

On-line Fusion of Functional Knowledge Within Distributed Sensor Networks

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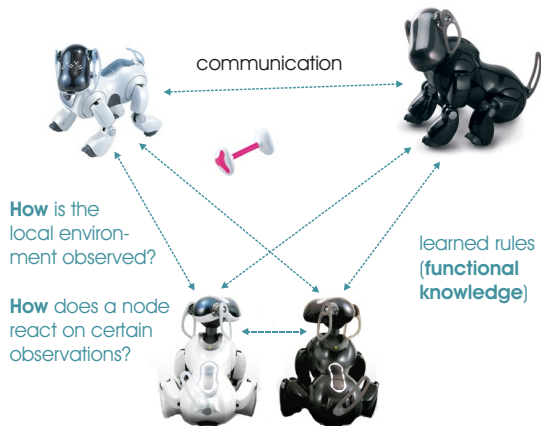
9th Colloquium of the DFG Priority Program 1183
“Organic Computing”
September 21./22. 2009, Augsburg

Overview

- Introduction
- Research Issues 2008/2009
- Rule Exchange with Meta Knowledge
- Phase III

Objectives of the Project

Collaboration of intelligent systems (e.g., teams of robots, smart sensor networks, software agents) by exchanging classification rules



Proposed Classifier Approach – 1

- Objective: Classify multivariate observations $\{\mathbf{x}_i\}$
- Assumption: Observations are generated by J stochastic processes
 - ▶ Observations form groups/clusters within the input space
 - ▶ Probabilistic modeling:

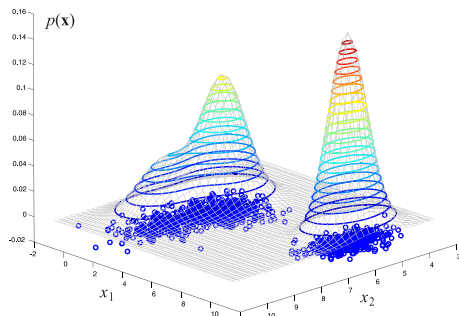
$$p(c|\mathbf{x}) = \sum_{j=1}^J p(c|j)p(j|\mathbf{x})$$

where

$$p(j|\mathbf{x}) = \frac{p(\mathbf{x}|j)p(j)}{p(\mathbf{x})}$$

Proposed Classifier Approach – 2

Example: Modeling with Gaussian distributions:

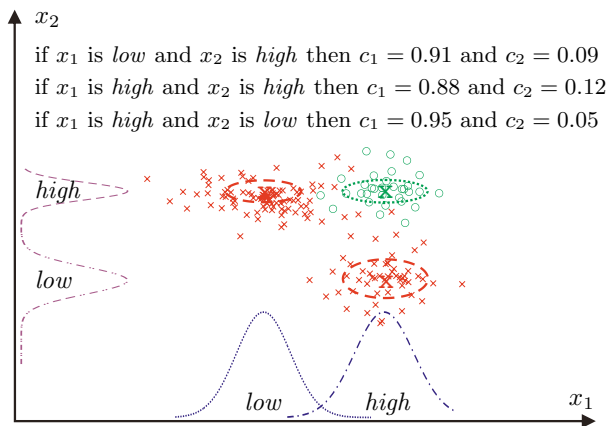


- $p(c|\mathbf{x}) = \sum_{j=1}^J p(c|j) \frac{p(\mathbf{x}|j)p(j)}{p(\mathbf{x})}$
- Class distribution $p(c|j)$:
 $\mathcal{M}(c|\xi)$
- Component densities $p(\mathbf{x}|j)$:
 $\mathcal{N}(\mathbf{x}|\mu_j, \Sigma_j)$
- Mixing coefficients $p(j)$:
 $\mathcal{M}(j|\pi)$

Proposed Classifier Approach – 3

Extraction of human readable classification rules:

