction, POS tagging, and lemmatization. The inputs consisted of simply raw text, without any segmentation or morphological annotations. A large number of submissions competed for the parsing task (Bhat, Bhat, and Bangalore 2018; Boroş, Dumitrescu, and Burtica 2018; Chen et al. 2018; Duthoo and Mesnard 2018; Jawahar et al. 2018; Ji et al. 2018; Kanerva et al. 2018; Kirnap, Dayanık, and Yuret 2018; Li et al. 2018b; Nguyen and Verspoor 2018; Qi et al. 2019; Rybak and Wróblewska 2020; Smith et al. 2018; Straka 2018; Wan et al. 2018): Each language was well represented in the datasets, which comprised treebanks from the Universal Dependencies 2.2 collection. Ancient Greek, for example, included 160k labeled words from Perseus and another 187k from PROIEL, while Latin data gathered 460k words. It is worth noting that the best performing method in ancient Greek and Latin was also the best method overall, combining contextual embeddings with ensembling (Che et al. 2018). These methods, such as Straka (2018), were built on prior work (Straka, Hajic, and Straková 2016) and were followed by Transformer-based

architectures (Straka, Straková, and Hajič 2019; Straka and Straková 2020), achieving an even higher performance. One of the most significant contributions of the CoNLL challenge was the resulting dataset for ancient languages, which has allowed subsequent research to investigate the data further (de Lhoneux, Stymne, and Nivre 2017) and expand existing resources to other ancient languages. For example, Keersmaekers et al. (2019) focused on ancient Greek and Bamman and Burns (2020) on Latin, both achieving the state-of-the-art in POS tagging with a Transformer-based architecture.

Ancient language-specific campaigns have also been organized by the workshop on Language Technologies for Historical and Ancient Languages (LT4HALA). In 2020, the EvaLatin (Sprugnoli et al. 2020) challenge focused on Latin POS tagging and lemmatization using texts from the Perseus dataset. The generalizability of competition submissions was evaluated using additional cross-genre and cross-time test sets. Most participants proposed RNN-based architectures (Straka and Straková 2020; Wu and Nicolai 2020; Bacon 2020; Stoeckel et al. 2020), while Celano (2020) used gradient boosting with pre-trained word embeddings, and Stoeckel et al. (2020) used an ensemble of classifiers for POS tagging. LT4HALA's EvaLatin 2022 campaign (Sprugnoli et al. 2022) focused on Latin POS tagging, lemmatization, and morphological feature identification using texts from the LASLA corpus, containing nearly 2 million words and corresponding to 133k unique tokens annotated by trained classicists, and 24k lemmas. The best performing participants Wróbel and Nowak (2022) trained Transformer-based models: an XLM-RoBERTa pre-trained on Latin for POS tagging and feature identification, and a ByT5 for lemmatization. Similarly, Mercelis and Keersmaekers (2022) started from a pre-trained small ELECTRA Transformer-based model for the POS tagging task, and handcrafted rules were added to handle lemmatization. The same year, LT4HALA introduced the first ancient Chinese word segmentation and POS tagging challenge, EvaHan 2022 (Li et al. 2022). The challenge used texts from ancient Chinese chronicles and featured a "closed" part involving limited data and a pre-trained RoBERTa model, and an "open" part without resource limitations. Some participants used traditional RNN architectures (Tang, Lin, and Li 2022) and CRFs (Yang 2022), while others focused on Transformer-based alternatives, adversarial training (Zhang et al. 2022b; Yang 2022), data augmentations, and ensemble learning (Zhang et al. 2022b; Yang 2022; Wei et al. 2022) to compensate for the limited and imbalanced training data.

