AI TRAINING RESOURCES FOR GLAM: A SNAPSHOT

A PREPRINT

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ABSTRACT

We take a snapshot of current resources available for teaching and learning AI with a focus on the Galleries, Libraries, Archives and Museums (GLAM) community. The review was carried out during 2021 and 2022. The review provides an overview of material we identified as being relevant, offers a description of this material and makes recommendations for future work in this area.

Keywords Galleries Libraries Archives and Museums · Machine Learning · Training Resources

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1 Introduction

In this review, we take a snapshot of current resources available for teaching and learning AI with a focus on the Galleries, Libraries, Archives and Museums (GLAM) community. In particular, we seek to assess the content and topics covered by the material, the methods of delivery used, the target audience and the current maintenance state of the materials. Most importantly we ask: How useful and relevant is the material for the GLAM community? Our objective is to identify to what extent existing materials, efforts, and approaches are useful and relevant for the GLAM community and to determine gaps where additional efforts are needed.

We argue that AI skill building in the GLAM sector is crucial for the following reasons:

1.1 GLAM staff need to be able to apply machine learning in their organizations appropriately and critically.

Machine learning and artificial intelligence (AI) are rapidly developing both as academic fields of research and as tools used in software and services across the public and private sectors. There is an increasing interest in using AI and machine learning in the GLAM sector, but there are challenges that may be unique to GLAMs. An absence of domain expertise and influence has been identified as one of the reasons that some of the academic advances in machine learning have not ‘translated’ into practical applications. For example, a recent review paper assessed machine learning work related to the detection and prognosis of COVID-19. Of the 64 studies included in the review after screening, they found “that none of the models identified are of potential clinical use due to methodological flaws and/or underlying biases.” Although the stakes may not usually be as high in the GLAM setting the potential benefits of AI/machine learning for the sector may not be fully realized if GLAM staff do not have the expertise to shape the application of machine learning.

1.2 GLAM staff need to be equipped to meet the challenges of working with their collections.

GLAM collections pose a range of challenges when used with modern machine learning methods and tools. GLAM organizations have increasingly looked at AI to improve the often overwhelming task of accessioning and processing archival material and making it digitally available. There are also specific ‘technical’ challenges, for example effectively applying OCR to historic fonts with poorly preserved materials. Other challenges come from working with collections that are closely linked to what gets archived and what eludes collection and preservation. Whilst collections can be comprehensive, the materials are often not representative and can significantly shape downstream models.

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2As identified in various recent reports, for example:
- Responsible Operations: Data Science, Machine Learning, and AI in Libraries
- Machine Learning + Libraries

3In Relation to GLAMS Task Force
- https://www.nature.com/articles/s42256-021-00307-0

4Whilst GLAM data is unlikely to be regularly used as the basis of clinical decision making there are other areas with high stakes where GLAM data is involved for example in historic climate research
- https://www.zooniverse.org/projects/drewdeepsouth/southern-weather-discovery
based on these collections. As an example, British collections related to the history of India are likely to be skewed towards English and Hindi language materials in comparison to other languages spoken in India. Administrators are looking for strategies to integrate AI into existing GLAM technologies and workflows, including catalogues and search interfaces. Similarly, administrators often face the challenge of institutional buy-in and access to staff and funding, which requires their ability to make a good case for AI at their institution.

1.3 GLAM staff are uniquely positioned to shape the ethical use of machine learning and AI beyond their organizations.

GLAM curators and archivists are experts in the selection, description, preservation, and access to archival materials, including those that are increasingly digital. A keen awareness of context informs GLAM practices of metadata development (classification) as well as collection development. The attention to provenance, in particular, helps place sources historically, socially, and politically and reveal patterns and absences, and this attention is sorely needed when it comes to the preparation of training data for machine learning.

The AI community has also struggled, and too often failed, to address concerns of privacy, protection of intellectual property, transparency, and democratization, all of which are core values that GLAM organizations have been developed to address. In the increasingly ethically challenged world of machine learning, GLAM staff are not only ideally positioned but have an obligation to bring their considerable experience and expertise to bear as stewards of training data -- its creation, documentation, preservation, and reuse.

