Journal of Advance Computational Research
Vol. 2 No. 1 (January-June, 2017)

Adaptable Framework for Cultural Response Measurement

Michael Gosnell, Joseph Barker, Brett Walenz, Robert Woodley and Warren Noll
Missouri Office at 199 E 4th St., Suite B, Fort Leonard Wood, MO 65473 USA
E-mail: mike.gosnell@21csi.com

Abstract: *Obtaining cultural measurements or analyses tends to be an intense, focused process, often providing a single cultural snapshot of the relevant population of interest. Population behavior, however, is extensible and malleable, adjusting to the culturally relevant events in real time. We present a robust framework designed to work independently of any specific cultural model, which can be utilized with both static and dynamic analyses. Following an initial training period, the framework can be implemented solely from the captured cultural characteristics. However, given continual updating using culturally cognizant, population-focused data, the framework can be used as a continual cultural model, adapting dynamically to the current cultural climate.*

Keywords: *ARTMAP, Behavior, Culture, Machine Learning, Modeling*

I. INTRODUCTION

Traditional social theory and cultural measurement techniques provide analyses through involved processes which often involve direct human interaction and post-hoc analysis methods. Results allow psychologists, anthropologists, and social scientists to draw conclusions about certain situations and circumstances as provided in the experiment. These data can be used to quantitatively define characteristics about persons or groups, but have not been extensively incorporated in computer software. When culture-related measurement or prediction software is available, it relies on static analyses, such as those based on Hofstede's cultural dimensions.

We present a cultural response framework designed to be used for dynamic predictive analysis following an initial setup period. This framework is unique in that is works independently of any specific cultural modeling technique. Any quantitative cultural measure can be used within the framework (examples are provided in Section IV). Section II provides cultural definitions used in the remainder of this paper. Section III presents the cultural response framework with a few example quantitative cultural models provided in Section IV. Section V presents some implementation results using two related cultural models (Grid and Group) and Section VI concludes with some additional considerations and development discussion.

II. CULTURAL DEFINITIONS

With the ambiguity often associated with "culture," the remainder of this paper will be focused with a preliminary discussion of culture and terminology usage. A population of interest will be identified as a Culture with some specified Cultural ID. The Cultural ID is a combination of Cultural Characterizers which are predetermined characteristics designed to be useful in describing populations of interest. Once specified, a Culture is defined or identified by its set of corresponding Cultural Traits (which are obtained from Cultural Features) measured from members of the population termed Entities. A difficulty exists in choosing appropriate Characterizers and Traits such that each population of interest can be distinguished from one another. However, the framework is robust enough to allow any Cultural Characterizer or Trait set to be used (as validated through external research, or suitable for a specific implementation). Each of the main cultural components is discussed individually below.

(A) Cultural Characterizers

A Cultural Characterizer is the most fundamental descriptive unit for characterization of cultural components. The Cultural Characterizers are classified as *static* or *variable* characteristics. Static characteristics reference traits which are unlikely to change (race, gender, national origin) while variable characteristics are more likely to change over a person's lifetime (religion, education, occupation). An illustrative set of Cultural Characterizers is provided here:

Static Characterizers

- Nationality
- Parents Nationality

- Gender
- Age (birth date)
- Race
- Citizenship (Current, Previous)
- Languages Spoken

Variable Characterizers

- Religion
- Type of government currently living under
- Occupation
- Education
- Current domicile location
- Previous domicile location

Cultural Characterizers must (1) identify characteristics of individuals in the population(s) of interest and (2) be quantifiable or distinguishable (for example, Male and Female are distinguishable – but not necessarily quantifiable). Cultural Characterizers are used as attributes of individuals as well as in specifying a Cultural ID as described in the next section.

(B) Cultural ID

A Cultural ID is a specific set of Cultural Characterizer values used to define a population of interest. Examples of Cultural IDs include {male}, {male, Iraqi}, and {male, Iraqi, 28 years old}. It is anticipated that an operator will enter as many qualifying Cultural Characterizers into the Cultural ID as is known; with the remaining characterizers acting in a *don't know / don't care / unknown* manner.