Outside competitions, several recent studies have focused on Transformer-based architectures. For example, Singh, Rutten, and Lefever (2021) used a corpus of modern, ancient, and Byzantine Greek texts to further pre-train a BERT model and then fine-tune it for ancient Greek POS tagging. A similar study was performed by Tian et al. (2021), who used Chinese articles, poems, and couplets dating between 1000 BCE and 200 BCE for pre-training a BERT model and then fine-tuning it to the classification and text generation tasks. Others have used more traditional approaches: Hellwig (2015) used maximum entropy classifiers and CRFs for the tokenization and morphosyntactic analysis of writings in ancient Sanskrit. A joint RNN-CRF architecture for ancient Chinese word segmentation and POS tagging was also presented by Cheng et al. (2020). Sahala et al. (2020b) used a finite-state transducer (FST) to address lemmatization and POS tagging for cuneiform tablets in Babylonian from the Oracc corpus. Phonological transcription is essential for the automatic morphological analysis of cuneiform. The same group of Sahala et al. (2020a) presented a character-level sequence-to-sequence model with attention for the automated phonological transcription of transliterated text. This was the first attempt to automatically transcribe Akkadian, and the predictions were evaluated using the FST of Sahala et al. (2020b). Finally, other efforts (Celano, Crane, and Majidi 2016; Vatri and McGillivray 2018, 2020) used off-the-shelf software.

6.4 Semantics

Computational semantics seeks techniques for automatically constructing semantic representations of expressions in natural language (Blackburn and Bos 2005).

In 2011, Bamman and Crane (2011) used k-NN, naive Bayes, and statistical language modeling for measuring Latin word sense variation using a processed collection of 7k books. Aligning a small collection of parallel texts, the authors introduced a bilingual sense inventory that was then used to tag a 389 million word corpus and track the rise and fall of word senses over 2,000 years. More recently, Yoo et al. (2022) introduced a dataset and a Transformer-based model for analyzing historical documents written in the Hanja writing system. Among other tasks, the model performed named entity recognition.

The rest of the literature focuses on ancient Greek literary texts. Perrone et al. (2019) designed a Bayesian mixture model for measuring the evolution of word sense over time, based on distributional information of lexical nature and genre. The model was evaluated on the Diorisis Ancient Greek Corpus (Vatri and McGillivray 2018), which contains a large collection of automatically and carefully lemmatized and POS tagged texts released by the same research group. The authors used expert-assigned sense labels for a small subset of words, presenting improvements over the previous state-of-the-art. In 2020, the follow-up work by Vatri and McGillivray (2020) benchmarked major lemmatizers (CLTK, GLEM) and datasets (Diorisis Corpus and the Lemmatized Ancient Greek Texts repository) against three highly proficient readers of ancient Greek. The most accurate labels came from the Diorisis corpus and the CLTK backoff lemmatizer. In 2020, Keersmaekers (2020) used a random forest to perform the semantic parsing of the Ancient Greek Dependency Treebanks, Harrington Trees, and Pedalion Treebanks with high accuracy. In the same year, Palladino, Karimi, and Mathiak (2020) introduced a CRF model for named entity recognition, based on n -gram features close to the target word and POS information. The model was evaluated on Herodotus' "Histories" (in ancient Greek) discovering ethnonyms and place names.

7. Textual Criticism

7.1 Stylometrics

Stylometric analysis attempts to statistically quantify the linguistic features of authorial style (Holmes 1998). In 2019, Gianitsos et al. (2019) introduced a stylometric feature-set for ancient Greek enabling the identification of texts as either prose or verse using a Random Forest classifier. The feature-set included several primarily syntactic features. Then, the authors classified a selection of the verses as belonging to either the epic or the drama genre. In an effort to better understand stylometric patterns, Ochab and Essler (2019) used different unsupervised clustering methods to group the authors of ancient Greek papyri on the basis of their stylistic features. Two years later, Alqasemi et al. (2021) compared the performance of a neural network, an SVM, and a decision tree for classifying different poetic metres occurring in Arabic poetry.

