Teachable AI for the Archival Professions – Module 1: **Introduction to Artificial Intelligence for the Archival Professions**

Kaila Fewster[1] and Richard Arias-Hernandez[2]

This educational module is part of a series of learning materials developed by InterPARES Trust AI[3] researchers and educators to train archival professionals and students to effectively leverage artificial intelligence in their archival work. The final draft was completed on October 11th,2024.

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[1] InterPARES Trust AI Graduate Academic Assistant, University of British Columbia.
[2] Associate Professor of Teaching, School of Information, University of British Columbia and InterPARES AI Trust Researcher. richard.arias@ubc.ca

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Module 1: Defining Artificial Intelligence

READ FOR THIS MODULE

Required:

- Colavizza, G., Blanke, T., Jeurgens, C., & Noordegraaf, J. (2021). Archives and AI: An Overview of Current Debates and Future Perspectives. Journal on Computing and Cultural Heritage, 15(1), 4:1-4:15. https://doi.org/10.1145/3479010

- Mordell, D. (2019). Critical Questions for Archives as (Big) Data. Archivaria, 87, 140–161.

Recommended:

- Boden, M. A. (2018). What is artificial intelligence? In M. A. Boden (Ed.), Artificial Intelligence: A Very Short Introduction. Oxford University Press. https://doi.org/10.1093/actrade/9780199602919.003.0001

- IBM. (2021, July 27). What is Computer Vision? IBM. https://www.ibm.com/topics/computer-vision

- IBM. (2023, August 26). What Is Named Entity Recognition. https://www.ibm.com/topics/named-entity-recognition

- IBM Data & AI Team. (2023). AI vs. Machine Learning vs. Deep Learning vs. Neural Networks. IBM. https://www.ibm.com/think/topics/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks

OVERVIEW

This module provides a foundational overview of AI as it relates to archives and how it relates to archival practice. Implementing AI in the archives should be informed by evolving archival theory and by an active role of the archivist to support these shifts. Early attempts to integrate AI into the archive have shown promise, and the field acknowledges the room to grow in developing and refining these computational methods to better support archival processes. This work requires collaboration with colleagues beyond the archival field in order to leverage each others' technical expertise in finding fit-for-purpose archival solutions.

LEARNING OBJECTIVES

By the end of this lesson, students will be able to:

- Explain the history of artificial intelligence as it relates to archives and archival practice;
- Differentiate between types of AI and their applications in archives and;
- Identify possibilities for AI integration in the archive.

Introduction

While discussions of Artificial Intelligence (AI) have recently boomed in popularity both academically and more broadly in popular culture, the roots of these discussions date back to the mid-20th century, when pioneers like Alan Turing and John McCarthy began exploring the foundational concepts of the field like machine learning, symbolic reasoning, and artificial neural networks (Collins et al., 2021). The AI field itself started in Computer Sciences with a Summer workshop in 1956 at Dartmouth College in Hanover, NH, that brought leaders in information theory and computer science together to develop a research programme based on the idea that "every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (McCarthy et al., 1955).

Although the concept of AI has always revolved around computational methods of high-level cognition (e.g., reasoning, learning, language, decision-making), there is still no set definition (Collins et al., 2021). Nevertheless, in the context of archives, AI is most often associated with machine learning (ML), a process in which data and algorithms are used to enable AI to imitate the way a human learns and digests information.

Introducing AI into the archive is not a new idea. Archivist J.B. Rhoads, working at the then National Archives and Records Service of the United States, advocated in 1969 for a ‘cybernetic approach’ to archival work, which proposes the computer as an extension of the archival researcher itself and as a comprehensive database of the archive’s records (Rhoads, 1969). Similarly, P.B. Hirtle and F.J. Stielow’s work highlights how some archivists considered AI’s integration into archival practice in the late 1980s and early 1990s (Hirtle, 1987; Stielow, 1992).

As archival collections are increasingly made up of born-digital records and digitized analog materials, manual archival processes are becoming less feasible and thus require a transformation using machine agents. As archives enter the territory of ‘big data’ organizations, archivists must put some trust in AI to organize their workflows around processing archival big data (Colavizza et al., 2021).

INTERACT

Visit the following link: https://libraryguides.mcgill.ca/ai/literacy to explore the different applications of computational cognition that fall under the AI terminology umbrella. Applications particularly relevant to archival practice, like machine learning (ML), for instance, will be discussed in further depth below.

