Human Computer Interaction

Sangeeta Ramachandra Yadav*

Faculty Head, Computer Science and Applications, S M Joshi College, Hadapsar, Pune-28

Abstract - In recent years, the multidisciplinary field of human-computer interaction has emerged as an exciting new area for study. The use of human-computer interaction to construction safety management has increased throughout the fourth industrial revolution, which has considerably aided the development of hazard detection in the construction sector. However, only a small number of researchers have thoroughly examined how human-computer interaction has evolved in the detection of building hazards. In this study, ACM Digital Library, Web of Science, Google Scholar, and Scopus were used to assess 274 relevant publications published between 2000 and 2021 in the field of human-computer interaction in construction hazard detection (CHR-HCI). Human-computer interaction has had a substantial impact on danger detection during the last two decades, according to the research. In addition, a number of new research areas have been created as a result of this work, Experiments that include multimodal physiological data analysis, intuitive gadgets and sensors as well as the development of a human-computer interface safety management platform using big data are all included in this project. Virtual reality, ergonomics, computer vision, and computer simulation will be the emphasis of future research modules. In this work, we constructed a theoretical map that reflected the findings of previous studies and their connections, and for the future development of human-computer interaction in the field of threat detection, we gave guidance.

Keywords - Human-Computer Interaction, Computer Science, Artificial Intelligence, Human Factors Engineering, Cognitive Science

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INTRODUCTION

Artificial intelligence (AI) is used to a system in machine learning (ML), where the system learns from its prior experiences without being explicitly programmed. Its main objective is to learn on its own, without assistance from humans, and to change how the systems behave. Systems use a number of models for learning. Using data streams produced by ubiquitous devices, these models may be created to learn online. This process is known as stream learning or online learning. In a process known as offline learning, models may also pick up new information from prior data.

One of the issues in computer-related applications that is expanding and gaining popularity most quickly is the integration of online data systems. Thanks to recent developments in communication technology, entities may communicate with one another. Entities are capable of listening, responding, and communicating with one another as well as with their environment. By 2020, it is anticipated that between 25 and 50 billion internet-connected gadgets will be in use for a variety of purposes. [1] Actuators and sensors are put in the outside world to sense parameters in Internet data. Through communication networks, these devices talk to one another. The same network is used at the collecting centers to provide the measured parameters as raw data. Given that the internet has grown to be one of the most significant sources of new data and raw data, data science offers a fresh and significant opportunity to improve the intelligence of online data applications.

LITERATURE REVIEW

Yang, J., et al. (2013) present Mem-Brain, a unique method that combines related mutations with several machine learning classifiers to identify trans-membrane inter-helix connections from amino acid sequences. Mem-Brain outperforms the best method currently available in the literature by 12.5 percent, attaining an average accuracy of 62% when tested on 60 non-redundant polytopic proteins using a stringent cross-validation approach that leaves one out. For 13 recently solved G protein-coupled receptors, the Mem-Brain contact predictions boosted the transmembrane TM-score of I-TASSER models by 37% when they were used. In the absence of all G protein-coupled receptor templates and homologous templates with sequence identity more than 30%, the number of foldable occurrences (TM-score >0.5) rose by 100%. Progress in contact prediction has been made, which suggests structural models of transmembrane proteins could be contact-driven.

Adhav, K., Gawali, S.Z., and Murumkar, R. (2014) demonstrate the potential applications of several methods, and GSRank, in addition to models for factor graphs and behavioural footprints and checks for rating consistency and temporal pattern discovery. In the past, word of mouth advertising for products was only allowed between individuals. Traditional marketing strategies move away from in-person contacts and toward online reviews as public relations technology develops. These online reviews serve as valuable input for both clients and service providers or enterprises. Making decisions on the caliber of goods or services is made easier with the help of these reviews. For marketing choices, service or product performance assessments, and improvement, businesses or suppliers use opinions. However, not all users or customers publishing reviews have the same objectives in mind. It's possible for reviews to be created to either praise or mock a product. Determining how many reviews are spam and how many are genuine is essential. Deceptive reviews, non-reviews, and brand-specific evaluations are just a few examples of the many different types of spam reviews. A single person or a group of people, known as a group reviewer, may write a review.