7.2 Stemmatology

The goal of *computational stemmatology* is to reconstruct the genealogy of different versions of a text, in order to obtain a text as close as possible to the authorial original (Roos and Heikkilä 2009). In 2010, Roelli and Bachmann (2010) computed the Character

Edit Distance between text strings from different versions of the Latin “Dialogus contra Iudaeos” by Petrus Alfonsi. The distances were used to produce a distance matrix and tree graphs visualizing the evolution of different parts of the text. In 2016, Koppel, Michaely, and Tal (2016) introduced a method based on expectation-maximization; given multiple corrupted versions of the same text, they aimed to reconstruct the authorial original. The method was applied to artificially generated manuscripts and the Talmud, showing how automated methods for reconstruction can be more effective than a naive majority rule. More recently, Jones, Romano, and Mohd (2022) cast the problem of stemmatology as a classification task. More specifically, using verses from Greek New Testament manuscripts with slight variations, they proposed a feature-set to identify whether a given verse belonged to the “gold standard” (the authorial original) or to a variant.

7.3 Intertextuality

Authors often convey meaning by referring to or imitating another text (e.g., prior works of literature), a process that creates complex networks of literary relationships, known as *intertextuality*. In recent years, computational approaches have introduced quantitative measures to aid large-scale analyses (Dexter et al. 2017).

Most research on this topic has focused on Latin. Early efforts worked on string-matching approaches and on the identification of lexical correspondences (Coffee et al. 2012a, b; Scheirer, Forstall, and Coffee 2016). In 2011, Forstall, Jacobson, and Scheirer (2011) used an SVM with character bi- and tri-grams and word bi-grams to determine to what extent, if any, the classical Roman poet Catullus had influenced the 8th century CE Latin poem “Angustae Vitae” by Paul the Deacon. The results showed notable stylistic similarities between two poems of Catullus and the “Angustae Vitae.” Bernstein, Gervais, and Lin (2015) computed the word frequencies of the Tesseræ corpus comprising over 300 works of Latin literature to identify instances where short passages, written between 1st century BCE and 6th century CE, shared two or more repeated words. Bjerva and Praet (2015, 2016) used word embeddings to analyse Cassiodorus’ “Variae,” a corpus of hundreds of state letters. The authors used word2vec and network analysis to find associations between Latin and Greek authors and a selection of ideological concepts (“liberty,” “antiquity,” “modern,” “Greekness” or “Romanness”). Focusing on the Roman authors Seneca and Livy, Dexter et al. (2017) proposed different stylometric features to distinguish citational material, including non-content words (e.g., articles, prepositions), syntactic constructions, and the length of sentences and clauses. They then used an SVM to identify the citational and non-citation material Livy might have loosely appropriated from earlier sources. Burns et al. (2021) compared different implementations of both word2vec and fastText on the CLTK-lemmatized (Johnson et al. 2021) “Argonautica” by Valerius Flaccus. By comparing the cosine similarities of bi-gram pairs, they showed that embeddings could enhance Latin intertextual detection, and produce state-of-the-art results.

Research on intertextuality has also been carried out on Biblical texts in Greek: Lee (2007) studied text reuse (“source alternation patterns”) in the New Testament. Considering the Gospel of Luke as the target text and the Gospel of Mark as the source text, the authors introduced a model for sentence-level quantitative text-reuse discovery. The model’s predictions were fine-tuned and evaluated against scholarly hypotheses, demonstrating the model’s ability to capture the researchers’ expert understanding of text reuse. Moritz et al. (2016) presented a linguistic analysis of text reuse in non-literal translations of Bible verses in ancient Greek and Latin. The authors used hundreds of

reused verse pairs, and used lexical databases of semantic relations of words and lemmas, together with POS information, to identify reuse. Their results showed that simple pre-processing, such as stemming and lemmatizing, may not be sufficient to capture the richness of the qualitative manual analysis. Shifting to ancient Greek literature, Büchler et al. (2012) studied text-reuse in Athenaeus' "Deipnosophistai": Editors have explicitly marked hundreds of instances of text being quoted or paraphrased from the Homeric epic poems. Using uni- and bi-gram frequency features and a wide window to preserve locality, the authors identified nearly all references annotated by editors. Finally, Monroe (2018) used frequencies of cuneiform signs to study the scholarly practices behind the composition of damaged and fragmentary examples of late Babylonian astrology.