Part of the inspiration to perform this review goes back to the recommendations of two prominent reports on AI in GLAMs related to training. Cordell in the Machine Learning + Libraries report (pp.60-63) recommends to:

- Develop Modules for ML Training in MLIS Programs (section 5.5.2.)
- Cultivate Opportunities for Professional Development in ML (section 5.5.3.)
- Develop Guidelines for Vendor Solutions (section 5.5.5.)

Padilla in Responsible Operations (p.18) suggests to:

1. Initiate evidence-based evaluations of existing data science, machine learning, and AI training opportunities within and outside of the library community.
2. Pilot and/or support the development of evidence-based data science, machine learning, and/or AI training options that are grounded in library use cases.
3. Explore, document, develop, and share sustainability models for keeping training opportunities free or low cost without sacrificing quality and fair compensation.

These two reports also have helped inform the ‘gaps’ we identify below and our recommendations. Appropriate professional development and training may partially address the challenges faced by GLAM institutions and mentioned in these reports.

2 Method

This review had two main goals:

- to gather a collection of teaching and learning materials for machine learning and
- to carry out an evaluation of these materials.

The collection is based on Google searches and GitHub searches as well as materials the members of this working group were familiar with. We primarily collected resources with potential relevance for GLAMs, but we also included some courses with a broader focus. It was beyond the scope of this review to capture all possible resources. It was also not feasible to work through the materials in detail and evaluate their quality. Instead, we aimed to provide a high level snapshot of current material and to identify strengths and limitations within a broader ecosystem. At the point of writing our spreadsheet contains 28 sources.

We assessed each teaching resource according to: topics covered, type of resource, study time required, creator/author, date published, updates, stated audiences, training data used, and whether the course had an explicit GLAM focus, either using GLAM collections or GLAM being mentioned as a target audience.

5Discovery can be a bit challenging. For example, searching for ‘machine learning + libraries’ did not produce relevant results.
3 Findings

3.1 Format

The following table breaks down the resources by type. Perhaps not surprisingly, more than half of the materials are based on Python and Notebooks. A few require running commands in a shell. About 40% of the materials consist of Web based texts. 25% include video clips and lectures and very few provide slides. We also identified 4 full length online courses.

| Type                          | Number | %  |
|-------------------------------|--------|----|
| Python (Jupyter or Colab Notebook) | 15     | 53.6 |
| Command line                  | 2      | 7.1 |
| Web page material             | 11     | 39.3 |
| Video Lectures                | 7      | 25  |
| Online Course / MOOC          | 4      | 14.3 |
| Powerpoint/Slides             | 2      | 7.1 |

Table 1: Form of material

Though some of the resources are provided within the context of a course or a workshop all the materials can be used self-directed and self-paced. The suggested time commitment ranges from about 1 to up to 50 hours. Many of the materials are relatively short, most are a ‘one shot’ learning experience, i.e. half-day workshop; there are few materials with a longer time horizon. The majority of the materials we identified (n = 21) were published more recently (2019 - 2021). Only 7 resources were published between 2016 and 2018. This might underscore the recent increase of interest in training accessible to a broader audience.

3.2 Content

There is a potentially overwhelming amount of material focused on teaching machine learning. Out of the material we reviewed, the scope ranges from complete MOOC courses aiming to teach machine learning “from scratch” to blog posts covering the details of one particular technique in great detail. Some well known MOOCs include; Andrew Ng’s Coursera Machine Learning course, which has over 4 million people enrolled and the fast.ai Practical Deep Learning for Coders course and Elements of AI which has the goal of educating 1% of European Citizens on the basics of AI and is notable for not focusing primarily on using coding examples or exercises as a method for teaching machine learning. There is also a growing trend for universities to share material for machine learning courses openly shortly after or alongside the delivery of courses. In addition, many machine learning frameworks and libraries offer courses for working with their tools. For example, the spaCy NLP library has an intro to NLP course the scikit-learn library has extensive tutorials and the Keras library has a growing number of code examples.