Behjat A.R. et al. (2013) provide a particle swarm optimization (PSO) based feature selection method that decreases dimensionality while enhancing spam email classification precision. When fish or birds gather in groups, PSO mimics their social behaviour. The optimal feature subsets are found by scanning the feature space using a PSO-based feature selection technique. The high dimensionality of the feature selection process and the low classification accuracy of spam emails are to blame for the problems with an email spam detection system. A global optimization issue known as feature selection (FS) in machine learning reduces unnecessary and undesired data while providing a set of acceptable outcomes with high accuracy. On the other hand A fitness function dictates the rate of evolution of the selection feature. Ling-Spam and Spam Assassin databases are used to evaluate classifier performance and feature vector length as inputs to classifiers. Using the PSO-based feature selection strategy, the researchers were able to obtain great feature selection outcomes with the fewest number of selected features due to the high accuracy of spam email classification using the Multi-Layer Perceptron (MLP) classifier.

Ott, M., et al. (2011) In this study, we explore misleading opinion spamfalse views that have been deliberately created to seem realcases of opinion spam that can be recognized by humans. Online ratings, reviews, and product research are all growing trends among consumers. As a consequence, websites with user reviews are increasingly being targeted by opinion spam. We create and evaluate three methods for spotting bogus opinion spam, On our gold-standard opinion spam dataset, a classifier developed using the work of computational linguistics and psychology was able to correctly classify more than 90% of the spam. On the basis of feature analysis of our learned models, we also provide a number of theoretical advances, such as establishing a relationship between inventive writing and incorrect beliefs.

The results of Fei et al. (2013) and human assessment indicate that the suggested approach outperforms reliable baselines, proving the strategy's utility. This opens the door for us to establish a network of reviewers who submit their work in spurts. Using a Markov Random Field (MRF) and the Loopy Belief Propagation technique (LBP), the next step is to assess whether a reviewer in the network is a spammer or not. We also provide a variety of features and make use of feature-induced message forwarding in the LBP framework for network inference. Additionally, based on supervised classification of their reviews, we provide a special evaluation method for automatically rating spammers that have been found. Additionally, we work with domain experts to do a human evaluation of the identified spammers and non-spammers.

METHOD AND DATA ANALYSIS

We used electronic mail to send out surveys to participants in order to get data regarding the use of ML in HCI work. The survey was based on a standardized methodology with five sections, numbered I through V. We employed sections I through III to record details about the location, task, and domain of HCI application usage by participants. The usage of ML in HCI work was recorded in Parts IV and V. Respondents had the option to explain why they have not employed machine learning in their HCI work in part V. A small team of HCI professionals gave the protocol's preliminary version a thorough analysis. Throughout this process, a number of ML and HCI-related topics were explained and improved. In the protocol, it is clear that neither ML approaches nor HCI areas of interaction, tasks or application domains are orthogonal. However, individuals who work in ML or HCI distinguish between ML approaches and aspects of HCI work using comparable concepts, and the protocol perpetuates this prejudice or reality. FTP access to the protocol and raw survey data is available at ftp.ics.forth.gr/pub/machine learning. The protocol is included in the file survey96.txt, while the raw survey answer data is contained in the file survey96.xls.

PART I: AREA OF HCI INVOLVEMENT

We identified eight distinct HCI engagement areas and asked respondents to choose which ones they were most actively interested in. Table 1 gives a summary of the replies. The majority of respondents chose user interface design and assessment. The majority of the unique comments (17) were from the same place (Table 1). Our contingency matrix provides 2'2 interactions between areas since several respondents claimed that they were active in various HCI areas multiple times. Table 2 presents an overview of the outcomes of the contingency.

1. The majority of responses—about 80%—concentrate on four HCI-related topics: computer-supported cooperative work (CSCW), product or service design and assessment, user interface design and evaluation, and education, training, and intelligent tutoring systems (ITS).

2. Only 25 respondents claimed they were involved in just one area. However, UI was chosen by 17 out of 25 people, or 68 percent, of those who made just one choice. Even when coupled with other areas, UI still remains the primary HCI participation; see Table 2.

Table 1. Areas of HCI Involvement

Area of HCI involvement	Abbreviation	Number of responses	Involvement in one area only
User interface design and evaluation (including display mouse devices)	UI	101	17
Product or services design and evaluation	PS	54	2
Concurrent engineering	CE	7	—
Computer-supported cooperative work	CSCW	37	2
Human-robot interaction	HRI	5	—
Education, training, and intelligent tutoring systems	ITS	34	—
Virtual reality	VR	19	1
Other	OTH	24	3
Total		281	25

3. As can be seen from Table 1's OTH item, we only missed 9% of the replies that were sent.

PART II: HCI TASK INVOLVEMENT

Indicative HCI exercises were added in the questionnaire's second section. Respondents were asked to indicate which duties in their professional or academic career they are most invested in. The distribution of the replies is shown in Table 3. It was suggested to the respondents to choose as many sections as they felt were required. Per respondent, an average of 4.90 tasks were chosen. We deliberately avoided making an orthogonal list of activities in order to make the survey participants' lives easier. People often use many names to refer to the same subject. Usability engineering (UE), user modelling (UM), creating and assessing multimedia systems (MU), and modelling were the most often occurring tasks.