7.4 Sentiment Analysis

Sentiment analysis is an NLP task where the goal is to extract subjective information and affective states from a text, for example, whether the text expresses positive, negative, or neutral emotions (Medhat, Hassan, and Korashy 2014). In ancient languages, the lack of labeled data can pose an obstacle to this task. To overcome this issue, Kumar, Pathania, and Raman (2022) introduced a zero-shot method for sentiment analysis using cross-lingual data. The authors collected a dataset of 12k samples of online English–ancient Sanskrit translations, to train a Transformer model to translate from Sanskrit to English. An additional GAN loss was used to improve the quality of the translations. Finally, the sentiment of the resulting English translations was classified with high accuracy using an RNN model. Pavlopoulos, Xenos, and Picca (2022) showed that the linguistic expression of sentiments may diverge between ancient and modern Greek. The authors annotated the sentiment of verses from the first Book of Iliad (translated into modern Greek) and fine-tuned Greek BERT on the task.

8. Translation and Decoding

8.1 Decipherment

Ancient texts are usable only in proportion to their intelligibility, but many ancient languages and scripts remain undeciphered (Robinson 2009). **Deciphering** an ancient written language involves understanding the original meaning of words in their context, often using descended and cognate languages or multilingual keys as aids.

Early statistical techniques focused on reconstructing linguistic structures. More specifically, Rao et al. (2009a, 2010) compared the statistical structure of sign sequences in the Indus script to those of a representative group of languages: Sumerian, Old Tamil, Vedic Sanskrit, English words and characters, and non-linguistic systems such as DNA and protein sequences. Using conditional entropy, they showed that Indus script inscriptions have an increased probability of representing language. Using the same corpus, Rao et al. (2009b) computed pairwise statistics using a Markov model. Their work suggested that specific signs often occur at the beginning of Indus script inscriptions and that, for any sign, there are other signs that have a high probability of occurring after. Such syntax patterns could pave the way to decipherment. Their Markov model was also applied to textual restoration, and Yadav et al. (2010) used it for further n -gram analysis of the Indus script. Their model could restore signs with a high accuracy. However, the statistical approach of these works was challenged by Sproat (2010), and Sproat (2014) later introduced a novel measure based on repetition turn

out, classifying the data for the Indus Valley script as a non-linguistic symbol system, thereby contradicting those earlier works.

The work of Snyder, Barzilay, and Knight (2010) focused on the alphabetic mappings and translations of Ugaritic words to their corresponding cognates in Hebrew. Using a non-parametric Bayesian model, they estimated distributions over bilingual morpheme pairs and assigned probability based on recurrent patterns: Each character in one language would map to a small number of characters in the other. The accuracy of cognate translations was measured with respect to complete word forms and morphemes. Berg-Kirkpatrick and Klein (2011) modeled the same problem as a combinatorial optimization, minimizing the edit-distance between a source word and target word, given alphabetical sign matching. Their results were better than Snyder, Barzilay, and Knight (2010) in cognate word accuracy, but lower in alphabet accuracy. The same model was also used to identify phonetic cognates between Spanish, Portuguese, and Italian. In 2013, Bouchard-Côté et al. (2013) presented a probabilistic model of sound change for reconstructing words occurring in the proto-languages from which modern Austronesian languages evolved. Over 85% of the system's reconstructions were within one character of the manual reconstruction provided by a linguist. In 2019, Luo, Cao, and Barzilay (2019) introduced a more general approach for automated decipherment based on a sequence-to-sequence neural network model, NeuroCipher, which captured character-level correspondences between cognates using optimization. NeuroCipher was used to map Ugaritic to Hebrew and Linear B to ancient Greek. In 2021, Luo et al. (2021) presented a model for deciphering unsegmented languages using phonetic conversion. The model was able to identify related known languages, and was used to extract cognates from undersegmented texts in Gothic, Ugaritic, and the undeciphered Iberian scripts.