The materials in our review touched on a broad range of topics. Based on the topics extracted from the materials the content broadly covers the following topical areas:

- Classification
- Clustering
- Natural Language Processing
- Word Vectors
- Digital Assistants
- What is AI?
- Use cases
- Neural Networks, Deep Learning
- Ethics / societal implications of AI

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6 As one example of this, a search for 'machine+learning+introduction' in the 'description' field of GitHub repositories returns 3024 results. Expanding this to 'machine+learning+introduction' in the 'readme' of GitHub repositories returns 88177 (search carried out 2021/09/29) [https://gist.github.com/davanstrien/df2be4b0d5c5944f3f5974f3f1c4085e](https://gist.github.com/davanstrien/df2be4b0d5c5944f3f5974f3f1c4085e)

7 For example Stanford: [http://web.stanford.edu/class/cs224n](http://web.stanford.edu/class/cs224n) and MIT: [http://introtodeeplearning.com/](http://introtodeeplearning.com/)
• Text
• Images
• Machine learning terminology and concepts
• Data
• AI Project management
• Python
• APIs and Data collection

(for details see the Training Resources Content Map)

Not surprisingly there is a certain overlap between the materials. Broadly speaking, they fall into the following categories:

3.2.1 General Introductions to Machine Learning

These workshops/materials aim to provide an introduction to machine learning methods and potentially their particular application to Digital Humanities (DH) and/or GLAMs. Examples include the Carpentries lesson Intro to AI for GLAM (under development), the webinar Artificial Intelligence in the Library and the Intro to Machine Learning with Python workshop materials. The high percentage of materials that require Python or command line skills indicate that the majority of the materials either focus on or require coding. Notably, elementsofai.com provides an introduction to AI and ML concepts that does not require any coding.

3.2.2 Introductions to a Specific Method or Tool

These materials focus on introducing a particular method or specific tools to do tasks, such as tutorials on Named Entity Recognition using spaCy or the CoreNLP library.

There are also tutorials supporting the use of particular machine learning tools for GLAM sectors. For example, Annif, a tool for automatic subject indexing, has associated tutorials that demonstrate the use of the tool.

3.2.3 Working with GLAM data

A few of the courses focus on accessing GLAM data for use with ML. Typically the focus is on a particular collection not on ML per se. Examples are the GLAM workbench for GLAM collections mainly from Australia and New Zealand, the data explorer from the US Library of Congress and the Cambridge Digital Library metadata.

3.3 Ethics

We identified four sources that teach and address ethics in the context of AI: Ethics of AI, Practical Data Ethics and Lesson 5 of the course FastAI Deep Learning for Coders, Lesson 9 of Full Stack Deep Learning. These materials cover a comprehensive and wide range of issues, including discrimination and bias, privacy and surveillance, accountability and fairness, explainability, as well as global and economic issues of AI, human rights and algorithmic colonialism.

3.4 Audience

The table below provides a summary of the training materials with GLAM staff in mind as the target audience, use GLAM collections as training data, or address applications and issues that are of particular relevance for GLAM workflows and operations. Assuming some disciplinary overlap between DH and GLAM, we included materials that had a focus on DH and as such are potentially useful for a GLAM audience. DH materials focused on topic modelling, for example, may focus on the use of topic models to answer a research question, rather than the use of topic models as a tool for information retrieval or collection management. This suggests that relying solely on DH material for a curriculum may lead to gaps in topic and method coverage.

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9These types of tutorials may overlap with a simple documentation of the functionality.
In our survey we were able to identify 17 resources (60.7%) that have relevance for GLAM, including DH focused material. Given that we specifically set out to identify GLAM relevant materials this large proportion may not be unexpected. The remaining 11 sources are introductions for a general audience, though they tend to lean towards an audience with some programming background.

