A SURVEY OF HUMAN-IN-THE-LOOP FOR MACHINE LEARNING

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ABSTRACT

Human-in-the-loop aims to train an accurate prediction model with minimum cost by integrating human knowledge and experience. Humans can provide training data for machine learning applications and directly accomplish some tasks that are hard for computers in the pipeline with the help of machine-based approaches. In this paper, we survey existing works on human-in-the-loop from a data perspective and classify them into three categories with a progressive relationship: (1) the work of improving model performance from data processing, (2) the work of improving model performance through interventional model training, and (3) the design of the system independent human-in-the-loop. Using the above categorization, we summarize major approaches in the field, along with their technical strengths/ weaknesses, we have simple classification and discussion in natural language processing, computer vision, and others. Besides, we provide some open challenges and opportunities. This survey intends to provide a high-level summarization for human-in-the-loop and motivates interested readers to consider approaches for designing effective human-in-the-loop solutions.

Index Terms— Human-in-the-loop, machine learning, deep learning.

1. INTRODUCTION

Deep learning is a frontier for artificial intelligence, aiming to be closer to its primary goal - artificial intelligence. Deep learning has seen great success in a wide variety of applications, such as natural language processing, speech recognition, medical applications, computer vision, and intelligent transportation system [1, 2, 3, 4]. The great success of deep learning is due to the larger models [5]. The scale of these models has included hundreds of millions of parameters. These hundreds of millions of parameters allow the model to have more degrees of freedom enough to awe-inspiring description capability.

However, the large number of parameters requires a massive amount of training data with labels [6]. Improving model
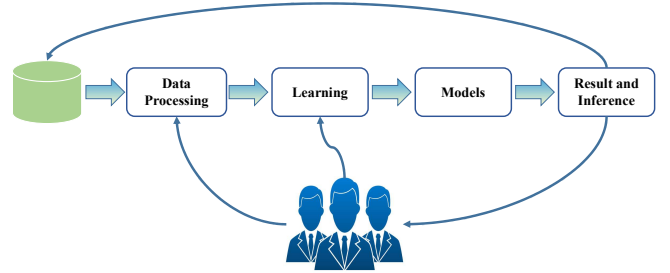

Fig. 1: The development cycle of model.

performance by data annotation has two crucial challenges. On the one hand, the data growth rate is far behind the growth rate of model parameters, so data growth has primarily hindered the further development of the model. On the other hand, the emergence of new tasks has far exceeded the speed of data updates, and annotating for all samples is laborious. To tackle this challenge, many researchers build new datasets by generating samples, thereby speeding up model iteration and reducing the cost of data annotation [7, 8, 9, 10, 11]. Besides, many researchers use pre-training methods and migration learning to solve this challenge [12, 13, 14, 15, 16], such as Transformers [17, 18], BERT [19] and GPT [20]. These works have achieved incredible results.

However, the generated data is only used as base data to initialize the model. In order to obtain a high-precision usable model, it is often necessary to label and update specific data. So some work based on weak supervision has been proposed [21, 22, 23, 24]. Some researchers have proposed using few-shot to push the model to learn from fewer samples [25, 26, 27].

Integrated a priori knowledge in the learning framework is an effective means to deal with sparse data, as the learner does not need to induce the knowledge from the data itself [28]. More and more researchers are beginning to try to incorporate pre-training knowledge into their learning framework [29, 30, 31, 32]. As special agents, humans have rich prior knowledge. If the machine can learn human wisdom and knowledge, it will help deal with sparse data. Especially in medical fields
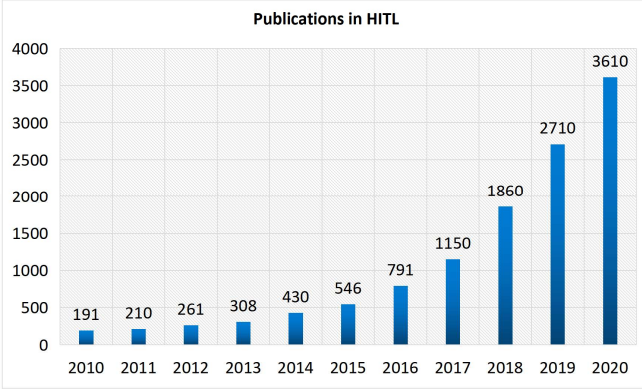
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Fig. 2: The increasing research interest in the human-in-the-loop, obtained through Google scholar search with keywords: "human-in-the-loop" and "machine learning".

such as clinical diagnosis and lack of training data [33, 34, 35, 36].

Some researchers have proposed using a method called "human-in-the-loop" (HITL) to tackle this challenge, which mainly addresses these issues by incorporating human knowledge into the modeling process [37].

As illustrated in Fig. 1, human-in-the-loop (namely "human-in-the-loop" and "machine learning") is an active research topic in machine learning, and there is a rich publication in the past ten years.

As shown in Fig. 2, a conventional machine-learning algorithm generally consists of three parts [38]. The first is data preprocessing, the second is data modeling, and the last is the developer modifying the existing process to improve performance. As we all know, the performance and results of machine learning models are unpredictable, which leads to a large degree of uncertainty in which part of the machine-human interaction can bring the best learning effect. Different researchers focus on manual intervention in different parts. In this paper, we classify these methods according to the processing methods of machine learning, divided into the data preprocessing stage and the model modification and training stage. In addition, more research focuses on the design of independent systems to help complete the improvement of the model. So in this paper, we first discuss the work of improving model performance from data processing. Next, we discuss the work of improving model performance through interventional model training. Finally, we discuss the design of the system independent "human-in-the-loop".

In Section 2, we investigate the data processing method based on human-in-the-loop and we will discuss data preprocessing, data annotation, and iterative labeling. In Section 3, we summarize and analyze some research on model training and reasoning using human-in-the-Loop, and we discuss human-in-the-loop from natural language processing and computer visual perspective, respectively. In Section 4, we review the human-in-the-loop on system construction divided by system components and applications and we discuss human-in-the-loop from the software and hardware integrated perspective, respectively. In Section 5, we propose some challenges based on the results of the survey. Finally, we conclude our work in Section 6.

2. DATA PROCESSING

At present, deep learning has played an irreplaceable role in many fields [1, 2]. The great success of deep learning is due to larger-scale models [5]. The scale of these models has included hundreds of millions of parameters. So many parameters allow the model to have more degrees of freedom enough to awe-inspiring description capability. However, the large number of parameters requires a massive amount of training data with labels [6]. As far as we know, annotate data requires much labor and lagging behind the growth in model capacity. The available datasets are quickly becoming outdated in terms of size and density [7]. So researchers pay more attention to how to use unlabeled data to improve the model capability. [6, 39, 40, 41]. However, not all unlabeled data are positive, and unlabeled data usually include incorrect samples. Suppose these incorrect samples are just sampled as a key sample, the errors brought about will be fatal [42]. To tackle this challenge, many researchers focus on exploring the way of generating samples to generate a more rich sample space so that the model can learn features more effectively [8, 43, 10]. Researchers spend more time to study sample space generation [8, 43, 10], trying to develop a universal model, such as Transformers [17], BERT [19] or GPT [20]. These works have achieved incredible results. Base on these successful methods, researchers consider using less data to obtain better results. These models can perform incredible results in more tasks by fine-tuning [44, 45, 46]. However, these methods still need to annotate a lot of data, which brings unnecessary trouble. However, we noticed that interference in the model performance only some key samples in the new dataset. Here is a key problem that needs to be solved urgently, *How do we find out the key sample, and whether we can more easily annotate key samples?*

The intuitive idea is to use the specific method to select some samples that the model can not recognize, then use the specific method to annotate selected samples, finally use the specific method to push the model to learn features from annotated samples. This allows the model to use the least cost and maximize the use of data information.

Many researchers try to use human-in-the-loop-based methods to optimize models from the perspective of data. According to surveys, scientists spend about 80% of their time on data processing compared to building models [47]. We investigated the data processing method based on human-in-the-loop and established a pipeline as shown in Fig. 3. We will discuss data preprocessing, data annotation, and iterative
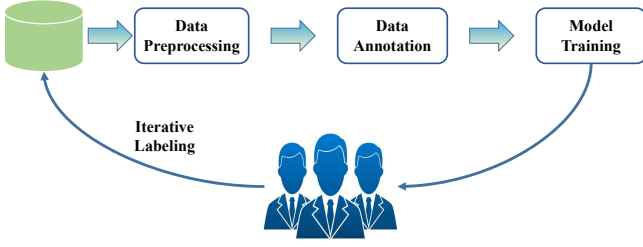
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Fig. 3: A Human-in-the-loop data processing pipeline.

Fig. 4: The architecture of explore and exploit.

labeling in this section.

2.1. Data Preprocessing

As we all know, the process of deep learning is a process of modeling data. The success of deep learning largely depends on the quality of the data. Some studies have found that compared to modeling data, 80% of researchers always spend their time in data processing [47]. Data analysis plays an irreplaceable role in building a more effective model. Data analysis is difficult to find a static method, and it requires data scientists to analyze existing data by using the experience of experts. Therefore, the challenge of data analysis is how to process some specific data. If you can explore an appropriate method to process the specific sample, it can bring significant improvement, especially by adding human experience and knowledge in a certain way [74]. The biggest challenge encountered in data analysis lies in the specific complexity of high-dimensional data. Due to the complexity of the data, it is challenging to use models to find the data structure. Generally, the exploration of data structures using models requires the adjustment of parameters. The adjustment of these parameters dramatically depends on the knowledge of data experts or domain experts. However, many data experts or domain experts do not have the ability and knowledge of parameter adjustment. Therefore, it is undoubtedly meaningful to develop a parameter adjustment method that uses user interaction to perform parameter adjustment. Based on this motivation, Self *et al.* [49] propose an interactive parameter adjustment mode convenient for users to participate. In addition, they also studied the usability of human-computer interaction for user data analysis. In particular, they bridge the gaps between a user's intention and the parameters of a weighted multidimensional scaling model during human-model interaction communication. With the development of research, researchers are no longer satisfied with solving specific problems in human-in-the-loop data analysis (HILDA). They are more concerned with several "big picture" questions regarding HILDA. The current data analysis technology can obtain the necessary information and knowledge from the data correctly by constructing a knowledge base or a knowledge graph. However, for the HILDA community or tools, the degree of attention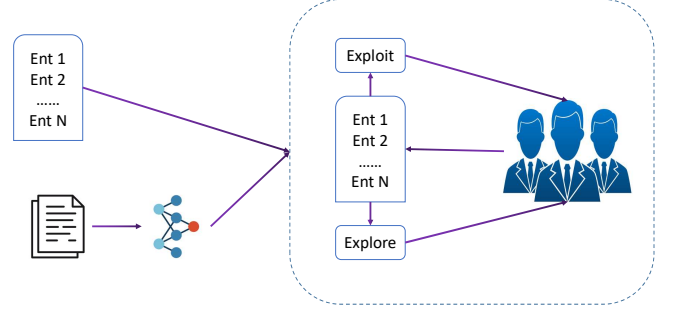 is not enough. Researchers should pay more attention to such issues and make them more popular in the user community to develop data repositories and tools. Therefore Doan *et al.* think establishing a benchmark is an effective means to solve this challenge [53]. Besides, data analysis mainly needs to consider two issues: one is how to carry out automated parameter analysis methods, and the other is how to explore the ability to establish a specific benchmark. To consider these two issues simultaneously, Laure expands based on Learn2Clean. They develop automated machine learning approaches (AutoML) that can optimize the hyperparameters of a considered ML model with a list of by-default preprocessing methods. This method is devoted to proposing a principled and adaptive data preparation approach to help and learn from the user to select the optimal sequence of data preparation tasks. Moreover, this method can obtain the best quality performance of the final result [57].