Using images as inputs, Daggumati and Revesz (2018) used a CNN with an SVM to generate similarity matrices and map linguistic family trees, showing that Indus script is visually close to Sumerian pictographs, while the Linear B script is close to the Cretan Hieroglyphic script. In a similar setting, de Lima-Hernandez and Vergauwen (2021) used a CNN to show that the Phoenician alphabet is much closer to the Indus script than to the Brahmi script. Recent studies such as Karajgikar, Al-Khulaidy, and Berea (2021) have carried out computational analyses using n -grams and word2vec embeddings on undeciphered scripts such as Linear A, and also tried to group symbols. Papavassiliou, Owens, and Kosmopoulos (2020) increased the amount of data by including related writing systems, such as Linear B, which could be the key to solving decipherment challenges. Recently, Corazza et al. (2022) introduced Sign2Vec, an unsupervised clustering method for analysing signs from 200 inscriptions in the undeciphered Cypro-Minoan syllabary. Sign2Vec used k -means on the outputs of a ResNet50, and incorporated additional contextual information from the surrounding signs, classifying two out of three signs correctly.

8.2 Machine Translation

The *translation* of ancient texts takes us an interpretative step closer to the mentality and *milieux* of ancient authors. Recent efforts of neural machine translation have allowed historians to harness all available data to create automated pipelines for ancient languages.

For Sumerian, in 2018 Chiarcos et al. (2018) presented a dictionary- and rule-based method for the morphological and syntactic annotation of administrative texts pertaining to the third Ur dynasty. The dataset was then used by Punia et al. (2020) to create

the first machine translation system for Sumerian transliterations. The authors used a stacked RNN sequence-to-sequence with GloVe embeddings and a Transformer model. Two human experts were asked to score 50 translations generated by each model. The problem of automatic transliteration of glyphs into Latin script was approached by Gordin et al. (2020), evaluating multiple models on 23k Neo-Assyrian cuneiform tablets from the Oracc dataset. The highest transliteration and segmentation accuracy was achieved using a bidirectional RNN model.

Zhang, Li, and Su (2019) proposed a bidirectional RNN sequence-to-sequence model for translating old Chinese documents into contemporary Chinese and vice versa. The model had a copying mechanism and local attention. Using only a small sentence-aligned corpus of 4k pairs, the authors addressed the matter of limited aligned corpora by introducing an unsupervised sentence alignment model using dynamic programming. However, the semantics of ancient Chinese are complex—for example, word polysemy introduces a one-to-many alignment with modern Chinese. Yang et al. (2021) showed that a BLEU (Bilingual Evaluation Understudy) score could not identify potentially correct translation results. Inspired by unsupervised dual learning, the authors introduced a Dual-based Translation Evaluation, able to evaluate the one-to-many alignment of ancient Chinese, and outperform BLEU in a human expert evaluation.

Park et al. (2020) presented an attention RNN and a Transformer-based model for ancient Korean translation. The authors used a shared vocabulary, byte pair encoding, and n -gram decoding. Using a processed dataset crawled from the Institute for the Translation of Korean Classics, the Transformer model performed better when combined with the RNN. On the same dataset, Park et al. (2022) presented a model using bilingual sub-word embedding initialization and priming, inspired by the cognitive science theory that two different stimuli influence each other. Their RNN model surpassed the previous transformer results. Furthermore, Kang et al. (2021) worked on translating and restoring the Hanja historical records of the Annals of Joseon Dynasty into old Korean using a Transformer-based model, which achieved fluent translations. Follow up research from Son et al. (2022), supports both translation into contemporary Korean and into English and uses a newer version of the Annals of Joseon Dynasty corpus.

