Article

Utilizing a bounding procedure based on Simulated Annealing to effectively locate the bounds for the parameters of Radial Basis Function networks

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Abstract: The Radial Basis Function (RBF) networks are an established parametric machine learning tool, which has been extensively utilized in data classification and data fitting problems. These specific machine learning tools have been applied in various scientific areas, such as problems in physics, chemistry, and medicine, with excellent results. A two-step technique is usually used to adjust the parameters of these models, which is in most cases extremely effective. However, it does not effectively explore the value space of the network parameters and often results in parameter stability problems. In this paper, the use of a bounding technique that explores the value space of the parameters of these networks using intervals generated by a procedure based on the Simulated Annealing method is recommended. After finding a promising range of values for the network parameters, a genetic algorithm is applied within this range of values to more effectively adjust its parameters. The new method was applied on a wide range of classification and regression datasets from the relevant literature and the results are reported in the current manuscript.

Keywords: Radial Basis Function networks; Simulated Annealing; Stochastic techniques; Evolutionary Computation

Citation: Tsoulos, I.G.; Charilogis, V.; Tsalikakis D. Utilizing a bounding procedure based on Simulated Annealing to effectively locate the bounds for the parameters of Radial Basis Function networks. *Journal Not Specified* **2023**, *1*, 0. https://doi.org/

Received:
Revised:
Accepted:
Published:

1. Introduction

2. Method description

3. Experiments

3.1. Experimental datasets

3.2. Experimental results

4. Conclusions

Author Contributions: V.C. and I.G.T. conducted the experiments, employing several datasets and provided the comparative experiments. D.T. and V.C. performed the statistical analysis and prepared the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: This research has been financed by the European Union : Next Generation EU through the Program Greece 2.0 National Recovery and Resilience Plan , under the call RESEARCH – CREATE – INNOVATE, project name "iCREW: Intelligent small craft simulator for advanced crew training using Virtual Reality techniques" (project code:TAEDK-06195).

Conflicts of Interest: The authors declare no conflict of interest.

Sample Availability: Not applicable.

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