User insights shaping machine learning applied to archives

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User Insights shaping Machine Learning applied to Archives

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ABSTRACT

Archives hold vast amounts of historical and cultural information, but navigating and extracting knowledge can be a daunting task. Machine learning (ML) offers immense potential to unlock these archives, yet its effectiveness hinges on understanding user needs. This paper explores how user insights can shape the development and application of ML in archives. Here "user" refers to editors and publishers who are crucial part of archival sorting and publication in the company. This paper emphasizes the importance of an iterative user centred design process to guide development and ensure user acceptance and empowerment. This approach reveals the distance between user expectations and functional integrity.

CCS CONCEPTS

• **Human-centered computing → User centered design**; *Interface design prototyping*; HCI theory, concepts and models; *User interface design.*

KEYWORDS

Machine Learning, user-centered designs, Archives, UI, UX

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1 INTRODUCTION

The application of Machine Learning (ML) techniques in archives has been a growing area of interest [1]. However, organizing and extracting knowledge for publication can be a time-consuming and laborious process for editors and publishers. In this case, a ML pipeline can help automate and enhance this process by providing text insights such as named entity recognition and copyright findings, as well as visual insights like object detection. The recent work in 2022 underscores the transformative potential of ML for extracting archival information and generating various metadata [5]. This metadata enrichment can improve discoverability and accessibility of archives. However, realising this potential in the form of a usable tool fit for editorial and publication purposes requires additional consideration of users needs. With this in mind a user-centered approach has been adopted.

Effectively integrating the backend ML pipeline with a usable interface is crucial for the capabilities of ML to full experienced and utlilised [2]. In our particular case user needs a front-end not only allowing interaction with the ML inference process, but also the desire to modify the results and even contribute to model improvement when performance falls short or when archive specific training is required. In order to design a user-centered interface, user involvement in every stage of development is crucial, and continuous user feedback is essential to refine and improve the ML experience. But, it is important to acknowledge that users may not always possess an adequate conceptual understanding of their own needs within the context of the ML pipeline and its integrity [4]. This is a common challenge in user-centered design, particularly when dealing with novel technologies. Our research will explore such a case in the following sections.

This paper delves into the critical role of user insights in shaping the development and application of ML for archives, highlighting the importance of understanding user behavior and research goals in guiding the selection and implementation of specific ML techniques.

2 USER-CENTERED DESIGN APPROACH

A user-centered design approach underpins the development of the user interface (UI) for our ML-powered archive system. This approach prioritizes the needs and publication workflows of editors and publishers, ensuring an intuitive and efficient interface. However in this context, ML functionalities are powerful yet unfamiliar to the users, and as such understanding and leveraging present both technical and user interface design challenges. While the core ML pipeline encompasses two sub-pipelines inference and training, this paper concentrates specifically on the design of the training interface.

The inference pipeline allows users to obtain automatically generated metadata for archival materials. The training pipeline, on the other hand, focuses on model improvement through the integration of new data, adhering to the principles of Human-in-the-Loop Machine Learning (HIL) [3]

This paper explores early design considerations for the training interface adopting a user-centered framework. Our objective is to create an interface that facilitates user participation in the HIL machine learning process, specifically focusing on model improvement through data annotation and feedback provision.

As Figure 1 outlines the application of user-centered design principles to develop an interface for training ML models specifically targeted towards users with a non-technical background. The user-centered design process is typically divided into four key stages.

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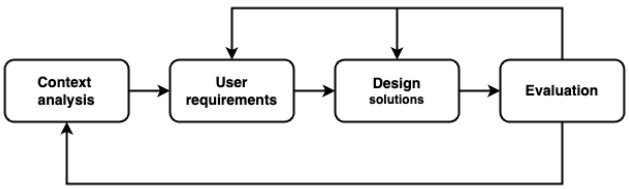

Figure 1: Simple user-centered design

2.1 Context Analysis

The initial stage involves the context analysis. In this case, this has been established through understanding the editorial and publishing processes that users engage in, and demonstrating the potential power of ML to users. It is also potentially important to note that users were educated to degree level or above but mainly in the arts domain. The potential of using their own datasets and training a model was also demonstrated. This provided the users with the potential for a new way of working, through enhancing their understanding of an archive using ML. This potential enhances technology acceptance, since using ML in this way is not purely replacing editorial skills.

2.2 User requirements

Following the context analysis, user requirements are meticulously identified. This stage focuses on defining the essential functionalities that must be integrated into the interface to enable users to successfully train their models. These requirements should address basic yet critical aspects of the interface, ensuring an intuitive and user-friendly experience. However, faced with novelty of ML as a novel technical process, requirements are used to create designs with the appreciation that they are likely to change and evolve. Few of the requirements stated below:

- Ability of train the models with their own datasets
- Ability to configure the model parameters
- Comparing the models and evaluting performance.

2.3 Design solutions

The design process commences only after establishing a good initial understanding of user requirements. This phase typically begins with the creation of low-fidelity prototypes, often employing paper sketches or wireframes. These initial prototypes evolve into digital wireframes, offering a more refined representation of the interface. Finally, a high-fidelity prototype, closely resembling the final product, is developed.

In early stages, alternative low-fidelity prototypes were developed to enable users to make comparative assessment and thus provide richer feedback. In our case we leverage a five person internal team for continuous design feedback.

2.4 Evaluation

The final stage involves a rigorous evaluation process. This typically involves extensive user testing and qualitative surveys designed to assess the effectiveness, efficiency, and overall user satisfaction of the interface. Based on the evaluation results, the design team may revisit the user requirements or refine the design solution to address any identified shortcomings and ensure it meets the established benchmarks.

Through an iterative user-centered design approach, incorporating user feedback throughout the design process, this framework aims to create an accessible and user-friendly interface that empowers non-technical users to leverage the power of ML by training models with their own data. Currently, the project is in the design phase, where various prototypes undergo continuous user feedback to refine the interface and ensure it effectively meets user requirements.

3 RESULTS AND DISCUSSION

During the iterative process of the designs with user feedback we observed how users respond to prototypes. We enhanced this process by early on providing alternative prototypes to enable comparative feedback that in turn generated greater user reflection and more insights.

Early insights resulting from the process were:

- The overall process of model training is contrary to non-technical user expectations of technologies. Initial expectations are for highly responsive and rewarding interfaces. However, the process of model for ML is one of data importing, considerate configuration and lengthy model training duration — in the scale of hours, not minutes or seconds.
- Non-technical users expectations of controlling the process were at odds with what would be considered good practice. One case in point was the desire to control the data used for model quality testing. While informally this sounds like a reasonable proposition, it is contrary to good practice and jeopardises a resulting model's quality.
- The nature of the process as a whole is not fully appreciated by non-technical users. There was a desire to backtrack and experiment with configurations. While this could be entertained at the level of UI and back-end processes, it demonstrates a poor understanding the notion of model of development and comparison. It suggests that the user might engage in exploratory model creation, opportunistically, when the value of a reliable model is that does not need creating for each new data set.

4 CONCLUSION

By adopting a user centred approach in the design of ML training interface, we have identified some of the development and design challenges such user interfaces encounter. From a development perspective, low-fidelity prototypes are of value but they need to not on convey layout and functionality they also need to incorporate a resource perspective, primarily "time to perform" particular processes. In terms of design challenges, the need to guide and moderate user expectations regarding "good practice" is essential. Within the context of our particular case, future user centred design work, will address these issues in subsequent iterations.

A valuable technical achieved of the work described enables ML model improvement through introduction data (Human-in-the-Loop Machine Learning), we have identified different range of challenges when considering "Human-in-the-Loop ML design".

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