ACTIVITY #1

After exploring the AI family tree from the link above, pick a case study of an application of AI in archives and records management from https://interparestrustai.org/trust/research_dissemination

Read through the case, identify the AI applications in the family that are put into practice in your chosen study, and discuss how AI has found an application niche in the archival profession.

Types of AI in the Archive

As briefly mentioned in the introduction, AI has no set definition, but can be thought of as an umbrella term for software which mimics human cognition in order to complete complex tasks (Collins, 2021). In the archival context, machine learning (ML) is the most applicable AI technology, as it relies on algorithms to glean insights and recognize patterns in datasets (Colavizza et al., 2021). The model then uses this information to learn about the data and make better decisions and outputs. In this sense, ML could help process large volumes of archival data that otherwise would take exponentially longer to be manually processed by the archivist.

A step further into machine learning leads to deep learning models, which use massive neural networks to learn complex patterns and make decisions without human input. Neural networks, in the context of AI, are computer models inspired by the biological structure of human brains to logically analyze data (IBM Data & AI Team, 2023). While deep learning models are still commercially experimental, it is unlikely their structure will be implemented into archival workflows any time soon. Nonetheless, understanding how deep learning models process information can be useful when tailoring ML models to archival purposes.

In order for AI, ML, and deep learning models to make decisions about datasets, they have to learn how to make these decisions first. There are two main approaches to training these models: supervised and unsupervised learning. Essentially, supervised learning trains the model on labelled data (pre-existing classifications normally created by humans), while unsupervised learning does not (Delua, 2021). Using labelled data allows for the model's inputs and outputs to be monitored for accuracy and learning over time, whereas unlabeled data allows the models to discover patterns hidden in the data without human intervention (Delua, 2021). Both methods aim to learn from the data, and in particular, unsupervised learning could be valuable in the archive to gain insights from large amounts of data.

Another type of AI that shows potential in archives is computer vision, which enables computers to acquire, process and understand data from images and videos (IBM, 2021). In practice, computer vision is also used to identify people and objects in audiovisual media. However, implementing computer vision requires massive amounts of data to be algorithmically processed through a deep learning neural network model (IBM, 2021). For audio and video, automatic speech recognition (ASR) is another application of AI that supports processing and learning from speech and audio data (Yu and Deng, 2015). This AI technology expands the scope of possibility for the application of AI to other types of records. Therefore, if archivists are to make use of computer vision or ASR, they must first have a strong understanding of AI and machine learning.

ACTIVITY #2

In this individual activity, go to https://www.recordpoint.com/data-trust-platform-tour and explore Recordpoint's Data Trust Platform to identify the different types and applications of machine learning throughout the program. Where do you find machine learning algorithms in this application? What are they intended to do? Are they supervised or unsupervised? What is the role of the archivist in interactions with this tool?

AI for archivists and records managers

Implementing AI into archival workflows naturally affects the archival concepts and theory that ground the profession. In particular, the digital transformation of the archive has brought the foundational concepts of provenance and original order into question. Reconceptualizing archival records as 'data' makes traditional appraisal methods less relevant and requires re-evaluating the ingrained archival assumptions of a record's authenticity, integrity, and trustworthiness (Mordell, 2019).

The transdisciplinary nature of the relationship between AI and archives calls upon archivists to become masters of data and focus on consistent training and retraining to mitigate skill and knowledge gaps that arise as AI technology continues to improve. This has made way for the emerging field of Computational Archival Science, which argues for a shift in archival thinking that centres usability and context in archival work in response to technical advances (Marciano et al., 2018).

A promising aspect of implementing AI into archival workflows is the potential to automate parts of the job and help speed up the processing of the backlogs of digital records. Recent studies illustrate that current automation attempts have been successful in appraising large amounts of digital records like emails; however, there is room for growth in using methods like natural language processing (NLP) and named entity recognition (NEP) to better support archival processes (Colavizza et al., 2021).

With the growing volume of digital-born records, traditional archival search and access methods are becoming increasingly inefficient and will require an overhaul to meaningfully serve the needs of archival users. Tools like predictive frameworks, information visualizations and full-text searches have all proved useful in improving digital archival search and retrieval processes (Colavizza et al., 2021). While these tools and other AI-based applications have faced some criticism in potentially obscuring records' context through highly specific information retrieval, it is necessary for archivists to engage critically with these tools when working with them to avoid perpetuating any potential biases in the programs (Colavizza et al., 2021).

