Abstract

How can we design Natural Language Processing (NLP) systems that learn from human feedback? There is a growing research body of Human-in-the-loop (HITL) NLP frameworks that continuously integrate human feedback to improve the model itself. HITL NLP research is nascent but multifarious—solving various NLP problems, collecting diverse feedback from different people, and applying different methods to learn from collected feedback. We present a survey of HITL NLP work from both Machine Learning (ML) and Human-Computer Interaction (HCI) communities that highlights its short yet inspiring history, and thoroughly summarize recent frameworks focusing on their tasks, goals, human interactions, and feedback learning methods. Finally, we discuss future directions for integrating human feedback in the NLP development loop.

1 Introduction

Traditionally, Natural Language Processing (NLP) models are trained, fine-tuned, and tested on existing dataset by machine learning experts, and then deployed to solve real-life problems of their users. Model users can often give invaluable feedback that reveals design details overlooked by model developers, and provide data instances that are not represented in the training dataset (Kreutzer et al., 2020). However, the traditional linear NLP development pipeline is not designed to take advantage of human feedback. Advancing on the conventional workflow, there is a growing research body of Human-in-the-loop (HITL) NLP frameworks, or sometimes called mixed-initiative NLP, where model developers continuously integrate human feedback into different steps of the model deployment workflow (Figure 1). This continuous feedback loop cultivates a human-AI partnership that not only enhances model accuracy and robustness, but also builds users’ trust in NLP systems.

Just like traditional NLP frameworks, there is a high-dimensional design space for HITL NLP systems. For example, human feedback can come from end users (Li et al., 2017) or crowd workers (Wallace et al., 2019), and human can intervene models during training (Stiennon et al., 2020) or deployment (Hancock et al., 2019). Good HITL NLP systems need to clearly communicates to humans of what the model needs, provide intuitive interfaces to collect feedback, and effectively learn from them. Therefore, HITL NLP research spans across not only NLP and Machine Learning (ML) but also Human-computer Interaction (HCI). A meta-analysis on existing HITL NLP work focusing on bridging different research disciplines is vital to help new researchers quickly familiarize with this promising topic and recognize future research directions. To fill this critical research gap, we provide a timely literature review on recent HITL NLP studies from both NLP and HCI communities.

This is the first comprehensive survey on the HITL NLP topic. We make two main contributions: (1) We summarize recent studies on HITL NLP and position each work with respect to its task,
goal, human interaction, and feedback learning method (Table 2); (2) We critically discuss existing knowledge gaps and highlight important research directions that we distilled from the survey.

2 Related Surveys

To our best knowledge, there is no existing survey work on this topic, as the field for HITL NLP just starts growing. Regarding interactive machine learning, related surveys like Amershi et al. (2014) focus on problems in interactive machine learning in general. Specifically for reinforcement learning and dialogue system, there is one overview article (Kreutzer et al., 2020) focusing on offline dialogue system. Different from the aforementioned articles, our survey provides a comprehensive review on HITL in NLP with critical discussions.

3 Human-in-the-Loop NLP Tasks

This section describes what NLP sub-problems currently can benefit from a HITL approach. Over recent years, researchers and practitioners have made great advancements in NLP — enabling many different NLP tasks and applications, such as text classification, summarization, and machine translation. To effectively integrate humans into these task-specific development loops, people have developed many application-specific HITL paradigms. In this section, we categorize surveyed HITL paradigms based on their corresponding tasks.

3.1 Text Classification

Text classification is a classic problem in NLP to categorize text into different groups. Trained on a set of text documents \((X)\) and their categorical labels \((Y)\), a text classifier can predict \(Y\) value of an unseen \(X\). For example, a movie review sentiment classifier can predict if one review is positive or negative. Many HITL frameworks are developed for this problem, where most of them start with training a text classifier, then recruiting humans to annotate data based on the current model behavior, and eventually retraining the classifier on the larger dataset continuously.

For example, Godbole et al. (2004) develop a HITL paradigm where users can interactively edit (add or remove) text features and label new documents. Also, Godbole et al. integrate active learning in their framework — instead of arbitrarily presenting data for users to annotate, they strategically choose samples that can maximize the expected information gain. With active learning, labelers can annotate fewer data to achieve the same model improvement of a framework using random sampling. Settles (2011) further improves this HITL workflow by extending the active learning component to features (words) sampling in addition to labels (documents). To ease the deployment of HITL text classifiers, Simard et al. (2014) develop a robust web-based tool that supports general text classification tasks. Researchers have also developed domain-specific HITL text classification systems. For instance, a rumor classification system developed for journalists tightly integrates model retraining, data collection, and data annotation in deployment (Karmakharm et al., 2019).

