Prediction of Human Activities using Machine Learning and CLE

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Abstract

The objective of this work is to propose a machine learning-based methodology system architecture and algorithms to find patterns of learning, interaction, and relationship and effective assessment for a complex system involving massive data that could be obtained from a proposed collaborative learning environment (CLE). Collaborative learning may take place between dyads or larger team members to find solutions for real- time events or problems, and to discuss concepts or interactions during situational judgment tasks (SJT). Modelling a collaborative, networked system that involves multimodal data presents many challenges. This paper focuses on proposing a Machine Learning - (ML)-based system architecture to promote understanding of the behaviours, group dynamics, and interactions in the CLE. Our framework integrates techniques from computational psychometrics (CP) and deep learning models that include the utilization of convolutional neural networks (CNNs) for feature extraction, skill identification, and pattern recognition. Our framework also identifies the behavioural components at a micro level, and can help us model behaviours of a group involved in learning.

Keywords: Machine Learning, Collaborative Learning, Deep Learning, Computational Psychometrics, Skills, Human Behaviour.

INTRODUCTION

Collaborative learning is a situation in which two or more people learn or attempt to learn something together. Unlike individual learning, people engaged in collaborative learning capitalize on one another's resources and skills (asking one another for information, evaluating one another's ideas, monitoring one another's work, etc.). More specifically, collaborative learning is based on the model that knowledge can be created within a population where members actively interact by sharing experiences and take on asymmetric roles.

Collaborative learning is very important in achieving critical thinking. In this method, individuals are able to achieve higher levels of learning and retain more information when they work in a group rather than individually, this applies to both the facilitators of knowledge, the instructors, and the receivers of knowledge, the students.

Collaborative learning methods have been implemented broadly by organizations at all stages, as research recommends that active human involvement in cohesive and micro group communications is critical for effective learning.

This paper proposes a three-stage method to explore and study collaborative group behaviours. The first stage integrates and processes multimodal data obtained in a collaborative learning environment (CLE) that includes sensor input, audio, video, eye tracking, facial expressions, movement, posture, gestures, and behavioural interaction log data. The second stage performs feature extraction and cloud computation using computational psychometrics (CP) and convolutional neural network (CNN)-based deep learning for skill, pattern, and trend identification. Finally, the third stage uses the parameters measured in the previous two stages to understand and model group interactions, competencies, and collaborative behaviour at a micro-level. The third stage uses machine learning for effective assessment and visualization of group dynamics such as correctly assessing the increase in the groups' level of shared understanding of different perspectives, and ability to clarify misconceptions.

METHODS AND STAGES

A. The system has the following stages:

1. Data Integration and Processing.

Data integration involves combining data residing in different sources and providing users with a unified view of them. This process becomes significant in a variety of situations, which include both commercial and scientific domains.

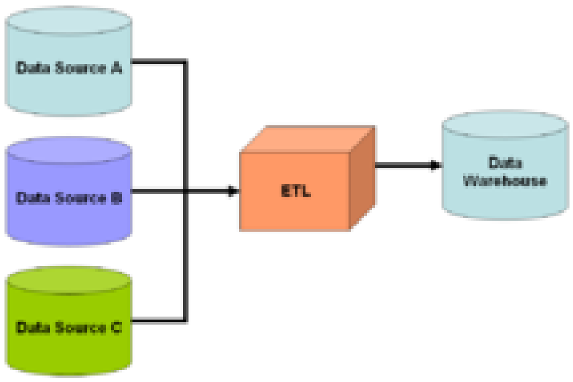

Fig. 1 Implementation of data integration

2. Massive data intensive CNN and CP.

In deep learning, a convolutional neural network is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing.

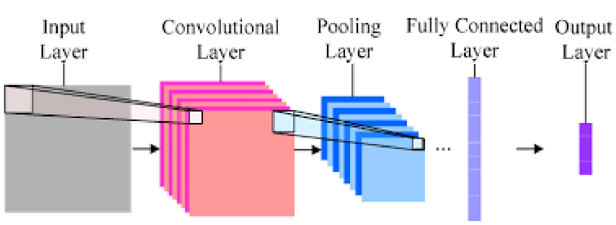

Fig. 2 Convolutional Neural Network

Computational Psychometrics is an interdisciplinary field fusing theory-based psychometrics, learning and cognitive sciences, and data-driven AI-based computational models as applied to large-scale/high-dimensional learning, assessment, biometric, or psychological data.