Using HITL methods to deal with natural language data has inherent advantages over using HITL methods to deal with other data (*i.e.*, speech recognition, medical applications, computer vision, and intelligent transportation system). Most of the HITL methods are used in the information extraction stage. As Fig. 4, Gentile *et al.* [55] propose an interactive dictionary expansion tool using two neural language models, it uses a human-in-the-loop method to construct a data dictionary in a proprietary domain. It does not need to perform phrase detection before building the model. However, it needs to use a neural language model to recognize that phrases with high confidence may not appear in the input text corpus and then use human experts to label. The algorithm is iterative, purely statistical, and does not require any feature extraction except for tokenization. It incorporates human feedback at each iteration to improve performance and control the semantic drift using human feedback. Many researchers add humans to natural language processing tasks(such as entity analysis, knowledge graphs, and so on) by using crowdsourcing [54, 55, 57, 59]. Ristoski *et al.* [66] propose a method of extracting instances from various web resources. This method dramatically improves the performance of the system by introducing human-recycling components. In addition, this method can integrate the human experience and knowledge to enable machines to achieve accurate intelligence. Consistent with

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Table 1: A overview of representative works in data processing. DP: data preprocessing; DA: data Annotation; IL: iterative labeling; CV: Computer Vision; NLP: Natural Language Processing; SP: Speech Processing.

Work	Data Processing			Year	Area				Task
	DP	DA	IL		CV	NLP	SP	Other	
Yu *et al.* [7]			✓	2015	✓				Scene and Object Categories
He *et al.* [48]			✓	2016		✓			CCG Parser
Self *et al.* [49]	✓			2016				✓	Data Analysis
Zhuang *et al.* [50]	✓			2017				✓	Knowledge Bases Integration
Li *et al.* [51]	✓			2017				✓	Data Integration
KIM *et al.* [52]		✓		2018			✓		Finding Sound Events
Doan *et al.* [53]	✓			2018				✓	Data Analysis
Dong *et al.* [54]	✓			2018		✓		✓	Entity Resolution;Data Fusion;DOM extraction
Gentile *et al.* [55]	✓	✓		2019		✓			Dictionary Expansion
Zhang *et al.* [56]		✓	✓	2019		✓			Entity Extraction
Laure *et al.* [57]	✓			2019	✓	✓	✓	✓	Data Preparation
Gurajada *et al.* [58]	✓			2019		✓			Entity Resolution
Lou *et al.* [59]	✓			2019		✓			Knowledge Graph Programming
Liu *et al.* [60]		✓	✓	2019	✓				Person Re-Identification
Wallace *et al.* [61]		✓		2019		✓			Question Answering
Fan *et al.* [62]			✓	2019	✓			✓	Network Anomaly Detection
Krokos *et al.* [63]			✓	2019	✓			✓	Knowledge Discovery
Klie *et al.* [64]		✓		2020		✓			Entity Linking
Chai *et al.* [47]	✓			2020				✓	Outlier Detection
Butler *et al.* [65]		✓		2020	✓				Facial Expressions
Ristoski *et al.* [66]	✓			2020		✓			Relation Extraction
Qian *et al.* [67]	✓			2020		✓			Entity Name Understanding
Le *et al.* [68]		✓	✓	2020	✓				Self-Annotation For Video Object Bounding Box
Bartolo *et al.* [69]		✓		2020		✓			Reading Comprehension
Cutler *et al.* [70]	✓			2021		✓			Entity Recognition
Meng *et al.* [71]		✓		2021	✓				3D Point Cloud Object Detection
Zhang *et al.* [72]		✓		2021	✓				Screentone and Manga Processing
Adhikari *et al.* [73]		✓		2021	✓				Object Detection

the method of dictionary expansion proposed earlier, the core idea of this method is also realized by expanding the existing dictionary. Specifically, given an input text corpus and a set of seed examples, first, construct the word2vec model and BiLSTM for processing. The model's output is an embedding matrix, where each term (word or phrase) from the vocabulary of the corpus is represented as an n-dimensional vector. Then using the embedding matrix, the dictionary expansion method runs in two stages, exploring and using it to identify new potential dictionary entries. Then filter by calculating the similarity score, and finally use manual labeling. In addition to the direct annotation, there are semantic disambiguation tasks in natural language processing. In many cases, the model alone cannot accomplish this task. However, humans have accumulated much knowledge in unconscious learning. If using the human knowledge intervene, the effect achieved will be significantly improved. Qian *et al.* [67] propose a deep learning-based entity name understanding sys-

tem called PARTNER, which provides a better way of interaction. PARTNER bases on active learning and weak supervision method. PARTNER can learn a model based on deep learning to recognize the entity name structure without workforce help. In addition, PARTNER also allows users to design complex normalization and variant generation functions without coding skills. In order to find those error-prone samples in the human-computer interaction process, it is necessary to use data screening technology for sample selection. Cutler *et al.* [70] propose a method that marking potentially incorrect labels with high sensitivity in the named entity recognition corpus.

Our summary of the previous paper finds very little work that uses HITL technology to perform data preprocessing on computer vision tasks. We believe that the essence of this phenomenon is that there is a lack perfect way to integrate the human experience into image processing. This part of the content will be discussed in detail in Section 5 part later.

2.2. Data Annotation

For new tasks, annotating data is crucial to realize artificial intelligence, but data labeling is a complex task. Therefore, many researchers have proposed using a HITL-based method for fast and accurate (compared to fragile labeling) operations. Data annotation in natural language processing tasks is divided into two categories, and one is the annotation of specific task datasets, such as entity extraction [55, 56], entity linking [64] and so on. The other is more abstract tasks, such as question and answer tasks [61] and reading comprehension tasks [69].

The entity processing task is critical in natural language processing, and its success or failure directly affects the performance of natural language processing [75]. At present, there are two critical methods for entity extraction, one is to formulate regular expressions for automatic extraction, and the other is the entity mentioned in the manual tagged document. However, neither of the two methods can efficiently and accurately extract entities. Zhang *et al.* [56] propose a human-in-the-loop-based entity extraction method to obtain the best return on investment in a limited time. It uses humans to formulate regular expressions and manually mark documents. First, they use regular expressions to scan the document corpus and generate weak labels to pre-train the neural network. Then, they manually annotate substring to fine-tune the network and use this fine-tuned network to identify continuously. Finally, they complete an entity extraction model suitable for tasks in the professional field. Besides, this regular expression model can also be continuously upgraded and trained to achieve an efficient and accurate general recognition effect. With the deepening of research, we need to deal with more and more tasks. The emergence of new tasks is beyond our expectations. Regular expressions can help handle common data, but there is no expected magic for never seen new data. To tackle this challenge, some studies proposed the use of a cross-domain approach to solving the cross-domain problem in entity links. First, they find the entities mentioned in the text, and then they sort the mentioned entities. Finally, they are filtering and discriminate the entities according to the sorting information. This method is especially suitable for semantic disambiguation tasks [64].

How to deal with more complex tasks is the focus of research now. Researchers attempt to incorporate the human experience and knowledge to teach machines more knowledge. The neural network model has understood the natural language well, but what level does the neural network understand natural language? To explain this problem and explore more interpretability of the neural network model, Wallace *et al.* [61] uses an interactive user interface to talk to the machine, thereby generating more language materials to help the researcher explain the model predictions. They develop an open application system and conduct questions and answers through real-world human-question models to collect more research data. The adversarial questions cover diverse phenomena from multi-hop reasoning to entity type distractors, exposing open challenges in full question answering. Following previous work, using the same idea of "humans create questions in reverse so that the model cannot answer these questions correctly, Bartolo *et al.* [69] try three different sets of annotation methods in the reading comprehension task to build a gradually more robust model in the annotation cycle. Moreover, they create a challenging dataset by collected 36,000 samples. This dataset explored some interesting issues, such as the reproducibility of adversarial effects, the transfer of data collected with different loop model strengths, and generalization to data collected without a model. They find that the training of reverse collection samples will lead to solid generalization to non-reverse collection datasets. However, with the enhancement of the cyclic model, the performance gradually deteriorates. In contrast, the more robust model can still learn from the data intensively collected by the weaker model in the loop.

At present, human-in-the-loop in computer vision mainly explores how to use weak labeling to provide feedback. Besides, it also explores how to provide users with a unified intervention experience. It is involved in many tasks, such as person re-identification, face recognition, 3D point cloud object detection, and object detection. Although many current pedestrian re-identification (Re-ID) methods can achieve superior results under the training of a large amount of labeled data, if these models are deployed in a natural environment, they do not produce an excellent performance as in the experiment. However, so much data is new in a natural environment because those data in the natural environment do not appear in the training set. Over time, these new data will constantly accumulate, which will cause the model to fail to work. To tackle this problem, Liu *et al.* [60] propose a human-in-cycle model based on reinforcement learning, which releases the limitation of pre-labeling and upgrades the model through continuously collected data. The goal is to minimize human annotation work while maximizing the performance of Re-ID. It alternately refines the reinforcement learning strategy and CNN parameters in an iterative update framework. In particular, they developed a deep reinforcement active learning (DRAL) method to guide agents (models in the reinforcement learning process) to select training samples by human users/annotators dynamically. Reinforcement learning reward is the uncertainty value of the sample chosen by each person. Binary feedback (positive or negative) marked by the human annotator is used to select samples for fine-tuning the pre-trained CNNRe-ID model. In addition to directly using reinforcement learning for dynamic learning, researchers are also paying attention to expanding and refining data on a new task. Facial expression recognition is an exciting task in computer vision, which is of great help to sentiment analysis and behavior analysis tasks. Traditional facial expression recognition can only deal with the seven simplest facial expressions

(*i.e.*happiness, sadness, fear, anger, disgust, surprise, and contempt). However, in real life, it is more important to deal with more micro-expressions. It is an interesting task that building more refined micro expression processing datasets based on existing expression identification. Butler *et al.* [65] propose a micro-expression recognition method based on the human-in-the-loop system. This method provides a flexible interface for manual proofreading of automatically processed tags, thereby ensuring the accuracy and usability of the extended dataset. In addition to directly constructing new datasets, it is also of great significance to explore existing datasets, especially for tasks that are difficult to label, such as target detection tasks, the labeling workload is enormous. To reduce the labor and time cost of annotation of the bounding box of video objects, Le *et al.* [68] propose an efficient and straightforward interactive self-annotation framework. The framework is constructed based on cyclic self-supervised learning, and the entire framework consists of automatic model learning and interactive processes. The automatic learning process makes the model learn faster and more fully to speed up the interaction process. In the interactive recursive annotation, the detector receives feedback from the human annotator to process the human loop annotation scene. In addition, to save labeling time, they propose a new level correction module, which strengthens the use of neighbor frames by CNN by reducing the distance of annotated frames at each time step. Based on the framework of Le *et al.*, Adhikari *et al.* [73] modify the framework to be completed in one stage, and the most significant work of humans in it has become to correct errors instead of performing full annotations, which further improves the user experience. For some more complex image tasks, such as 3D point cloud labeling tasks, simply using the above two methods is ineffective. Because the effect of using only one stage for labeling is limited, Meng *et al.* [71] propose a multi-stage human-in-the-loop labeling method based on predecessors. The first stage uses the BEV center click annotation strategy to generate cylindrical object proposals based on inaccurate original information and inaccurate supervision information. The second stage is based on the informal learning of the first stage to predict the cuboid and the confidence score in a coarse-to-fine cascade and uses a human-in-the-loop method to label a small part of the object finely. The previous work only started from the perspective of data annotation. It did not integrate human experience and knowledge into the model to the greatest extent to integrate human knowledge and intelligence more effectively. Zhang *et al.* [72] considered specific talents and skills of humans in painting, and this skill cannot be fully quantified as rules and knowledge. If the model can learn painting skills, it will undoubtedly help human-in-the-loop application takes a significant step forward. They propose a data-driven framework for generating comics from digital illustrations. To achieve this framework, they converted digital illustrations into three corresponding components that can be
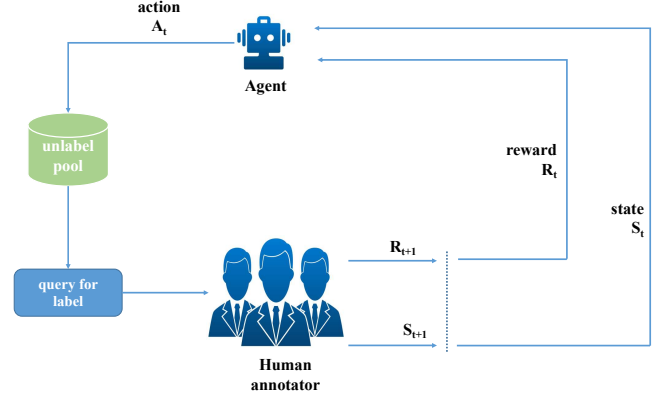

Fig. 5: The HITL framework based on reinforcement learning.

directly composed into comic images: comic line drawings, regular screen images, irregularities, and screen texture. To further create high-quality comics, these three components are humanely annotated by the artist.