Our search was aimed at materials for beginners i.e. they were introductions to a topic rather than assuming some previous knowledge of a topic and diving more deeply into one aspect of that topic. However, whilst they were introductory in nature, they often assumed at least some minimal Python knowledge and some familiarity with Jupyter notebooks for interacting with code, thus limiting the audience to GLAM staff with a certain familiarity of programming.

Although not aimed specifically at the GLAM sector, many of the not explicitly DH or GLAM focused courses have the potential to be used for teaching in the GLAM sector; the [Elements of AI] and fastai [course](https://github.com/AI4LAM/fastai4GLAMS) though not originally designed with GLAM in mind, have both been used by GLAM staff study groups.

### 3.4.1 Pedagogy

Broadly speaking, materials can be divided into those that are shared as-is (“here it is, now you’re on your own”) and courses, as for example [AI for Everyone](https://github.com/cncoleman/elementsofai4glam), both specifically designed with pedagogical and learning goals in mind. [elementsofai](https://github.com/cncoleman/elementsofai4glam) and [buildingai](https://github.com/AI4LAM/fastai4GLAMS) have support structures in place and are linked to a discussion forum where participants engage with each other and the creators of the lessons. [elementsofai](https://github.com/cncoleman/elementsofai4glam) additionally includes peer reviews of assigned short essays.

It is the nature of the web-based materials that they are generally self-directed and to be used independently, which can be convenient for some users. It is also the nature of web-based materials that they are often not very interactive. Jupyter notebooks can remedy this, though the interaction often does not go beyond executing and perhaps experimenting with the code.

Two resources explicitly outline their teaching philosophies: [Carpentries](https://github.com/cncoleman/elementsofai4glam) and [fast.ai](https://github.com/AI4LAM/fastai4GLAMS).

### 3.4.2 Example Training Data

Example ML training data used in the materials covered several types of data. The table below provides an overview of those training resources that included data, which are 22 within our collection. Over three quarters of the training data are based on text, and about one third uses images. Tabular data and audio visual materials are less represented.

| Type of data | Number | %  |
|--------------|--------|----|
| text         | 17     | 77.2 |
| image        | 8      | 36.4 |
| tabular      | 2      | 9.1  |
| audio, video | 1      | 4.5  |

Some of the reviewed materials use GLAM data, but many use “generic” machine learning datasets or synthetically generated ‘toy’ data.

A few of the lessons use GLAM data, for example [OCR](https://github.com/cncoleman/elementsofai4glam) and [Machine Translation](https://github.com/cncoleman/elementsofai4glam) uses data from the Wilson Center Digital Archive’s collection on Iran-Soviet relations.

There is also a growing body of materials that aim to provide introductions to working with particular GLAM collections, like [https://glam-workbench.github.io/](https://glam-workbench.github.io/)

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[10] https://github.com/cncoleman/elementsofai4glam
[11] https://github.com/AI4LAM/fastai4GLAMS

[10] multiple types possible per resource
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https://github.com/BL-Labs/Jupyter-notebooks-projects-using-BL-Sources, and https://github.com/LibraryOfCongress/data-exploration

Whilst these materials are not always focused on machine learning directly they may help lower barriers to accessing collections and cover some of the required preprocessing steps for working with GLAM data for machine learning tasks.

The training data have limitations for teaching and learning in the GLAM sector:

- It is often tidier than would be found in the ‘real world’; for example there are no missing labels, or the labels are equally distributed between classes.
- It may have labels that are not as relevant for GLAM applications, making it harder for learners to translate the material to their own work.
- The results may be better than would be achieved on real-world data, leading to unreasonable expectations of performance.

