

7 Conclusions

We have introduced an approach to obtain sparse LGMLVQ models by interpreting the relevance matrix as a projection matrix and searching for sparse approximations. In the results, we showed that it becomes possible to remove more than 90% of the features this way without deteriorating performance. Such sparse models are particularly interesting for its efficient realization in hardware, on edge devices, or real-time classification models. Furthermore a smaller model is easier to study and interpret.

References

- [1] Jake Snell, Kevin Swersky, and Richard S. Zemel. Prototypical networks for few-shot learning. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA*, pages 4077–4087, 2017.
- [2] Hong-Ming Yang, Xu-Yao Zhang, Fei Yin, and Cheng-Lin Liu. Robust classification with convolutional prototype learning. In *2018 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2018, Salt Lake City, UT, USA, June 18-22, 2018*, pages 3474–3482, 2018.
- [3] Viktor Losing, Barbara Hammer, and Heiko Wersing. Incremental on-line learning: A review and comparison of state of the art algorithms. *Neurocomputing*, 275:1261–1274, 2018.
- [4] Michael Biehl, Barbara Hammer, and Thomas Villmann. Prototype-based models in machine learning. *WIREs Cognitive Science*, 7(2):92–111, 2016.
- [5] David Nova and Pablo A. Estévez. A review of learning vector quantization classifiers. *Neural Computing and Applications*, 25(3-4):511–524, 2014.
- [6] Thomas Villmann, Marika Kästner, Andreas Backhaus, and Udo Seiffert. Processing hyperspectral data in machine learning. In *21st European Symposium on Artificial Neural Networks, ESANN 2013, Bruges, Belgium, 2013*.
- [7] Gert-Jan de Vries, Steffen C. Pauws, and Michael Biehl. Insightful stress detection from physiology modalities using learning vector quantization. *Neurocomputing*, 151:873–882, 2015.
- [8] Benjamin Paaßen, Bassam Mokbel, and Barbara Hammer. Adaptive structure metrics for automated feedback provision in intelligent tutoring systems. *Neurocomputing*, 192:3–13, 2016.
- [9] Lukas Pfannschmidt, Christina Göpfert, Ursula Neumann, Dominik Heider, and Barbara Hammer. Fri-feature relevance intervals for interpretable and interactive data exploration. In *IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology, CIBCB 2019, Siena, Italy, July 9-11, 2019*, pages 1–10, 2019.
- [10] Rick van Veen, L. Talavera Martinez, R. V. Kogan, Sanne K. Meles, Deborah Mudali, Jos B. T. M. Roerdink, F. Massa, M. Grazzini, Jose A. Obeso, Maria C. Rodriguez-Oroz, Klaus Leonard Leenders, Remco J. Renken, J. J. G. de Vries, and Michael Biehl. Machine learning based analysis of FDG-PET image data for the diagnosis of neurodegenerative diseases. In *Applications of Intelligent Systems - Proceedings of the 1st International APPIS Conference 2018, Las Palmas de Gran Canaria, Spain, 8-12 January 2018*, pages 280–289, 2018.
- [11] Petra Schneider, Michael Biehl, and Barbara Hammer. Adaptive relevance matrices in learning vector quantization. *Neural Computation*, 21(12):3532–3561, 2009.
- [12] Kerstin Bunte, Petra Schneider, Barbara Hammer, Frank-Michael Schleif, Thomas Villmann, and Michael Biehl. Limited rank matrix learning, discriminative dimension reduction and visualization. *Neural Netw.*, 26:159–173, 2012.
- [13] Johannes Brinkrolf, Christina Göpfert, and Barbara Hammer. Differential privacy for learning vector quantization. *Neurocomputing*, 342:125–136, 2019.
- [14] Lydia Fischer, Barbara Hammer, and Heiko Wersing. Optimal local rejection for classifiers. *Neurocomputing*, 214:445–457, 2016.
- [15] Alexander Schulz, Bassam Mokbel, Michael Biehl, and Barbara Hammer. Inferring feature relevances from metric learning. In *IEEE Symposium Series on Computational Intelligence, SSCI 2015, Cape Town, South Africa, December 7-10, 2015*, pages 1599–1606. IEEE, 2015.
- [16] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. "why should i trust you?": Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16*, pages 1135–1144, New York, NY, USA, 2016. ACM.
- [17] Michael Biehl, Barbara Hammer, Frank-Michael Schleif, Petra Schneider, and Thomas Villmann. Stationarity of matrix relevance LVQ. In *2015 International Joint Conference on Neural Networks, IJCNN 2015, Killarney, Ireland, July 12-17, 2015*, pages 1–8, 2015.
- [18] Martin Riedel, Fabrice Rossi, Marika Kästner, and Thomas Villmann. Regularization in relevance learning vector quantization using l1-norms. In *21st European Symposium on Artificial Neural Networks, ESANN 2013, Bruges, Belgium, 2013*.
- [19] Noah Simon, Jerome Friedman, Trevor Hastie, and Robert Tibshirani. A sparse-group lasso. *Journal of Computational and Graphical Statistics*, 22(2):231–245, 2013.
- [20] Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001.
- [21] Geoffrey M. Davis, Stephane G. Mallat, and Zhifeng Zhang. Adaptive time-frequency decompositions. *Optical Engineering*, 33(7):2183 – 2191, 1994.
- [22] Atsushi Sato and Keiji Yamada. Generalized learning vector quantization. In *Advances in Neural Information Processing Systems 8, NIPS, Denver, CO, November 27-30, 1995*, pages 423–429. MIT Press, 1995.
- [23] Ming Yuan and Yi Lin. Model Selection and Estimation in Regression With Grouped Variables. *Journal of the Royal Statistical Society Series B*, 68:49–67, 2006.
- [24] Christina Göpfert, Lukas Pfannschmidt, and Barbara Hammer. Feature Relevance Bounds for Linear Classification. In *25th European Symposium on Artificial Neural Networks, ESANN 2017, Bruges, Belgium, 2017*.
- [25] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, and Jorge Luis Reyes-Ortiz. A Public Domain Dataset for Human Activity Recognition using Smartphones. In *21st European Symposium on Artificial Neural Networks, ESANN 2013, Bruges, Belgium, 2013*.
- [26] Isabelle Guyon, Steve Gunn, Asa Ben-Hur, and Gideon Dror. Result Analysis of the NIPS 2003 Feature Selection Challenge. In *Advances in Neural Information Processing Systems*, volume 17, 2004.
- [27] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.