Annals of the Institute of Statistical Mathematics (2024) 76:35–37
https://doi.org/10.1007/s10463-023-00886-2

INVITED ARTICLE: FOURTH AKAIKE MEMORIAL LECTURE

Discussion of "Identifiability of latent-variable and structural-equation models: from linear to nonlinear"

Hiroshi Morioka[1]

Received: 23 June 2023 / Accepted: 4 July 2023 / Published online: 1 November 2023

I would like to congratulate Professor Aapo Hyvärinen for receiving the fourth Akaike Memorial Lecture Award. It is also a great pleasure for me as well to see such a great achievement of him as one of his collaborators. I believe no one would be doubtful about his considerable contribution in this field. I also admire his great personality, passion, and deep insight into a variety of fields. He is always open to new ideas, and now even trying to propose a new concept connecting learning by humans and that by artificial intelligence (AI) (Hyvärinen, 2022). I strongly believe his continued success in the coming future, and am really looking forward to seeing what he is going to show us.

Our collaboration started almost 10 years ago, when I finished my PhD and was kindly invited as a postdoctoral researcher of his laboratory at University of Helsinki. That was exactly when he came up with the basic idea of the "identifiable" nonlinear independent component analysis (NICA) (Hyvärinen and Morioka 2016, 2017), and since then we have been working continuously on this completely new direction to show its great potential (Morioka et al. 2020, 2021; Morioka and Hyvärinen, 2023). Since then, the concept of identifiable NICA has gained increasing attention, amid many representation learning frameworks were being proposed based on deep learning, such as VAE (Kingma and Welling 2014) and GAN (Goodfellow et al. 2014), without theoretical guarantee of identifiability (Hyvärinen and Pajunen 1999; Locatello et al. 2019). Thanks to the intensive works made by many researchers engaged in this field, we now have much deeper insight in which conditions NICA problems can be solved and made identifiable (Hälvä et al. 2021; Hyvärinen et al. 2019) (though some types of assumptions, such as local isometry of the observational mixing, can be controversial as shown in this article). Nowadays identifiability is considered to be a crucial property of nonlinear representation learning models, which is expected to be clearly discussed by authors when they are proposed. This shows how significantly his works affected this field.

The Related Articles are https://doi.org/10.1007/s10463-023-00884-4; https://doi.org/10.1007/s10463-023-00885-3; https://doi.org/10.1007/s10463-023-00887-1.

✉ Hiroshi Morioka
hiroshi.morioka@riken.jp

[1] Computational Brain Dynamics Team, RIKEN Center for Advanced Intelligence Project (AIP), 2-2-2 Hikaridai Seika-cho, Sorakugun, Kyoto 619-0288, Japan

This article reviews his contribution and the surrounding areas, with being divided into four parts: establishment of linear ICA theorems (e.g., (Hyvärinen 1999)), extension of linear ICA to causal discovery based on state-equation models (SEMs) (Hyvärinen et al. 2010; Shimizu et al. 2006; Zhang and Hyvärinen 2009), extension of ICA to nonlinear models with theoretical guarantee of identifiability (Hälvä et al. 2021; Hyvärinen and Morioka, 2016, 2017; Hyvärinen et al. 2019), and then application of NICA to nonlinear causal discovery (Monti et al. 2020). Especially linear ICA and SEMs seem to have established a solid position and are being used nowadays as the gold standard in a variety of fields, including neuroscience. Extension of them to nonlinear models also gave a substantial impact. Although it still seems to be controversial how identifiability is essential in practice for nonlinear models, they would contribute to the developments of trustable (interpretable) AI and so on, as discussed by the authors.

Since this article reviewed those topics thoroughly and gave sufficient discussions in which readers would be interested, I do not really have anything additionally to discuss about in theoretical aspects. I instead would like to ask him about his opinion of a more conceptual point, the possible connections of the ICA algorithms to the brain functions, which would be somewhat related to his recent interest (Hyvärinen 2022):

Discussion 1: Since we are also working on the neuroscience field, this question would be inevitable; how ICA is implemented in the brain? Even though our sensory inputs from the outside world are very complex and highly nonlinear, with dependency and a lot of confounders, we can somehow disentangle them into fundamental information. Proper understanding of such segregation (and also integration) of information in the brain is one of the unsolved problems in neuroscience. Although some studies proposed (possibly) bio-plausible algorithms of ICA (Asabuki and Fukai 2020; Isomura and Toyoizumi 2016, 2019, 2021), there is still no clear evidence what kinds of algorithms and criteria are used in the brain.