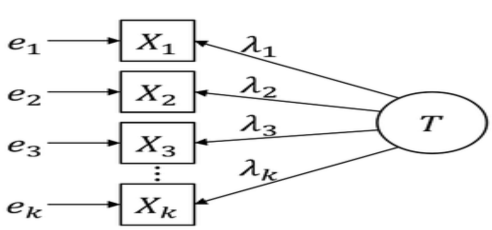

Fig. 3 Computational Psychometrics

3. Effective Assessment

The effective assessment (EA) module locates and retrieves data after the computation is finished using the Convolutional Neural Network and Computational Psychometric modules. The CNN and CP modules carry out feature extraction, model training, and pattern identification from two player dyadic gameplay logs and behavioural data. Through effective assessment, we aim to analyse human behaviour as it relates to specific situations in the game, to detect the dynamics of group behaviour, such as shared understanding and engagement at the micro level.

The EA module identifies/detects clusters of interactions, and abilities based on degree, connected components, and it performs collaborative learning skill analysis i.e., whether there is any change (increase) in group understanding for a given problem or situation.

The EA module also performs predictive decision-making based on group behaviours.

This module stores future patterns which can be used for any exploratory analytics and effective visualization of past and present group interactions and relative performance.

Biometric data is analysed for biometric database matching and for biometric image processing. Biometric data are unique physical characteristics such as face, eye tracking/ iris, and fingerprints, which can be used for automated recognition.

Fig. 4 Effective Assessment in Machine Learning

B. System Architecture:

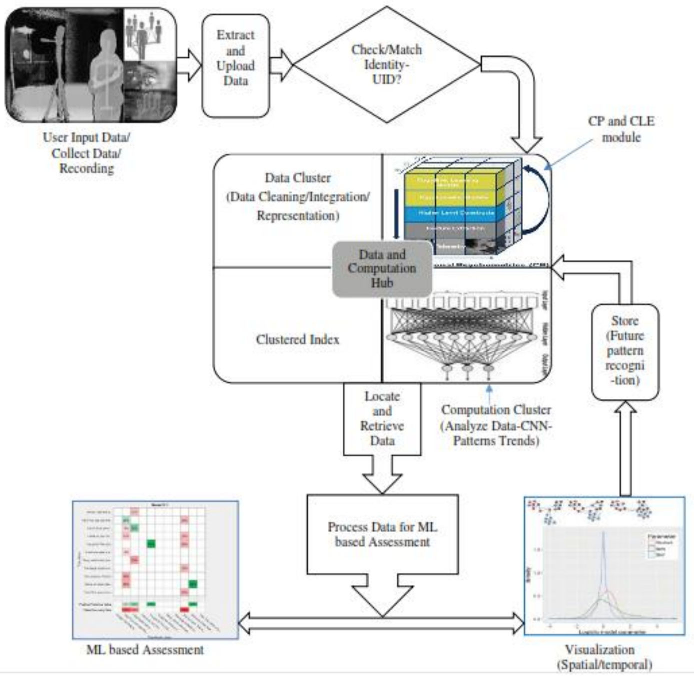

Fig. 5 System Architecture

As shown in Fig. 5, this study focused on collecting the following: game log data, user eye tracking, and user portrait video/audio, chat logs (conversation flow), behavioural expressions, object clicks, time in-game & between games. Our objective is to use this CPS human human (HH) game log-data for team interaction analysis and for finding teamwork skill evidence based on the CPS construct. As illustrated in Fig. 5, from two player dyadic CPS game interactions, we extract four types of data files: video, eye tracking, audio, and chat/text. We then use all these source files for identity matching or for naming convention purposes. Then we perform CNN-based machine learning analysis for feature extraction, correlation, and pattern identification. We processed video files through Noldus Face reader and observer analysis which produces different behavioural markers (third block in Fig. 5).