(C) Cultural Traits

A Cultural Trait is a clearly defined measurable characteristic (quantitative or qualitative) which will be used to measure and differentiate between populations of interest. Cultural Traits are expected to come from existing scientific literature, and a few examples are provided in Section IV. Calculation and validation of the Cultural Trait value is assumed to rely on external soft science research or literature – which can allow use of subject matter expertise indirectly, without needing a full-time scientist in order to use the framework. A Cultural Trait value is composed from Cultural Feature values, as described in the following section.

(D) Cultural Features

Cultural Features are discrete, individual measures which have been shown (in existing literature or research) to contribute toward a defined Cultural Trait. Cultural Trait (CT) calculation can be considered a function f of Cultural Features (CF) expressed as $CT1 = f\{CF1,..., CFn\}$ where Cultural Trait CT1 is calculated over some function f from Cultural Features CF1 through CFn. While it is possible to require only a single Cultural Feature value for calculating a Cultural Trait, multiple Cultural Features are typically utilized.

(E) CULTURAL ENTITIES

Loosely defined, a Cultural Entity is a person and their corresponding Cultural Characterizers and Cultural Features (which can be used to determine their individual Cultural Trait values). When dealing with a Cultural ID of interest, a person is classified as a Cultural Entity if the Cultural Characterizers of the Cultural ID are entirely contained within the Cultural Characterizers of the person. In other words, if Cultural ID $C_{ID}1$ is defined with Cultural Characterizers $C_{ID}1$ = {male, Iraqi, 28}, a person identified with {male, Iraqi} or {male, Iraqi, 29} would not be an Entity with respect to that Cultural ID. However, {male, Iraqi, 28} and {male, Iraqi, 28, Muslim} would both be Entities with respect to $C_{ID}1$ as the Cultural ID's Cultural Characterizers are completely contained within the person's Cultural Characterizers.

Fig. 1 illustrates the relationship of Cultural Characterizers, Traits, and Features with the Cultural Entities defined as above. In this illustration, a portion of the population falls within the Cultural Characterizers of interest. These corresponding Cultural Entities, falling within the Cultural ID of interest, are indicated as blue stick-figures and their data is used to calculate the Cultural Trait values of that particular "Culture" of interest. The persons not completely falling within the Cultural ID are indicated as red stick-figures and their data is not used within the analysis.

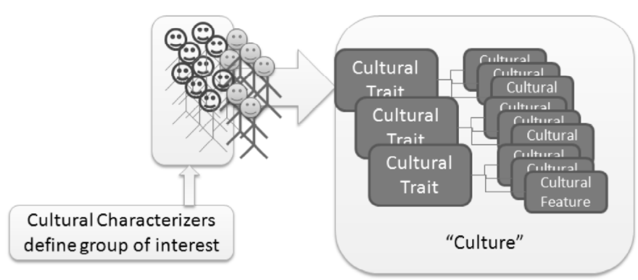

Figure 1: Relationship of Cultural Characterizers, Features, and Traits

III. FRAMEWORK

Our framework is designed around the Cultural Characterizers, Features, and Traits depicted at a conceptual level in Fig. 1. Fig. 2 shows the framework and the Cultural Characterizers and Cultural Features as the two main data input within the system. These data can be obtained from any method, but the system input will be specified as either direct (such as survey data) or indirect (such as information retrieval through Natural Language Processing of open data sources). The Cultural Characterizers restrict the Cultural Entities scope which can limit the data required for Information Processing.