Bag-of-words feature is commonly used in text classifiers. However, Jandot et al. (2016) explore alternative feature representations to better support a HITL pipeline. A dictionary, also called lexicon and gazetteer, is a set of words sharing the same semantics. Well-defined dictionaries give higher accuracy and are more interpretable than bag-of-words. In Jandot et al.’s HITL system, users can easily create semantic dictionaries through a web-based user interface, and the text classifier is continuously trained on new dictionaries.

3.2Parsing and Entity Linking

Besides classifying documents, recent research shows great potential of HITL approach in enhancing the performance of existing parsing and entity linking models. Parsing in NLP is a process to determine the syntactic structure of the input text. Entity linking aims to assign unique identity to entities in the text, such as names and locations.

Advancing traditional Combinatory Categorial Grammars (CCG) parsers, He et al. (2016) crowdsource parsing tasks — a trained parser is uncertain about — to non-expert mechanical turks, by asking them simple what-questions. Using human feedback as a soft constraint to penalize the parser during retraining, the performance of the original parser improves significantly. Similarly, Klie et al. (2020) recruit humans to interactively annotate correct entities in text samples where an entity linking model performs poorly. Also, with more strategic sampling methods to select instances to present to humans, a smaller set of feedback can quickly improve the entity linking model performance (Klie et al., 2020; Lo and Lim, 2020).
### 3.3 Topic Modeling

In addition to using a HITL approach to enhance learning the low-level semantic relationships, researchers apply similar frameworks to topic modeling techniques that are used to analyze large document collections. People traditionally use take it or leave it algorithms for this task, such as information retrieval and document clustering. Over the past few years, there is a growing research body of HITL topic modeling (Lee et al., 2017). For example, Hu et al. (2014)’s and Jaegul Choo et al. (2013)’s systems allow users to refine a trained model through adding, removing, or changing the weights of words within each topic. Then, using the user-updated features and weights, trained models are more likely to generate useful topics.

More recently, researchers focus on developing more human-centered HITL topic modeling methods. These methods emphasize the needs of topic modeling end users, mostly NLP non-experts, instead of only collecting algorithmically convenient human feedback (Lee et al., 2017). For example, Kim et al. (2019) develop an intuitive visualization system that allows end users to up-vote or down-vote specific documents to inform their interest to the model. Smith et al. (2018) conduct users studies with non-experts and develop a responsive and predictable user interface that supports a broad range of topic modeling refinement operations. These examples show that HITL NLP systems can benefit from HCI design techniques.

### 3.4 Summarization and Machine Translation

Besides using a HITL approach to analyze existing documents, researchers also apply them to generate new texts. Text summarization and machine translation have seen major breakthroughs in re-
cent years (Brown et al., 2020), which draw attentions from both NLP and HCI communities to design and develop HITL systems. For example, Stiennon et al. (2020) collect human preferences on pairs of summaries generated by two models, then train a reward model to predict the preference. Then, this reward model is used to train a policy to generate summaries using reinforcement learning. Similarly, Kreutzer et al. (2018) collect both explicit and implicit human feedback to improve a machine translation model by using the feedback with reinforcement learning. Experiments show that the model trained on human preference data has higher accuracy and better generalization.

3.5 Dialogue and Question Answering

Recently, many HITL frameworks have been developed for dialogue and Question Answering (QA) systems, where the AI agent can have conversation with users. We can group these systems into two categories: (1) online feedback loop: the system continuously uses human feedback to update the model; (2) offline feedback loop: human feedback is filtered and aggregated to update the model in batch (Kreutzer et al., 2020).

**Online feedback loop.** Traditionally, there is a mismatch of the training set and online use case for dialogue systems. To tackle this challenge, online reinforcement learning can be used to improve the model with human feedback. For example, Liu et al. (2018) collect dialogue corrections from users during deployment, while Li et al. (2017) collect both binary explicit feedback and implicit natural language feedback. Also, Hancock et al. (2019) propose a lifetime learning framework to improve chatbot performance. The chatbot is trained not only to generate dialogues but also to predict user satisfactions. During deployment, the chatbot predicts user satisfaction after generating responses, and asks for user feedback if the predicted satisfaction score is low. Then, the chatbot uses the feedback as a new training example to retrain itself continuously.

**Offline feedback loop.** With offline HITL, model is updated after collecting a large set of human feedback. For example, Wallace et al. (2019) invite crowd workers to generate adversarial questions that can fool their QA system, and use these questions for adversarial training. Offline feedback loop can be more robust for dialogue systems, because user feedback can be misleading, so directly updating the model is risky (Kreutzer et al., 2020).

