

Humans in Loops for Deep Learning Transfer Based on Principles of Recursive Neural Networks

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ABSTRACT

With advancement of HCAI and HCI design, human centered artificial intelligence is mainly focused on AI design support, moreover our past research aspects are concerned with facilitate social participation which we referred as data screening methodology based on ITU recommendations. Shneiderman mentioned about three approaches out of which we considered first one *i.e.*, two dimensional HCAI frame works which shows possibility of balancing high levels of human control and automation. Basically automated human control is on trajectory of artificiality based on statistical measure between complexity of artifacts and de-materialization, moreover automation and human control is based on involvement of people's thought process where state of mind unleashes idea's or errors in cyclic order which is referred as "human in loops" (HITL) based on decision making process or "translations" scientific definition. To be precise it's a two dimensional space where human intuition works on principles of machines.

Keywords: Human computer; Artificial intelligence; Temporal data

INTRODUCTION

Human-Computer Interaction (HCI) is an interdisciplinary field that primarily focuses on the interaction between users and machines. According to Professor Alan Dix, the foundation of HCI lies in computer design, making it an integral part of technological advancements. Initially, HCI was primarily concerned with the interface between humans and computers in the context of information theory. However, as technology evolved, the discipline expanded to include the study of Human-Centered Artificial Intelligence (HCAI). Human-centered AI aligns closely with information coding theory, which is particularly relevant to research focused on spatial and temporal data. In my present research work, we have concentrated on these aspects, emphasizing their connection to information theory and its implications in AI-driven applications [1].

Overview of my research activities

Inappropriate developments in Artificial Intelligence (AI) can have profound effects on human mental conditions due to user experience factors. This is particularly significant in multimedia applications, where visual complexity influences cognitive stress. According to Pashike et al., the complexity of visual content leads to spatial distortions, which, when combined with temporal impairments, can result in mental stress disorders. These distortions arise due to missing motion vectors in video content, which disrupts the natural flow of visual information.

In our research, we explored two key theoretical frameworks to analyze the impact of missing motion vectors on human cognition. The first theory posits that missing motion vectors can be quantified through error concealment techniques, allowing for an assessment of how disruptions in video coding affect user experience. The second theory focuses on the implications of non-default rate-distortion settings. In cases where motion vector features are unavailable, spatial distortions can be evaluated using a metric called motion dynamics, which measures the intensity of movement within visual content. By employing these approaches, our research aims to better understand the cognitive and psychological effects of AI-driven multimedia applications and how they can be mitigated through improved coding techniques.

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LITERATURE REVIEW

This literature review explores current challenges in HCI, particularly regarding the transition from traditional humancomputer interactions to AI-driven computing intelligence. The primary focus is on the limitations and opportunities presented by Human-Centered AI (HCAI) systems. Researchers such as Garibay et al. have highlighted the need for a structured approach to assess the limitations of existing HCAI models and proposed strategies for improving AI-driven interactions [2].

Outlined six grand challenges in human-centered AI, developed through an international collaboration involving academia, industry and government institutions. Their findings, based on insights from 26 leading experts in HCAI, emphasize the importance of aligning AI development with human cognitive abilities and emotional intelligence. One of the key aspects of their study is the need for AI systems to be transparent, inclusive and accountable, thereby preventing negative side effects such as bias and ethical concerns.

The authors also stress that effective HCAI systems should be designed with human cognition in mind, ensuring that AI complements rather than replaces human decision-making processes. By incorporating principles of emotion management, AI systems can be developed to provide more intuitive and user-friendly experiences. The study further recommends that HCI professionals play a crucial role in shaping the development of AI systems by implementing strategic guidelines that prioritize user well-being and inclusivity [3].

DISCUSSION

As AI continues to advance, it is essential to address the challenges associated with human-computer interactions in complex digital environments. Our research highlights the critical need for improved motion vector analysis and coding techniques to reduce cognitive strain in multimedia applications. By integrating findings from HCI and HCAI, future research can explore novel approaches to enhance user experience and mitigate the negative psychological impacts of AI-driven content.

