

Human-AI communication for human-human communication: Applying interpretable unsupervised anomaly detection to executive coaching

Riku Arakawa^{*1} and Hiromu Yakura^{*2,3}

¹Carnegie Mellon University, Pittsburgh, USA

²University of Tsukuba, Tsukuba, Japan

³National Institute of Advanced Industrial Science and Technology (AIST), Tsukuba, Japan
rarakawa@cs.cmu.edu, hiromu.yakura@aist.go.jp

Abstract

In this paper, we discuss the potential of applying unsupervised anomaly detection in constructing AI-based interactive systems that deal with highly contextual situations, i.e., human-human communication, in collaboration with domain experts. We reached this approach of utilizing unsupervised anomaly detection through our experience of developing a computational support tool for executive coaching, which taught us the importance of providing interpretable results so that expert coaches can take both the results and contexts into account. The key idea behind this approach is to leave room for expert coaches to unleash their open-ended interpretations, rather than simplifying the nature of social interactions to well-defined problems that are tractable by conventional supervised algorithms. In addition, we found that this approach can be extended to nurturing novice coaches; by prompting them to interpret the results from the system, it can provide the coaches with educational opportunities. Although the applicability of this approach should be validated in other domains, we believe that the idea of leveraging unsupervised anomaly detection to construct AI-based interactive systems would shed light on another direction of human-AI communication.

1 Introduction

Social signal processing is one of the prominent application areas of machine learning [Vinciarelli *et al.*, 2012; Rudovic *et al.*, 2017]. Conventionally, supervised learning has been leveraged in combination with handcrafted features to obtain useful information from human conversation data [Sanchez-Cortes *et al.*, 2012; Beyan *et al.*, 2018]. For example, Sanchez-Cortes *et al.* [2012] designed various audiovisual features, such as the number of segments where the amount of one's body movement exceeded a certain threshold, to detect emergent leaders within a group discussion. Rule-based methods have also been employed, especially to provide feedback based on social signal processing [Tausczik

and Pennebaker, 2013; Damian *et al.*, 2015; Tanveer *et al.*, 2015; Damian *et al.*, 2016]. In this case, both conversation [Tausczik and Pennebaker, 2013; Damian *et al.*, 2016] and public speaking [Damian *et al.*, 2015; Tanveer *et al.*, 2015] have been dealt with.

However, such approaches based on some rules or supervised learning have a risk of oversimplifying our nature of social interaction, which is highly contextual [Becker, 1974]. Indeed, most of us would agree that keeping one's arms crossed for a while in public speaking constitutes a negative behavior. Thus, giving users feedback to refrain from doing it, in a similar manner as Damian *et al.* [2015] did, would be beneficial. However, in everyday conversation, we cannot conclude that crossed arms immediately represent a defensive attitude [Navarro and Karlins, 2008], because it might be a sign of one's perseverance in finding an answer to a given question [Friedman and Elliot, 2008].

A more extreme case is given by executive coaching, in which coaches are asked to observe the nonverbal behavior of coachees during one-on-one sessions [Bloom *et al.*, 2005]. Here, coaches are required to infer a coachee's internal status from the nonverbal behavior of the coachee to complement the verbal communication [Cox *et al.*, 2009]. In particular, the importance of observing such nonverbal behavior is emphasized in terms of reading the nuance of what the coachee said (and not said) [Drake, 2009]. In this case, naïve rules or simplified classifications used with supervised learning would not be sufficient to construct computational support or might even misguide coaches in capturing the complex dynamics of humans.

Given this background, we have developed a practical approach for supporting executive coaching by exploiting unsupervised anomaly detection to provide coaches with interpretability. Based on our experiences, in this paper, we discuss the importance of securing interpretability in implementing collaboration between AI and experts within such highly contextual situations. In addition, we present the educational effect of designing a computational support tool with the approach based on our observation about how this type of human-AI communication can affect human-human communication.

^{*}These authors contributed equally and are ordered alphabetically.