These word embedding are combined with n-grams features and word sentiment polarity score features to form a sentiment feature set of tweets. The feature set is integrated into a deep convolution neural network for training and predicting sentiment classification labels. We experimentally compare the performance of our model with the baseline model that is a word n-grams model on five Twitter data sets, the results indicate that our model performs better on the accuracy and F1-measure for twitter sentiment classification. Sentiment Analysis, also called opinion mining or emotion AI, is the process of determining whether a piece of writing is positive, negative, or neutral.

It identifies the existing theoretical frameworks and empirical research that focus on CPS and also provides examples of how recent technologies can automate analyses of CPS processes and assessments so that substantially larger data sets can be analysed and so students can receive immediate feedback on their CPS performance. By using collaboration and communication, members often learn from one another and construct meaningful knowledge that often leads to better learning outcomes than individual work.

C. Flowchart:

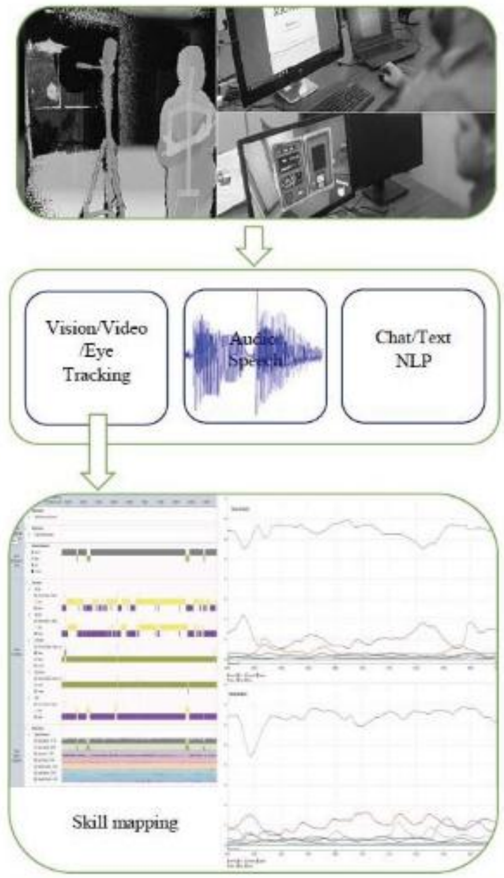

Fig. 6 Flowchart

As illustrated in Fig. 6, from two-player dyadic CPS game interactions, we extract four types of data files: video, eye tracking, audio, and chat/text. We then use all these source files for identity matching or for naming convention purposes. Then we perform CNN-based machine learning analysis for feature extraction, correlation, and pattern identification. We processed video files through Noldus Facereader and observer analysis which produces different behavioural markers and emotional states for dyadic gameplay (third block in Fig. 6). We also performed in-depth learning analysis using fine-grained data obtained from numerical and behavioural analysis

LITERATURE REVIEW

Previous Research on existing Prediction of Human Performance using Machine Learning:

A. Krizhevsky, I. Sutskever, and G. Hinton in their work have presented an application of ImageNet classification with deep convolutional neural networks in 2012. ImageNet is a dataset of over 15 million labelled high resolution images belonging to roughly 22,000 categories. The images were collected from the web and labelled by human labellers using Amazon's Mechanical Turk crowd sourcing tool. Starting in 2010, as part of the Pascal Visual Object Challenge, an annual competition called the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) has been held. ILSVRC uses a subset of Image Net with roughly 1000 images in each of 1000 categories. In all, there are roughly 1.2 million training images, 50,000 validation images, and 150,000 testing images. [1]

Aliaksei Severyn and Alessandro Moschitti have developed a Twitter Sentiment Analysis with Deep Convolutional Neural Networks in 2015. Twitter sentiment analysis technology provides the methods to survey public emotion about the events or products related to them. Most of the current researches are focusing on obtaining sentiment features by analysing lexical and syntactic features. These features are expressed explicitly through sentiment words, emoticons, exclamation marks, and so on. In this paper, we introduce a word embedding method obtained by unsupervised learning based on large twitter corpora, this method using latent contextual semantic relationships and co-occurrence statistical characteristics between words in tweets. [2]

