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Adaptive Resonance Lib: A Python package for Adaptive Resonance Theory (ART) models

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Summary

The Adaptive Resonance Theory Library (**artlib**) is a Python library that implements a wide range of Adaptive Resonance Theory (ART) algorithms. **artlib** currently supports eight elementary ART models and 12 compound ART models, including Fuzzy ART (Gail A. Carpenter et al., 1991b), Hypersphere ART (Anagnostopoulos & Georgiopulos, 2000), Ellipsoid ART (Anagnostopoulos & Georgiopoulos, 2001a, 2001b), Gaussian ART (Williamson, 1996), Bayesian ART (Vigdor & Lerner, 2007), Quadratic Neuron ART (M.-C. Su & Liu, 2001; M. Su & Liu, 2005), ART1 (Gail A. Carpenter & Grossberg, 1987a), ART2 (Gail A. Carpenter et al., 1991a; Gail A. Carpenter & Grossberg, 1987b), ARTMAP (G. A. Carpenter et al., 1991), Simplified ARTMAP (Gotarredona et al., 1998), SMART (Bartfai, 1994), DeepARTMAP (Niklas M. Melton et al., 2025b), TopoART (Tscherepanow, 2010), Dual Vigilance ART (Silva et al., 2019b), CVIART (Silva et al., 2022), BARTMAP (Xu et al., 2012; Xu & II, 2011), Fusion ART (Tan et al., 2007), FALCON (Tan, 2004), and TD-FALCON (Tan et al., 2008). These models can be applied to tasks such as unsupervised clustering, supervised classification, regression, and reinforcement learning (Silva et al., 2019a). This library provides an extensible and modular framework where users can integrate custom models or extend current implementations, allowing for experimentation with existing and novel machine learning techniques.

In addition to the diverse set of ART models, **artlib** offers implementations of visualization methods for various cluster geometries, along with pre-processing techniques such as Visual Assessment of Tendency (VAT; Bezdek & Hathaway, 2002), data normalization, and complement coding.

Adaptive Resonance Theory (ART)

ART is a class of neural networks known for solving the stability-plasticity dilemma, making it particularly effective for classification, clustering, and incremental learning tasks (Grossberg, 1976, 1976, 1980, 2013; Silva et al., 2019a). ART models are designed to dynamically learn and adapt to new patterns without catastrophic forgetting, making them ideal for real-time systems requiring continuous learning.

Over the years, dozens of ART variations have been published (Silva et al., 2019a), extending the applicability of ART to nearly all learning regimes, including reinforcement learning (Tan, 2004; Tan et al., 2008), hierarchical clustering (Bartfai, 1994), topological clustering (Tscherepanow, 2010), and biclustering (Xu et al., 2012; Xu & II, 2011). These numerous models provide an ART-based solution for most machine learning use cases. However, the rapid pace of bespoke model development, coupled with the challenges students face in learning ART's foundational principles, has contributed to a scarcity of open-source, user-friendly implementations for most

ART variants.

The ability of ART to preserve previously learned patterns while learning new data in real-time has made it a powerful tool in domains such as robotics, medical diagnosis, and adaptive control systems. **artlib** aims to extend the application of these models in modern machine learning pipelines, offering a unique and approachable toolkit for leveraging ART's strengths.

Statement of Need

The Adaptive Resonance Library (**artlib**) is essential for researchers, developers, and educators interested in adaptive neural networks, specifically ART algorithms. While deep learning dominates machine learning, ART models offer unique advantages in incremental and real-time learning environments due to their ability to learn new data without forgetting previously learned information.

Currently, no comprehensive Python library implements a variety of ART models in an open-source, modular, and extensible manner. **artlib** fills this gap by offering a range of ART implementations that integrate seamlessly with machine learning workflows, including scikit-learn's `Pipeline` and `GridSearchCV` (Pedregosa et al., 2011). The library is designed for ease of use and high performance, with all modules leveraging Python's scientific stack: i.e. NumPy (C. R. Harris et al., 2020), SciPy (Virtanen et al., 2020), and scikit-learn (Pedregosa et al., 2011), a subset of modules also provide C++ and Torch implementations for even faster numerical computation.

The modular design of **artlib** enables users to create novel compound ART models, such as Dual Vigilance Fusion ART (Silva et al., 2019b; Tan et al., 2007) or Quadratic Neuron SMART (Bartfai, 1994; M.-C. Su & Liu, 2001; M. Su & Liu, 2005). This flexibility offers powerful experimental and time-saving benefits, allowing researchers and practitioners to evaluate models on diverse datasets efficiently.

Additionally, the library serves as a valuable educational tool, providing well-documented code and familiar APIs to support hands-on experimentation with ART models. It is ideal for academic courses, personal projects, and research in artificial intelligence and machine learning, making **artlib** a versatile resource.

artlib is actively maintained and designed for future extension, allowing users to create new ART models, adjust parameters for specific applications, and explore ART's potential for novel research problems. Its integration with popular Python libraries ensures its adaptability to current machine learning challenges.

Comparison to Existing Implementations

While there are several open-source repositories that provide python implementations of specific ART models (AI OpenLab, 2023; Birkjohann, 2023; Dilekman, 2022; Dixit, 2020; Inyoot, 2021; Ray11641, 2023; Stepanov, 2022; Valixandra, 2021; Wan, 2022), they lack modularity and are limited in scope, often implementing just one or two models. For instance, MATLAB-based ART toolboxes (Boitet, 2022; M. Harris, 2000; Schwenker, 2004b, 2004a) provide implementations of Fuzzy ART, TopoART, ART1, and ARTMAP models, but they lack the flexibility and modularity required for broader experimentation. The most significant existing ART implementation exists in Julia and provides just five models (Petrenko & Wunsch, 2022) but, like the previously listed MATLAB-based toolboxes, it is not easily accessible to Python-based work flows and lacks a modular design. Further, no public ART implementations provide configurable match-tracking (Niklas M. Melton et al., 2025a).

These existing implementations of ART models may provide standalone versions of individual models, but they are often not designed to integrate seamlessly with modern Python libraries such as scikit-learn, NumPy, and SciPy. As a result, researchers and developers working in Python-based environments face challenges when trying to incorporate ART models into their machine learning pipelines.

In contrast, **artlib** offers a comprehensive and modular collection of ART models, including both elementary and compound ART architectures. It is designed for interoperability with popular Python tools, enabling users to easily integrate ART models into machine learning workflows, optimize models using scikit-learn's `GridSearchCV`, and preprocess data using standard libraries. Further, **artlib** provides users the flexibility to construct their own compound ART modules (those art modules deriving properties from other, elementary modules) which may or may not exist in published literature. **artlib** also provides a template in the source code to encourage users to develop and experiment with their own custom ART algorithms. This flexibility and integration make **artlib** a powerful resource for both research and practical applications.

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