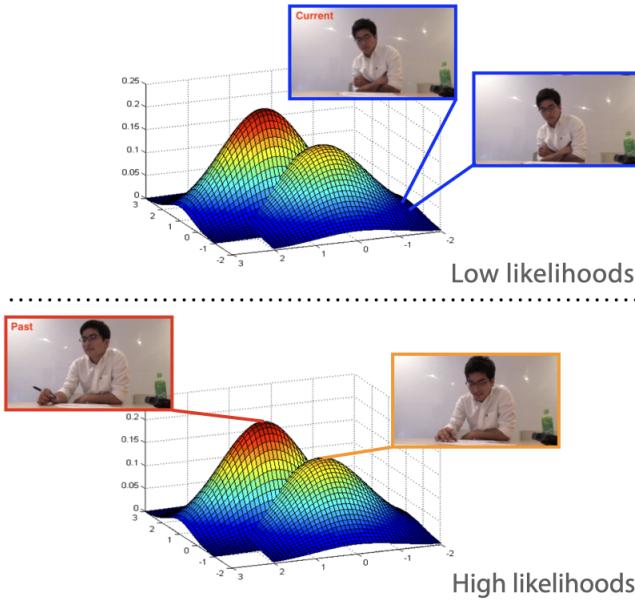


Figure 1: *R*E*s*CUE [Arakawa and Yakura, 2019] can determine changes in nonverbal behavior along with past representative states using GMM.

2 Why unsupervised anomaly detection?

As mentioned above, human conversation, particularly in executive coaching, is highly context dependent [Paul Watzlawick, 2011; Cox *et al.*, 2009]. This point broke our initial attempt to apply supervised learning algorithms in developing computational support. Specifically, we first deployed existing supervised-algorithm-based methods for recognizing emotions [Dhall *et al.*, 2017] and detecting important utterances [Nihei *et al.*, 2017] in conversation during executive coaching sessions. However, we found that expert coaches begin to ignore the outputs from a computer once the outputs contradict their observation or intuition. As per their comments, the coaches found it difficult to rely on outputs based on simplified categories that are indifferent to the subtle changes in the nonverbal behavior of the coachees, leading them to disregard the computer.

With this finding, we developed *R*E*s*CUE [Arakawa and Yakura, 2019], an alternative approach that harnesses multimodal anomaly detection. R*E**s*CUE is designed to detect subtle but meaningful changes in a coachee's nonverbal behavior that seem to be outliers from their behavior trends. It then presents the changes to a coach as cues to infer the coachee's internal status. Then, the coach can read what exists behind the detected cues by considering the context of their conversation. This approach frees us from implicit assumptions about human nonverbal behavior that have been introduced by heuristic rules or training data in conventional methods.

Furthermore, the anomaly detection algorithm of R*E**s*CUE, which utilizes the Gaussian mixture model (GMM), enables an interpretable presentation of the nonverbal cues. As illustrated in Figure 1, R*E**s*CUE can determine the moments that the coachee exhibited the most outlying behavior, which has



Figure 2: The detected nonverbal cues are visualized in an interpretable manner by being supplied with past representative states (taken from Figure 6 of [Arakawa and Yakura, 2019]).

the minimum likelihood according to the GMM. At the same time, it can determine the moments that the coachee exhibited representative states among their past behavior analogously by looking for those having the maximum likelihood. Then, just by arranging them as in Figure 2, R*E**s*CUE can visualize the cue so that the coach can intuitively interpret its implications during one-on-one sessions.

The design of R*E**s*CUE is principled in the separation of observation and interpretation. From our initial attempt, we learned that expert coaches in fact do not have difficulty in interpreting the implications of nonverbal cues they observed. Rather, they are afraid of missing out on some cues while mentally demanded to manage sessions by, for example, finding an appropriate question that can provide a chance for coachees to have an effective reflection. Thus, we designed R*E**s*CUE to devote itself to supporting only the observation part and delegate the interpretation part to coaches via visualizing the observed cues in an interpretable manner, instead of directly inferring the meaning of the cues based on rules or simplified classifications. The effectiveness of this design was experimentally confirmed, and now, R*E**s*CUE is practically deployed as a supporting tool for executive coaching.