4 Human-in-the-Loop Goals

Among surveyed papers, the most common motivation for using a HITL approach in NLP tasks is to improve the model performance. There are different metrics to measure model performance, and experiments in our surveyed papers show that HITL can significantly and effectively improve model performance with a relatively small set of human feedback. For example, for text classification, HITL improves classification accuracy (Smith et al., 2018; Jandot et al., 2016). Similarly, dialogue and question answering systems have higher ranking metric hits after adapting a HITL approach (Hancock et al., 2019; Brown et al., 2020). Researchers also find HITL improves model’s robustness and generalization on different data (Stiennon et al., 2020; Jandot et al., 2016).

In addition to model performance, HITL can also improve the interpretability and usability of NLP models. For example, Jandot et al. (2016) enable users to create semantic dictionaries. These features have semantic meanings and are more interpretable to humans. Wallace et al. (2019) guide humans to generate model-specific adversarial questions that can fool the question answering model. These adversarial questions can be used as probes to gain insights of the underlying model behaviors. On the other hand, HITL can also improve the user experience with NLP models. For example, Smith et al. (2018) develop an interface for topic modeling users to intuitively interact and control their models. User studies show that users gain more trust and confidence through the HITL system.

5 Human-machine Interaction

This section discusses the mediums that users use to interact with HITL systems and different types of feedback that the systems collect. This section is strongly correlated with section 6, which describes how existing works leverage user feedback to update models. By first describing how and what user feedback may be collected (this section), we can more easily ground our discussion on how to leverage the feedback (next section).

5.1 Interaction Mediums

There are two common interaction mediums shared by our surveyed systems: graphical user interface and natural language interface.
5.1.1 Graphical User Interface

One of the commonly used interaction mediums for collecting user feedback is the Graphical User Interface (GUI). The GUI provides a user interface that allows users to interact with systems through graphical icons and visual indicators such as secondary notations. Some HITL NLP systems allow users to directly label samples in the GUI (Simard et al., 2014; Godbole et al., 2004; Settles, 2011). The GUI also makes feature editing possible for end-users who do not develop the model from initial (Jandot et al., 2016; Simard et al., 2014; Godbole et al., 2004). Some other works even use the GUI for users to rate training sentences in the text summarization task (Stiennon et al., 2020) and rank the generated topics in the topic modeling task (Kim et al., 2019). One obvious advantage of the GUI is that it visualizes the NLP model running in the black box, enhancing the interpretability of the model as seen in section 4. In addition, compared to text-based user interfaces, the GUI supports Windows, Icons, Menus, Pointer (WIMP) interactions, providing users more accurate control for refining the model.

5.1.2 Natural Language Interface

Another commonly used interaction medium in HITL NLP systems is natural language interface. A natural language interface is an interface where the user interacts with the computer through natural language. As this interface usually simulates having a conversation with a computer, it mostly comes with the purpose of building up a dialogue system (Hancock et al., 2019; Liu et al., 2018; Li et al., 2017). The natural language interface not only supports users to provide explicit feedback (Liu et al., 2018; Li et al., 2017), such as “agree” or “reject” (Liu et al., 2018; Li et al., 2017). As binary user feedback only contains two categories, this kind of user feedback is usually easy to collect but sometimes may over-simplify users’ intention by ignoring the potential intermediate situations. Binary user feedback can be used to provide explicit feedback for the system to update training datasets or directly manipulate models, as discussed in section 6.

5.2 User Feedback Types

Above, we discussed that the GUI and the natural language interface are two common interaction mediums implemented in the HITL systems we surveyed for collecting user feedback. In the following, we will discuss four major types of user feedback supported by the two interaction mediums, including binary user feedback, scaled user feedback, natural language user feedback, and counterfactual example feedback.

5.2.1 Binary User Feedback

Binary user feedback is the feedback which has two categories that are usually opposite to each other, such as “like” and “dislike”. It can be collected by both the GUI and the natural language interface. As discussed above, the GUI can collect binary user feedback from the user’s adding or removing labels (Simard et al., 2014) and features (Godbole et al., 2004). The natural language interface can also support binary user feedback collection with simple short natural language response, such as “agree” or “reject” (Liu et al., 2018; Li et al., 2017). As binary user feedback only contains two categories, this kind of user feedback is usually easy to collect but sometimes may over-simplify users’ intention by ignoring the potential intermediate situations. Binary user feedback can be used to provide explicit feedback for the system to update training datasets or directly manipulate models, as discussed in section 6.