3.4.3 Maintenance

Based on information from the website or GitHub commits we tried to determine when the materials were last updated. An overview is provided in the table below.

| Year published | Year of last update | Number |
|----------------|---------------------|--------|
| 2016           | 2016                | 1      |
| 2017           | 2020                | 1      |
| 2017           | 2021                | 1      |
| 2018           | 2018                | 2      |
| 2018           | 2019                | 1      |
| 2018           | 2020                | 1      |
| 2019           | 2019                | 5      |
| 2019           | 2020                | 1      |
| 2019           | 2021                | 2      |
| 2020           | 2020                | 5      |
| 2020           | 2021                | 3      |
| 2021           | 2021                | 5      |

Table 4: Year published and year last updated

With regard to evaluating maintenance, we face the issue of later materials being less in need of updating. About half of the earlier materials were updated at least until the following year, while the other half of the materials published 2019 and earlier (8 out of the 15) were not kept updated in later years. We observed some link rot with datasets for some lessons.

Creators of the materials are affiliated with academic institutions, libraries, private companies (fastai), or are software developers (scikit learn). It appears that often material was prepared for a particular workshop or event and not updated subsequently. This is not necessarily a problem, but as software libraries change and machine learning develops, it may be desirable to have material updated semi-regularly over time. In a similar vein, we considered whether the material was ‘community developed’, i.e. developed and maintained by a larger group with a straightforward process for contributing. Whilst community developed materials are by no means always desirable, there may be duplication of efforts by creating some similar material independently. There may also be more scope for continued improvement, review and refinement of materials when developed collectively.

4 Recommendations for teaching and learning AI for GLAM

The greatest value for teaching and learning AI will come from a GLAM specific focus on the unique issues faced by GLAM institutions, targeting GLAM use cases and institutional contexts. Below are the priorities we have identified, many of which do not appear in the materials reviewed.

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¹²This was easier to assess for materials hosted on GitHub where contributions are more visible. For material hosted on Github the average number of contributors was 6, however this is skewed by a few materials having large number of contributors (maximum was 37). The mode value was 1.
4.1 There is a need for machine learning concepts (without coding)

As has been discussed above, there are many important parts of the Machine Learning pipeline that do not require or involve writing code. This includes many important steps with implications for the success of machine learning projects, but also a conceptual understanding of the process and how the models are trained. We recommend that the AI4GLAM community seek to ensure that not all materials focus on writing code as the primary way of engaging with machine learning. Whilst some of this material might be introductory in nature it is also useful to have non-introductory material focused on more ‘advanced’ or specialised topics which don’t include coding.

To consider training and skill building for the various GLAM roles more specifically we developed a number of [stick figure personas]. The audiences we think are not addressed adequately are shaped by the personas discussed above. For example, one of the personas is ‘Metadata M’ who [work as a metadata librarian at a large academic library and has joined a campus-wide AI initiative. M is enthusiastic to learn as much AI so they can be an active contributor to the group. They don’t expect to do much coding, but would like to try.]

Keeping this type of persona in mind we can identify the lack of materials that don’t focus on coding as a problem.

Whilst many parts of the machine learning pipeline and machine learning projects involve writing code, this is not the only part of such projects and potentially not even the most critical part of the process. For example, clearly defining the business use case for machine learning, including how machine learning will integrate into workflows, might be more important than a specific method or tool being used. These skills often require domain expertise and some broad understanding of machine learning and its limitations but often don’t require code to be written.

4.2 Where coding is necessary, python is important

Python and Jupyter Notebooks are standard tools for machine learning and thus constitute a large part of the training material, even if introductory. Even in GLAM focused materials, some Python knowledge is often required. This raises the question if introductory Python and Jupyter Notebooks training should be provided for GLAM staff before teaching basic ML concepts and if so, how that could or should be done, particularly for those without coding background. On the other hand, we should consider and explore alternative approaches for hands-on approaches to teaching AI, that are interactive and intuitive and do not rely on coding.

4.3 Community building and project-based work will improve learning.

Much of the AI training material is oriented to teaching machine learning to engineers and developers. As a result, learners are typically left to their own devices to work through it and be resourceful in solving problems or answering questions they might have. Often the material is presented as step-by-step instructions or Jupyter notebooks to follow along.

As we have noted, integrating AI into the GLAM sector has implications for many different roles and areas of expertise beyond engineering. It will involve changes to our practices and processes. If we are to move from learning machine learning to learning how to integrate machine learning methods into our practices and processes, a collaborative learning experience is necessary, with GLAM engineers and coders working side-by-side with subject experts, curators, and others.