3 Lens of Parasuraman's framework of automation

In the context of human-AI communication, the advantage of R*E**s*CUE can be understood by using the framework of Parasuraman *et al.* [2000], which provides an objective basis for automation design. They presented that automation can be applied to four classes of functions: information acquisition, information analysis, decision & action selection, and action implementation. Then, they defined a 10-point scale to evaluate the automation level for each function, from level 1 ("the computer offers no assistance: human must take all decisions and actions") to level 10 ("the computer decides everything, acts autonomously, ignoring the human"). This framework allows us to assess the suitability of automation design by determining whether the automation level of each function is appropriately situated within the trade-off between human performance, automation reliability, and cost of consequences.

Parasuraman *et al.* [2000] takes an example of the ground proximity warning system (GPWS) that alerts pilots when their aircraft is flying into the ground. They classified it as level 4 (“suggests one alternative”) in decision & action selection because it does not execute any countermeasures but makes suggestions for pilots with an audio message saying “pull up!” However, when such an alert is triggered, the performance of pilots is often degraded but its cost of consequences can be too high, i.e., resulting in a crash. Therefore, GPWS is now being replaced with an automatic ground collision avoidance, which exhibits level 7 (“executes automatically, then necessarily informs the human”) automation by taking control automatically if the pilot does not.

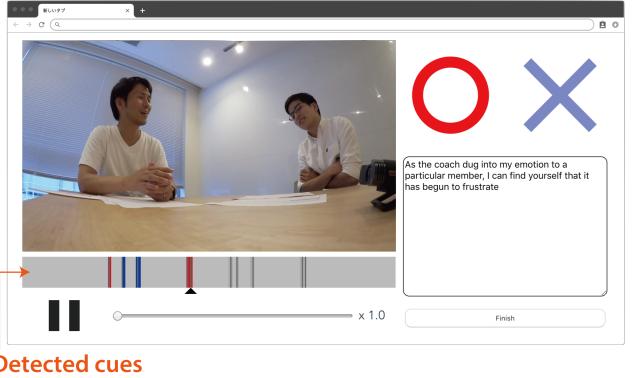
In this framework, REsCUE shows its distinctive design approach; it retains level 10 for both information acquisition and information analysis while exhibiting level 1 for both decision & action selection and action implementation. Specifically, REsCUE acquires the information about a coachee’s nonverbal behavior and analyzes its outlierness, working independently from the coach. However, it touches neither decision & action selection nor action implementation; it leaves the coach to interpret the observed cues and make a necessary action (e.g., asking the coachee another question to figure out the reason behind it).

This is rationalized by considering the trade-off between human performance, automation reliability, and cost of consequences. As mentioned in Section 2, coaches’ performance in observing coachees’ nonverbal behavior is not consistent due to the mental demand of carrying out the sessions. On the contrary, we found that the reliability of REsCUE in detecting nonverbal cues is quite high because it does not introduce any heuristics or biases caused by training data. Furthermore, its interpretable visualization (see Figure 2) allows the coach to ignore the cues when they are not implicative, which minimizes the negative cost of consequences.

A similar discussion can be applied to the interpretation part, i.e., high human performance with low automation reliability. In addition, the cost of consequence is higher than the observation part because misinterpretation of the nonverbal cues can mislead the session. To sum, the reason behind coaches’ affirmative reception of our approach can be attributed to this automation design strategy. This suggests that the clear distinction between the observation and interpretation that is enabled by unsupervised anomaly detection can support human-AI communication in highly contextual situations.

4 Asking humans to explain

Following the deployment of REsCUE, we found that this approach can be applied to supporting the education of novice coaches. This is because the ability to infer one’s internal status from such nonverbal cues, which is often associated with emotional intelligence [Salovey and Mayer, 1990], plays an important role in successful executive coaching [Waslyshyn *et al.*, 2012]. However, intensive training is often required in cultivating such an ability [McEnrue *et al.*, 2009]. We thus presumed that REsCUE can help the transfer of the ability from expert coaches to novice coaches, leading us to de-



Detected cues

Figure 3: *INWARD* [Arakawa and Yakura, 2020] provides an interface for reflecting on coaching sessions with detected nonverbal cues.