Table 2. Interdependence of HCI's many facets

	PS	CE	CSCW	HRI	ITS	VR	OTH
UI	51	6	34	3	34	17	20
PS		5	17	2	20	10	13
CE			5	1	4	—	2
CSCW				1	15	7	9
HRI					1	3	—
ITS						10	8
VR							4

Entries show concurrent participation in two different areas. For instance, 51 replies that indicated participation in both product design and user interface design (UI) were obtained (PS). For an explanation of the acronyms, see Table 1.

Table 3. Involvement in various parts of the HCI job distribution

HCI task involvement	Abbreviations	Number of responses
Adapting, customizing, or optimizing systems according to user need and requirements	AD	80
Interoperability between systems	IO	17
User modeling	UM	61
Usability engineering	UE	66
Modeling of cognitive behavior	CB	44
Knowledge elicitation of human expertise	KE	31
Knowledge acquisition	KA	14
Network access and network services	NW	23
Work methods and organizational design	WO	28
Multimedia system design and evaluation	MU	57
Planning and scheduling	PL	16
Natural langauge understanding	NL	9
Classification and prediction	CL	14
Conflict resolution	CR	5
Information retrieval	IR	35
Case based reasoning	CA	10
Execution and control	EC	13
Critiquing and error engineering	CE	11
Safety and risk management	SR	11
Verification and validation	VV	6
Other	OTH	9

Each respondent had the option to pick several tasks. 4.90 tasks are completed on average by each respondent. There are 560 respondents and tasks total. Cognitive behavior (CB), followed by information retrieval, is the task abbreviation (IR). They represent more than 60% of all responses taken together. Few significant interactions between tasks were found by contingency analysis of answers (see Table 4). In order to achieve the highest level of adaptability and system optimization, user modelling (UM), usability engineering (UE), and multimedia system design and assessment (AD) were all used together (MU). Additionally, there are significant correlations between MU and information retrieval, AD and UE, UM and cognitive behavior modeling (CB), and UM and MU (IR). On the other hand, a number of other activities within the overall universe of tasks managed to attain quite modest contingency interaction. This multidisciplinary approach may be seen in Tables 3 and 4. Supporting such job with ML or any other technological source is not an easy task.

PART III: HCI APPLICATION INVOLVEMENT

The final section of the survey asked about respondents' application demographics. Table 5 provides a summary of the replies. Participants had the option of choosing more than one HCI application area. Table 3 lists the task abbreviations for education, training, and public. Rows having a contingency less than or equal to ten are excluded from the calculation. Sector, media, and aviation/aerospace are the most active HCI application domains. An average of 1.88 application domains were participated in by each responder. The public sector, education/training, and media/entertainment sectors all attained their maximum levels of contingency, as did the public sector and media/entertainment. Additional than 8, there were no other contingencies. However, comments about application involvement are consistent with those for HCI task and involvement area. They give a comprehensive view of HCI work and research as a whole.

Table 5. Responses from various HCI application areas distributed evenly

Application	Number of responses
Aviation/aerospace	21
Chemical/food industry	6
Electric power industry	3
Manufacturing	16
Shipping industry	6
Medicine	14
Education and training	51
Media or entertainment	25
Public sector	31
Software engineering/telecommunications	12
Other	25
Total	210

PART IV: EXPERIENCE AND USE OF MACHINE LEARNING IN HCI WORK

Section 4 of the questionnaire questioned respondents how often they used ML in their HCI work and how much they knew about alternative ML paradigms, and their level of happiness with ML. In a variety of ML paradigms, we asked participants to judge their own performance. Earlier work on ML research and application categorization provided the inspiration for the paradigms. Regardless of their degree of ML competence, we also asked participants to say if they had utilized machine learning in their work and to name the various ML paradigms they had used.

We asked respondents to grade themselves on a discrete seven-point scale using the following categories: There are three levels of familiarity: none, some knowledge, and some information that has been applied or extensively studied at least once. To map out the distances between locations, we used intermediate points. We provide a summary in Table 6. Out of 112 participants, 41 acknowledged utilizing or currently employing machine learning in their job. Table 6 shows how often the 41 ML users used each of the ML paradigms. Users of ML, on the other hand, seldom adhere to a single paradigm. Table 7 presents the results of two contingency analyses and estimates of the frequency of ML use, which demonstrate that each respondent has used an average of 2.3 paradigms. Contingency analysis across ML paradigms used in HCI work shows the substantial roles that neural networks (NNL), statistical learning methods (SL), rule induction (RI), and case-based learning (CBL) have played in the construction of HCI-ML applications.