Finally, Yousef et al. (2022) fine-tuned a pre-trained multilingual BERT-based language model to automatically translate ancient Greek to Latin texts following a novel alignment workflow.

9. Conclusions

In this survey, we set out to examine all interdisciplinary machine learning contributions to the study of ancient languages to date. While reviewing the literature, we identified a recurring set of factors that are either driving research or posing challenges to be overcome.

9.1 Impact and Data Availability

The increased availability of digitized, linked, open, and rich data for ancient languages has been recognized as the *sine qua non* condition for advancing machine learning research for ancient languages. Many such datasets are created and exploited in the context of conferences and competitions (such as ICFHR, ICDAR, CoNLL, LT4HALA). At the same time, large datasets paired with large-scale models such as Transformer-based architectures have resulted in significant improvements over traditional approaches, allowing a scale and precision unattainable by human researchers alone. To support

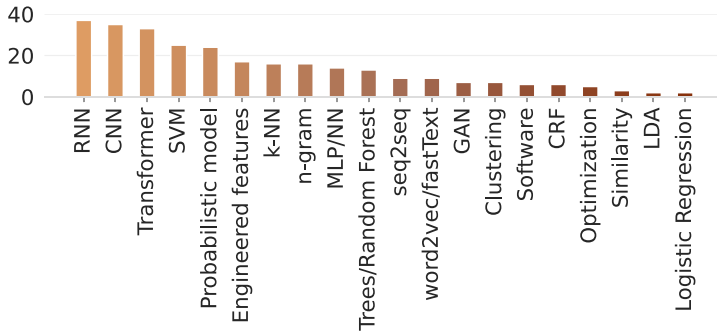


Figure 3

Distribution of machine learning model architectures (with ≥ 2 articles per architecture). Under Engineered Features we've grouped works using PCA, HOG, HOOSC, word frequencies, and other similar methods for further analysis. Under Software, we include all methods using third party or standalone software.

this momentum, standardized data encoding (Bodard 2010) in accordance with Findable, Accessible, Interoperable, Reusable principles (Wilkinson et al. 2016) is crucial to advancing future research. Indeed, our evaluation has also shown that the adoption of shared data standards (as seen in certain works) successfully fosters a more scientific approach to evaluation and metrics, which are vital to tracking progress and impact in machine learning research.

9.2 Machine Learning Observations

In this survey we analyzed over 230 interdisciplinary works. The majority, 149 in total, utilized textual inputs, while 59 operated on visual inputs and 18 on both modalities.² Out of the works reviewed, 137 used supervised learning, 33 were self-supervised, and 26 used unsupervised or weakly supervised methods. In Figure 3 we present the distribution of machine learning model architectures utilized: 117 studies used deep learning architectures, 66 used machine learning, and 42 used statistical models. It is particularly noteworthy that several works used existing architectures, such as computer vision or language models, that were retrained to solve new tasks. This is illustrated in Figure 4: One may also note that, among others, BERT, word2vec ResNet, and VGG exhibit a substantial uptake. A subset of 36 works used existing pre-trained models, which once again goes to demonstrate the impact of open-source pre-trained models on such research. We refer the reader to Appendix A for further details.

9.3 Future Research

Future research should address the extant challenges. Firstly, machine learning methods are quintessentially data-dependent, and all major breakthroughs surveyed in this article build upon digitization and labeling efforts—which should therefore be prioritized and rewarded. At the same time, given the current extent of unlabeled data, it

² The numbers may not add up to the total number of studies due to some being reviews or summaries of competitions.