4.4 Maintenance and discovery of training materials for the GLAM sector will benefit from community organizing.

We identified a certain extent of duplication of effort and the potential risks of material not being updated. This raises the issue of sustained support structures for training materials. There may be some scope for developing a shared approach to creating, reviewing and maintaining teaching materials via community development, review and maintenance strategies. This is a significant undertaking and would require broad community support.

There are examples to draw from, for example the Carpentries and Programming Historian, both of which have maintained a growing body of teaching materials for significant time periods. A first step would be to further explore the benefits and feasibility of developing these shared resources and assessing potential models for undertaking this type of project.

When researching materials for this report we followed a variety of pointers. There is no one stop shop for this kind of material. The [CENL Awesome List] is one example we found of curating a directory of GLAM focused machine learning materials. These are intended to help make the assessment of systems or in this case teaching materials easier in relation to the needs of these different personas.
learning resources. While offering a potential route to increasing discoverability, long-term maintenance of this type of list may be challenging.

Alternatively, there are potentially ‘quick wins’ to aid discover that don’t require as much maintenance:

• Applying GLAM or other similar topics to materials shared on GitHub would make it easier to disambiguate GLAM-focused material from other material, and for example help distinguish a search for ‘machine learning libraries’ (which provides an introduction to Named Entity Recognition for historic text) from ‘machine learning libraries’ (which provide an introduction to Pytorch).

• Considering Search Engine Optimization when sharing teaching materials. There is a large volume of blogs, notebooks, and YouTube videos related to machine learning and data science. Relying solely on ‘generic’ machine learning keywords may limit how many people discover your material.

4.5 An emphasis on critical data practices and the ethical implications of Machine Learning is necessary

Data is a central component of machine learning but isn’t always given the same attention as models. Since GLAM institutions already play such a central role in the collection, description, organization, transformation and dissemination of data, it is potentially even more important that data is given a prominent part in a GLAM-focused AI curriculum. This becomes even more important when considering the potential ethical ramifications of using data held by GLAM institutions. Strategies, tools and workflows for building training data, also include questions of provenance, metadata, and labeling and how to produce datasheets[14] for GLAM data used for training ML models.

Much of the material we reviewed focused on building the ‘model’ part of the machine learning pipeline. Often materials start with a prepared training set (often with a pre-created training/validation/test split). The data collection and preparation stages of the ML pipeline, such as sampling, choosing labels, and annotating data are too often left out. There is little attention given to the processes involved to actually get there: how to generate training data, decide labels, inter-annotator agreement etc., and the issues around these, that involve awareness of the biases and ethical implications of that process.

In addition, while there are several materials addressing ethics generally, none of them address ethics in the GLAM context. Given the nature of GLAM collections and the particular awareness around ethical issues already existing in GLAM organizations, it is of particular importance to consider the implications for machine learning and steps which can be taken to mitigate ethical risks.

The process of creating machine learning models involves a range of different stages including (but not limited to):

• Collecting data
• Sampling and processing data
• Creating training sets including:
  – Choosing (appropriate) labels
  – Identifying existing metadata schema to integrate with
  – Creating training, validation and test splits
  – Identifying biases in data
• Tracking the provenance of various models and datasets
• Integrating models into tools or systems
• Integrating or making use of predictions as part of existing or new workflows
• Monitoring data drift and model performance overtime
• Documenting models and data
• Communication to external and internal audiences

The broader data science community is also focusing increasingly on the data component of machine learning[15] so there are likely to be potential synergies with non GLAM focused initiatives that will help with the development of data focused teaching materials.

[14]https://arxiv.org/abs/1803.09010
[15]For example https://https-deeplearning-ai.github.io/data-centric-comp/
4.6 GLAM specific training data will improve teaching and learning.