Table 6. Understanding of machine learning concepts and the regularity with which ML paradigms are used

Machine learning paradigm	Abbreviation	Average score ($N = 112$)	Frequency of use
Neural networks (or connectionist models)	NNL	3.6 ± 1.4	12
Genetic algorithms	GA	2.4 ± 1.3	6
Case-based learning (or instance-based learning)	CBL	2.8 ± 1.6	9
Rule induction	RI	3.0 ± 1.7	19
Statistical learning models	SL	2.8 ± 1.7	18
Reinforcement learning	RL	2.3 ± 1.6	4
Knowledge discovery in databases (data mining)	KDD	2.5 ± 1.5	3
Knowledge refinement systems	KRS	2.5 ± 1.5	6
Conceptual clustering	CC	2.3 ± 1.7	10
Inductive logic programming	ILP	2.3 ± 1.4	7

The responses are scored on a seven-point discrete scale, with 1 indicating complete unfamiliarity (with the related ML paradigm) and 7 denoting extraordinary familiarity (with the paradigm). The average values are accompanied by estimates of the standard deviation. 2.20 is the average contingency. Table 6 introduces abbreviations. There are no missing entries. Inductive logic programming (ILP) is a major improvement since it provides the user with advanced knowledge representation, inference, and learning processes and is expected to enable application development in the future. ML knowledge scores were not particularly high on average; they varied from 2.3 for inductive logic programming to a minimum of 2.3 for reinforce-ment learning, conceptual clustering, and neural networks (NNL) (ILP). Average rating, however, masks people' true ML abilities. A distinct image appears if we average numbers using the highest evaluations for each participant. In any case, we shouldn't expect responders to be masters of every ML paradigm. In fact, this isn't even true among ML researchers, according to a study by Moustakis et al. So we took the top evaluations from each participant, regardless of whether they had or had not used ML in HCI work, and averaged them over all ML paradigms and responders. The approach's average rating was 4.8 1.5, which is approximately the same as the rating for using it at least once or doing extensive study on it.

Table 7. Relationship between the highest degree of ML awareness and the use of ML in HCI research or work

	ML rank higher than (or equal to) 4	ML rank lower than (or equal to) 3
Has used ML in some HCI task(s)	40	1
Has not used ML in any HCI task(s)	44	27

If you're familiar with machine learning, we recommend using a threshold of 4, which is halfway between knowing a little bit and having done extensive research on the topic. As a whole, the number of respondents (N = 112) and their responses to the survey are correlated. individuals who have at least a basic understanding of the ML paradigms. On the other hand, ML usage in HCI work seems to have been affected by good ratings for at least one ML paradigm. By using the number 4 as a criterion (which sits between the knowledge levels "has some knowledge of" and "used it at least once or studied extensively"), we were able to determine that 40 out of the 41 ML users had ML skills that were above the cutoff point. There was a wide range in the average degree of familiarity across all ML users, from having used it just a few times to having done substantial research on it. While 44 respondents claimed to be knowledgeable about machine learning (ML) at a level of 4 or above, they had not yet used ML in their HCI work. Also included in this component of the questionnaire was a satisfaction rating for those who have used ML in HCI research. It was determined by a five-point scale: 1 poor, 2 little, 3 good; 4 excellent; 5 excellent. There is an average level of satisfaction for all ML users of 3.3, which is greater than the a goodo norm.

PART VI: WHY ML HAS NOT BEEN USED IN HCI WORK

Finally, respondents were asked to explain why they did not employ machine learning in their job. Respondents were invited to choose as many justifications from a selection of five options as they needed. There were three primary reasons given by people who didn't utilise ML in their HCI work: a lack of awareness that ML may be beneficial to their job, or a lack of success stories from other fields that were comparable to their own. In fact, examination of the interrelationships between the reasons for nonusewhich aren't detailed here for the purpose of brevityfound a substantial interaction between the aforementioned elements. We opted to continue guided analysis once descriptive analysis of survey data was finished in accordance with the following study questions:

DO USERS OF ML DIFFER FROM NONUSERS?