2.3. Iterative Labeling

At present, there is still a high degree of coupling between deep learning tasks and data, and the performance of deep learning largely depends on the quality of the data. For a new task, if you want to obtain better performance, you need to provide a large amount of high-quality labeled data. However, the labeled data requires a large amount of labor. In addition, large-scale data annotation takes a long time, and many iterations of tasks cannot wait such a long time. Unlike weak annotate and automatic annotate, HITL-based methods emphasize finding the key samples that play a decisive factor in new sample data.

Yu *et al.* [7] proposed a partially automated labeling scheme for labeling, freeing up human labor, and using deep learning of human-in-the-loop. Iteratively sample each subset from a large set of candidate images for each category, ask people to label them, classify them with the trained model, and divide the set into positive, negative, and unlabeled according to the classification confidence. Then use the unlabeled set to iterate. This constitutes the basic prototype of simple iterative annotation. With the promotion of reinforcement learning, Liu *et al.* [60] used reinforcement learning to carry out iterative labeling. In addition to implementing the simple manual intervention, they took person Re-Identification as a research task. They try to explore how to minimize human annotation work while maximizing improve the performance of Re-ID. They pay more attention to the comfort of user intervention and the user experience of user intervention. Fan *et al.* [62] set out to solve the data challenge in the task of network anomaly detection. Moreover, they propose a new intelligent labeling method, and

the method combines active learning and visual interaction to detect network abnormalities through the iterative labeling process of users. The difference is that they began to pay attention to the connection between the algorithm and the visual interface, and their algorithm and the visual interface are tightly integrated. Their main goal is to allow users to intervene in data labeling rather than implement simple user labeling.

Unlike the data annotation mentioned above, data iterative labeling pays more attention to the user experience, not just directly allowing users to perform data annotation. His goal has been changed in the following two aspects, and one is to begin to focus on how to add the knowledge and experience to the learning system, the other is to begin to focus on the interaction with users.

3. MODEL TRAINING AND INFERENCE

In many fields of Artificial Intelligence, such as Natural Language Process (NLP) and Computer Vision (CV), there are a variety of different approaches that leverage human intelligence to train and infer experimental results. For both NLP and CV, related research spans deep learning techniques and human-machine hybrid methods. These heuristic methods have taken the diverse quality of human creativity into account to achieve high-quality results.

3.1. Natural Language Process

For Natural Language Process(NLP), there are increasing studies about combining Human-in-the-loop (HITL) with various NLP frameworks to solve various NLP problems. The novel HITL NLP approaches can continuously integrate and collect diverse feedback from different individuals and apply them to train and infer the results to contribute to the model performance. Fig 6 briefly illustrates the cooperation between the individuals and the model training and inferencing process in the Natural Language Processing Loop. The continuous executive loop develops a more reliable human-AI partnership to a certain extent, contributing to higher accuracy and stronger robustness of the NLP system.

3.1.1. Text Classification

Text Classification (TC) is a fundamental NLP task that aims to categorize a sentence/text into its corresponding category. Karmakharm *et al.*[76] propose a rumor classification system; the core idea of this system is to obtain additional manual feedback from the journalists to retrain a more accurate machine learning model. This framework first exploits a Rumour Classification System to classify collected social media posts and sends this information back to the journalists. Then, several examples are selected for journalists to annotate and store

in a database. When a dataset with user-provided annotations is constructed, it is utilized for retraining the model. As most state-of-the-art text classification approaches are dominated by the deep neural network, which is generally considered as "black boxes" by end-users, another motivation for the researcher to construct the human-in-the-loop framework for TC is to overcome the opaqueness of those models, make them more explainable. For achieving this purpose, Zaidan *et al.* [77] first propose to invite a human expert to highlight some pieces of text in a document as a rationale. These highlighted pieces of each text can be considered as evidence/clues to tell the machine learner why the text/example belongs to the corresponding category. This learning process is finished by incorporating the rationale into the loss function of an SVM classifier to constrain the prediction labels. Similar work has been done via different ways of combining human feedback and neural network [78]. However, these studies have ignored some potential issues during human involvement, such as the quality of rationales might fluctuate due to the different levels of expertise and varying motivation. Arous *et al.* [79] put forward a hybrid human-AI framework that gives a principled idea to reinforce human reliability in merging human rationales into a deep learning algorithm. In their work, they present MARTA, a Bayesian framework that jointly learns and updates the model parameters and human reliability via an iterative way, enabling the learning processes of parameters and human reliability can benefit from each other until the label and rationales reach agreements.

3.1.2. Syntactic and Semantic Parsing

Besides text classification, HITL approaches for syntactic and semantic parsing are also promising. Syntactic Parsing is a process to obtain the valid syntactic structure of input sentences. The goal of Semantic Parsing is to map natural language to formal domain-specific semantic representations. A human-in-the-loop parsing method [48] is proposed to improve the parsing accuracy of CCG parsing by employing non-expert to answer simple what-questions generated from the parser's output. These answers are treated as soft constraints when re-training the model. This work is the first attempt at introducing human-in-the-loop for syntactic parsing. Since then, human feedback has been demonstrated as a crucial contribution of semantic parsing [80, 81, 82]. However, most parsing technologies still face several challenges: (1) the purpose or expression of users can be ambiguous or vague under some circumstances, posing obstacles for them to get the ground truth in one shot, (2) in the real-world scenario, the performance of state-of-the-art parsers are generally not high enough, and (3) since the mainstream neural network-based models are known as "black-box", which indicates the lack of explainability, it is difficult for end-users to verify the parsing results independently. Currently, Yao *et al.* [83] propose to allow semantic parsers system to ask end-users clarification
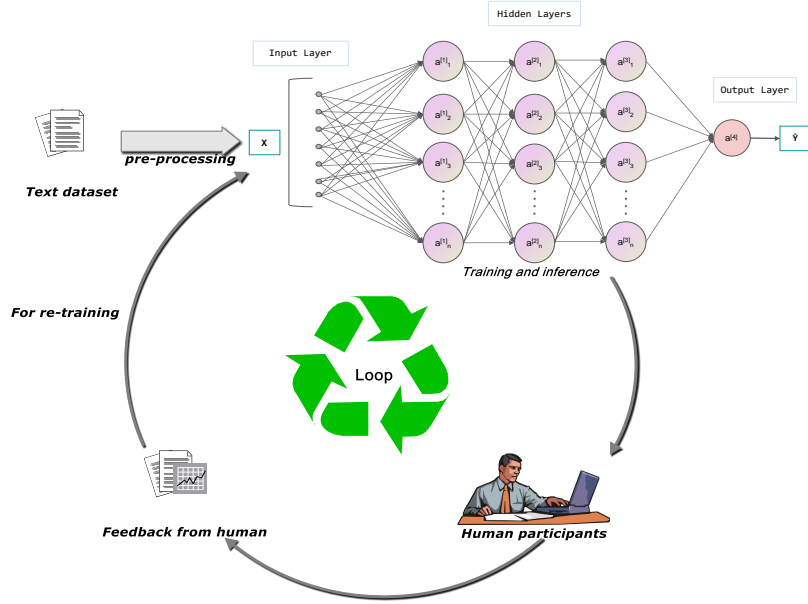
Fig. 6: The model training and inferencing workflow of Human-in-the-loop(HITL) in Natural Language Processing. The human participants provide various feedback in the stage of model training and inferencing according to specific tasks to boost the performance of NLP models.

questions and produce an If-Then program at the same time. Su *et al.* [84] have proven that end-users particularly preferred a parser system based on an interactive manner over the non-interactive counterpart for NLP interfaces to web APIs. Although recent works successfully verified the effectiveness of interactive semantic parsing in practice, they are generally restricted to a specific type of formal language. Yao *et al.* [85] develop a model-based interactive semantic parsing (MISP) as the general principle for interactive semantic parsing. The MISP is introspective of the whole reasoning process, and a world model [86] module inside assists it in knowing when the model may need human supervision and intervention as well as soliciting user feedback in a human-friendly way.

3.1.3. Topic Modeling

In addition to the NLP tasks above, some researchers also explore the application of similar HITL frameworks in Topic Modeling (TM), which is commonly applied to analyze extensive document collections. Compared to classic methods that visualize static topic models [94, 95], human-in-the-loop topic modeling (HITL-TM) offers additional humanized mechanisms to allow non-expert users to refine changing topic models. Based on this conception, numerous mechanisms have been designed. For instance, Hu *et al.* [87] extend a statistical framework [96] to allow end-users to add, remove, or change the weights of words within each topic. Then, the user-updated feedback is exploited to assist the model's training process in producing more valuable topics. However, the drawbacks of the approach are apparent: the

possible set of refinements that can be supported are limited; the common interactive machine learning issues such as unpredictability, latency, and complexity that can affect user experience are ignored. Smith *et al.* [88] put forward an interactive machine learning framework that offers a broad range of topic modeling refinement operations and codes four common challenges to explore how end-users are affected by the complexity, unpredictability, and lack of control in a fully interactive HITL-TM system. Moreover, Kim *et al.* [89] develop an interactive target building module to allow users to express their ideal target model by editing several positive/negative user relevance feedback. This feedback is used for modeling the targets and their representative vectors to re-train the model. The last two examples above have demonstrated that more human-centered HITL NLP systems can benefit from human-computer interaction (HCI) design techniques.

3.1.4. Text Summarization

Besides applying a HITL framework to topic modeling, researchers also use them to generate new texts. Text Summarization (TS) generates a shorter version of a given sentence/text while attempting to preserve its meaning [97]. In recent years, there have been some significant breakthroughs in this field. For instance, Ziegler *et al.* [90] fine-tune pre-trained language models with reinforcement learning by exploiting a reward model trained from human preferences. Then the model is used to generate summaries over Reddit TL; DR and CNN/DM datasets. However, one limitation

Table 2: A brief overview of representative works in HITL NLP. Each row represents one work. Works are sorted by their task types (TC: Text Classification. SSP: Syntactic and Semantic Parsing. TM: Topic Modeling. TS: Text Summarization. QA: Question Answering. SA: Sentiment Analysis). Each column corresponds to a dimension from the two subsections (task, motivation).