One potential direction for future research involves developing adaptive AI models that can dynamically adjust visual content based on user preferences and cognitive load. This approach would require interdisciplinary collaboration, bringing together experts from AI, psychology and multimedia computing. Additionally, ensuring that AI systems remain transparent and accountable will be a crucial step in fostering user trust and preventing bias [4].

The intersection of human-computer interaction, information theory and human-centered AI presents numerous opportunities for improving digital experiences. By addressing the challenges identified in this study and implementing usercentric design principles, the development of AI systems can be guided towards more ethical, inclusive and effective outcomes. Continued research in this field will be essential for shaping the future of AI-driven technologies in a manner that prioritizes human well-being and cognitive compatibility.

Development of data annotation

It's a process of labeling individual elements of unstructured data or need to be organized into labeled information for easy recognizing to machines in order to train or test a machine learning model and moreover, just like optimization of supervised or unsupervised learning methods are mostly concerned with methodology like feature extraction, optimization of data annotation also play vital role during training rather than testing in case of randomization or randomly permuting data with corresponding labels or targets in case of human centered AI based on non-human interaction [5].

Unsupervised learning method based on data annotation optimization principle

Singam et al., worked on feature execution using unsupervised method based methodology which was similar to data annotation optimization, i.e., optimization of feature extraction technique was based on variance of individual feature which correlates well with human centered AI.

Ethical and safety implications for human centred AI

Generalization means degree of uncertainty or incomplete information, in reality it falls in small subset of samples which usually occurs in unstructured data, so we need machine teaching or human centered AI, *i.e.*, human supervision is needed, only in case of unstructured or non-organized data because it may not be provably safe and moreover results of nonlabeled data is not recognized for research practice in case of machine learning based AI due to advancement of data annotation. Coming to the point, as mentioned in one of previous section of this paper, speaking about "human in loops" (HITL) topic, in some cases the automation and human control may produce errors in cyclic order due to negligence of labeling the data, which is referred as data annotation [6].

DISCUSSION

Human in loops? Its machine teaching or human centred AI

In collaboration of machine learning and teaching, specifically in case of unsupervised learning its always inconsistency even in reality, so data annotation optimization is mostly required for instance look into geocentric model that resembles with degree of uncertainty where loops location should be labeled towards proper identification of specific location at nth rotation and in case of supervised learning, it's always consistency where optimization of data annotation is not required for heliocentric model (F) [7].



Human in loops II or its out of loop?

The mostly crucial things which makes complexity of human values easiest towards encoding into loops is consistency of human features such as language, ethics, principles or morals based on errors, towards optimization of objective or subjective annotation firstly for experts based on decisions and for crowds or public based on consistency [8].

Human in loops with deep learning or interpretation

Deep Learning Transferring (DLT) or Deep Transfer Learning (DTL): In technical terms, loops are born out of a continuous phenomenon, for instance it's a thought process were sequential execution of error in cyclic order leads to formation of loops and moreover recursive neural networks is most convenient one where this type neural networks works on principle of applying same weights recursively on a structured input [9].

Deep learning transferring is a sub category within deep learning process in the field of artificial intelligence and machine learning concepts which describes attempts to understand functionality of human brain unlike deep transfer learning which is based process of human brain imitation.

Data annotation based DLT or data interpretation based on DTL: The complexity of human values towards encoding into loops becomes higher when values of human features or principle within recursive neural networks become complicated. In other case, looking into things deeply which can only been seen by humans through perceptions, it is referred as interpretation and Deep Transfer Learning (DTL) works with convolutional neural networks principles [10].