Discussion 2: The other question is the possibility of reverse engineering of those neuroscientific findings to the developments of novel ICA theorems or algorithms. It would be very exiting if we could show that a brain-inspired algorithm can defeat the current standard algorithms of ICA, in the sense of the robustness against outliers, noises, latent confounders, and high dimensionality, sample efficiency, generalizability, and so on.

Although I do not really expect there exists a clear answer, I still would be grateful if Prof. Hyvarinen could give us his opinions about those points and tell us how promising he is feeling now about them.

References

Asabuki, T., Fukai, T. (2020). Somatodendritic consistency check for temporal feature segmentation. *Nature Communications, 11*(1), 1554.

Goodfellow I., Pouget-Abadie J., Mirza M., Xu B., Warde-Farley D., Ozair S., Courville A., Bengio Y. (2014). Generative adversarial nets. *Advances in Neural Information Processing Systems, 27*, 608.

Hälvä, H., Le Corff, S., Lehéricy, L., So, J., Zhu, Y., Gassiat, E., Hyvärinen, A. (2021). Disentangling identifiable features from noisy data with structured nonlinear ica. *Advances in Neural Information Processing Systems, 34*, 1624–1633.

Hyvärinen, A. (1999). Fast and robust fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural Networks, 10*(3), 626–634.

Hyvärinen A. (2022) *Painful intelligence: What AI can tell us about human suffering*. https://www.cs.helsinki.fi/u/ahyvarin/painintl/.

Hyvärinen A., Morioka H. (2016). Unsupervised feature extraction by time-contrastive learning and nonlinear ICA. *Advances in Neural Information Processing Systems, 29*, 3765–3773.

Hyvärinen A., Morioka H. (2017). Nonlinear ICA of temporally dependent stationary sources. *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics,* 54, 460–469.

Hyvärinen, A., Pajunen, P. (1999). Nonlinear independent component analysis: Existence and uniqueness results. *Neural Networks, 12*(3), 429–439.

Hyvärinen, A., Zhang, K., Shimizu, S., Hoyer, P. O. (2010). Estimation of a structural vector autoregression model using non-Gaussianity. *Journal of Machine Learning Research, 11*(56), 1709–1731.

Hyvärinen, A., Sasaki, H., Turner, R. (2019). Nonlinear ICA using auxiliary variables and generalized contrastive learning. *Proceedings of the Twenty-Second International Conference on Artificial Intelligence and Statistics,* Vol 89, 859–868.

Isomura, T., Toyoizumi, T. (2016). A local learning rule for independent component analysis. *Scientific Reports, 6*(1), 28073.

Isomura, T., Toyoizumi, T. (2019). Multi-context blind source separation by error-gated hebbian rule. *Scientific Reports, 9*(1), 7127.

Isomura, T., Toyoizumi, T. (2021). On the achievability of blind source separation for high-dimensional nonlinear source mixtures. *Neural Computation, 33*(6), 1433–1468.

Kingma, D.P., Welling M. (2014). Auto-encoding variational bayes. *2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings*.

Locatello, F., Bauer, S., Lucic M., Raetsch, G., Gelly, S., Schölkopf B., Bachem O. (2019). Challenging common assumptions in the unsupervised learning of disentangled representations. *Proceedings of the 36th International Conference on Machine Learning*, Vol 97, 4114–4124.

Monti, R.P., Zhang K., Hyvärinen A. (2020). Causal discovery with general non-linear relationships using non-linear ICA. *Proceedings of The 35th Uncertainty in Artificial Intelligence Conference*, Vol 115, 86–195.

Morioka, H., Hyvärinen A. (2023). Connectivity-contrastive learning: Combining causal discovery and representation learning for multimodal data. *Proceedings of The 26th International Conference on Artificial Intelligence and Statistics,* vol 206, 3399–3426.

Morioka, H., Calhoun, V., Hyvärinen, A. (2020). Nonlinear ica of fmri reveals primitive temporal structures linked to rest, task, and behavioral traits. *NeuroImage, 218*, 116989.

Morioka H., Hälvä H., Hyvärinen A. (2021). Independent innovation analysis for nonlinear vector autoregressive process. *Proceedings of The 24th International Conference on Artificial Intelligence and Statistics,* vol 130, 1549–1557.

Shimizu, S., Hoyer, P. O., Hyvärinen, A., Kerminen, A. (2006). A linear non-Gaussian acyclic model for causal discovery. *Journal of Machine Learning Research, 7*(72), 2003–2030.

Zhang, K., Hyvärinen A. (2009). On the identifiability of the post-nonlinear causal model. *Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence*, 647–655.