A. von Davier developed a Computational Psychometrics in support of collaborative educational assessments using Machine Learning in 2017. The behaviour of each individual affects the behaviour of others and, conversely, each one behaves considering the crowd as a whole and the individual others. Modelling behaviour is possible at the micro level through computational neuroscience and at the macro level (society) through computational psychology (e.g., social network analysis and mathematical modelling). Computational Psychometrics is an interdisciplinary field fusing theory-based psychometrics, learning and cognitive sciences, and data-driven AI based computational models as applied to large-scale/high-dimensional learning, assessment, biometric, or psychological data. Computational psychometrics is frequently concerned with providing actionable and meaningful feedback to individuals based on measurement and analysis of individual differences as they pertain to specific areas of enquiry. [3]

J. Fletcher and R. Sottilare have designed and implemented shared mental models in support of adaptive, instruction for teams using the GIFT tutoring architecture. Under the GIFT architecture, a set of tools is available for instructors to author, deliver, and evaluate intelligent tutoring applications. An essential component of GIFT is a domain-independent pedagogical module that manages instruction based on a learner's unique information. The purpose of this pedagogical module is to tailor and induce interventions via empirically- based generic instructional strategies. The goal of this research paper is to present GIFT's engine for Macro Adaptive Pedagogy (eMAP), an algorithm in the form of a decision tree that is able to inform adaptation based on generalized characteristics associated with the learner and the targeted domains. [4]

L. Lei, J. Hao, A. von Davier, P. Kyllonen, and J-D. Zapata-Rivera presented the measurement of collaborative problem solving in which it is mentioned that collaborative problem solving (CPS) has been receiving increasing international attention because much of the complex work in the modern world is performed by teams. However, systematic education and training on CPS is lacking for those entering and participating in the workforce. In 2015, the Programme for International Student Assessment (PISA), a global test of educational progress, documented the low levels of proficiency in CPS. This result not only underscores a significant societal need but also presents an important opportunity for psychological scientists to develop, adopt, and implement theory and empirical research on CPS and to work with educators and policy experts to improve training in CPS. [5]

Aitor Almeida, Gorka Azkune in their paper have implemented a modelling behaviour dynamics using computational psychometrics within virtual worlds. This paper presents a conceptual classification of the user behaviour in intelligent environments according to the different levels of granularity used to describe it. Using this classification, we also describe the algorithm developed to automatically model the inter-activity behaviour. This algorithm uses long short-term memory networks (LSTMs) to create a probabilistic model of user behaviour that can predict the next user action and detect unexpected behaviours. [6]

RESULTS

Figure 7, 8 and 9 show the results for each type of experiment. In the case of the architecture experiments, adding more LSTM layers (A4) or smaller, densely connected layers (A5) reduced the overall accuracy of the model no matter the number of predictions. The usage of bidirectional LSTMs (A6) was also detrimental. Generally, higher dropout regularization values (A2 and A3) produced better results. Overall, the A3 configuration offered the best results across the board. As can be seen in the table, the use of embedding obtained better results when compared to the same configurations using one-hot vectors (A3 vs. A7, A2 vs. A8 and A4 vs. A9). A more semantically rich representation of the actions allows the same architecture to better model the user behaviour to enhance better user interactions.

ID	acc_at_1	acc_at_2	acc_at_3	acc_at_4	acc_at_5
A1	0.4487	**0.6367**	0.7094	**0.7948**	0.8461
A2	0.4530	0.6239	**0.7222**	0.7692	0.8504
A3	**0.4744**	0.6282	0.7179	0.7905	**0.8589**
A4	0.4444	0.5940	0.6965	0.7735	0.8247
A5	0.4402	0.5982	0.7136	0.7820	0.8418
A6	0.4487	0.6068	0.7136	0.7905	0.8376
A7	0.4572	0.6153	0.7094	0.7820	0.8376
A8	0.4529	0.5811	0.7051	0.7735	0.8376
A9	0.4102	0.5940	0.7008	0.7777	0.8247