Work	Task						Motivation		
	TC	SSP	TM	TS	QA	SA	Performance	Interpretability	Usability
Zaidan et al. (2007) [77]	✓						✓	✓	
Zhang et al. (2016) [78]	✓						✓	✓	
Arous et al. (2021) [79]	✓						✓	✓	
Karmakharm et al. (2019) [76]	✓						✓		✓
He et al. (2016) [48]		✓					✓		
Su et al. (2018) [84]		✓					✓	✓	✓
Yao et al. (2019) [83]		✓					✓	✓	✓
Yao ZiYu et al. (2019) [85]		✓					✓	✓	
Hu et al. (2014) [87]			✓				✓		
Smith et al. (2018) [88]			✓				✓	✓	✓
Kim et al. (2019) [89]			✓				✓		✓
Ziegler et al. (2019) [90]				✓			✓		
Stiennon et al. (2020) [91]				✓			✓		
Hancock et al. (2019) [92]					✓		✓		
Wallace et al. (2019) [61]					✓		✓		✓
Liu et al. (2021) [93]						✓		✓	

of their framework is that there are low agreement rates between labelers and researchers. Stiennon *et al.* [91] propose first to gather a dataset composed of human preferences between pairs of summaries, then the prediction of the human-preferred summary is generated by a reward model (RM), which is trained via supervised learning. Lastly, the score produced by the RM is maximized as much as possible by a policy that is trained via reinforcement learning (RL). Their method ensures relatively higher labeler-researcher agreement by doing the above steps and separates the policy and value networks successfully.

3.1.5. Question Answering

Recently, various HITL related frameworks have been designed to apply dialogue and Question Answering (QA). The purpose of this task is to allow chatbots/agents to have a conversation with users. These HITL dialogue intelligent systems can be divided into two main categories: online feedback loop and offline feedback loop [98]. For the online feedback loop, human feedback is utilized to update the model continuously. Compared with traditional approaches that mismatch the training set and online use case for dialogue systems, researchers have demonstrated that the application of online reinforcement learning can improve the model with human feedback. For instance, a lifetime learning framework is proposed by Hancock *et al.* [92]. The self-feeding mechanism in this framework enables the chatbot to generate new exam-ples when the conversation with users goes well, and these new examples are used to re-train itself continuously. For the offline feedback loop, a large set of human feedback needs to be collected as a training set first; then, this training set is used to update the model. For instance, Wallace *et al.* [61] employ "trivia enthusiasts" to creatively generate adversarial examples that are able to confuse their QA system, and these examples are finally utilized for adversarial training. Since some of the end-user feedback can be misleading, offline systems may be more appropriate for improving the robustness of the model.

3.1.6. Sentiment Analysis

Sentiment Analysis (SA) is one of the popular research branches of Opinion Mining (OM). The research scope of SA is about the computational study of individual's opinions and attitudes toward entities mentioned in a text. The entities generally refer to individuals, events. Recently numerous neural network-based approaches have been widely utilized and demonstrated their effectiveness in solving sentiment analysis tasks [99, 100, 101, 102]. Most deep learning-based methods for SA use accuracy and F1-score as evaluation metrics. Since these metrics can only evaluate the predictive performance, they lack the mechanisms to explain details on when and why the sentiment models give false prediction in run-time [103]. Liu *et al.* [93] introduce an explainable HITL-SA framework for sentiment analysis tasks. The execution

of their framework can be divided into the following three steps: First, the HITL-SA model analyzes local feature contributions. This is achieved by executing a data perturbation process. Next, local features are aggregated for calculating the explainable global-level features and humans participate in this loop to assess the relevance of the top-ranked global features to the ground truth, report the errors they find in this process. Finally, the system calculates an erroneous score based on both global-level and local-level sentimental features for each instance, scores higher than a specific threshold are indicated as wrong predictions.

Summarization for Human-in-the-Loop In NLP

A brief overview of representative works in HITL NLP is shown in Table 2. For most of the surveyed papers above, their original purpose is to apply HITL techniques to various NLP tasks to assist the model in achieving better performance. The effectiveness of the approaches proposed by these surveyed papers is evaluated via various metrics. The experimental results in the papers we investigated show that a relatively small set of human feedback can dramatically and effectively boost the model performance. For instance, the HITL technique improves the classification accuracy for both text classification and topic modeling [76, 88]. Similar situations occur in dialogue and question answering where the QA systems have higher ranking metric hits [92]. Besides, HITL techniques have also enhanced the model's robustness and generalization [91]. In addition to improving model performance, some studies have demonstrated that HITL methods enable models to be more interpretable and usable in solving NLP problems. For instance, Arous *et al.* [79] incorporate human rationales into an attention-based Bayesian framework in a reasonable way while weighing worker reliability, thus providing a more human-understandable interpretation of classification results and enhancing the model performance at the same time. Liu *et al.* [93] chose uni-grams as the explainable feature for LIME [104]; thus, the proposed system allows the end-users to better understand the overall contribution of each word to the final sentiment classification made by the model. Wallace *et al.* [61] invite "trivia enthusiasts" to creatively generate specific adversarial questions that confuse the intelligent question answering system. These questions can be treated as probes further to explore the inherent characteristics of the underlying model behaviors.

3.2. Computer Vision

In recent years, neural network-based Deep Learning methods (DL) have emerged as the state-of-the-art technique for performing many computer vision tasks [105, 106, 107, 108]. In order to further improve the performance of these methods, feedback from humans has been integrated into the deep learning architecture to make the whole system more intelligent in solving complex cases that can not be handled politely by the model. Since humans play a crucial role in providing feedback, researchers increasingly pay attention to combine the human-in-the-loop framework with DL for computer vision. A typical HITL framework for Computer Vision is outlined in Fig 7.

3.2.1. Object Detection

Object detection, as one of the most fundamental and challenging problems in computer vision, has received great attention in recent years [109]. Object Detection (OD) have been widely explored in computer vision [110, 111, 112, 113]. The goal of object detection is to detect instances of visual objects of a certain class (such as individuals, vehicles or other creatures) in digital images. Yao *et al.* [114] point out that iterations between queries may be expensive or time-consuming, making it unrealistic for executing interaction with end-users. They present an interactive object detection architecture to employ individuals to correct a few annotations proposed by a detector for the un-annotated image with the maximum predicted annotation cost. Different from [114], Roy *et al.* [115] first introduce HITL methods combined with deep learning algorithm for object detection and the annotation costs in their method are supposed to be equal for each image during the whole training process. In their proposed approach, a batch of images are first randomly selected from the unannotated pool, then the individuals annotate them and train the SSD on these annotated images to obtain a preliminary model. Subsequently, a fixed set of images are picked up by them deliberately, these images are annotated and SSD is trained on all the newly annotated samples. This human-in-the-loop learning/training phase continues until the function of the total percentage of queried images is exhausted or an ideal performance of accuracy is achieved. However, it is still difficult to detect some occluded objects, tiny objects, and blurred objects for these approaches. Madono *et al.* [116] put forward a efficient human-in-the-loop object detection framework composed of bi-directional deep SORT [117] and annotation-free segment identification (AFSID). The role humans play in this architecture is to perform verification for the object candidates that bi-directional deep SORT can not detect automatically. Then train the model over the supplementary objects annotated by individuals.

3.2.2. Image Restoration

Image restoration (IR) aims to recover the preliminary version of damaged images [118]. The image inpainting frameworks proposed by previous studies can be bifurcated as exemplar-based [119, 120, 121] approaches and deep learning-based [122, 123, 124] methods. Although deep learning-based works are the mainstream and show decent results, when trained on a large dataset, neural network-based approaches constantly suffer from over-fitting when only a relatively small training set is available. Besides, in a real-world application, the restored images are often filled with unknown artifacts like
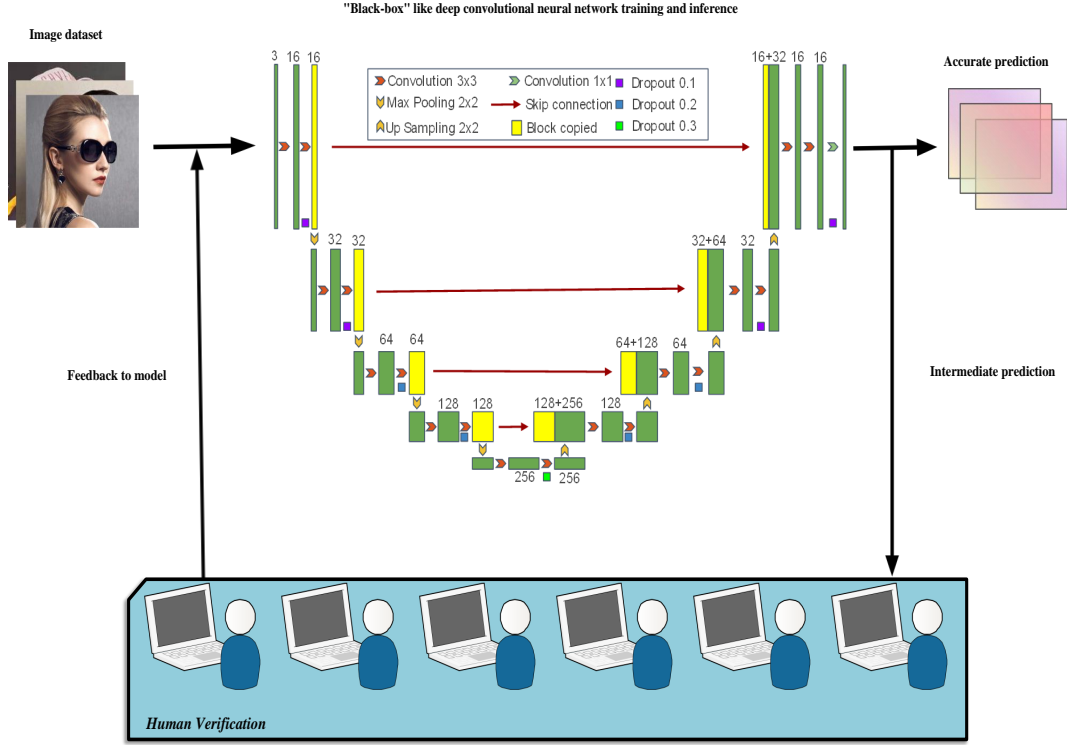
Fig. 7: Overview of general human-in-the-loop frameworks for model training and inferencing in Computer Vision. The model training and inferencing step produces an intermediate prediction to the human experts/users, the feedback from them is sent to the model for re-training to obtain the accurate prediction.

inconsistent texture or monotone color due to the missing crucial semantic information in severely corrupted areas. When missing image features are obvious from semantic but not structural context, it is hard for deep learning algorithms to deduce this missing information, but not for humans. Since this kind of knowledge-based enhancement can dramatically enhance the robustness of restoration, it is necessary to incorporate human knowledge in image inpainting to improve the quality of restored images. Weber *et al.* [125] propose an interactive machine learning system for image restoration based on Deep Image Prior (DIP) [126]. Their proposed HITL framework allows humans to embed their knowledge into the training process by the following steps: initially, the images from the dataset are sent to the automated DIP for preliminary restoration. Secondly, the operators can actively refine the images via a pre-designed user interface. Thirdly, the refined images are then sent back to the input of DIP again for further polishing. Finally, the whole loop continues until the restoration reaches the user's expectations. In some specific domains of computer vision, the HITL framework is also being applied to Image Restoration. For instance, in the field of Electron Microscopy, one drawback of automation is that it generally ignores the expertise of the microscopy user that comes with manual analysis. To alleviate such a challenging problem, Roels *et al.* [127] propose a hybrid

HITL system that incorporates expert microscopy knowledge with the power of large-scale parallel computing to enhance the Electron Microscopy image quality by exploiting image restoration algorithms. The HITL workflow in the system consists of six steps and the training and inference interaction between individuals and the framework in the region of interest selection and interactive parameter optimization.

