Open PhD Position in **"Parameter-wise Transfer Learning"**

The term Transfer Learning denotes a problem setting with a number of different but closely related learning tasks (scenarios). Knowledge extracted from previous/original source should be transferred and applied to one or more different but similar target tasks. Learning in new but somehow similar scenarios should then be performed quicker, with less training data, and/or result in more robust and consistent models.
Starting with the end of the 90s, topics of transfer learning are appearing in machine learning research and publication. There are still few generally usable approaches for the application of Transfer Learning in complex regression problems.

The goal of the proposed PhD topic belongs to the parameter/structure transfer approach. For certain model architectures, the question is how to best transfer parameters of models for already learned neighboring scenarios to a new one. An initial model usually starts close to the neighboring scenario. Then, as data from the new scenario arrives, the model should be updated or newly created to optimally take the new information into account (e.g. within incremental regularized optimization procedures). The more data becomes available, the less important and influential the information from neighboring scenarios will probably be, achieving a kind of convergence (stability).
Depending on the chosen model architecture and on the similarity between the old and new data set(s), it should be analyzed when and how different types of adaptation approaches work (global vs. local, full vs. sparse, speed etc.). For instance, there might be specific model parameters and local structures which should be adapted in a different way to new data than others. Model architectures relevant for this work will be linear and polynomial models for studying theoretical and practical properties of the developed approach. Further candidates are non-linear techniques such as symbolic regression, neural networks as well as integrated learning engines for identifying the regression models.

The developed approaches should be tuned and evaluated on real-world data from projects in the domain of energy consumption and production optimization, and of analytical chemistry. The position will be located at the Department of Knowledge-Based Mathematical Systems (Fuzzy Logic Laboratory Linz, FLLL), with further supervision and mentoring at Software Competence Center Hagenberg GmbH (SCCH).

References:
[1] S. Thrun, "Is learning the n-th thing any easier than learning the first," In Advances in Neural Information Processing Systems (NIPS), vol. 8, pp. 640-646, 1996.
[2] S. J. Pan and Q. Yang, "A Survey on Transfer Learning," IEEE Transactions on Knowledge and Data Engineering, vol. 22, no. 10, pp. 1345-1359, Oct. 2010.

Profile/Personal Qualification of the candidate:

Applicants should preferable have a completed master in Mathematics/Informatics/Mechatronics and already have some knowledge in data-driven modeling and machine learning techniques; willingness for preparing publications in international journals and conferences. Interest in transfer learning and evolving systems is warmly welcome.

Contact – please send your applications to:
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Our Related Expertise: machine learning, evolving systems, adaptive models, transfer and deep learning, various model architectures, see also
https://www.flll.jku.at/aboutus/machinelearning
https://www.scch.at/de/data-analysis-systems

Duration: at least 1.5 years, maximal 3 years, 30 hours per week
Deadline of Application: Fr, 16th of August 2013
Finance: 1955 Euro gross per month