

# <sup>1</sup> NiaARM.jl: A Julia Framework for Numerical Association Rule Mining Using Nature-Inspired Optimization Algorithms

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## Software

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## <sup>6</sup> Summary

<sup>7</sup> NiaARM.jl is an open-source Julia package for Numerical Association Rule Mining (NARM) based on stochastic population-based nature-inspired optimization algorithms ([Telikani et al., 2020](#)). It brings the capabilities of the original Python-based NiaARM framework ([Stupan & Fister, 2022](#)) to the Julia ecosystem, enabling researchers and data scientists working with datasets with mixed attribute types (consisting of categorical and numerical attributes) to discover numerical association rules. NiaARM.jl supports loading datasets, preprocessing, association rule mining, and extraction of discovered rules with associated interestingness metrics. In line with the rule mining part, this package also implements several well-known stochastic population-based nature-inspired algorithms, such as Differential Evolution (DE) ([Storn & Price, 1997](#)), Artificial Bee Colony (ABC) ([Karaboga & Basturk, 2007](#)), Particle Swarm Optimization (PSO) ([Kennedy & Eberhart, 1995](#)), and several other metaphor-based nature-inspired algorithms to act as solvers for the numerical association rule mining task. The entire numerical association rule mining workflow is further supported by visualization methods for numerical association rules, which is achieved through NarmViz.jl, a package well integrated with NiaARM.jl ([Fister Jr et al., 2024](#)).

## <sup>22</sup> State of the Field

<sup>23</sup> Classical association rule mining (ARM) is well supported in general purpose libraries such as the R package *arules* ([Hahsler et al., 2005](#)), the SPMF Java library ([Fournier-Viger & others, 2020](#)), and the Julia package RuleMiner.jl ([Schwartz, 2024](#)). These tools focus on frequent itemset and rule mining over categorical or discretized data. Frameworks such as uARMSolver ([Fister & Fister Jr, 2020](#)) go a step further by formulating ARM as an optimization problem and supporting numerical attributes.

<sup>29</sup> Dedicated support for NARM is currently provided mainly by the original Python based NiaARM framework ([Stupan & Fister, 2022](#)) and the more recent *niarules* package for R ([Fister Jr et al., 2026](#)). Both adopt population-based nature-inspired algorithms to search for numerical association rules.

<sup>33</sup> NiaARM.jl is designed as a Julia native, modular re-implementation of this line of work rather than a wrapper around existing frameworks. It combines the full NARM pipeline (data handling, problem formulation, optimization, and rule representation) with extensibility for new interestingness measures and optimization algorithms, and integrates tightly with NarmViz.jl for visualization. In this way, NiaARM.jl complements existing Python and R frameworks while filling a gap in the Julia ecosystem for high performance NARM.

## 39 Software Design

40 The core of NiaARM.jl is organized around four main modules: (1) the Dataset module,  
 41 which handles loading and preprocessing of transaction data from CSV files or DataFrames,  
 42 representing numerical attributes as interval features and categorical attributes as sets of  
 43 categories; (2) the Problem module, which formulates numerical association rule mining as a  
 44 continuous optimization problem, where candidate solutions are encoded as real-valued vectors  
 45 and decoded into association rules; (3) the optimization algorithms module, which provides  
 46 implementations of various nature-inspired algorithms that explore the search space to identify  
 47 rules; and (4) the Rule module, which represents discovered association rules and provides  
 48 methods for computing interestingness measures.

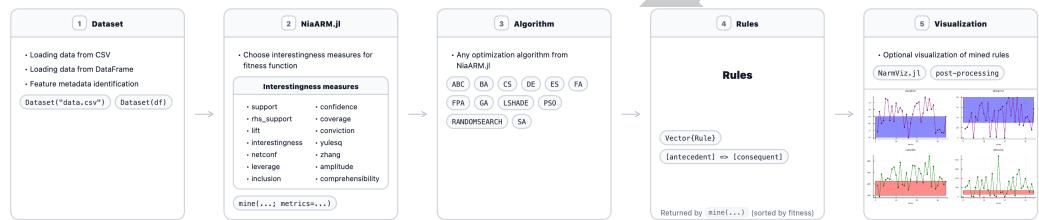


Figure 1: NiaARM.jl flow.