3.2.3. Image Segmentation

Image segmentation (i.e., semantic segmentation) is a ubiquitous step in most image studies. Image segmentation (IS) aims at assigning a class label to each pixel in the image [128], notably pixel-level image labeling. This field has recently become explosive popularity due to it plays a crucial role in a wide range of computer vision applications [129, 130, 131, 132]. However, few works explore how to expose failures of top-performing semantic segmentation models efficiently and how to rectify the models by utilizing such counter-examples reasonably. Wang *et al.* [133] present a two-step hybrid system with human efforts for troubleshooting pixel-level image labeling models. The hybrid system first automatically picks up un-labeled images from a large pool, then these selected unlabelled images are used to compose an unlabeled set, which is the most informative

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in exposing weaknesses of the target model. To reduce the number of false positives, individuals are employed to filter the unlabeled set to obtain a smaller refined set. In the second step, they fine-tune and re-train the target model to study from the counter-examples contained in the refining set without ignoring previously seen examples. Finally, the whole loop continues, ensuring the advanced troubleshooting of image segmentation models. Researchers have also explored domain-specific HITL approach for semantic segmentation systems. For example, due to data annotation is always immensely difficult and expensive in the medical image process domain [134], Ravanbakhsh et al. [135] introduce a training protocol based on combining the conditional Generative Adversarial Network (cGAN) and human workers in an interactive way. To be more specific, they first utilize supervised data to train G and D. G denotes the generator which learns how to produce segmentations by conditioning on images and D is the discriminator applied for detecting the uncertainty of the segmentations. For complex cases, human experts are responsible for annotating them. These newly annotated images are used to continue the training and inference procedure. All in all, this human-in-the-loop system is achieved by an iterative and interactive continuous update of ground truth data.

3.2.4. Image Enhancement

As one of the challenging issues in computer vision, the purpose of Image Enhancement (IE) is to process an image and generate a new, improved one so that the generated one is more suitable than the original image for a specific application [142]. The research field of image enhancement has attracted ample attention from researchers in recent years, especially after the emergence of deep neural network algorithms [143, 144, 145]. However, most current frameworks have ignored the user preferences and experiences, enhancing the image only via a black-box style, which has the potential to leave end-users with sub-optimal results that are not suitable for their specific taste. Kapoor et al. [136] introduce an enhanced human-in-the-loop framework that can learn personal user preferences in a collaborative way. Their system accomplishes this goal by executing two steps: initially, they build an individual profile by picking up diverse images in the collection and requesting the individual to train and inference the model utilizing this preliminary dataset. Secondly, they develop a general and straightforward interface, this interface first displays some representative enhanced image of the original image to the end-user, the end-user then chooses the version that he/she enjoys the best by clicking on it, and the entire procedure is repeated around the selected image. These two steps continue until the end-user selects the unmodified image. In this interactive procedure, users are the capacity to control the step size exploited to produce the variations. Another HITL framework proposed by Murata et al. [137] also

take user preference into account. The user first provides an example to their system, the image enhancement functions in the framework are applied to the example image via randomly selected parameters. Several objective images are produced and the end-user needs to give a score to each of the images. Then the RankNet [146] is exploited to learn the user's preference from these scores. During the learning process, based on the scores given by users, parameters are optimized to make the generated enhanced images suitable for the taste of users. Fischer et al. [138] argue that it is necessary to incorporate the user's particular taste of aesthetics into the whole image enhancement process (e.g., before, during, and after the enhancement process.). Thus, they propose Neural Image Correction and Enhancement Routine (NICER) for accomplishing this purpose. A component called the Image Manipulator in the NICER first exploits a series of learned image operations (e.g., contrast, brightness) with variable magnitude onto the original image provided by users. Another module named Quality Assessor is followed to evaluate the final enhancement quality by generating related scores. This system iteratively optimizes the parameters of the image enhancement functions to maximize the scores given by the Quality Assessor. Users are able to modify the parameters of the Image Manipulator before, during, and after the optimization process, guiding the optimization procedure towards more satisfying local optima, making the enhanced images match the user's aesthetic as much as possible.

3.2.5. Video Object Segmentation

The goal of video object segmentation (VOS) is to segment a particular object instance in the entire video sequence of the object mask on a manual or automatic first frame [147]. This research area has become popular in the computer vision community [148, 149, 150]. Since there are some intrinsic characteristics of videos such as motion blur, bad composition, occlusion, etc, it is harder for fully automatic approaches to accurately segment more complex sequences. From another perspective, employing user input for each frame is unrealistic due to its expensive costs and time consumption. Thus, the human-in-the-loop framework is adopted for solving such problems. Benard et al. [139] introduce an novel Interactive Video Object Segmentation method based on [151]. The core idea of their HITL framework is to utilize the current segmentation mask as an additional input. In this way, by incorporating the user assistance to the input in clicks, the system can iteratively refine an initial segmentation. Caelles et al. [140] propose another interactive architecture for the video object segmentation that can further reduce the individual effort. There is the round-based interaction in the proposed system, which means that individuals initially give annotations on a chosen frame and a deep neural network-basednetwork-based algorithm outputs the segmentation maps for all video frames in a batch process. The

Table 3: A brief overview of representative works in HITL CV. Each row represents one work. Works are sorted by their task types (OD: Object Detection. IR: Image Restoration. IS: Image Segmentation. IE: Image Enhancement. VOS: Video Object Segmentation). Each column corresponds to a dimension from the two subsections (task, motivation).

Work	Task					Motivation		
	OD	IR	IS	IE	VOS	Performance	Interpretability	Usability
Yao et al. (2012) [114]	✓					✓		
Roy et al. (2018) [115]	✓					✓		✓
Madono et al. (2020) [116]	✓					✓		
Roels et al. (2019) [127]		✓				✓	✓	
Weber et al. (2020) [125]		✓				✓		
Wang et al. (2020) [133]			✓			✓		
Ravanbakhsh et al. (2020) [135]			✓			✓		
Kapoor et al. (2014) [136]				✓		✓		
Murata et al. (2019) [137]				✓		✓		
Fischer et al. (2020) [138]				✓		✓		
Benard et al. (2017) [139]					✓	✓		✓
Caelles et al. (2018) [140]					✓	✓		✓
Oh et al. (2019) [141]					✓	✓		✓

process above is iteratively repeated until the results reach the user's expectation. Another effective framework for interactive segmentation scenario is designed by Oh *et al.* [141], named Interaction-and-Propagation Networks (IPN). The IPN is composed of two modules and the key architecture of these two modules is deep convolutional neural networks. The main operations of these two modules are interaction and propagation, respectively. For the interaction network, individuals are allowed to interact with the proposed model several times; meanwhile, the feedback is provided in scribbles on multiple frames during this interactive procedure. Its functionality is to transfer the object mask calculated in the source frame to other neighboring frames for the propagation network. For each sample, the training process includes multiple rounds of individual interactions mentioned before. As the user interaction process iteratively repeated, the model parameters are continuously optimized to refine the previous round's results by learning the user's feedback and intention.

Summarization for Human-in-the-Loop In CV A brief overview of representative studies in HITL CV is displayed in Table 3. It can be observed from Table 3 that the motivation of all the surveyed HITL works for computer vision is to boost the model performance. From the experiment results of all these surveyed papers, although the evaluation criteria are different from each other, the system that incorporates the HITL method does perform better than without combining it. Taking Madono *et al.* [116] as an example, they conduct experiments for pedestrian detection and the results have proven at least two advantages for this task: For one thing, the proposed approach boosts the recall rate by 11 % at most over deep SORT. For another, the amount of unlabeled samples that need manual annotation is decreased by

67 % at most compare with bi-directional deep SORT without AFSID, which dramatically improves the overall model performance. Associating the contents in Table 2, this phenomenon in CV is similar to NLP, which demonstrates that the core motivation of almost all HITL studies in both CV and NLP serves the purpose of boosting model performance. We also notice that in Table 3, only one work [127] tries to bring interpretability for the model. Roels *et al.* [127] have validated the potential enhancements that DenoisEM can provide in 3D EM image interpretation by denoising SBF-SEM image data of an Arabidopsis thaliana root tip. Besides, HITL conception can also improve the usability of CV models. For instance, Roy *et al.* [115] have proven that their framework is advantageous/practical in scenarios where obtaining annotations is a costly affair. Oh *et al.* [141] validate the usefulness and robustness of their Interaction-and-Propagation Networks with real interactive cutout use-cases.

4. SYSTEM CONSTRUCTION AND APPLICATION

The idea of building up a human-computer interaction system is the beginning of human-in-the-loop researches and also can be the destination. In general, an interaction system can be a software system such as security systems on the computers and also can be a more complex system with both hardware and software so-called Cyber-Physical Systems (CPS). In all these scenes, handling the working loop between machine intelligence and human intelligence is mainly discussed. The research on human-in-the-loop was proposed for two purposes, utilizing fewer low-level manual operations and utilizing more higher-level human intelligence. Unlike the studies on dataset construction and methodologies, the

Table 4: An overview of representative applications for software-based HITL systems. (SECS: Security Systems. CP: Code Production. SIMS: Simulation System. SE: Search Engine.)

Systems	Application					Year	Role of human				Discription
	SECS	CP	SIMS	SE	Others		Supervisor	Supervisee	Collaborator	User	
Brostoff & Sasse [152]	✓					2001		✓		✓	Security system for traditional tasks
Cranor [153]	✓					2008		✓		✓	Security system for traditional tasks
MacHiry et al. [154]		✓				2013			✓		Software testing
Kovashka et al. [155]				✓		2015				✓	Image-based searching engine
Louis Rosenberg [156]					✓	2016			✓		Crowdsourcing
Yan et al. [157]		✓				2017	✓		✓		Software testing
Wogalter [158]	✓					2018			✓	✓	Security system for traditional tasks
MA [159]		✓				2018	✓				AI model optimizing in training
Salam et al. [160]		✓				2019	✓				AI model optimizing in testing
Plummer et al. [161]				✓		2019				✓	Image-based searching engine
Fredrik Wrede & Andreas Hellander [162]					✓	2019	✓		✓		Stochastic gene regulatory
Singh and Mahmoud [163]	✓					2020		✓	✓	✓	Security system for traditional tasks
Demartini et al. [164]	✓					2020	✓		✓		Security system for modern tasks
ODEKERKEN & BEX [165]	✓					2020			✓		Security system for modern tasks
Bohme et al. [166]		✓				2020	✓				Program repairing
Renner [167]		✓				2020	✓		✓		AI model optimizing in the whole steps
Demirel [168]			✓			2020				✓	Digital human modeling
Metzner et al. [169]			✓			2020				✓	Simulated human-robot collaboration system
Zhou et al. [170]			✓			2020			✓	✓	Melody composition interactive system
Polisetty & Avinesh [171]				✓		2020				✓	Searching engine
Zhu et al. [172]					✓	2020	✓		✓		Renal Pathology
Li et al. [173]					✓	2020			✓		Model checking

usage of human-in-the-loop on system construction is comprehensive, and the works are different among the application scenarios. This section will review the human-in-the-loop on system construction divided by system components and applications in this section, following the baseline of engineering requirements.

4.1. Software based HITL Systems

For software-based human-computer interaction systems, the idea of human-in-the-loop has been widely used in various of scenes such as security systems and search engines. Due to the wide range of application scenarios, different human-in-the-loop systems are constructed with visible gaps on an interactive interface, algorithm, and the role of humans. However, a constant idea of designing these systems is a less manual operation and better performance. As an overview of the software-based HITL systems and their application, we provide Table 4 summarized the representative works in different scenes. The following part will summarize the human-in-the-loop for software-based human-computer interaction systems by the application scenarios.