5.2.2 Scaled User Feedback

Scaled user feedback is the feedback which has scaled categories and is usually in numerical formats, such as the 5-point scale rating. It often can only be collected through the GUI as it is difficult to express accurate scaled feedback in natural language. Such user feedback is collected in the GUI when users rate their preferences of training data or model results (Kreutzer et al., 2018) and adjust features on a numerical scale (Simard et al., 2014). Similar to binary user feedback, scaled user feedback can provide explicit feedback for the system to update the models but with more options to cover intermediate cases (e.g. adjusting the weight of one feature from 1 to 3 on a scale of 5 points). Besides, the scaled ratings of user preferences can also be used as implicit guidance for the system to improve the model, as discussed in subsection 6.1 and subsection 6.2.

5.2.3 Natural Language User Feedback

Compared with binary user feedback and scaled user feedback, natural language user feedback is
Table 2: Relationship between the user feedback types and how they are used. Each row represents one feedback type (subsection 5.2), and each column corresponds to a model learning method (section 6).

| Feedback Type                  | Offline Model Update                        | Online Model Update                        | Model Direct Manipulation |
|-------------------------------|---------------------------------------------|--------------------------------------------|---------------------------|
| Binary                        | Klie et al. (2020), Lo and Lim (2020), Trivedi et al. (2019), Kar-makharm et al. (2019), Wallace et al. (2019), Godbole et al. (2004), etc. | Kim et al. (2019), Kumar et al. (2019), Smith et al. (2018), Liu et al. (2018), Li et al. (2017) | Liu et al. (2018), Li et al. (2017) |
| Scaled                        | Stiennon et al. (2020), Simard et al. (2014) | Kumar et al. (2019), Smith et al. (2018)   | Kreutzer et al. (2018)    |
| Natural Language              | Kaushik et al. (2019), Trivedi et al. (2019), Wallace et al. (2019), Lawrence and Riezler (2018), Li et al. (2017) | Hancock et al. (2019), Liu et al. (2018), Li et al. (2017) | Liu et al. (2018), Li et al. (2017) |
| Counterfactual Example        | Kaushik et al. (2019), Wallace et al. (2019), Lawrence and Riezler (2018) | —                                           | —                         |

5.3 Counterfactual Example Feedback

Similar to the natural language user feedback, counterfactual example feedback is usually in the form of natural language text and collected through the natural language interface. A counterfactual example describes a causal situation in the form: "If X had not occurred, Y would not have occurred." The HITL NLP systems collect and analyze user-modified counterfactual text examples and retrain the model accordingly (Kaushik et al., 2019; Lawrence and Riezler, 2018), as more details covered in subsection 6.1.

5.4 Intelligent Interaction

In addition to the choice of the interaction medium and the collected user feedback types, some HITL NLP systems also leverage intelligent interaction techniques to enhance human-machine interaction. As discussed in section 3, active learning and reinforcement learning are two commonly used techniques we observed in our surveyed systems. Active learning allows the system to interactively query a user to label new data points with the desired outputs (Godbole et al., 2004; Settles, 2011; Lo and Lim, 2020). By strategically choosing samples to maximize information gain with fewer iterations, active learning not only reduces human efforts on data labeling but also improves the efficiency of the system. Compared to active learning, reinforcement learning takes actions based on user feedback to maximize the notion of cumulative reward (Stiennon et al., 2020; Kreutzer et al., 2018; Li et al., 2017; Liu et al., 2018). By considering each user feedback as a new action, reinforcement learning supports accurate understanding of human intention and updating the model accordingly, as discussed in section 6.

6 How to Use User Feedback

This section summarizes how existing HITL NLP systems utilize feedback. Different feedback types described in subsection 5.2 are leveraged by the systems with different update methods (Table 2). In the following, we will discuss two major update methods, including data augmentation and model direct manipulation.

6.1 Data Augmentation

One popular approach is to consider the feedback as a new ground truth data sample. For example, a user’s answer to a model’s question can be a data sample to retrain a QA model. We describe two types of techniques to use augmented data set: Of-
**Offline update** retrains NLP model from scratch after collecting human feedback, while **Online update** trains NLP models while collecting feedback at the same time.

**Offline model update** is usually performed after certain amount of human feedback is collected. Offline update does not need to be immediate, so it is suitable for noisy feedback with complex models which takes extra processing and training time. For example, Simard et al. (2014) and Karmakharm et al. (2019) use human feedback as new class labels and span-level annotations, and retrain their models after collecting enough new data.