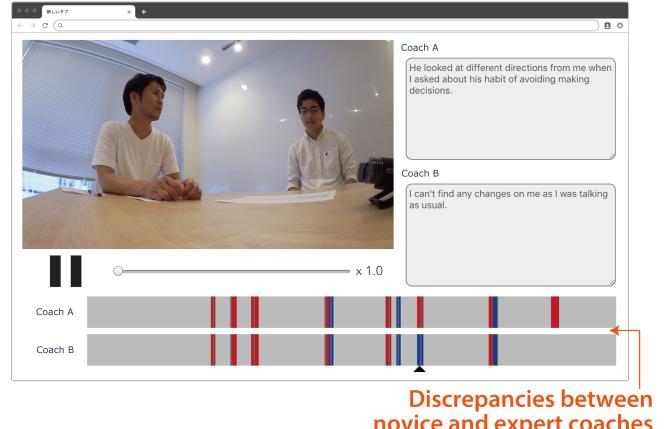


Figure 4: *INWARD* [Arakawa and Yakura, 2020] then visualizes the discrepancies in the interpretations of the coaches to encourage their meta reflection.

velop a computational supporting tool: *INWARD* [Arakawa and Yakura, 2020].

As shown in Figure 3, this tool provides an interface displaying the recording of a coaching session as well as nonverbal cues detected by REsCUE [Arakawa and Yakura, 2019]. It assumes that a novice coach who had the session and an expert coach who supervises the novice coach use the interface separately to reflect on the session. In this video reflection phase, the coaches are requested to annotate each detected cue whether or not it provides insights about the coachee’s internal status and to explain the reason for such an annotation. After that, this tool invites both the coaches to a meta reflection phase, in which the discrepancies between their annotations are displayed, as depicted in Figure 4, so that they can discuss their interpretations. Through these phases, the novice coach can learn how the expert coach reads information from subtle nonverbal cues.

Here, we cannot deny the possibility that the novice coach

can learn the way of interpreting such nonverbal cues equivalently without the computational support of INWARD; for example, they can watch the recording along with the expert coach while being explained about the interpretations of the expert coach. However, the user study of INWARD revealed that its detection results serve as a neutral ground for their discussion. Specifically, during the video reflection phase, the novice coach can construct their own hypothesis regarding the tendency in the coachee's nonverbal behavior through interpreting and annotating each detected cue. Subsequently, the novice coach can argue with the expert coach without unthinkingly accepting the interpretations of the expert coach on account of authority bias.

In addition, we found that the design of REsCUE, which separates observation and interpretation, fosters the effectiveness of INWARD. As REsCUE is based on unsupervised anomaly detection, it can detect apparent behavioral changes, such as when the coachee takes their personal organizer out of a briefcase. Most of them would not provide meaningful information about the coachee's internal status, but occasionally, expert coaches draw insights with regard to why the coachee did it at the moment. Such open-ended interpretations would not be available unless the tool completely delegates the interpretation part to humans while providing interpretable results.

Through the development of INWARD, we learned another advantage of making AIs interpretable, i.e., they can offer educational opportunities for humans by actively asking them to interpret and explain along with supplying interpretable results. Needless to say, the transparency of the AIs is crucial not to make humans feel quizzed by computers. Besides, we found that unsupervised algorithms would have an affinity to highly contextual situations, such as executive coaching, as they can induce open-ended interpretations from humans. We believe that applying this approach to other domains sheds light on a new direction of AI techniques in interpersonal communication.