Application1: security system

As an essential usage of the human-computer interaction system, the security system often requires humans to make sure the system safety (Fig 8). However, to avoid operator attacks or reduce the work intensity of administrators, the manual intervention needs to be moderate and controllable. Studying the effectiveness of warnings in a security system, Wogalter [158] proposed the C-HIP model for analyzing the reason for ineffective warnings begins with a source delivering a warning to a receiver. After several information pro-

cessing steps, the model will determine if the warning leads to behavior changes. Since the proposal of Norman's action cycle and James Reasons' Generic-Error Modeling System (GEMS), these two theories were applied to avoid the gulfs of execution and evaluation in system design [174]. Following the idea of GEMS, Brostoff and Sasse [152] focused on the difference between GEMS described active failures and the latent failures and proposed a model for describing the error in five areas in a more organization-centric way. Considering the idea that humans often fail for security roles, Cranor [153] proposed a human-in-the-loop system in a more user-centric way for reasoning about the human behaviours and identifying potential causes for human failure and analyze the root cause of security failures that have been attributed to "human error". Targeting the situational awareness(SA) error, Singh and Mahmoud [163] proposed a SA component for HITL systems in the Nuclear Power Plant (NPP) and Commercial aviation industry for detecting N time-steps before accident events. The system contains a natural language processing (NLP) model for real-time detect operator HITL error detection via modeling industrial Human Machine Interface (HMI) state transitions. Nowadays, the HITL based security system or components have been widely used in industries.

With the development of internet technology, the security system becomes a wider concept that contains misinformation filtering and fraudulence protection. The workflow of the human-in-the-loop security system for modern tasks can be summarized as Fig 9 in which the artificial intelligence algorithm and humans(experts or crowdsourcing workers) usually collaborate all together. Demartini et al. [164] discussed the challenges and proposed a system combined with machine learning algorithms, crowdsourcing and experts for fighting online misinformation. In their framework, by handling the
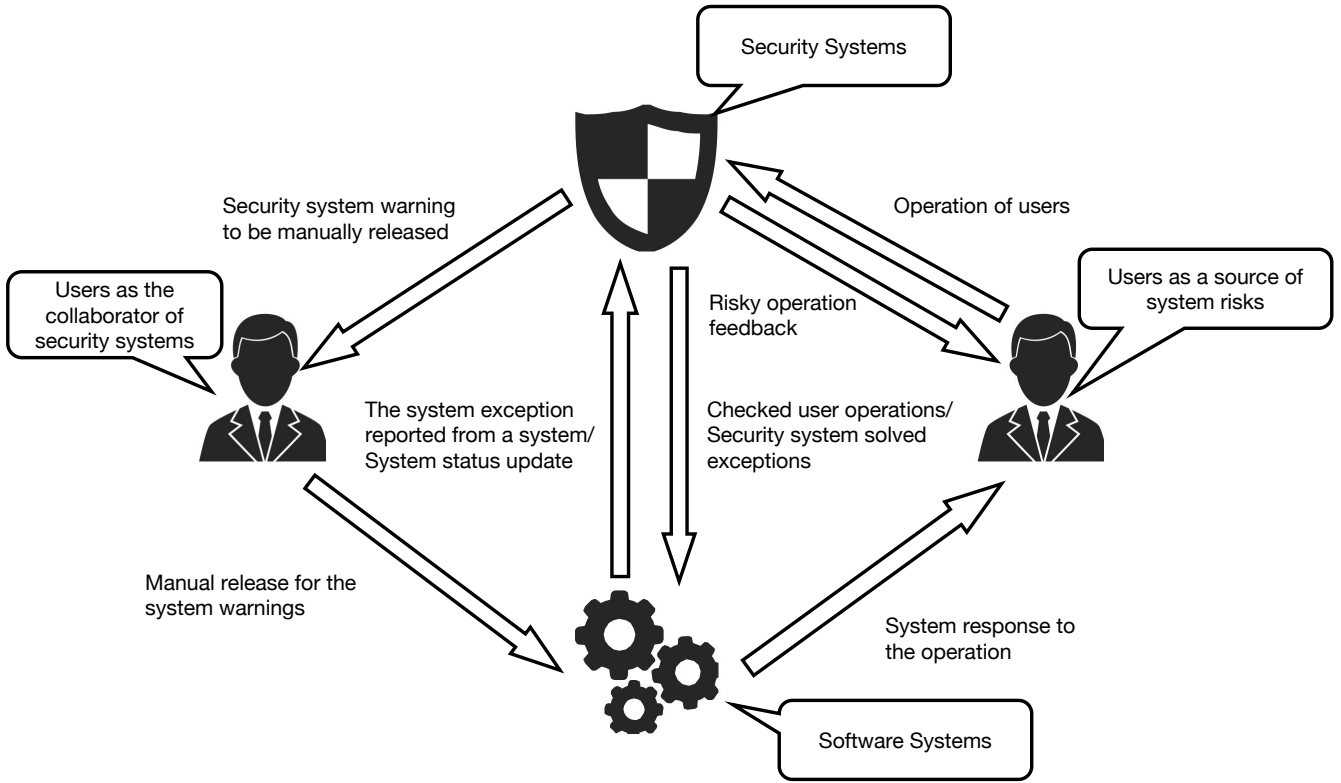
Fig. 8: The workflow of the human-in-the-loop security system.
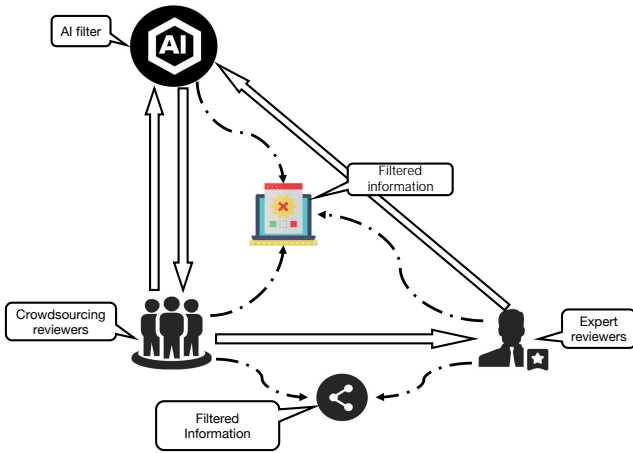

Fig. 9: The workflow of the human-in-the-loop security system in modern tasks

main problem of " who should do what", the cost and effectiveness of three roles can be balanced and the credibility can be improved. For the same purpose, ODEKERKEN and BEX [165] proposed an agent architecture for fraudulent web-shops classification which combined legal case-based reasoning with dynamic structured argumentation. In this system, the human analyst can add new factors to update

system outcomes and present suggestions to the classification algorithm as a supervisor. In recent years, with the further development of Internet Technology, the security system will be an urgently needed area. However, instead of focusing on virus detection and fraudulent information filtering, the usage of human-in-the-loop on more nearly appeared issues such as privacy protection, authentication attack prevention and spam filtering also have great practical value.

Application2: Code Production Tools

In recent years, the industry's requirements for code output have promoted the development of programming tools. Nowadays, what the programmers need is an IDE and a complex system with code checking, programming assistance, and software testing. Moreover, with the proposal of machine learning, the concept of programming tools has been extended to model checking and attribute design. To satisfying the requirement of coders, several systems have been proposed. With the help of these tools the developers in the loop can collaborate on a project with a computer instead of composing the project from scratch (Fig 10). For software testing, MacHiry *et al.* [154] proposed an input generation system for fuzz test of unmodified Android apps called Dynodroid. A novel randomized algorithm with four states and three stages was used to generate testing inputs in their system. In the observer stage, the system determined the layout of
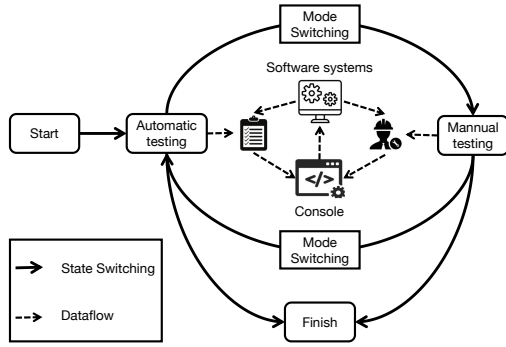
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Fig. 10: With the help of HITL system, human can collaborate a project with computer.

Fig. 11: HITL system in machine learning algorithm optimizing.

widgets and expected input. Moreover, in the selector stage, the randomized algorithm will choose the widget for testing, while finally, in the executor stage, the system executes the testing process. For generating both individual events and sequences of events, Dynodroid allows users to observe an app reacting to events and change the mode to generate arbitrary events during the testing procedure manually. Also targeting human-assisted automatic software testing, Yan *et al.* [157] proposed a human-assisted tool-centered vulnerability analysis system with large scale programs available and better human resources usage. For the practical application, coders often require a tool that can debug and correct a program. The proposed human-in-the-loop debugging tools are usually followed with test-driven repair tools that can achieve ideal performance. Bohme *et al.* [166] proposed the first human-in-the loop semi-automatic program repair system called LEARN2FIX. The LEARN2FIX can be divided into two stages named debugging and repairing. In the debugging stage, similar to the previous works, LEARN2FIX used the mutational fuzzing for test inputs generating and active learning to build up Satisfiability Modulo Linear Real Arithmetic SMT. Afterward, in the second stage for repairing, the GenProg automatic repair tool [175] was used to repair the program with a test suite manually constructed or produced by the debugging stage. The productized tools of human-in-the-loop systems in software engineering have brought great convenience to programmers. In the future, the application of HITL in this area will be expanded from debugging and software testing to most coding procedures. Especially to point out that with the proposal of pre-trained models like BERT [19] and GPT [20], the human-machine collaborative programming is now becoming a new heating point.

Since machine learning entered the applicable stage, the concept of code production tools also has been expanded. To train a machine learning model, in the process of optimizing an algorithm, engineers usually prefer to use automatic tools rather than only relying on their experiences (Fig 11). For the study of model optimizing 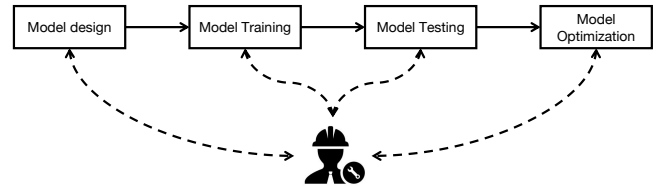in the whole process of machine learning, Renner [167] focused on two aspects named transparency (how to explain a system to humans) and control (how users provide feedback or guide systems) in interactive machine learning. The system combined a novel topic visualization technique and a human-centered interactive topic modeling system. It revealed how the users comprehend and interact with machine learning models and provided a guideline for the further development of HITL systems. In the stage of model design, Salam *et al.* [160] proposed an optimization method for designing attributes of the classification model, which is available in the condition of entirely agnostic to the underlying structures. The method contains two stages: top-k buckets design to provide choices for users. Moreover, the top-l interactive snippets generation for the design of final attributes in which candidates from the former stage were recommended to engineers by the algorithm with their visualized distributions until done crafting the attributes. In the procedure of training, MA [159] proposed a collaboration system that is focusing on execution across iterations optimization by appropriately reusing intermediate results. With the workflow management module and the visualization tool, the user can develop the machine learning model with real-time interaction. The semi-automatic code production tools in machine learning are a new topic but have great potential to be applied by the industry. However, to fulfill this conception, the barrier of model interpretability and the changes of machine learning workflow are still vital issues.

Application3: Simulation System

The simulation system usually uses a virtual system to simulate an object widely applied by many industries such as the entertainment industry, manufacturing industry, and education industry. Due to the feature of these applications, interaction with a human is indispensable. So usually, the role of humans in the loop is the collaborator. In manufacturing, the simulation system is usually used to imitate the operation of humans and its feedback. Demirel [168] proposed a digital human modeling system that injects human factors engineering principles via digital human modeling into a computational design environment to assess the safety and performance of human-product interactions early in design. With the help of this system, the form and function of the characters in the workflow can be pre-designed, and the

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ergonomics evaluation metrics can be used in working loop Implementation. With the usage of robotics in manufacturing, simulation systems have to concern the operators and robots. Metzner *et al.* [169] proposed a simulated human-robot collaboration system that combined virtual reality, motion tracking and standard simulation software of industry robots. The system is utilizing the virtual reality system to simulate the workplace of robots and its collaborator, a motion tracking system to capture the action of humans with the fusion of two subjects. It will evaluate the performance of the human-robot collaboration system safety control and fulfillment of the defined requirements. Moreover, in entertainment, music composition is a complex but exciting task with strict requirements for venues and artistic literacy. To make the opportunity of music composition available to the public, Zhou *et al.* [170] proposed a melody composition interactive system with human-in-the-loop Bayesian optimization. During the process of melody composition, following the idea of deep generative models, the system simulates the composer and studio scene, which generates candidate melodies and the humans in the loop. It will evaluate the favorite one and feedback to the system with the imitating of composer's workflow, several iterations ordinary people can also make good music.

