Ozone forecasting across Belgium with co-evolutionary Neural Architecture Search

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Abstract. Air pollution was the 4th leading risk factor for early death in 2019. Models capable of forecasting nonlinear atmospheric phenomena are difficult to train and optimize consistently. Island Transpeciation [21] is a co-evolutionary neural architecture search technique that can train and optimize architectures and hyperparameters of day-ahead forecasting deep neural networks. Using several years of real-world historical air-quality and meteorological data, we managed to outperform random model search and previous machine learning techniques in accurately predicting ozone across Belgium.

Keywords: forecasting · neural architecture search · deep learning · meta-learning

1 Motivation

Around 400,000 premature deaths per year are caused by air pollution in Europe [3] [9] [10]. Accurate forecasting allows governments to promptly warn the public with low air-quality alerts [7]. Our objective is the search for accurate, country-wide models, for next-day ground-level ozone (O_3) [1] forecasting. This extended encore abstract describes the prior work on Island Transpeciation [21].

2 Main contributions

We developed *island transpeciation* [20] [21] (Fig. 1), to optimize Deep Neural Networks (DNN) [18] [11] [4] in forecasting. Co-evolution between different optimizers [14] [22] is achieved via the transpeciation evolutionary operator, under a Neural Architecture Search (NAS) [6] [25] [24] setting. **Contributions:**

- A new Evolutionary Algorithms (EA) [23] operator: *transpeciation*.
- Island transpeciation: an automated parallel [17] [5] and distributed [12] [2] NAS, featuring hardware hot-plugging and fault-tolerance.

– Multiple-Input Multiple-Output (MIMO), Nonlinear Auto Regressive eXogenous (NARX) DNN: A single model prototype for country-scale air quality forecasting.
– Ozone forecasting deep learning model configuration suggestions.

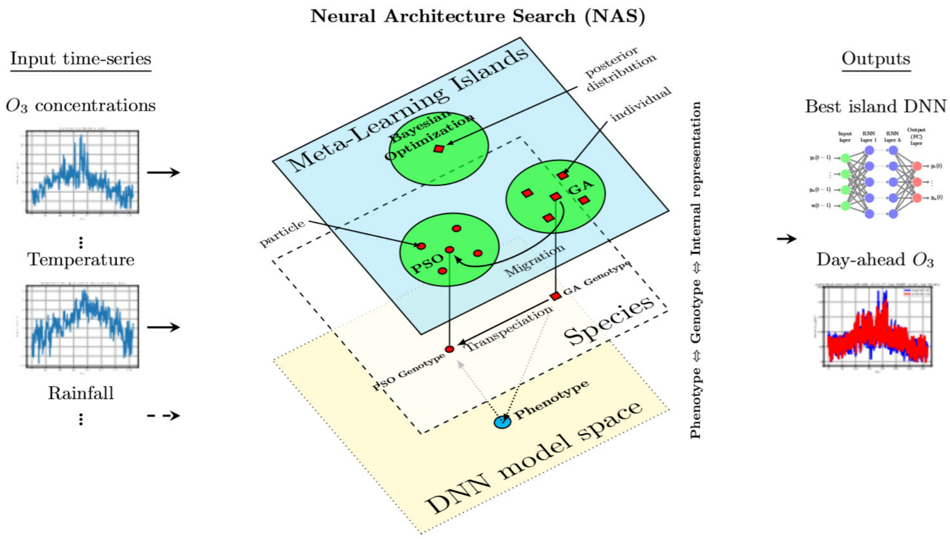

Fig. 1. Day-ahead ozone forecasting top-level view, using the island transpeciation NAS [21]. The transpeciation operator (middle layer: species) allows the cooperation and competition between incompatible optimizers via: transformation and migration of candidate model solutions. In this illustration: Bayesian Optimization (BO) [15] island cooperates with a Genetic Algorithm (GA) [16] [8] and Particle Swarm Optimization (PSO) [19].

3 Results and Conclusion

MIMO NARX DNN (Fig. 1) can successfully predict country-wide, next-day O_3 pollution episodes, on real-world time-series (46 Belgian monitoring stations [1] data, from 1990 to 2018). The main negative is extended model training times. This co-evolutionary meta-learning [13] approach balances model training times versus model size trade-offs, via the asynchronous cooperation and competition of the underlying optimizers. Finally, there should be a balanced consideration between the number of islands and the total amount of NAS iterations.