5 On-going work

To this end, we are currently working on applying this approach based on unsupervised anomaly detection in another domain of human communication, that is, human assessment. Human assessment is a process in human resource development aimed to evaluate and make decisions on candidates regarding their suitability for certain types of employment [Sartori *et al.*, 2020]. Typically, professional assessors have an interview session with candidates through which the candidates' skills as a manager in their organizations are examined [Roberts *et al.*, 2014]. The assessors are required to monitor and evaluate the candidates' behavior during the interview. This process is similar to executive coaching in terms of analyzing one's behavior during a one-on-one conversation, involving highly contextual situations. At the same time, it is different in the sense that the goal of human assessment is to make a judgment on candidates' suitability for jobs while executive coaching focuses on nurturing coachees by having them deeply reflect on their internal states. As a result, the ongoing work possesses a unique challenge with respect to



Figure 5: Prototype being developed for the ongoing work: supporting assessors in human assessment.

how to support professionals' decision-making with AIs. Our hypothesis is that our approach of unsupervised anomaly detection can detect scenes that can be served as a basis for the assessors to evaluate candidates, making the process more effective and efficient. If this is supported through empirical studies, the boundary of this approach's capability regarding what types of scenes the anomaly detection algorithm can capture within human communication will be clearer. To conduct such studies, we are developing a prototype interface as shown in Figure 5, while exploring useful features to be used for anomaly detection in a collaboration with professional assessors.

6 Conclusions

In this paper, we have discussed the importance of deploying interpretable AIs in highly contextual situations, such as human conversation, by introducing our cases in executive coaching. In these situations, we argue that it would be worth thinking about delegating the interpretation part to humans, instead of persuading them by presenting possible explanations, while fully supporting their interpretation by providing interpretable outputs. This approach also has the potential to provide users with educational opportunities by intentionally requesting them to interpret the outputs, as we discussed by taking an example of INWARD [Arakawa and Yakura, 2020].

In this sense, we envision that unsupervised anomaly detection will be utilized more widely in the future as an alternative approach in constructing human-AI communication for effective collaboration. As discussed above, human nature is often too complex to be simplified into well-defined problems tractable by regular supervised learning algorithms. Then, applying the existing explainable AI techniques designed for supervised algorithms to such a situation might not be a remedy. Instead, when we can assume the involvement of experts as the counterpart of AIs, we suggest delegating the interpretation part to them, namely, trusting them, to induce their open-ended interpretations.

Acknowledgments

This work was supported in part by JST ACT-X Grant Number JPMJAX200R and JSPS KAKENHI Grant Number JP21J20353.