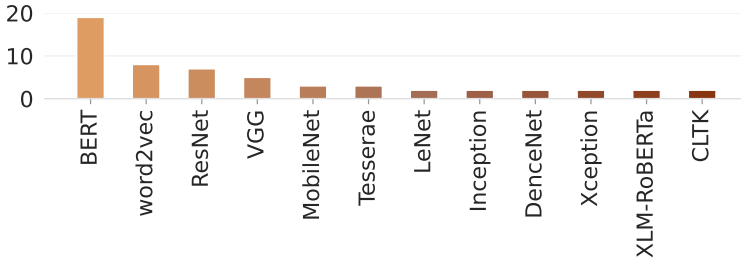


Figure 4 Distribution of existing machine learning models utilized (with ≥ 2 articles per model).

would be auspicious to explore the potential of pre-trained large-scale foundation models, further fine-tuned to the tasks addressed in our taxonomy.

Secondly, some of the most impactful works reviewed were those developed by interdisciplinary teams bringing together computer scientists and historians, linguists, or subject-specific specialists. This can easily be appreciated by the more thoughtful experiment designs, the use of accurate terminology, and the overall better results achieved in the reports (e.g., Tracy and Papaodysseus 2009; Popović, Dhali, and Schomaker 2021; Assael et al. 2022). Multidisciplinary teams may more effectively address the challenges posed to machine learning methods by ancient writing systems, as they will be better informed of the idiosyncrasies of the textual material, more aware of the machine learning techniques best suited to address them, and will devote themselves to veritably worthwhile research questions. Moreover, it is only through such interdisciplinary collaborations that greater trust in digital methods may be built within scholarly communities in the humanities on one hand, and on the other hand the truly pressing questions and challenges posed by ancient texts might be more meticulously addressed by computer scientists.

Thirdly, it is a commonly acknowledged fact that ground truths are unattainable when dealing with ancient texts, as the original written form (physical or textual), exact date and place of writing, and so forth, could have been lost over the centuries. One can only test a model’s predictions exclusively against the assumptions of experts, a situation where “data circularity” might arise, whereby existing scholarly conjectures are included within the training set. We found the studies that did acknowledge this situation were particularly insightful, and hopefully will motivate further research harnessing machine learning methods for denoising and debiasing data. On that note, imbalanced datasets are known to introduce bias, prejudice, and unfairness, which may perpetuate systemic bias, obfuscate evidence, or point to misleading patterns in the data. This review has highlighted how not all languages, histories, or geographies are equally represented (Figure 5) in the field under review, and this lack of representation may result in “digital colonialism” (McGillivray et al. 2020). This remains an active area of research in AI ethics and in studies of the ancient world.

Fourthly, historians are constantly seeking novel methodological aids to advance their research, and should therefore be open to the opportunities offered by technology. In tandem, scientists working with ancient texts should direct their efforts towards augmenting the interpretability of their model’s results, rather than on merely maximizing metrics. We furthermore found that comparing prior literature of our taxonomy was especially challenging due to the lack of standardized benchmarks and the constant use

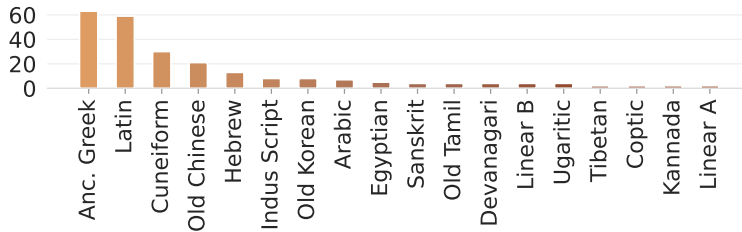


Figure 5

Distribution of publications per language (with ≥ 2 articles per language). Under “cuneiform” script, we include the Akkadian, Sumerian, and Babylonian languages.

of different datasets. Such inconsistencies hamper the ability to draw clear conclusions and evaluate the true progress of different approaches. Moreover, the absence of universally accepted evaluation metrics and benchmarks further complicates the process of comparing the performance of models, as the results are often not directly comparable. This could ultimately slow down the advancement of research, as it becomes more challenging for researchers to identify promising directions, replicate results, and build upon previous work in a reliable and transparent manner. Thus, we’ve included an Appendix section tracking the uptake of different models per year, which confirms our assumptions expounded in Section 2. We hope that this survey will be adopted as a reference point for prior work and help bridge this gap.