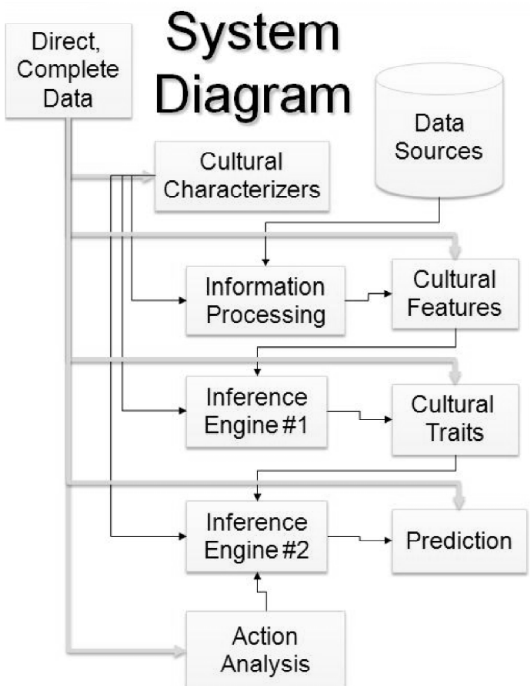

Figure 2: Cultural Response Framework System Diagram

The framework System Diagram (Fig. 2) shows the interaction of the main system components including Information Processing or input, Inference Engine 1 (responsible for providing Cultural Trait scores from the Cultural Features and Characterizers), and Inference Engine 2 (responsible for predicting the response based on an action impact analysis). Each of these key areas is described in more detail below.

(A) Information Processing

Input data comes from one of two methods: direct or indirect. Direct data is obtained directly from some sort of querying process (e.g. survey or interview) while indirect data is observed data not directly solicited. Direct data is assumed to be more accurate and also more likely to be complete with respect to the cultural characteristics to be used as input (as questions can be prepared *a priori*) while indirect data may be complete or incomplete. Our system is constrained by the supervised learning aspect of the Inference Engines. Supervised learning requires known good data which is shown as Direct, Complete Data in the System Diagram above. This data is used to train the system with known Cultural Characterizers, Features, Traits, and Action/Reaction data. While this may seem excessive, once the initial training is complete, the system can operate from direct or indirect data with either complete or incomplete information. Data Sources captures these additional direct or indirect data and the Information Processing coupled with Cultural Characterizers parses out relevant Cultural Features from the Data Sources (with respect to the Cultural Characterizers of interest).

(B) Inference Engine 1

Inference Engine 1 is a supervised learning algorithm designed to handle multiple variable types and, following the training phase, incomplete data. This component takes Cultural Characterizers and Features as input and outputs Cultural Trait values. Although the Cultural Trait values are calculated from known functions, typical literature only includes complete data. Quantitative cultural measures (Cultural Features) are usually correlated within the Cultural Trait they define, but do not necessarily correlate equally to the overall measure. Our framework includes Inference Engine 1 to capitalize on these differences inherently within the machine learning algorithm, allowing differing degrees of uncertainty depending on the available input in the presence of incomplete information. The Cultural Characterizer and Trait values are used in Inference Engine 2 along with an Action Analysis to provide a behavioral prediction.

(C) Inference Engine 2

Inference Engine 2 inputs the set of Cultural Traits of the Cultural ID of interest along with the Action Analysis. This analysis can be an existing behavioral model, or eventually this might be a more robust generic analysis as outlined below. The Action Analysis depicted as Inference Engine 2 begins as a qualitative, subjective measure of impact to the populous of interest. The Action Analysis is measured on three independent dimensions: Life, Liberty, and Property (LLP). Each of these dimensions is assigned over a quantitative scale measured above and below a point of neutrality (no change).

One end of the LLP dimensionality spectrum indicates an Attack, Threat, or Reduction (ATR) in that respective dimension while the other end indicates Defense, Protection, or an Increase (DPI) in the dimension. For example, the action of driving your car off a cliff would result in a large ATR measure for Life and Property leaving Liberty with virtually no action impact. In this way, any action can be encoded and reduced to a quantitative measure for each LLP dimension as depicted in Fig. 3.

Figure 3: Depiction of the LLP Dimensions with Sample ATR/DPI Measurements Indicated as Deviations from the Neutral Point

With this input, the output from our Inference Engine 2 is a probabilistic-centered estimation indicating the propensity for responses over a response frame indicating Fight\Freeze\Flee, Negative\Neutral\Positive, Red\Gray\Blue forces, etc. as fits the input action. The output concept is similar to the Action Analysis inputs in that there is a neutral middle ground with additional positive and negative opportunities.