- Prerequisite: Gaussians with diagonal covariance matrices
- Every component can be seen as classification rule



Research Issues 2008/2009

Research Issues 2008/2009

- Classifier paradigm and training techniques:
 - ▶ Comparison to other functionally equivalent paradigms [FKSO09]
 - ▶ Comparison of generative and discriminative training methods [FS09]
 - ▶ Support for categorical input dimensions
 - ▶ Extension to time series classification [FGS09]
- Online training, knowledge exchange and knowledge fusion
 - ▶ Incremental learning
 - ▶ Improved novelty detection techniques [FJKS09]
 - ▶ Fusion of uncertain expert knowledge [AHS08] (*best paper*)
 - ▶ Knowledge exchange augmented by meta knowledge (i.e., information about knowledge) [FJKS09]
- Application studies
 - ▶ Intrusion detection: Aggregation of intrusion alerts [HS09]
- Collaboration with other groups
 - ▶ Study on evolvable hardware [GTG+08] (*best paper*)
 - ▶ Study on emergence in technical systems [MS08]

Research Issues 2008/2009

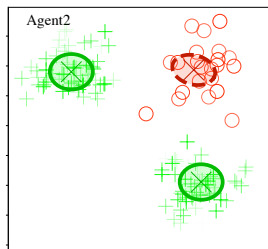
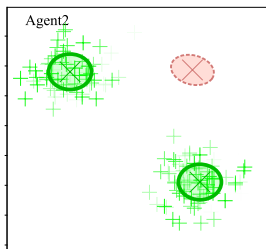
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Rule Exchange Enhanced with Meta Knowledge

- Intention: Agents mutually exchange newly acquired knowledge (i.e., rules)
- However, different agents rarely observe the exact same situation and use the same classifier
- Not all received rules from other agents are really helpful!
 - ▶ Inadequate rules may even deteriorate the decision boundary!
 - ▶ Key question: Which rules should be integrated?
 - ▶ Solution: Assess received rules with respect to different criteria (i.e., meta knowledge / **interestingness**)

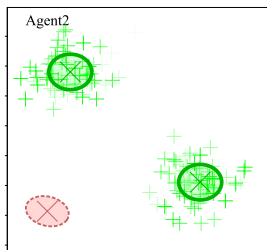
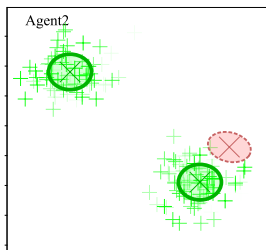
Meta Knowledge of Rules – Usefulness

- Assessment if a rule is useful to classify local observations
 - ▶ Rule stored in a cache and rated over time
 - ▶ Useful, if a sufficient amount of samples can be assigned to the rule



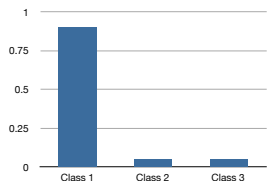
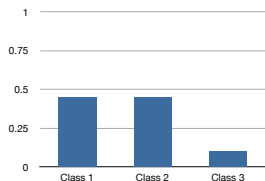
Meta Knowledge of Rules – Informativeness

- A received rule is considered informative if it describes a **really new** kind of data-generating process
 - ▶ The more distant a new rule is with respect to the existing rules, the more confident we are that there really is a new process



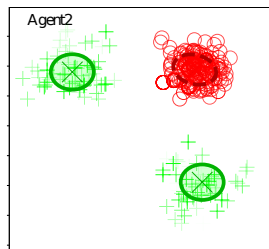
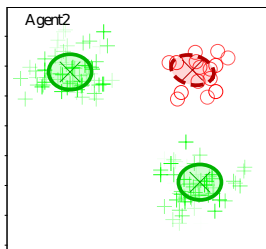
Meta Knowledge of Rules – Uniqueness