As AI implementation into the archive continues, it is important for archivists to reach out and collaborate with their digital humanities and computer scientist peers to develop fit-for-purpose archival solutions leveraging AI techniques and reflect on the implications of AI on recordkeeping practice, or vice versa. Furthermore, the theoretical foundations of the profession need to be integrated into the ongoing development of AI in the archive to support the transformation of these experiments into archival practice and infrastructure.

ACTIVITY #3

Continuing with activity #1, students will be assigned a case study and corresponding bibliography based on an existing AI implementation in records processing from https://interparestrustai.org/trust/research_dissemination. Each group will prepare a short presentation (<5 minutes) for the class on their assigned case study with the expectation of identifying both the type(s) of AI used in the case, the role of the archivist or records manager in the application of the AI tools in each case, and key critical considerations.

SUMMARY

To summarize, while AI is not new, the rise of these technologies in archival contexts has begun reshaping practice and thus has forced archivists to re-evaluate how to integrate the field’s traditional theories with new technologies. Machine

Learning (ML), in particular, has demonstrated potential for automating tasks in archival workflows; however, challenges exist in reconciling the integration of ML into archival workflows primarily grounded in concepts like provenance and original order. As a result, archivists must remain flexible in integrating AI into their workflows and continue to foster their data management skills as technology continues rapidly improving. Subsets of machine learning, including deep learning and computer vision, hold promise for processing and analyzing vast amounts of digital data. However, their implementation requires careful consideration of algorithmic biases and context preservation. Ultimately, ongoing collaboration between archivists and AI specialists is essential for developing tailored technological solutions to archival problems and meaningfully integrating AI into archival workflows.

If you want to know more:

Hutchinson, T. (2020). Natural language processing and machine learning as practical toolsets for archival processing. *Records Management Journal*, *30*(2), 155–174. https://doi.org/10.1108/RMJ-09-2019-0055

Lemieux, V. L., & Werner, J. (2024). Protecting Privacy in Digital Records: The Potential of Privacy-Enhancing Technologies. *Journal on Computing and Cultural Heritage*, *16*(4), 83:1-83:18. https://doi.org/10.1145/3633477

GLOSSARY

Artificial Intelligence (AI)

As discussed throughout this module, there is no set definition of Artificial Intelligence (AI); however, it can be broadly understood as the capability of machines to imitate aspects of human intelligence with the goals of solving problems or adapting to a changing environment (Sennott et al., 2019). In general, AI has two main goals. The first is technological, wherein computers are used to complete useful tasks; the second is scientific, where AI concepts and models help answer questions about human beings and life on earth (Boden, 2018).

Computer Vision

Computer vision is a type of AI that allows a computer program to understand and process visual information (Sennott et al., 2019). It uses neural networks to process information pixel by pixel and can classify images based on their shared characteristics (Sennott et al., 2019).

Named Entity Recognition (NER)

Named Entity Recognition (NER) is a component of natural language processing that identifies pre-determined object categories within a body of text (IBM, 2023). Essentially, NER takes a string of text and identifies and classifies it into entities like objects, individuals, organizations, locations, etc., into their respective categories.

Natural Language Processing (NLP)

A subfield of computer science and AI, natural language processing (NLP) is "defined by computer processes that focus on recognizing and generating natural human language" (Sennott et al., 2019). Like AI, NLP is not new; older iterations of the process involved close analysis of grammar and syntax to solve contextual problems; however, modern NLP relies on machine learning and statistical analysis to find, predict, and analyze linguistic patterns (Sennott et al., 2019; Boden, 2018).

Machine Learning (ML)

While there are many kinds of machine learning algorithms and strategies, the concept can best be understood as a subfield of AI that focuses on the ability of computers to imitate the way humans learn without being explicitly programmed to do so. In other words, machine learning (ML) requires that systems observe their performance on any given task and use this knowledge to perform more accurately in the future (Sennott et al., 2019). Several approaches to creating an ML program based on its input data, like supervised and unsupervised learning, are further discussed in the module.

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Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*, 102383. https://doi.org/10.1016/j.ijinfomgt.2021.102383

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Marciano, R., Lemieux, V., Hedges, M., Esteva, M., Underwood, W., Kurtz, M., & Conrad, M. (2018). Archival Records and Training in the Age of Big Data. In J. Percell, L. C. Sarin, P. T. Jaeger, & J. C. Bertot (Eds.), *Re-Envisioning the MLS: Perspectives on the Future of Library and Information Science Education* (Vol. 44B, pp. 179–199). Emerald Publishing Limited. https://ai-collaboratory.net/wp-content/uploads/2020/10/Marciano-et-al-Archival-Records-and-Training-in-the-Age-of-Big-Data-final.pdf

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