(D) Inference Engine Implementation

Our Inference Engines are implemented as an extension of Fuzzy Adaptive Resonance Theory (Fuzzy ART) known as Fuzzy ARTMAP. Adaptive Resonance Theory (ART) falls within the neural network classification but can provide added benefits over a traditional neural network. Xu and Wunsch summarize [1]:

> Adaptive Resonance Theory (ART) was developed by Carpenter and Grossberg. ART can learn arbitrary input patterns in a stable, fast, and self-organizing way, thus overcoming the effect of learning instability that plagues many other competitive networks. ART is not, as is popularly imagined, a neural network architecture. It is a learning theory hypothesizing that resonance in neural circuits can trigger fast learning. As such, it subsumes a large family of current and future neural network architectures with many variants. ART1 is the first member, which only deals with binary input patterns … although it can be extended to arbitrary input patterns by utilizing a variety of coding mechanisms. Fuzzy ART (FA) incorporates fuzzy set theory and ART and can work for all real data sets.

ARTMAP, a predictive ART implementation, extends the ART concept into two ART networks in a supervised learning structure [2] along with a Fuzzy ARTMAP (FA) variant introduced by [3], shown in Fig. 4.

Following supervised learning, the Fuzzy ARTMAP can be used for predictions without additional updating. Our algorithm extends this traditional implementation by including additional data types above the traditional fuzzy logic types. We are able to handle categorical input such as “what is your favorite color?” which cannot traditionally be natively captured within ART networks.

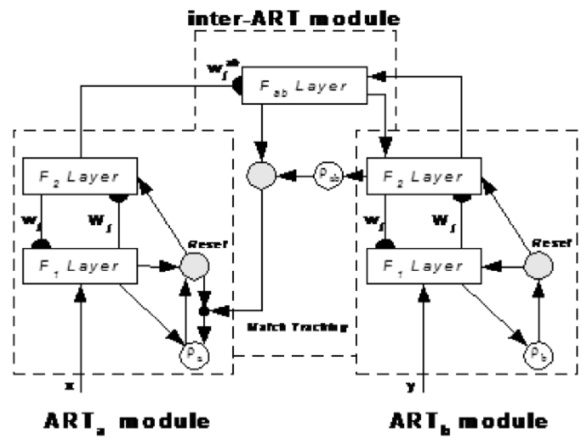

Figure 4: Fuzzy ARTMAP Block Diagram Consisting of Two FA Modules (input ARTa and output ARTb) Interconnected via an inter-ART Module

Current ART network methods (along with most any other classifier systems) allow categorical entries to be implemented as a set of n-1 binary-encoded inputs such that the combination of these entries contains the entirety of the categorical information. Our Inference Engines replace this approach with a multi-dimensional probability encoding of the categorical selections. This enhanced Fuzzy ARTMAP utilizes the instances of the training data to incrementally record a probability distribution of these categorical data. In the subsequent prediction phase, the probabilities are used as the closeness measures where the input category is matched with the corresponding stored probability distribution.

Our Fuzzy ARTMAP algorithm is also distinguishable in our handling of incomplete data. In these instances, the individual missing dimensions are handled by marking them as maximum closeness. In other words, each of the existing clusters is equally rejected along the missing dimensions while the available dimensions are handled normally.

(E) Information Processing Implementation

While a survey or other direct method might provide some of the best and most comprehensive data, it can be desirable in many situations to have a non-invasive, indirect method of obtaining cultural measures. Initial efforts have been toward a natural language processing proof of concept. However, it is anticipated that other methods might be utilized in obtaining measures for some of these cultural characteristics without direct user querying. Potential methods for future investigation could include visual- or audio-based crowd analysis techniques, natural language processing, data mining, or other textual information retrieval techniques. Combining analyses from these methods might provide corroborated methods for verifying direct user input (surveys) or baseline measures in the absence of existing survey or direct-input data.

