ART2 vs. ARTMAP

Parkinson’s Disease Classification from

Biomedical Voice Measurements

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Abstract—In this study, two varieties of Adaptive Resonance Theory (ART), a set of unsupervised learning algorithms, was used to categorize patients based on provided sampled voice data. This data was used to determine whether the patient in question was afflicted by Parkinson’s Disease, with elements such as frequency, harmonic/noise ratio, and frequency spread being featured. ART2, a variety of ART enabling the classification of continuous-valued real inputs, was used and compared against ARTMAP, a supervised variety of ART combining ART modules together with an inter-ART layer.

Key Words— Adaptive Resonance Theory, Resonance, ART, ART2, ARTMAP, Artificial Intelligence, Classification

1. Introduction

Adaptive Resonance Theory, a concept originally developed in 1987 by Gail Carpenter and Stephen Grossberg, is a self-organizing unsupervised learning model that is able to categorize a set of given input vectors without any external interaction. This concept is an expansion upon the idea of a traditional feedforward neural network, a very common neuron-based computational model. A different approach to this same concept, ARTMAP, introduces supervised learning, allowing the user to provide expected outputs to train the network against.

In this paper, these two models are compared to determine relative efficiency in determining whether a given patient had Parkinson’s Disease. As input, each network was provided with a vector representing a number of vocal measures and elements for a specific voice sample from a specific patient. The networks then preformed calculations which gave rise to the categorization of each patient into one of two recognition categories. These categories represented the set of patients who were classified as having Parkinson’s Disease and the set of patients who were classified as not having said disease.

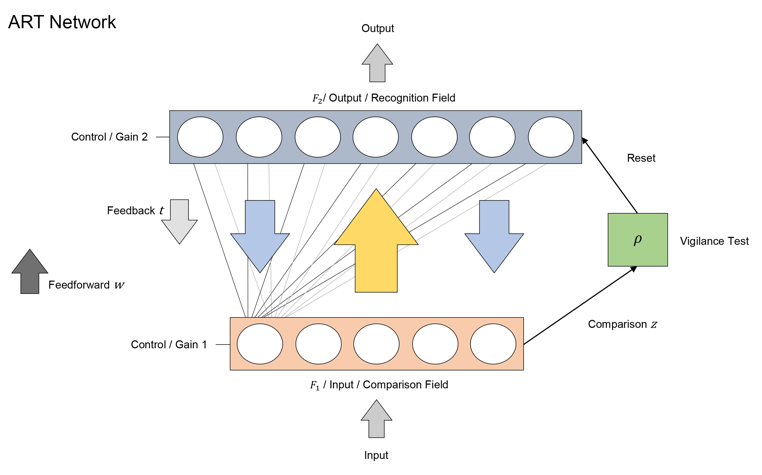
1. Adaptive Resonance Theory

Adaptive Resonance Theory (ART) represents a family of unsupervised self-stabilizing categorization algorithms, each implementing the Adaptive Resonance concept into their learning and categorization models to a varying degree. The central concept of ART resides in the resonance – as patterns are learned and recognized, patterns that fall within a certain degree of match are said to *resonate* with the given category choice. As the chosen categorical winner resonates within the input, the category learns and *adapts* based on the applied input and previously learned patterns.

Each incremental iteration of the ART architecture resulted in an improvement to the core concept of the adaptive resonance learning model. ART1, the original intelligence presented by Carpenter and Grossberg, was only capable of categorizing binary-valued inputs. This was improved in the second iteration, ART2, by allowing for continuous, real-valued inputs. To handle the diversity of this new type of input, a number of other elements were introduced into the system – most notably of which is the more complex orienting subsystem. ART3 improved this further by introducing neurochemical distributions based on values of such found in human neural pathways and bodies, making the model a more realistic representation of an actual, biological neural model. Fuzzy ART, a variation applicable to each of these, applied fuzzy logic to the categorical recognition process, allowing for a degree of overlap for categorical choices within a given range. ARTMAP, rather than being a separate learning model in and of itself, is instead an adaptation of the ART architecture that, by means of combining ART modules together, allows for supervised learning to occur via the Adaptive Resonance architecture.