Finally, and building upon that point, it is essential to emphasize that progress in machine learning relies not only on models, but also on the quality and quantity of data, metrics, and evaluation. We wish to emphasize: (a) the direct correlation between the characteristics of a dataset and a model’s performance, and (b) the importance of robust hypothesis testing, with data partitioning (train, test and validation sets), or data resampling to train different models and statistically analyze generalizability (e.g., cross-validation).

9.4 The Value of Interdisciplinarity

To conclude, the synergy between the study of ancient languages and machine learning achieves its full potential when historians and scientists work together to identify the problems and find the solutions best tailored to the ancient data’s idiosyncrasies. In this review, we set out to map a nascent field and highlight the scholarly benefits of collaboration between two seemingly unrelated disciplines. Our review has determined that machine learning for ancient languages is not only a well-established field with its own research questions, but holds significant potential for the large scale and scientific exploration of a wide-range of historical questions, and in doing so can open up new areas of research.

Appendix A. Taxonomy Analysis: Modalities used per Section

Table A.1

Summary of each taxonomy section, showing the number of works using the text and visual modalities.

Section	Text	Visual	Both
Authorship attribution	12	0	0
Chronological attribution	5	4	1
Decipherment	10	1	2
Fragment reassembly	1	4	0
Geographical attribution	2	0	0
Intertextuality	12	0	0
Language identification	8	0	0
Machine translation	9	1	0
POS tagging and Parsing	45	0	1
Palaeographic analysis and writer identification	0	22	1
Quality enhancement	0	9	0
Recognition	0	17	12
Representation learning	6	0	0
Semantics	7	0	0
Sentiment analysis	2	0	0
Stemmatology	3	0	0
Stylometrics	3	0	0
Textual restoration	10	0	0
Topic modeling, genre detection	5	0	0
Word segmentation and boundary detection	9	1	1

Appendix B. Taxonomy Analysis: Model Types per Year

Table B.1

Summary of the different machine learning model types employed per year. Models that were used 2 or less times were omitted. Under Engineered Features we've grouped works using PCA, HOG, HOOSC, word frequencies, and other similar methods for further analysis. Under Software, we include all methods using third party or standalone software.

Model	2000–2010	2010–2015	2015–2020	2020–2023	Total
CNN	0	0	10	25	35
CRF	0	2	2	2	6
Clustering	0	1	2	4	7
Engineered features	0	1	13	3	17
GAN	0	0	0	7	7
k-NN	0	2	9	5	16
MLP/NN	1	3	6	4	14
Optimization	0	2	3	0	5
Probabilistic model	2	6	9	7	24
RNN	0	1	20	16	37
SVM	0	4	14	7	25
Similarity	0	1	1	1	3
Software	1	2	2	1	6
Transformer	0	0	3	30	33
Trees/Random Forest	0	1	5	7	13
<i>n</i> -gram	2	6	4	4	16
seq2seq	0	0	3	6	9
word2vec/fastText	0	0	5	4	9

Appendix C. Taxonomy Analysis: Ancient Languages Researched per Year

Table C.1

Summary of the different ancient languages researched per year. Languages that were used 2 or less times were omitted. Finally the results may not sum to the total number of papers as we include review works in our literature.

Language	2000–2010	2010–2015	2015–2020	2020–2022	Total
Anc. Greek	6	4	32	21	63
Arabic	0	3	3	1	7
Cuneiform	0	5	14	11	30
Devanagari	0	0	1	3	4
Egyptian	0	1	1	3	5
Hebrew	0	2	8	3	13
Indus Script	3	2	2	1	8
Latin	3	6	29	21	59
Linear B	0	0	2	2	4
Old Chinese	0	1	6	14	21
Old Korean	0	0	0	8	8
Old Tamil	0	0	3	1	4
Sanskrit	0	0	3	1	4
Ugaritic	0	2	1	1	4

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