Supporting Qualitative Coding with Machine-in-the-Loop

Matthew K. Hong, Francine Chen, Yan-Ying Chen, Matt Klenk
Toyota Research Institute
Los Altos, CA 94040
{matt.hong,francine.chen,yan-ying.chen,matt.klenk}@tri.global

1 Introduction

Qualitative coding describes a method of data analysis for deriving meaningful insights from unstructured text data. The allure of machine learning and AI for qualitative data analysis is undeniable as it takes considerable human effort and time to parse, label, and organize unstructured text in large datasets. ML models trained on manually labeled data, in effect, allow humans to partially automate qualitative analysis by recognizing patterns in seen and unseen data.

As such, prior research in machine-assisted qualitative data analysis has focused on a humans-in-the-loop (HITL) approach, where humans provide carefully labeled and curated data in exchange for a larger labeled dataset. While being convenient, such automation comes at the cost of reduced human oversight and overall granular insight into the data.

Qualitative coding is an inherently human-centered process where humans exercise decision-making agency with care and nuance to ensure the data is fully represented in the codes they create. For instance, grounded theory methodology, which is among the most well known and tested approaches to organize qualitative data[2, 13, 5], consists of multiple stages of coding, in which human coders 1) break text documents into discrete excerpts, 2) label (code) and aggregate similar excerpts, 3) and draw hierarchical relationships among codes to develop a coding scheme[1].

In line with this view, recent work in ML and HCI research proposed a more collaborative, human-centered approach, namely machine-in-the-loop (MITL), that prioritizes the human role in human-AI interaction by amplifying human decision making and control over coded data[4, 6]. Below, we draw comparisons among HITL and MITL and unpack how MITL can help augment qualitative coding.

2 Qualitative Coding with Humans-in-the-loop

Research in ML-assisted qualitative data analysis has largely focused on the HITL approach which inserts humans into a computational pipeline by asking humans to generate labels or feedback needed for training machine learning models[9]. Qualitative coding with HITL can thus be conceptualized as a highly supervised approach where the primary goal is to assist machines in automating high performance data annotation by employing multi-class text classification[14]. This approach typically comprises three iterative steps.

- **Human annotation**: Human coders manually code a sample of a dataset to provide gold standard data for machine annotation
- **Machine annotation**: Machine uses gold standard data developed by human coders to train an ML model that classifies and labels a large portion of the dataset.
- **Human correction**: Human coders provide corrections to machine-generated labels and classification errors. The loop between human correction and machine annotation continues to expand the

[1]This paper will focus on the initial data exploration and code identification (otherwise known as open-coding) phase, which has been identified as a bottleneck in qualitative coding[8].

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model's capabilities via active learning[9], resulting in a higher-quality training set to enhance the performance of the ML model.

Many computer-assisted qualitative data analysis tools and active learning systems already support this approach. For example, MAXQDA, ATLAS.ti and NVivo augment the human annotation process with the goal of generating a labeled dataset. DisplayR and Amazon SageMaker support classification of unlabeled text using pre-defined labels. A number of interactive topic modeling systems have been developed, wherein users are prompted with a tool to correct and retrain the topic model by creating, splitting, and merging topics[7, 1]. While HITL enables large-scale qualitative coding, it falls short on helping humans manage the coding scheme and incrementally explore emerging themes or patterns[2] when existing codes are applied to unseen data.

3 Augmenting Qualitative Coding with Machine-in-the-loop

On the contrary, machine-in-the-loop (MITL) is an approach where machines provide a supporting role to amplify humans' ability to engage in high-level decision making. In particular, MITL describes a computational system in which the loop begins with the human providing specific content to be augmented by the machine, and the machine responds with a suggestion, where the human has more control over the final output[4].

When applied to qualitative coding, the goal of MITL is to assist humans in the cognitively challenging parts of the process and not just automating the tedious aspects. For instance, creating an initial dataset requires ML expertise as well as insight into qualitative coding. Computational tool support however is limited primarily to matching sequences of words to the data and assigning the matches to a code label. MITL could augment the coding process by making context-specific suggestions while giving humans a bird's eye view of the data along with the agency to control the organization of codes. We suggest three iterative phases in which MITL can play a role in qualitative coding.

- **Human context**: Human coder provides minimum necessary context (initial input) for the machine to act upon. This context could include the human entering search terms, dictating how they want to segment text documents into discrete excerpts, and even generating tentative code labels.
- **Machine suggestion**: Machine employs unsupervised, semi-supervised (e.g.,few-shot learning) and foundation (e.g., GPT-3) models to overcome ML's bottleneck–the need for large human-labeled training data. These models can help provide structure to data early in the coding process, suggest relevant codes along with initial assignments of codes to data, and suggest new ways of abstracting unstructured information. Explanations could accompany these suggestions.
- **Human decision-making**: Human coder engages in high-level decision-making tasks by referencing machine-suggestions (e.g., clusters, labels or rules) and reviewing machine-generated explanations (e.g., rationale, confidence, summaries) to accept, reject and elaborate on the suggested output. The loop continues with human decisions triggering additional machine suggestions, such as alternative assignments of codes to data if initial ones are rejected.

Recent work in HCI illustrates ways of inserting ML into the qualitative coding process that preserve human agency[10]. For example, based on codes provided by users, Cody suggests possible search-style code rules that users can edit and apply to a text corpora[11].

One challenge of MITL is the need to account for automation bias while providing enough transparency over machine-generated suggestions. Does statistical information or explainable AI techniques prompt data exploration or induce automation bias? One possible direction, as Chen[3] notes, is to assist coders in identifying ambiguity in the context of collaborative qualitative coding, where multiple coders contribute human-driven measures (e.g., inter-rater reliability) to balance the types of information available to the human coder.

4 Conclusion

This paper describes both MITL and HITL approaches to enable machine-assisted qualitative coding and calls for a need to consider more human-centered approaches that prioritize the human role by augmenting human-decision making, instead of optimizing the data annotation process. Mitigating automation bias remains an important challenge to be addressed by HCI and ML researchers.

[2]In active learning, the machine determines what new data points need more manual labeling to obtain a high quality training set[12].

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