Proposal for a tutorial at IJCNN'14

Prototype based methods: Mathematical foundations, interpretability, and data visualization

Organizer

Barbara Hammer is currently professor at CITEC Centre of Excellence, Bielefeld University, Bielefeld, Germany. She received her Ph.D. and her venia legendi in Computer Science from the University of Osnabrück, Germany, where she led the research group LNM, before becoming professor for Theoretical Computer Science at Clausthal University of Technology, Germany in 2004. In 2010, she joined the CITEC centre of excellence at Bielefeld University, Germany, where she is professor for Theoretical Computer Science for Cognitive Systems. She is chairing the IEEE CIS Technical Committee on Data Mining in 2013, the task force of the IEEE CIS Data Mining Technical Committee on Data Analysis and Visualization, and the Fachgruppe Neural Networks of the German Computer Science Society. She is co-chair of IEEE CIDM'13, and CIDM'14. Her current research projects cover diverse areas such as autonomous learning, data visualization, learning interpretable models, machine learning applications in bioinformatics, intelligent tutoring systems, as well as industrial applications, funded by different research organizations including DFG and BMBF. She has published more than 200 articles in international journals and conferences.

Prof. Hammer has strong expertise as regards the proposed tutorial topic, since she has been working on the area of prototype based methods since more than ten years together with colleagues. In particular, she actively contributed to the following topics which will be covered in the tutorial:

- the principle of relevance and matrix learning for learning vector quantization (LVQ) [7,11,15,16],
- the learning theoretical background of LVQ [10,16,18],
- the connection of low rank matrix learning to discriminative visualization tasks, [4,5,11,12],
- extensions of LVQ and VQ mechanisms to general similarities or dissimilarities [3,8,9],
- efficient linear time realizations of kernel (L)VQ approaches and extensions to streaming data [1,2,6,9,12,14],
- biomedical applications [13,17].

Goal of the tutorial

Prototype based techniques such as supervised learning vector quantization (LVQ) or unsupervised counterparts enjoy a wide popularity in particular when constraints such as restricted computational resources, online capability, model interpretability, or life-long learning ability have to be met. The classical LVQ algorithm strikes practitioners due to its very simple and intuitive, cognitively inspired training and classification model. Its exact mathematical investigation, however, has long been an open question. Recent developments close this gap, modeling LVQ schemes based on principled mathematical objectives such as margin optimization or the data likelihood. This way, extensions can easily be integrated such as powerful matrix learning or extensions to non-vectorial data. Intuitive classification schemes result which naturally lend itself to online and lifelong learning strategies, classifier visualization, and model interpretation. The goal of the tutorial is to give an overview about recent developments in this domain, covering in particular principled approaches as concerns training of LVQ schemes and its mathematical foundations, extensions to metric learning and more general data structures, and model interpretability and links to data visualization.

Covered material

The following items represent the topics of the tutorial:

- Learning vector quantization(LVQ): basic definition; LVQ schemes based on cost functions - generalized LVQ as large margin approach, robust soft LVQ as probabilistic model; extensions; learning theoretical results
- Typical applications of learning vector quantization: example from the biomedical domain and robotics vision.
- Metric learning: relevance and matrix adaptation; model interpretability; data visualization using low rank matrices; theoretical results as concerns convergence and uniqueness,
- LVQ for general data structures: kernelization; relational approaches; issues of interpretability and complexity,
- how to extend LVQ schemes for life long learning and big data

Tutorial format and accompanying resources

The tutorial will be a regular tutorial with two hours presentation (including examples and demonstrations). It will be accompanied by a web site with access to the slides, links to further material such as publications, and links to available code.

Bibliography

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