References

1. AirBase - The European air quality database, https://www.eea.europa.eu/data-and-maps/data/airbase-the-european-air-quality-database-8
2. VLAAMS SUPERCOMPUTER CENTRUM ANNUAL REPORT 2018 (2018), https://www.vscentrum.be/
3. Health Effects Institute. State of Global Air 2019 (2019), www.stateofglobalair.org
4. Chollet, F., others: Keras (2015), https://keras.io
5. Dalcin, L.D., Paz, R.R., Kler, P.A., Cosimo, A.: Parallel distributed computing using Python. Advances in Water Resources (2011). https://doi.org/10.1016/j.advwatres.2011.04.013
6. Elsken, T., Metzen, J.H., Hutter, F.: Neural Architecture Search. In: Automated Machine Learning: Methods, Systems, Challenges, pp. 63–77. Springer International Publishing (2019). https://doi.org/10.1007/978-3-030-05318-5{_}3
7. European Commission: Directive 2002/3/EC of the European Parliament and of the council of 12 February 2002 relating to ozone in ambient air. Official Journal of the European Union (2002). https://doi.org/L102/15
8. Fortin, F.A., De Rainville, F.M., Gardner, M.A., Parizeau, M., Gagńe, C.: DEAP: Evolutionary algorithms made easy. Journal of Machine Learning Research **13**(70), 2171–2175 (2012)
9. Guerreiro, C., de Leeuw, F., Ortiz, A.G., Viana, M., Colette, A.: Air quality in Europe — 2018 report. Tech. rep., European Environment Agency (2018). https://doi.org/10.2800/62459
10. Hill, L., Flack, M.: The Physiological Influence of Ozone. Proceedings of the Royal Society B: Biological Sciences **84**(573), 404–415 (12 1911). https://doi.org/10.1098/rspb.1911.0086
11. Hochreiter, S., Schmidhuber, J.: Long Short-Term Memory. Neural Computation **9**(8), 1735–1780 (1997). https://doi.org/10.1162/neco.1997.9.8.1735
12. Hohpe, G., Woolf, B.: Enterprise integration patterns : designing, building, and deploying messaging solutions. Addison-Wesley (2004)
13. Hutter, F., Kotthoff, L., Vanschoren, J.: Automated Machine Learning Methods, Systems, Challenges. Springer International Publishing, (2019)
14. Izzo, D., Ruciński, M., Biscani, F.: The generalized Island model. Studies in Computational Intelligence **415**(January 2012), 151–169 (2012)
15. Kandasamy, K., Neiswanger, W., Schneider, J., Póczos, B., Xing, E.P.: Neural Architecture Search with Bayesian Optimisation and Optimal Transport. In: Proceedings of the 32nd International Conference on Neural Information Processing Systems. p. 2020–2029. NIPS'18, Curran Associates Inc., Red Hook, NY, USA (2018)
16. Lu, Z., Whalen, I., Boddeti, V., Dhebar, Y., Deb, K., Goodman, E., Banzhaf, W.: NSGA-Net: Neural architecture search using multiobjective genetic algorithm. In: Proc. Genet. Evol. Comput. Conf. pp. 419–427 (2019)
17. Mattson, T.G., Sanders, B.A., Massingill, B.: Patterns for parallel programming. Addison-Wesley (2005)
18. Rumelhart, D.E., Hinton, G.E., Williams, R.J.: Learning representations by back-propagating errors. Nature **323**(6088), 533–536 (1986). https://doi.org/10.1038/323533a0
19. Sun, Y., Xue, B., Zhang, M., Yen, G.G.: A Particle Swarm Optimization-Based Flexible Convolutional Autoencoder for Image Classification. IEEE transactions on

neural networks and learning systems **30**(8), 2295–2309 (8 2019). https://doi.org/10.1109/TNNLS.2018.2881143
20. Theodorakos, K.: Air-quality forecasting in Belgium using Deep Neural Networks, Neuroevolution and distributed Island Transpeciation. M.Sc. thesis. Katholieke Universiteit Leuven. Faculty of Engineering Science. Department of Electrical Engineering. ESAT-STADIUS (9 2019)
21. Theodorakos, K., Agudelo, O.M., Schreurs, J., Suykens, J.A.K., Moor, B.D.: Island Transpeciation: A Co-Evolutionary Neural Architecture Search, applied to country-scale air-quality forecasting. IEEE Transactions on Evolutionary Computation (2022). https://doi.org/10.1109/TEVC.2022.3189500
22. Tomassini, M.: Spatially Structured Evolutionary Algorithms. Springer (2005). https://doi.org/10.1007/3-540-29938-6
23. Vikhar, P.A.: Evolutionary algorithms: A critical review and its future prospects. In: 2016 International Conference on Global Trends in Signal Processing, Information Computing and Communication (ICGTSPICC). pp. 261–265. IEEE (12 2016). https://doi.org/10.1109/ICGTSPICC.2016.7955308
24. Yao, X.: Evolving artificial neural networks. Proceedings of the IEEE **87**(9), 1423–1447 (1999). https://doi.org/10.1109/5.784219
25. Zhou, X., Qin, A.K., Gong, M., Tan, K.C.: A Survey on Evolutionary Construction of Deep Neural Networks. IEEE Transactions on Evolutionary Computation **25**(5), 894–912 (2021). https://doi.org/10.1109/TEVC.2021.3079985