Fig. 7 Architecture Experiments

ID	acc_at_1	acc_at_2	acc_at_3	acc_at_4	acc_at_5
A3	**0.4744**	0.6282	0.7179	0.7905	**0.8589**
S1	0.4553	0.5957	0.7021	0.8	0.8553
S2	0.4255	0.6255	0.7021	**0.8085**	0.8382
S3	0.4658	**0.6452**	**0.7264**	0.7948	0.8504
S4	0.4700	0.6196	0.6965	0.7692	0.8461
S5	0.4592	0.6351	0.7210	0.7896	0.8369
S6	0.4192	0.5589	0.6593	0.7554	0.8122

Fig. 8 Sequence Length Experiments

ID	acc_at_1	acc_at_2	acc_at_3	acc_at_4	acc_at_5
A3	**0.4744**	**0.6282**	**0.7179**	**0.7905**	**0.8589**
T1	0.4487	0.6239	0.7094	0.7692	0.8076
T2	0.4487	0.6111	0.7008	0.7692	0.8247
T3	0.3846	0.5940	0.7051	0.7564	0.8076

Fig. 9 Time Experiments

For the sequence-length experiments (Fig. 9), the best results were achieved using sequences with a length of 4 (S3) or 5 (A3) actions. In this specific case, the optimal sequence length was closely related with each deployment, being determined by the average action length of the activities in each scenario. This value should be adjusted in each specific case in order to achieve the best results, and it cannot be generalized.

Finally for the time experiments, the evaluation shows that none of the proposed options to take into account the timestamps (T1, T2 and T3) improved the results. When comparing these with architecture with a similar configuration and no timestamps (A3), the results were clearly worse. Our initial intuition was that taking into account the timestamps would help to model the temporal patterns in the actions, but the results show that this information is not so relevant for the behaviour modelling task. We expect that the temporal data will be much more relevant in the activity recognition task, particularly when discriminating between activity patterns with similar actions that happen at different periods.

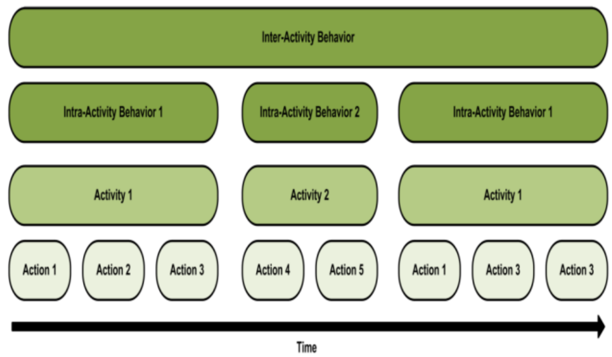

Fig. 10 User Behavior

CONCLUSION

In this paper, a machine learning (ML)-based system architecture has been presented to identify evidence about teamwork skills from the behaviour, group dynamics, and interactions in the CLE. We developed a three-stage robust architecture for data intensive computing and efficient assessment of teamwork CPS skills. In this paper, we have proposed a multilevel conceptual model that describes the user behaviour using actions, activities, intra-activity behaviour and inter-activity behaviour Using this conceptual model, we have presented a deep learning architecture based on LSTMs that models inter activity behaviour. Our architecture offers a probabilistic model that allows us to predict the user’s next actions and to identify anomalous user behaviours. We have evaluated several architectures, analysing how each one of them behaves for a different number of action predictions. An attempt to build text-based Natural Language Processing (NLP) / Machine Learning (ML) models to identify or classify various performances of CPS sub skills from the chat logs, audio/video interactions data collected throughout the study.

FUTURE ENHANCEMENTS

Additional feature extraction that may be used during this phase will be implemented for CNN based pattern identification. As future enhancement, the next step is to continue studying how the temporal and spatial information could be integrated into the architecture to improve the statistical model. We would like to explore other deep learning architectures, for example, using convolutional neural networks (CNNs) instead of LSTMs.

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