49 The flow of the NiaARM.jl framework is shown in Figure 1. Users can construct a dataset  
 50 either from a CSV file (via a file path) or directly from DataFrame. The dataset is then  
 51 used to build the numerical association rule mining optimization problem together with user-  
 52 selected interestingness measures, which are used in the computation of the fitness function.  
 53 The optimization problem can be solved using any of the population-based nature-inspired  
 54 algorithms implemented in NiaARM.jl (e.g., DE, ABC, PSO) to mine numerical association  
 55 rules from the dataset. The discovered rules are returned as a collection of Rule objects and  
 56 can be further analyzed, exported (e.g., to CSV in downstream post-processing), or visualized  
 57 using NarmViz.jl (Fister Jr et al., 2024), which provides several visualization methods for  
 58 numerical association rules.

## 59 Statement of need

60 Despite the growing importance of NARM in domains such as finance, sport, and medicine, the  
 61 Julia ecosystem has lacked a dedicated and efficient framework for this task. NiaARM.jl fills this  
 62 gap by providing a comprehensive, optimization-driven approach to numerical association rule  
 63 mining based on stochastic population-based nature-inspired algorithms. The package enables  
 64 researchers and data scientists to mine numerical association rules from mixed-type datasets  
 65 while leveraging Julia's strengths in performance, composability, and scientific computing.  
 66 Altogether, the main benefits of NiaARM.jl can be summarized as follows:

- 67   ■ The framework enables researchers to easily apply the full NARM pipeline, i.e. from  
   68   dataset loading to visualization of the identified rules.
- 69   ■ The package contains a vast collection of stochastic population-based nature-inspired  
   70   algorithms.
- 71   ■ Julia's performance allows for significantly faster discovery of numerical association rules  
   72   compared to the Python version.
- 73   ■ The framework is designed in a modular way, allowing components to be flexibly combined  
   74   and extended.

## 75 Research Impact Statement

76 NiaARM.jl framework lowers the barrier to high-performance NARM by making NARM  
77 accessible, faster than previous implementations especially on complex datasets, and extensible  
78 within the Julia ecosystem. By providing a dedicated Julia framework for dealing with NARM  
79 tasks, the package extends an established methodology that was previously available primarily  
80 in the Python programming language. It allows researchers and practitioners who rely on  
81 Julia for high-performance scientific computing to solve NARM tasks. NiaARM.jl is also well  
82 integrated with other packages, for example NarmViz, which extends the rule mining pipeline  
83 to include visualization.

84 In addition to its applied impact, NiaARM.jl contributes to methodological research by providing  
85 reference implementations of multiple stochastic population-based nature-inspired algorithms  
86 within a unified framework. This supports reproducibility, benchmarking, and comparative  
87 studies in metaheuristic optimization beyond solving NARM tasks alone. The modular design  
88 of the framework encourages community-driven extensions, enabling rapid prototyping of new  
89 algorithms, fitness functions, and interestingness measures.

## 90 AI Usage Disclosure

91 During the preparation of this work the authors used language tools such as Lumo (the AI  
92 assistant from Proton), Grammarly in order to improve the article's readability. After using  
93 these tools, the authors reviewed and edited the content as needed and take full responsibility  
94 for the content of the published article. During codebase development, AI-assisted tools were  
95 used for documentation refinement and code readability. The majority of the codebase had  
96 been designed and implemented prior to the widespread adoption of AI-assisted development  
97 tools, ensuring that the conceptual design, architectural decisions, and core algorithmic  
98 implementations are entirely the result of the authors original work.

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