Application4: Search Engine

The search engine itself is a human-machine collaboration system, in which the engine utilizing the feedback of users and refreshing the recommended information and search result priority. Nowadays, focusing on the multimedia search method, the researches mainly focused on the recommendation system and image-based searching. For the recommendation system, Polisetty and Avinesh [171] proposed a new joint recommendation system with review summarizing and rating prediction with a web-based interface for refining the methods by human-machine interaction. Designing two application scenes, imagining parents, and exploring large document collections, the system has shown better interactive performance and recommendation accuracy. With the development of computer vision, searching via images on a searching engine has become a new common practice in daily life. However, the task of information extraction and similarity matching is still an issue affecting the interactive performance and search results having great potential to be improved via introducing users into the work loop (Fig 12). In this area, Kovashka *et al.* [155] proposed an interactive image search system allowing users to communicate preferences through visual comparisons at query time. The system can provide users with a set of exemplar images and collecting the user-initiated and actively system-initiated responses. The system can provide more accurate search results with less user interaction with the iterative learning process than conventional passive and active methods. Following the idea of Kovashka *et al.* [155], Plummer *et al.* [161] proposed

an attribute-based interactive image search system with the ability to iteratively refining the search result via human-in-the-loop feedback. The system is constructed around a deep reinforcement model that was proposed for learning the informative images. The Conditional Similarity Network was used to appending global similarity in training visual embeddings. The system is self-renewable and can provide more accurate image search results. The searching engine is an application satisfying personalized requirements. As a result, the ability of HITL systems to continuously adapt user needs through interactive learning can well meet this need.

Except for the listed applications, the HITL system has also been used in other areas [162, 176, 172, 177, 178, 173] such as bioinformatics, smart healthcare, crowdsourcing. At the same time, the supplement for HITL systems is also a vital direction. For example, Fredrik Wrede and Andreas Hellander [162] proposed human-in-the-loop semi-supervised learning for stochastic gene regulatory, Louis Rosenberg [156] proposed the artificial Swarm Intelligence dispatch system for crowdsourcing tasks and Li *et al.* [173] proposed the model checking approach for human-in-the-loop systems. With the further development of human-computer interaction-based systems and the expansion of application scenarios, the human-in-the-loop will be used on more occasions. However, there is one thing that has to doubt that, as the system structure becomes more and more complex, the usage of pure software systems in daily life is limited. Moreover, the introduction of hardware components can be a vital means to improve the performance of HITL systems. From our point of view, with the development of human-computer interaction technology, the HITL systems will become more comprehensive in most scenarios. However, a few scenes for software-based HITL systems will also exist.

4.2. Software & Hardware Integrated HITL System

The software & hardware integrated HITL (SHI-HITL) system, a system with mechanical structure entity and software control system, is a more complex system that contains the control algorithm, software-hardware communication, and the interactive interface for humans. In these systems, the role of humans in the loop becomes more diversified such as controller, assistant, supervisor, collaborator and even the environmental factors. Nowadays, various SHI-HITL systems have been widely applied in interactive wearable devices, healthcare, robotics, etc., and the application of SHI-HITL is now expanding rapidly to other regions such as traffic dispatch systems and home automation. Similar to the software HITL systems, human roles can be distinguished via the application scenarios, which will be the mainline of this paragraph. A brief overview of SHI-HITL system works and applications is provided in Table 5.

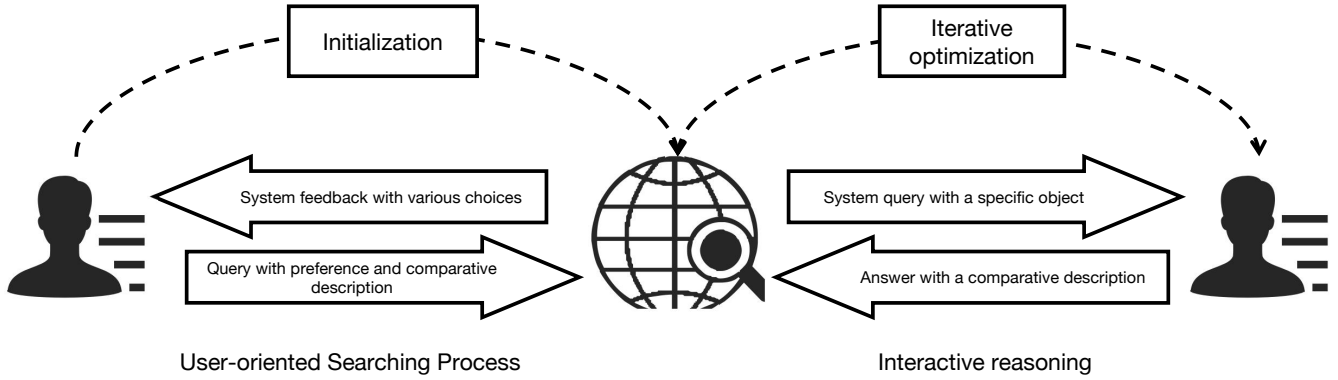**Application1: Robotics**

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Fig. 12: The HITL usage for image search system.

As one of the most complex software systems, the robot systems are usually composed of perception mechanism, control mechanism and executive mechanism. In the control loop of robots, the common roles of people are controller and collaborator. However, people tend to ignore that in some robot-centric applications, humans usually play some supporting roles such as the supervisor (supervise the execution of robots) and assistant (robot's helper). Moreover, the humans themselves are the influencing factors of robots in some scenes. Adolfo and Yu [190] proposed a method for robot end-effector with the Euler angles solution in which the operator, a co-worker and supervisor, of the robot can feedback to the robot of the information about how close the end-effector of the destination reference is in the outer control loop. Afterward, via the Euler angles-based parsing, the robot end-effector optimizes the trajectory. Conor Walsh [186] focused on the soft wearable robots development, which utilizes the method of offline simulation and online optimization. In this workflow, the human is designed as the assistant (auxiliary motion control optimization) and the controller (the user of robots), optimizing the robot system step-wise. Considering the safety of human collaborators, Eder *et al.* [181] summarized the emerging standards, requirements and approaches in machine learning-based robotic algorithms. Afterward, eyes on the human-centric robot systems, the work proposed a criterion for high levels of safety and ultimately trusted in human-robot collaboration systems. Considering the human as a controller in robot systems with cyber systems, Dimitrov and Padir [182] proposed a universal control architecture for robots in multiple scenes via cyber system transportation. In the system, the control instruction of humans is converted and uniformly coded by the cyber system and encoded by machine-adapted instruction set afterward. Gopinath *et al.* [184] focused on user-driven customization of shared autonomy for assistive robotics and proposed the interactive method with personalized optimization. In this system, except for the original offline training and online execution, the proposed optimization procedure made the human supervisor and controller available to tune the robot performance by personal optimality criterion. In this work, an issue is also be focused on the controllers of the assistive robots usually prefer retaining more control instead of better performance which cannot be ignored in HITL robotic system design. Abraham *et al.* [200] proposed a solution of robot and human collaboration for vision tasks. In the system, the human was required to make decisions for the doubts thrown by the robotic vision control system. Through interactive learning, the robot vision system has the ability to autonomously optimization.

Application2: System Optimization

Except for constructing a comprehensive human-in-the-loop system such as robots, focusing on the performance optimization of an SHI-HITL system such as energy-saving and interactive optimization also be a task. Unlike the systems in which people as controllers or collaborators, in this application, humans' role tends to be the impact factor of the system. To be distinguished from the role of humans actively interacting with the system, humans as an impact factor usually passively interact with humans via information such as physiological signals or posture. Aiming to cut the energy waste of SHI-HITL systems, MUNIR *et al.* [180] discussed that the energy waste in a HITL system usually appears during the opening of the interactive interface when it is not needed. As a result, in the work [180] a control loop with multilevel sensing and adaptive timeout interval was proposed with experiments that proved an 80.19% energy waste cut for the SHI-HITL system. On the other aspect, reducing the energy cost of the user in the SHI-HITL systems is also a vital task. Fang and Yuan [191] targeting to the wearable robot application and proposed the Computed Muscle Control (CMC) tool with OpenSim software interface and Bayesian optimization. By detecting the specified movement of users, the system can find the optimal design scheme to reduce the human metabolic energy cost. Except for focusing on energy waste, better feedback mechanisms and interact optimiza-

Table 5: An overview of representative applications for SHI-HITL systems. (ROB: Robotic Systems. SO: System Optimization. SH: Smart Healthcare.)

Systems	Application				Year	Role of human					Discription
	ROB	SO	SH	Others		Supervisor	Controller	Assistant	Collaborator	Impact Factor	
Bauckhage et al. [179]				✓	2005		✓		✓		Interactive vision system
Munir et al. [180]		✓			2013					✓	Energy saving
Eder et al. [181]	✓				2014	✓			✓	✓	Safe collaboration
Dimitrov & Padir [182]	✓				2014		✓				Universal robotic control
Lam & Sastry et al. [183]		✓			2014					✓	Ergonomics
Gopinath et al. [184]	✓				2016			✓	✓		Shared autonomy
Holzinger [185]			✓		2016	✓	✓	✓	✓	✓	Interactive system application
Conor Walsh [186]	✓				2018		✓	✓			Soft wearable robots
Sutton et al. [187]			✓		2018	✓			✓		Trustworthiness mechanism
Inoue et al. [188]		✓			2019	✓			✓		Weakly control
Mello et al. [189]			✓		2019		✓				Ergonomics
Adolfo & Yu [190]	✓				2020	✓	✓				Robotic sport control
Fang and Yuan [191]		✓			2020		✓			✓	Ergonomics
Papallas et al. [192]		✓			2020		✓				Group control
Zhou et al. [193]			✓		2020	✓			✓		Privacy protection
Paikens et al. [194]				✓	2020				✓		Service industry
Lee et al. [195]				✓	2020	✓					Traffic control
Usman et al. [196]				✓	2020	✓			✓		Traffic control
Cicirelli et al. [197]				✓	2020		✓			✓	Home automatic
Cimini et al. [198]				✓	2020		✓		✓	✓	Production systems
Gil et al. [199]				✓	2020				✓		Interactive system theory
Abraham et al. [200]	✓				2021	✓			✓	✓	Shared autonomy
Ciabattoni et al. [201]			✓		2021	✓	✓				Trustworthiness mechanism
Fosch-Villaronga et al. [202]			✓		2021	✓	✓	✓	✓	✓	Surgery automation

tion can be another issue. Lam and Sastry [183] proposed a unified framework called partially observable Markov decision process(POMDP) for modeling the feedback of three components of SHI-HITL systems named human model, the observation model and the dynamic machine model. The proposed framework benefits from reasoning human internal state, handling observation errors, and balancing the feedback to humans and machines. In order to deeply optimize the control work for humans-in-the- loop, the concept of weak control has been proposed with a basic idea of "decision of the decisions". Inoue *et al.* [188] proposed a weak control framework for SHI-HITL systems. In the framework, when the manual decision is required, humans can be provided several automatic choices by controllers. What users should do is choose one based on their preferences. Afterward, with the execution of the control actions, the controller can be fine-tuned to make more effective choices in the next loop. When the system becomes more complex with multiple SHI-HITL systems in parallel, the control becomes a more difficult task, sometimes leads to a system crash. For handling the problem of high-dimensional solution searching and uncertainty problems, Papallas *et al.* [192] proposed an online-replanning method for the systems. The systems have to search for trajectories and the human can be focusing on solving the task of high-dimensional solution searching. With the prospect of the framework in paper [192], the required effort can be minimized and a single human controller can instruct more parallel SHI-HITL systems. The human-in-the-loop for system optimization can be widely used for human-computer interaction systems with the income of reducing workforce and energy expenditure, which significantly benefits the industries.

