Riemann Manifolds and Hierarchical Structures

Bálint Daróczy

Institute for Computer Science and Control,
Hungarian Academy of Sciences (MTA SZTAKI), Hungary

We suggested in [1] the family of similarity kernels as a class of kernels applicable for classification and regression. The methods are capable of defining a single unified kernel even in the case of rich data types. The final kernels are define a generative model (Markov Random Field) on pairwise similarities and the Fisher information. The kernels do not depend on the parameters of the random graph and therefore we do not need to determine the relative importance of the basic modalities [2]. We extended the model for time-series classification in [1] and measuring similarity between subgraphs [3]. During the talk we consider the case of low order polynomials as Hamiltonians following the results in [4]. The expressive power of deep structures with a special family of metrics [5], extended Hessian metrics with proper quasi-arithmetic means, suggest us sparse representations and we investigate how the quality of approximation connected to the geometrical properties of the learning methods in certain hierarchical, deep structures without efficient "flattening".

References

[1] B. Daróczy, P. Vaderna, and A. Benczúr. *Machine learning based session drop prediction in LTE networks and its SON aspects.* In Proceedings of the 81st IEEE Vehicular Technology Conference (VTC Spring), 2015, Glasgow, Scotland, UK, pp. 1–5, IEEE

[2] B. Daróczy, D. Siklósi, R. Pálovics, and A. Benczúr. *Text Classification Kernels for Quality Prediction over the C3 Data Set.* In Proceedings of the 24th International Conference on World Wide Web (WWW'15), Florence, Italy, pp. 1441-1446, ACM

[3] J. Wachs, B. Daróczy, A. Hannák, K. Páll, and C. Riedl. *And Now for Something Completely Different: Visual Novelty in an Online Network of Designers.* accepted as full paper at the 10th ACM Conference on Web Science 2018, Amsterdam, Netherlands, ACM

[4] Henry W. Lin, Max Tegmark, and David Rolnick. *Why does deep and cheap learning work so well?* Journal of Statistical Physics 168(6), 2017, pp. 1223–1247, Springer

[5] Shun-ichi Amari and John Armstrong. *Curvature of Hessian manifolds.* Differential Geometry and its Applications 33, 2014, pp. 1–12, Elsevier