1. ART2

Like many ART varieties, ART2 is separable into a number of layers or *fields* with an additional orienting subsystem that corrects for match errors in categorization. Specifically, ART2 consists of three main fields, with each field being composed of a number of nodes. These fields will be denoted in sequential order with the increasing subscript of F.



* 1. *The Field*

Also known as the *Input Field*, the Field represents the data provided in the input vector for a given pattern to be presented to the network. The number of nodes present in the field is directly correlated with the number of elements in the pattern vector. Each node feeds via a direct and non-adaptive pathway into a single node, with one node per input element.

* 1. *The Field*

Representing the *short-term memory* of the ART2 system, the Field contains a series of equations connected via directed pathways through which the input node value is passed. As the values passed into this field may change on a pattern-by-pattern basis, the equations only calculate for the currently given input value. This gives rise to the term of *short-term memory*, as no categorical learning or recognition takes place in this field, only pure input calculation. The output of each node in this field is passed up to the F2 layer, in which the pattern is either recognized and learned, or passed completely in the case of total mismatch.

Inside each neuron, the input value is passed from the field up into a series of six equations, with the output of each function passing directly into another function within the same neuron. All these equations are calculated in a specific order: with representing the input for the neuron .

***Fig. 3.1: ART2 STM Equations***

The only exceptions to this are and , which feedback to and respectively. Each of the other letters represent a specific function on the prior function’s output for that specific neuron. For three of these equations – denoted as , , and – the values passed to the next function are simply a normalization of the previous function’s output. Node is the only point at which the and layers are allowed to interact.

* 1. *The Field*

Also known as the *long-term memory* for the system, this field stores all learned recognition categories and uncommitted categorization nodes. Nodes in this field – the number of which is prescribed by the programmer – learn pattern representations fed up by the node of a specific neuron in the field through a matrix of bottom-up weights. Until a categorization node is chosen, a parallel search is run to find a category in which the pattern can be classified – this is decided by the orienting subsystem, which will be detailed in section III-E.

* 1. *LTM Traces*

Long-Term Memory Traces (LTM) are the weights on the pathways between the and fields. These weights change and adapt as new recognition categories are learned and strengthen through category recognition.

The LTM Trace field is composed of two sets of weights – the top-down (TD) and bottom-up (BU) weights. Top-down weights act upon the returning signals from the field back to the field in the case of proper category matches. Bottom-up weights act upon the signals originating from the nodes in the layer that are passed up to the field for category recognition.

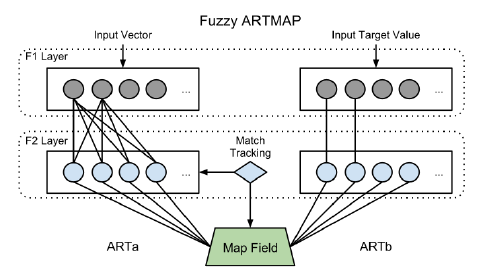
* 1. *Orienting Subsystem*

The orienting subsystem of the ART2 network handles cases of mismatch between the and fields. This feature is absent from the previous ART1 network, since binary patterns may be compared through bitwise comparisons. For continuous-valued parameters, such as is seen in ART2 and future ART implementations, a match function is defined to determine the degree of match between a selected category representation ( neuron) and an input category (from ).

In the parallel search of the field for a given input from the field, the degree of match between the two is compared against a programmer-defined constant . Should the degree of match, denoted as the magnitude of the vector , fall below the *vigilance parameter* , a mismatch is said to occur. This triggers a reset of the active category node and signals for the continuation of the parallel search for a proper categorical match for the input data.