Application3: Smart Healthcare

As a particular application, healthcare requires more than performance and Interaction fluency, which is the privacy protection, credibility, and low time latency. In this application, the role of humans mainly tends to be supervisor, controller and assistant. Except for the point of humans' roles, we also keep eyes on how systems can meet the unique requirements in this application. As a life-critical application scenario, the healthcare system is highly dependent on the human supervisor as the last insurance. However, this has also led to the long-term drawbacks that intelligent systems can only play an auxiliary role and cannot free users from operations and decision-making. Aiming at this problem, Sutton *et al.* [187] proposed the system with verifiable trust for collaborative health research using blockchain technology. In order to build up trust between humans and AI tools, in this system, the developer makes it available that the transformations of data are transparent and verifiable to all the users. The work [187] also defined the trustworthiness mechanism and the architecture based on trust requirements. For the disabled users or the inexpressible scenes, the brain-computer interaction (BCI) system can provide another path to supervise the system. Ciabattoni *et al.* [201] proposed a safe navigator with BCI for the intelligent wheelchairs. In this system, BCI was equipped to supervise the safety when possible problems happened to the system, such as wrong action and environmental conditions dangers. During the automatic path

planning, when the system is in a dangerous state, the BCI can transfer the error-related potentials signals (ErrPs) of humans into warnings and modify the trajectory planning. Except for trustworthiness, privacy protection is another issue. Zhou *et al.* [193] designed a scheme of HITL-aided healthcare system with consideration of privacy protection. The system contains block-designed hospital equipment, wearable health devices, the patients and doctors by which the data can be processed uniformly. Besides, the diagnoser is unavailable to the patient's personal information with the specially designed workflow and the distribution mechanism. For which the diagnosis can be guaranteed by professionals and will not reveal personal privacy. For a specific intelligent healthcare system, time latency and processing capabilities limitations are common and restrict system functions and performance. With the proposal of cloud computation, the SHI-HITL system can transfer some operations that require large-scale calculations to the cloud with the cost of increasing time consumption on data transportation. To develop a HITL intelligent healthcare system, Mello *et al.* [189] tried to balance the local and cloud computing for automatic operations with less time latency and better performance when collaborating with the controllers. For further analyzing the performance and latency, infrastructure-related quality of service (QoS) and user-perceived quality of experience (QoE) metrics were introduced. Taking an intelligent walking-assistant system as an example, Mello *et al.* [189] found out the interplay mechanism among QoE requirement, QoS and system performance. Except for the system optimization for the HITL smart-care systems, some works also focused on more conceptual issues. For example, Holzinger [185] further discussed the usage of SHI-HITL systems in smart healthcare and the challenges. Besides focusing on surgery automation, Fosch-Villaronga *et al.* [202] further discussed the role of humans with a prospect of six automation levels. Healthcare is a human-centered application with a long way to mature technology. As a result, using human-in-the-loop systems in smart healthcare applications will last for a long time until the arrival of fully automatic.

Except for the application scenes of SHI-HITL system summarized above, the system has also been utilized in the service industry [194], traffic control [195, 196], home automatic [197], production systems [198] as well as other interaction systems [199, 179, 203].The SHI-HITL system will be continuously studied, and new sensors, control algorithms and interaction mechanisms will be applied in this field. Besides, as a trend for decreasing the human work intensity and using human supervision and decision-making in the most important places, more detailed human role division will become another focus of system construction.

Summarized from the previous works in both software-based and the software & hardware HITL applications, three directions have been focused on during the development of HITL system named performance, fluency and reliabil-
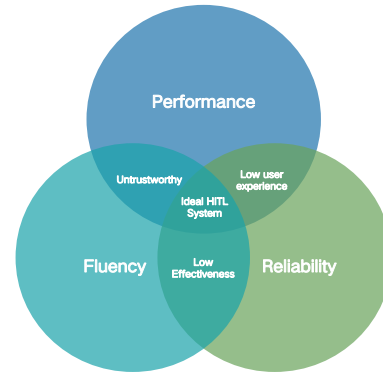

Fig. 13: The ideal HITL system can trade-off the Performance, fluency and reliability.

ity(Fig 13) [204]. For the purpose of performance, the human usually plays the role of collaborator for the calculation refinement. While for the fluency, a new mechanism for interaction as well as new interface such as BCI [201, 205, 206, 207] have been proposed. Moreover, the human can be the impact factor and the supervisor for detecting errors and danger for reliability. To be pointed out, different from the works of scientific research tend to pay more attention to accuracy, the system application has to trade-off the user experience and performance as well as the special requirements of the scenes. The HITL system is a complex class of systems still expanding its application scenarios and providing users with better performance and experience [88, 208, 209, 210]. And it can prospect that the involvement of humans will decrease in quantity and increase in quality until the arrival of the fully automated phase.

5. DISCUSSION AND FUTURE DIRECTIONS

In this section, we first discussed HITL in NLP and CV, then we will discuss the challenges of HITL in real-world applications, and finally, we will summarize these challenges and propose some Interesting questions. To facilitate more researchers developing more advanced human-centered HITL NLP systems, we summarize the following concrete challenges for HITL NLP systems:

- For systems like a chatbot, automatic summarization tool, or commercial machine translation, when users interact with them, individuals can only give a reward signal to the one output that is sent to them, which leads to the sparsity in feedback concerning the size of the output space [211].

- More intelligent questions about other types of parsing uncertainties needed to be explored to obtain feedback for syntactic parsing [48].

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- For human-in-the-loop topic modeling, lack of trust or confidence is a challenge to consider [88].

- On the AI safety side, among existing HITL techniques, some of them also allow malicious individuals to efficiently train models that serve their purpose, which may cause damages to all aspects of society. For example, they could exploit human feedback to fine-tune a language model to be more persuasive and manipulate humans' beliefs, instilling radical ideas, committing fraud and so on [91].

To facilitate more researchers developing more advanced human-centered HITL CV systems, we summarize the following concrete challenges for HITL CV systems:

- It is necessary to pay attention to predictive parameter optimization based on supervised regression models and scientifically analyzing correlations between the parameters of different algorithms for HITL image restoration [127].

- In order to obtain a better estimation of cluster membership with the fewest image enhancements by the user, how to include an active selection of images is still a research problem [136].

The challenges both NLP and CV have in common:

- Human supervision may be preferable due to various levels of expertise and with the increase of work overload, erroneous decisions are potential to occur [212].

- Collect and share more human feedback datasets for different tasks of NLP and CV.

- We should consider user credibility to affect the influence of their annotations by analyzing the quality of provided feedback[76].

- More rigorous in-depth user studies need to be designed and conducted to evaluate the effectiveness and robustness of human-in-the-loop frameworks in addition to model performance [88].

- How to formulate a paradigm to rate the quality of collected user feedback since it can be sometimes noisy and even misleading [211]?

- How to find an efficient way to dynamically pick up the most representative and valuable feedback to collect [213]?

- How to display what exactly the model has learned from the feedback and what kind of feedback is crucial? How to visualize the changing process of the model after incorporating the human feedback [214]?

And the challenge in real-world applications can be more complex, which contains the trade-off among the requirement, system configuration, and the user experience. And this derives the following challenges:

- To avoid frequent human feedback, it is very important to choose an appropriate artificial intervention time. Especially the tasks with strong demand for reliability and safety, frequent responses are exhausting, while the untimely manual intervention is unacceptable.

- For a system with human-computer interaction, users' expectations of experience usually take precedence over performance. As a result, the consideration of more than tasks is also a challenge for engineers.

- With the introduction of new sensors for human-computer interaction, the unique modeling of these signals is significant for system integration. Especially since the proposal of BCI, the unified coding of abstract and concrete information is still a challenge.

- Human hints are still stuck on simple judgment such as accept/ decline or the directions. This kind of information utility is difficult to be used by algorithm systems to improve performance. So, the improvement of the feedback mechanism also is a challenge.

- Different from the preset conditions for scientific research, real-world applications have to confront more influencing factors, including the domain variation, the interference, and the "out of range" samples. This requires the system algorithm to have high robustness and generalization ability.

- With the limitation of computing power, the lightweight of the local algorithm system has become a vital link. However, this often leads to the decline of performance. With the proposal of cloud computing, these new methods seem to tackle this problem. However, usually, the time latency is unacceptable due to user experience and task requirements. As a result, balancing the computation for local and for cloud platforms will be a new issue.

Besides, we introduce some exciting questions. **How to add human experience and knowledge to computer vision tasks?** By our review of the previous work, we find most of the human-in-the-loop research only still focuses on natural language processing. Analyzing the reasons, it is difficult to directly allow people to interact with images effectively(except for direct labeling) and to add human's experience and knowledge to the model throughout the cycle. With the development of multi-modal technology, using multi-modality for image representation may be an effective way [215].
How does the model learn human knowledge and experience from a higher dimension? The goal of human-in-the-loop is to connect humans to the model loop in some way

so that the machine can learn human knowledge and experience during the loop. Most of the current methods achieve this goal through human data annotation, but data annotation is only the most basic realization process. We should think about how to help agents acquire this knowledge effectively [216]. Language is an experience accumulated in the human learning process. At present, researchers focus on using human intervention in dialogue to enable machines to learn human knowledge in dialogue and push the to machines approach human intelligence better [217]. In addition, many reasoning tasks contain higher-dimensional knowledge. By integrating humans into the reasoning loop, the machines can also learn more human experience [153]. Image quality evaluation and design tasks are a higher level of human activity. Although human aesthetics and design inspiration can constitute the theory, however, more inspiration and aesthetics still come from human experience [218]. If we can find a way to let the model learn more expert experience, the model's improvement is significant.

How to select key samples? The key technology for the human-in-the-loop is obtaining key samples and labeling them with human intervention. At present, researchers mostly use confidence-based methods to obtain key samples. This method plays an irreplaceable role in classification tasks [219, 220, 221, 222]. However, for other tasks (for example, semantic segmentation, regression, and target detection tasks), confidence is not the effect is not so obvious. Active learning aims to train an accurate prediction model with the least cost by marking the examples that provide the most information. There are many mature and worthy reference methods in selecting examples, and perhaps we can obtain inspiration from these methods [223].

How to construct an evaluation benchmark? For the development of the entire community, providing an effective test benchmark is an important task, it means can attract more researchers to conduct research. At present, there is no uniform standard for human-in-the-loop research benchmarks. To better explore this research topic, it is important to study how to develop evaluation methods and benchmarks for human-in-the-loop systems. Moreover, the formation of a unified benchmark is also conducive to the further refinement of research [47]. The current human-in-the-loop-based research is a bigger direction for exploring ways that are more conducive to human-in-the-loop. Besides creating the standards for these interaction methods, restricting and theorization are also particularly important.

Is it possible to realize a more general multitasking model through human-in-the-loop based on a structure similar to transform? The real-world task is complex, and in the current form, it is not easy to completely solve it by one characterization [224]. With the emergence of a unified large-scale pre-training model [225, 17], we have seen the hope of achieving a universal model through human-in-the-loop fine-tuning. However, there are still many problems that need to be solved in this process.

6. CONCLUSION

In this paper, we review existing studies in human-in-the-loop techniques for machine learning. We first discuss the work of improving model performance from data processing. Then, we discuss the work of improving model performance through interventional model training. Finally, we discuss the design of the system independent "human-in-the-loop". Besides, we provide open challenges and opportunities and introduce some exciting questions.

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