Data is a central component of machine learning but isn’t always given the same attention as models. Since GLAM institutions already play such a central role in the collection, description, organization, transformation and dissemination of data, it is potentially even more important that data is given a prominent part in a GLAM-focused AI curriculum.

The lack of training data has been identified as a barrier to adopting machine learning in libraries. This is not only a problem of implementation, it is also a problem for teaching and learning. Using GLAM specific data is crucial for helping the learner see the relevance of AI to their work. It offers opportunities to discuss challenges GLAM projects might face, e.g. poor OCR, grayscale images, historical language etc.

Time and money are barriers to developing training data both in academia and industry. Training materials focused on this topic may help lower the barrier. The process of developing these datasets requires subject expertise and skills in data manipulation.

4.7 Effective implementation requires a focus on teaching the design and management of ML projects

None of the materials identified in this study address issues around the implementation and management of ML projects in GLAM organizations. Issues to be addressed should include:

- Communicating the results of machine learning to other staff and the public
- How to collect annotated data for machine learning
- How to document training data (for example writing datasheets)
- How to document models (for example writing model cards)
- How to evaluate model performance (in particular, in relation to a specific GLAM task or use-case as opposed to ‘out of the box’ evaluation metrics)
- Deployment of ML in libraries and how this might not always match industry approaches
- Communicating with end-users about the use of machine learning, e.g. how to share metadata produced through machine learning methods with end-users and how much disclaimer needs to be attached etc.
- Examples for the entire workflow of a ML project, that would move from collection through an ML process and interpretation

GLAM projects that share materials associated with both successful, and importantly, unsuccessful projects would contribute to learning resources. Topics that such material would cover are:

- Why was the project chosen? How does it fit into a broader institutional context?
- What approach was taken by the project? Why was machine learning chosen as opposed to another approach?
- What data was available? How it was gathered? How were labels chosen? Who did the annotation? Were there challenges in shaping the annotation guidelines?, etc.
- How was the model ‘deployed’ or used by the institution?
- What challenges, barriers and failures were encountered along the way?

Another model, suggested by Cordell (2020) is that of “Implementation Toolkits”:

“The specific workflows outlined in the existing literature can be hard to generalize from, particularly for teams new to ML work. To that end, funders and leading ML libraries should support the development of ML Implementation Toolkits for distinct data types (e.g. text, image, audio, video) or in particular domains. These toolkits would include:

1. Model training data, with descriptions of annotation processes undertaken and an intellectual justification of the same.

https://labs.loc.gov/static/labs/work/reports/Cordell-LOC-ML-report.pdf
https://arxiv.org/abs/1803.09010
https://arxiv.org/pdf/1810.03993.pdf
Machine Learning + Libraries
2. An inventory of existing resources, including open-access, domain-specific collections; ML models, algorithms, and code that could be used or adapted; and prospective pre-training data from earlier ML projects in the domain.
3. A walkthrough of the full technical pipeline from related project, including training, validation, and application of the model.
4. Model code from related experiments.” (Cordell, 2020, p 58)

These toolkits would cover a broader range of the pipeline and would serve as a guide for institutions wishing to work with machine learning.

We would challenge, however, the idea of these toolkits being produced only by “leading” libraries or GLAM institutions. Whilst some institutions may invest more in machine learning and should be encouraged to share lessons and guidance based on this experience, we believe broad sharing of lessons learned across the GLAM sector would be beneficial. For example, the lessons learned in one setting, a national library, may not be as relevant to a local archive service.

5 Conclusion

While this review of materials, methods and target audiences for AI training is a snapshot from the period of time in which it was compiled, it brings to light a significant trend toward both upskilling and reskilling within the GLAM community. Though not all GLAM resources are digitized and many may never be digitized, the training reviewed here can be applicable to GLAM work at the level of metadata. At the same time, as the amount of digitized and born digital cultural heritage continues to grow, it seems abundantly clear that GLAM practices will need to adopt and adapt techniques from data science and, specifically, machine learning in order to keep pace. To this end, this review offers guidance for the GLAM community about current offerings and future directions.