Deep learning transfer based on set of weights

This method actually detects and discards the observations within observers based on decisions of votes given and similarly,

the distribution of scores are normal or not is confirmed by the means of β_2 test, moreover mean u^{-*}_{jklr} , standard deviation S^*_{jklr} and the coefficient β^*_{2jklr} for each of the time windows of each test configuration are calculated.

$$\beta_{2jklr}^* = \frac{m_4}{(m_2)^2}.$$
 (1)

Where

$$m_x = \frac{1}{N} \cdot \sum_{n=1}^{N} (u_{njklr}^*)^x$$

The centered scores u*_{njklr} are computed as follows.

$$u_{njklr} = u_{njklr} - u_{nklr} + \bar{u}_{klr}.$$

The mean score for each test configuration is computed as:

$$\bar{u}_{klr} = \frac{1}{N.J} \sum_{n=1}^{N} \sum_{j=1}^{J} u_{njklr}$$

 u_{njklr} is score of ith observer for jth time window and kth test condition for l video *sequences* with repetition r. The mean score for observation of each observer and for each test configuration is computed as:

$$\bar{u}_{nklr} = \frac{1}{J} \sum_{j=1}^{J} u_{njklr}.$$

We need to calculate P_i^* and Q_i^* , for *i*th observer and where P_i^* and Q_i^* are maximum and minimum scores of test sequences given by *i*th observation of an individual subject or observer.

If
$$(2 \le \beta_{2jklr} \le 4)$$
 then:

i

$$f u_{njklr}^* \ge \bar{u}_{jklr}^* + 2S_{jklr}^* \text{ then } P_i^* = P_i^* + 1$$

$$f u_{njklr} < \bar{u}_{i,llr}^* - 2S_{jklr}^* \text{ then } Q_i^* = Q_i^* + 1$$

if $u_{njklr} \ge \bar{u}_{jklr}^* + \sqrt{20S_{jklr}^*}$ then $P_i^* = P_i^* + 1$

if
$$u_{njklr} \leq \bar{u}^*_{jklr} - \sqrt{20S^*_{jklr}}$$
 then $Q^*_i = Q^*_i + 1$
f $\frac{P^*_i + Q^*_i}{JKLR} \geq 0.1$ or $\frac{P^*_i - Q^*_i}{D^*_i + O^*_i} \geq 0.3$ then reject observation of each observer

- n is number of observations within individual observers.
- j is number of time windows within combined test sequence and condition.
- k is number of test conditions.
- l is number of test sequences
- r is number of repetitions.

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CONCLUSION

Basically automated human control is on trajectory of artificiality based on statistical measure between complexity of artifacts and de-materialization, moreover automation and human control is based on involvement of people's thought process where state of mind unleashes idea's or errors in cyclic order which is referred as "human in loops" (HITL) based on decision making process or "translations" scientific definition. To be precise it's a two dimensional space where human intuition works on principles of machines.

REFERENCES

- Ozmen Garibay O, Winslow B, Andolina S, Antona M, Bodenschatz A, Coursaris C, et al. Six human-centered artificial intelligence grand challenges. Int J Hum Comput Interact. 2023;39(3):391-437.
- Pashike VR, Singam AK, Shahid M. Human perceptions based on translations of recurrent neural networks principles for low latency applications.
- Shneiderman B. Human-centered artificial intelligence: Reliable, safe and trustworthy. Int J Hum Comput Interact. 2020;36(6):495-504.

- Singam AK, Lovstrom B, Kulesza WJ. Comparative studies of unsupervised and supervised learning methods based on multimedia applications. 2023.
- 5. Yu F, Seff A, Zhang Y, Song S, Funkhouser T, Xiao J. Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop. 2015.
- Budd S, Robinson EC, Kainz B. A survey on active learning and human-in-the-loop deep learning for medical image analysis. Med Image Anal. 2021;71:102062.
- Mosqueira-Rey E, Hernandez-Pereira E, Alonso-Rios D, Bobes-Bascaran J, Fernandez-Leal A. Human-in-the-loop machine learning: A state of the art. Artif Intell Rev. 2023;56(4):3005-3054.
- 8. Wu X, Xiao L, Sun Y, Zhang J, Ma T, He L. A survey of human-in-theloop for machine learning. Future Gener Comput Syst. 2022;135:364-381.
- 9. Alahmari S, Goldgof D, Hall L, Dave P, Phoulady HA, Mouton P. Iterative deep learning based unbiased stereology with human-in-the-loop. 2018.
- 10. Kumar S, Datta S, Singh V, Datta D, Singh SK, Sharma R. Applications, challenges, and future directions of human-in-the-loop learning. 2024.