References

- Riku Arakawa and Hiromu Yakura. REsCUE: A framework for REal-time feedback on behavioral CUEs using multimodal anomaly detection. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, New York, NY, 2019. ACM.
- Riku Arakawa and Hiromu Yakura. INWARD: A computer-supported tool for video-reflection improves efficiency and effectiveness in executive coaching. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, New York, NY, 2020. ACM.
- Gary S. Becker. *A Theory of Social Interactions*. Stanford University Press, Stanford, CA, 1974.
- Cigdem Beyan, Francesca Capozzi, Cristina Becchio, and Vittorio Murino. Prediction of the leadership style of an emergent leader using audio and visual nonverbal features. *IEEE Transactions on Multimedia*, 20(2):441–456, 2018.
- Gary S. Bloom, Claire L. Castagna, Ellen Moir, and Betsy Warren. *Blended Coaching: Skills and Strategies to Support Principal Development*. Corwin Press, Thousand Oaks, CA, 2005.
- Elaine Cox, Tatiana Bachkirova, and David Clutterbuck. *The Complete Handbook of Coaching*. SAGE Publications, Los Angeles, CA, 2009.
- Ionut Damian, Chiew Seng Sean Tan, Tobias Baur, Johannes Schöning, Kris Luyten, and Elisabeth André. Augmenting social interactions: Realtime behavioural feedback using social signal processing techniques. In *Proceedings of the 33rd ACM SIGCHI Conference on Human Factors in Computing Systems*, pages 565–574, New York, NY, 2015. ACM.
- Ionut Damian, Tobias Baur, and Elisabeth André. Measuring the impact of multimodal behavioural feedback loops on social interactions. In *Proceedings of the 18th ACM International Conference on Multimodal Interaction*, pages 201–208, New York, NY, 2016. ACM.
- Abhinav Dhall, Roland Goecke, Shreya Ghosh, Jyoti Joshi, Jesse Hoey, and Tom Gedeon. From individual to group-level emotion recognition: Emotiw 5.0. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, pages 524–528, New York, NY, 2017. ACM.
- David B. Drake. Narrative coaching. In *The Complete Handbook of Coaching*. SAGE Publications, Los Angeles, CA, 2009.
- Ron Friedman and Andrew J. Elliot. The effect of arm crossing on persistence and performance. *European Journal of Social Psychology*, 38(3):449–461, 2008.
- Mary Pat McEnrue, Kevin S. Groves, and Winny Shen. Emotional intelligence development: Leveraging individual characteristics. *Journal of Management Development*, 28(2):150–174, 2009.
- Joe Navarro and Marvin Karlins. *What Every BODY Is Saying: An Ex-FBI Agent's Guide to Speed Reading People*. HarperCollins, New York, NY, 2008.
- Fumio Nihei, Yukiko I. Nakano, and Yutaka Takase. Predicting meeting extracts in group discussions using multimodal convolutional neural networks. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, pages 421–425, New York, NY, 2017. ACM.
- Raja Parasuraman, Thomas B. Sheridan, and Christopher D. Wickens. A model for types and levels of human interaction with automation. *IEEE Transactions on System, Man, and Cybernetics—Part A*, 30(3):286–297, 2000.
- Don D. Jackson Paul Watzlawick, Janet Beavin Bavelas. *Pragmatics of Human Communication: A Study of Interactional Patterns, Pathologies and Paradoxes*. W. W. Norton, New York, NY, 2011.
- Chris Roberts, Tyler Clark, Annette Burgess, Michael Frommer, Marcia Grant, and Karyn Mossman. The validity of a behavioural multiple-mini-interview within an assessment centre for selection into specialty training. *BMC Medical Education*, 14(1):1–11, 2014.
- Ognjen Rudovic, Mihalis A. Nicolaou, and Vladimir Pavlovic. Machine learning methods for social signal processing. In Judee K. Burgoon, Nadia Magnenat-Thalmann, Maja Pantic, and Alessandro Vinciarelli, editors, *Social Signal Processing*, pages 234–254. Cambridge University Press, Cambridge, UK, 2017.
- Peter Salovey and John D. Mayer. Emotional intelligence. *Imagination, Cognition and Personality*, 9(3):185–211, 1990.
- Dairazalia Sanchez-Cortes, Oya Aran, Marianne Schmid Mast, and Daniel Gatica-Perez. A nonverbal behavior approach to identify emergent leaders in small groups. *IEEE Transactions on Multimedia*, 14(3-2):816–832, 2012.
- Riccardo Sartori, Arianna Costantini, and Andrea Ceschi. Psychological assessment in human resource management: Discrepancies between theory and practice and two examples of integration. *Personnel Review*, ahead-of-print:1–15, 2020.
- Mohammad Iftekhar Tanveer, Emy Lin, and Mohammed (Ehsan) Hoque. Rhema: A real-time in-situ intelligent interface to help people with public speaking. In *Proceedings of the 20th ACM International Conference on Intelligent User Interfaces*, pages 286–295, New York, NY, 2015. ACM.
- Yla R. Tausczik and James W. Pennebaker. Improving teamwork using real-time language feedback. In *Proceedings of the 2013 ACM SIGCHI Conference on Human Factors in Computing Systems*, pages 459–468, New York, NY, 2013. ACM.

Alessandro Vinciarelli, Maja Pantic, Dirk Heylen, Catherine Pelachaud and Isabella Poggi, Francesca D'Errico, and Marc Schröder. Bridging the gap between social animal and unsocial machine: A survey of social signal processing. *IEEE Transactions on Affective Computing*, 3(1):69–87, 2012.

Karol M. Wasylyshyn, Hal S. Shorey, and Jason S. Chaffin. Patterns of leadership behaviour: Implications for successful executive coaching outcomes. *The Coaching Psychologist*, 8(2):74–85, 2012.