1. ARTMAP

Unlike other models in the ART family, the ARTMAP subcategory represents a set of supervised learning algorithms which also implement the Adaptive Resonance architecture. This is done not by directly modifying the methodology by which ART networks learn, but instead by implementing a pair of adaptive resonance networks.



* 1. *Structure*

Rather than being an entirely new structure in and of itself, ARTMAP works on the same principle as ART, but uses a pair of ART modules to provide supervised learning capabilities. These modules work in conjunction through an inter-ART layer, which provides an interface between the separate fields of each module.

* + 1. *Sub-ART Modules*

Each of the constituent ART modules in ART map is, on its own, a fully functional unsupervised learning machine. As such, if disconnected, each module will self-learn and self-categorize its given input data. This allows the core facets of the Adaptive Resonance Theory to remain fully in play for all learning scenarios, as at its core ART is a wholly unsupervised learning algorithm.

Instead of modifying an ART module to force supervised learning, ARTMAP implements an inter-ART layer. This layer is external to the two self-contained ART systems, and provides an interface between the categorical layer of each. As categorical recognition data is stored in the nodes of the layer for each ART module, this layer provides an indirect interface in which the learned categories of each may compare with each other without direct influence on the other’s categories.

* + 1. *Supervised Learning with Sub-ART Modules*

To implement supervised learning in ARTMAP, each sub-ART is presented with roughly the same input data. The only difference is the second sub-ART, denoted , is given the correct expected categorization data alongside the original data vector. Given there exists a direct and non-adaptive pathway between this module and the inter-ART category field, category choice is not so much decided as it is prescribed. However, learning still occurs just as is found in a typical ART module.

On the other side of the inter-ART field, there exists another ART module, denoted here as . This module is a standard ART module that learns and categorizes as usual, but with an additional step. After categorization, a comparison occurs between the field (the field of ) and the inter-ART system. As stated previously, this field takes values from each sub-ART and compares between. As contains the correct categorization data, this allows for the ARTMAP system to determine whether the correct categorization has occurred for a given input pattern.

When both and are active, learning occurs within the inter-ART field. This is where the true category recognition of ARTMAP occurs, as having both fields active means that the selected category matched the correct category – thus, is shown to have correctly categorized its input data.

* 1. *Inter-ART Field*

The key feature of the ARTMAP algorithm is the *inter-ART field*, which allows for recognition category comparisons to happen between the expected categories and the projected categories. As this field is external to either of the two constituent ART modules making up ARTMAP, this allows Adaptive Resonance Theory to work as originally intended within these models whilst being able to compare externally against each other to enforce supervised learning.

* + 1. *Map Field*

The *Map Field* in ARTMAP in the location where all categorical learning takes place within the inter-ART module. Connected via a bidirectional non-adaptive pathway to and a bidirectional adaptive pathway to , this field compares and combines compressed, symbolic categorical representations when allowed by the *Gain Control Signal*.

* + 1. *Map Field Gain Control*

The *Map Field Gain Control* subsystem emits a constant signal into the Map Field, preventing Map Field categorical representations from being learned when the projected categorical choice differs from the expected category. However, this signal is removed when these categories are matched, removing the inhibitory signal feeding into the Map Field and allowing pattern recognitions to be learned for that specific Map Field node.

* + 1. *Map Field Orienting Subsystem*

Each component of the ARTMAP system has its own vigilance parameter – for , for , and for the inter-ART module. In the case of a categorical mismatch between and , the Map Field Orienting Subsystem implements a feature known as ‘*match tracking’*. This allows the ARTMAP system to differentiate very similar input vector values into separate values if separate expected categories are given. This also allows ARTMAP to categorize very different input vectors if their expected category choices are the same. When a mismatch occurs, match tracking allows the Map Field Orienting Subsystem to slightly modulate the value of , keeping the system from repeating its mistakes.