**Online model update** is applied right after user feedback is given. This is effective for dialogue systems and conversational QA systems where recent input is crucial to machine’s reasoning (Li et al., 2017). Incremental learning technique is often used to learn augmented data in real-time (Kumar et al., 2019). It focuses on making an incremental change to current system using the newly come feedback information effectively. Interactive topic modeling systems and feature engineering systems widely use this technique. For example, Kim et al. (2019) incrementally updates topic hierarchy by extending or shrinking topic tree incrementally. Also, some frameworks use the latent Dirichlet allocation (LDA) to adjust sampling parameters with collected feedback in incremental iterations (Smith et al., 2018).

### Model Direct Manipulation

Collected numerical human feedback are usually directly used to adjust model’s objective function. For example, Li et al. (2017) collect binary feedback as rewards for reinforcement learning of a dialogue agent. Similarly, Kreutzer et al. (2018) use a 5-point scale rating as reward function of reinforcement and bandit learning for machine translation. Existing works have focused more on numerical feedback than natural language feedback. Numerical feedback is easier to be incorporated into models, but provides limited information compared to natural language. For future research, incorporating more types of feedback (e.g., speech, log data) will be an interesting direction to gain more useful insights from humans. With more complex feedback types, it is critical to design both quantitative and qualitative methods to evaluate collected feedback, as they can be noisy just like any other data.

### Research Directions & Open Problems

#### Broader Roles of HITL NLP System

Improving model performance is the most popular goal among surveyed NLP HITL frameworks. However, researchers have found HITL method also enhances NLP model interpretability (Wallace et al., 2019) and usability (Lee et al., 2017). Therefore, we encourage future NLP researchers to explore HITL as a mean to better understand their models and improve the user experience of model end users. For example, user feedback can be used to mitigate harms caused by NLP model bias (Blodgett et al., 2020). While many recent models gain feedback from **mechanic turks** (He et al., 2016), future researchers can consider involving **model engineers** and **end users** in their NLP development loop (Hancock et al., 2019). For example, one can develop a web-based tool where end users can interactively modify the feature weights of a text classifier and observe the model behavior at run time. By performing these “what-if” operations, users can gain additional insights of how model internally uses these features. Similarly, a HITL chatbot could grant users more control by supporting model parameter modification through natural language input. For instance, a non-binary user Alex could correct the chatbot’s pronoun use by typing “Hello chatbot, could you use they/them/their to refer me in the future please?”

#### Human-centered System Design

In this survey, we found most of the HITL NLP systems and techniques are designed and developed by NLP researchers. We believe that this area of research will be greatly benefited from a deeper involvement of the HCI community. Human feedback is the key for HITL systems. However, with a poorly designed human-machine interface, the collected human feedback are more likely to be inconsistent, incorrect, or even misleading. Therefore, better interface design and user studies to evaluate HITL system interface can greatly enhance the quality of feedback collection, which in turn improves the downstream task performance.

To shed light on HITL NLP research from a HCI perspective, Wallace et al. (2019) explore the effect
of adding model interpretation cues in the HITL interface on the quality of collected feedback; Schoch et al. (2020) investigate the impacts of question framing imposed on humans; similarly, Rao and Daumé III (2018) study how to ask good questions to which humans are more likely to give helpful feedback. There are many exciting research opportunities and challenges in designing and evaluating HITL interface. As a starting point for developing more human-centered HITL NLP systems, we provide the following concrete research directions:

- As human feedback can be subjective, who should HITL NLP systems collect feedback from? Is there any expertise levels required to perform certain tasks (Kreutzer et al., 2020)?
- How to present what the model has learned and what feedback is needed? How to visualize the model change after learning from user feedback (Lee et al., 2017)?
- How to dynamically choose the most helpful feedback to collect (Settles, 2011)? How to guide users to provide useful feedback (Wallace et al., 2019)?
- How to evaluate the collected human feedback as it can be noisy and even misleading (Kreutzer et al., 2020)?
- Conduct rigorous user studies to evaluate the effectiveness of HITL systems in addition to model performance (Smith et al., 2018).
- Open-source tools and share user study protocols when publishing new HITL NLP work.
- Create and share human feedback datasets.

8 Conclusion

In this paper, we conduct a comprehensive survey on HITL NLP. We summarize recent literature on HITL NLP from both NLP and HCI communities, and position each work with respect to its task, goal, human interaction, and feedback learning method. The field of HITL NLP is still relatively nascent, and we see very diverse system design methods. To help new researchers and practitioners quickly familiarize with the field, we recognize the great potential of HITL NLP systems in different NLP tasks and highlight open challenges and future research directions. The research directions rest on a greater collaboration between NLP and HCI researchers and practitioners—a paramount step to create next-generation NLP technologies that deeply align with people’s needs.

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