- Assessment of a rule's conclusion $p(c|j)$
 - ▶ Measures how distinct the conclusion is
 - ▶ Evaluates the difference between the largest and the second largest class probability value



Meta Knowledge of Rules – Importance

- Assessment of the sender's mixing coefficient $p(j')$ of the received rule j'
 - ▶ Very important if $p(j')$ is far above the average mixing coefficient $\frac{1}{J}$ of the sender
 - ▶ J : Total number of rules in the sender's classifier



Phase III

Phase III – 1

Fusion of parameter estimates

- Parameter estimates of rules based on observed data
- Uncertainty regarding the parameter estimates explicitly modeled with second order probabilities (i.e., distributions over parameters)
 - ▶ Rule premises
 - ▶ Rule conclusions
- Agents exchange distributions over parameters
 - ▶ Must be fused

Phase III – 2

Provision of an OC-Toolbox for self-reflection and self-adaptation techniques

- Self-Reflection: Ability of an organic system to recognize on its own
 - ▶ The emergence of a new sample-generating process (i.e., the need for new knowledge)
 - ▶ The termination of an existing sample-generating process (i.e., the obsolescence of knowledge)
- Self-Adaptation: Ability to (semi-)autonomously react on detected changes in the environment
 - ▶ Create new rules for new processes (premises learnt unsupervised, conclusions provided by human experts, for instance)
 - ▶ Remove existing but obsolete rules from the classifier

Phase III – 3

Application Scenarios:

- Driver assistance systems
- Distributed intrusion detection systems

List of Publications

- [FKOS09] Fisch, D. and Kühbeck, B. and Sick, B. and Ovaska, S., **So Near And Yet So Far: New Insight Into The Relationship Between Some Well-Known Classifier Paradigms**, Information Sciences, 2009 (revised version under review)
- [FS09] Fisch, D. and Sick B., **Training of Radial Basis Function Classifiers With Resilient Propagation and Variational Bayesian Inference**, Proceedings of the "International Joint Conference on Neural Networks (IJCNN 2009)", pp. 838-847, Atlanta, 2009
- [FGS09] Fisch, D. and Gruber, T. and Sick, B., **SwiftRule: Mining Comprehensible Classification Rules for Time Series Analysis**, IEEE Transactions on Knowledge and Data Engineering, 2009 (under review)
- [FJKS09] Fisch, D. and Jänicke, M. and Kalkowski, S. and Sick B., **Learning by Teaching versus Learning by Doing: Knowledge Exchange in Organic Agent Systems**, Proceedings of the IEEE Symposium Series on Computational Intelligence 2009 (SSCI 2009), pp. 31-38, Nashville, 2009
- [AHS08] Andrade, D. and Horeis, T. and Sick, B., **Knowledge Fusion Using Dempster-Shafer Theory and the Imprecise Dirichlet Model**, Proceedings of the "2008 IEEE Conference on Soft Computing in Industrial Applications (SMCia/08)", pp. 142-148, Muroran, 2008
- [HS09] Hofmann, A. and Sick, B., **On-Line Intrusion Alert Aggregation With Generative Data Stream Modeling**, IEEE Transactions on Dependable and Secure Computing, 2009
- [GTG+08] Glette K., Torresen J., Gruber T., Sick B., Kaufmann P, Platzner M, **Comparing Evolvable Hardware to Conventional Classifiers for Electromyographic Prosthetic Hand Control**, Proceedings of the "3rd NASA/ESA Conference on Adaptive Hardware and Systems (AHS-2008)", pp. 32-39, Noordwijk, 2008
- [MS08] Müller-Schloer C., Sick B., **Controlled Emergence and Self-Organization**, R. P. Würtz(Ed.): Organic Computing, ch. 4, pp. 81-104, Series on Understanding Complex Systems, Springer Verlag, Berlin, Heidelberg, New York, 2008

Thanks a bunch for your attention!

More information: <http://www.cis-research.de>