1. Experimental Details

Utilizing biomedical data from 31 separate patients, the algorithms described above were applied to classify said patients into one of two categorizations. Voice measurement data from vocal samples provided by these individuals was analyzed to determine if the patient in question was a sufferer of Parkinson’s disease. This categorization could then be applied to subjects outside of the original dataset to determine whether another patient is, within a degree of uncertainty, afflicted by such as well.

* 1. *Data Representation*

The data provided was gathered from 31 patients, 23 of whom were confirmed to have Parkinson’s disease. The remaining 8 patients were, conversely, confirmed to not be afflicted by Parkinson’s. Each patient provided between 5 to 7 samples, with the average by far being 6 samples per patient.

Each sample for each patient was then analyzed, giving rise to 22 elements representing features or groups of features of the given sample. Some of these features include: frequency in hertz, jitter and shimmer measurements, noise-to-tonal components, and fundamental frequency variation, amongst others. A number of these, such as frequency, was further separated, giving rise to categories such as: average frequency, maximal frequency, and minimal frequency. A full list of all features is available in Appendix A.

* 1. *Data Input*

Each input vector was presented to the networks in randomized order. This was done to minimize the probability of the networks learning specific patterns or categorizations based solely on presentation order, rather than by the vector components as was desired. As all samples provided by a single patient were originally clustered together in the data set, this also prevented the network from learning on a per patient basis.

ART2, being an unsupervised learning algorithm was provided with the entirety of the data set for classification. As ARTMAP is a supervised learning model, 85 vectors out of the 195 provided were used as a training set. After training, the network was then provided with the entirety of the dataset for classification.

* 1. *Experimental Parameters*

For the ART modules presented, the overlapping programmer-provided parameters and constants retained the same functionality for both ART2 and ARTMAP. However, the values given were varied through testing to find parameters that best fit each individual model. The parameters prescribed to each algorithm are presented in the tables below.

For the orienting subsystem, dictates the degree of match that a given input pattern must not fall beneath to be allowed to select that category as its ‘winner’ node. is a signal threshold element present in the piecewise-linear signal activation function found in *Figure 3.1*. Parameters and (also sometimes denoted as and ) are weighting constants also found in functions seen in the aforementioned figure. The final two values, and , are used throughout the LTM Trace equations, as well as in mismatch sensitivity calculations.

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**Fig. 5.1: ART2 Parameters**

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**Fig. 5.2: ARTMAP Parameters**

1. Results and Comparisons

For the given data set, the supervised ARTMAP proved to me much more efficient than the unsupervised ART2 system. This is as was expected, as ARTMAP was given negative feedback from its expected subsystem in the case of a mismatch. This allowed the ARTMAP algorithm to learn categorization components that may have not been clearly present in an unsupervised scenario, where categorization may have been based off an entirely different set of parameters.

For specific figures, ARTMAP classified 77.95% of patients correctly whereas ART2 was only able to classify 59.27% of the presented 195 patient samples into the correct category. However, the results returned by ART2 could be interpreted either way since, being entirely unsupervised, the ART system only ends up classifying patients it believes to be similar with no regard for human interpretation. This means that either the first or second node in the layer could represent the presence of Parkinson’s – disregarding the readability provided by ARTMAP, which classified the presence of Parkinson’s into the second node in the layer with absence being in the first. These categories can then be read out as category 0 being the absence and category 1 as being the presence of Parkinson’s, which matches with Boolean truth values, thus removing ambiguity from the returned results.

1. Appendix A
   1. *Experimental Variables*

* MDVP: Fo(Hz)
  + Average vocal fundamental frequency
* MDVP: Fhi(Hz)
  + Maximum vocal fundamental frequency
* MDVP: Flo(Hz)
  + Minimum vocal fundamental frequency
* MDVP: Jitter(%), Jitter(Abs), RAP, PPQ, Jitter: DDP
  + Several measures of variation in fundamental frequency
* MDVP: Shimmer, (dB), APQ3, APQ5, APQ,Shimmer: DDA
  + Several measures of variation in amplitude