AutoClass generated three classes from 112 binary data vectors including 21 attributes, concentrating on HCI task engagement and clustered answers, to examine the differences between ML users and nonusers. Activity-related attributes were valued as either yes when the respondent demonstrated participation with the task or no when they weren't. Due to the fact that duties are universal and apply to all HCI activity, independent of industry or application domain, we choose to concentrate just on them (see Tables 3 and 5, respectively). To prevent skewing the outcomes, the usage or nonuse of ML was not taken into account. The procedure culminated in the creation of classes A, B, and C. Table 10 summarises our findings. Case-based reasoning emerged as the most significant task or characteristic in the formation of a class.

Table 8. Term influence values across classes

		Class			
HCI task	Abbreviation	A (54)	B (48)	C (10)	Global
Adapting, customizing, optimizing systems according to user need and requirements	AD	0.136	0.151	0.199	0.368
Interoperability between systems	IO		0.009	0.165	0.132
User modeling	UM	0.021		0.400	0.320
Usability engineering	UE	0.131	0.094	0.313	0.407
Modeling of cognitive behavior	CB	0.076	0.013	0.729	0.619
Knowledge elicitation of human expertise	KE	0.065	0.018	0.334	0.316
Knowledge acquisition	KA	0.065	0.082	0.042	0.143
Network access and network services	NW			0.036	0.028
Work methods, organizational design	WO	0.063	0.032	0.136	0.175
Multimedia system design and evaluation	MU	0.080	0.068	0.071	0.166
Planning and scheduling	PL	0.023	0.004	0.207	0.176
Natural language understanding	NL	0.007	0.002	0.092	0.076
Classification and prediction	CL		0.097	0.736	0.631
Conflict resolution	CR		0.022	0.340	0.274
Information retrieval	IR	0.180	0.128	0.073	0.288
Case-based reasoning	CA	0.066	0.014	1.242	1.000
Execution and control	EC		0.077	0.771	0.642
Critiquing and error engineering	CE	0.026	0.007	0.745	0.588
Safety and risk management	SR			0.003	0.003
Verification and validation	VV	0.026	0.031	0.002	0.044
Other	OTH	0.030	0.032	0.012	0.057
Has used ML in HCI work		18	21	2	

Influence values provide a rough estimate of each attribute's relative weight when differentiating classes from the entire data set. The values are standardized globally. The number in parenthesis indicates the proportion of each class's responses. It seems there are no omissions. the CB model, the CE model, the EC model, the CL model, and the Table 10 model of cognitive behaviour. This finding is consistent with the survey's intent to connect ML usage in HCI work since leading qualities are intelligent activities that are often linked with the use of ML and are not limited to HCI work and research alone. These activities had the most effect on class formation while being tangential to HCI. Table 10 additionally includes influence values for each class. No single task had a significant impact on either class A or class b, but a collection of tasks had a significant impact on class C formation.

Classes A and B account for almost equal shares of the ML users in the HCI work; class A included 18 ML users, class B included 21, and class C included 2 users. Machine learning (ML) and traditional methods were shown to be equally effective in class creation. There were no effects or interactions at the a = 0.05 level in repeated two-tailed paired t-tests of means utilising HCI tasks, HCI areas of application, and HCI areas of participation data. No trends were found in either the CN2 or C4.5 models that could be linked to the use or nonuse of ML, despite the relatively high statistical correctness of learned rules. For example, by adding machine learning (ML) skills to the list of attributes, we were able to conduct trials using the same data as AutoClass with CN2 and C4.5.

CONCLUSION

The application of machine learning (ML) in HCI work was identified and modelled using a systematic survey that served as the foundation for this study. We have developed some important early findings as a result of the analysis of 112 replies from top HCI experts, particularly the following. Many HCI professionals (from both business and academia) are quite familiar with and informed with ML. Over a third of HCI professionals have admitted to utilizing machine learning (ML) in their work and being happy with the outcome. It's a task for the future to enhance the average level of satisfaction. For HCI activities, using machine learning (ML) is not an easy process. Since HCI work is synthetic, ML application is required. This is a significant barrier for ML, which must develop enough before it can play well in artificial games. It will also need efficient process models, which will result in an action plan that is suitable for the current predicament. A significant portion of survey respondents, like just under two-thirds, do not employ ML in their HCI work. The text reports a few examples of these arguments. The idea that machine learning is not essential, the major reasons for this are a dearth of real-world examples and an ignorance of the possibilities. In reality, as seen in Table 15 contingency matrix, these causes interact with one another. Leading correlations between misconception and a lack of specific case studies and awareness are these two. To get beyond these obstacles, individuals should attempt to spread the word about their projects and scholars from both domains should work together to enhance ML pedagogy. A few years back,

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Corresponding Author

Sangeeta Ramachandra Yadav*

Faculty Head, Computer Science and Applications, S M Joshi College, Hadapsar, Pune-28