Initial work has commenced on a proof of concept non-invasive implementation for obtaining Cultural Features from open data sources. This Natural Language Processing (NLP) approach is briefly outlined below along with discussion of the main features of this implementation. The NLP (or information processing component) is responsible for obtaining and mapping information to Cultural Features such as a semantically oriented statement from an Entity (e.g., "Free markets are a detriment to society"). The end goal is to produce a system capable of identifying Cultural Characterizers and Cultural Features of Entities from a variety of information sources (entire document, a statement, a paragraph, video, image, or other formats).

The information processing implementation is comprised of two main subcomponents: a search engine capable of acquiring the information to be used in the analysis process, and a sentiment analysis engine capable of analyzing a document with respect to Cultural Features. Initial development focus has been on the sentiment analysis engine, also known as a Feature Orientation Classifier (FOC).

(1) Sentiment Analysis

Sentiment analysis is an aspect of NLP that deals with determining the attitude of a speaker or author toward a particular discussion topic. Sentiment Analyses can be classified into two main approaches: statistical and linguistic. Statistical approaches rely heavily on mathematical and statistical analyses and comparisons of text occurrences, whereas a linguistic approach tries to build a set of rules and compare the analyzed text against these semantic fundamentals [4-6]. Automated sentiment analyses of digital texts uses elements from machine learning such as latent semantic analysis, support vector machines, bag of words, or pointwise mutual information [7].

The information processing feature orientation classifier takes a document set and produces an annotated set. The annotated set is a superset where each member is an annotated document composed of features and annotations. Features are key/value pairs which define properties of a document or specific annotations. Annotations are references to a portion of text. Person,

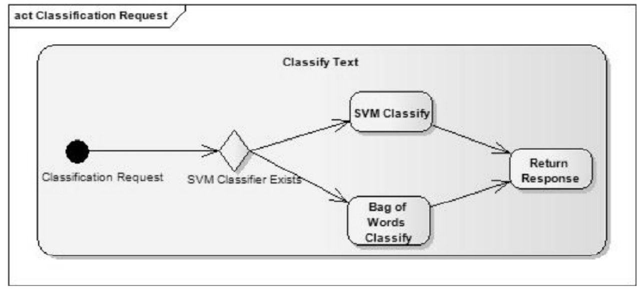

Figure 5: Overview of FOC Classification Process

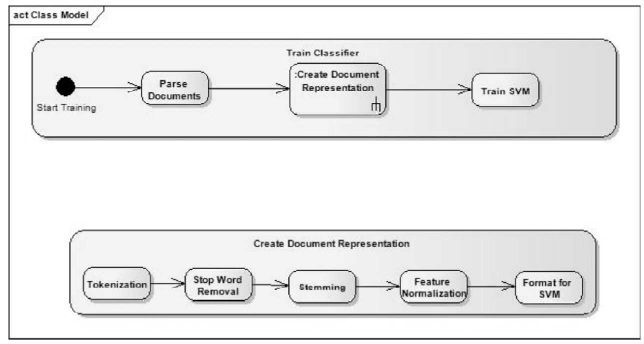

Figure 6: SVM Parsing and Preprocessing for Training

Location, and Sentence are sample annotations. The preliminary FOC produces numerical scores based on the semantic orientation of a document to a Cultural Feature. Furthermore, if evidence within the document is available, the FOC can produce a feature score on specific entities.

The preliminary FOC has two available classifiers: a support vector machine that uses training data to build models of features, and a bag of words classifier that is a general purpose approach when training data is not available. Incoming data is pre-processed to determine which classifier method is appropriate. Both methods output an XML document with the features matched and extracted entities marked up. The classifier process is illustrated in Fig. 5.

(2) Support Vector Machine

A Support Vector Machine (SVM) is a supervised learning method used for a variety of purposes including classification (handwritten digit recognition, object recognition, speaker identification, etc.) and regression [8]. Classification is obtained through multidimensional hyperplanes which are placed around the input vectors. A technical overview of SVM can be found in [9] and unsupervised SVM-based clustering methods are also available [1,10].

In order to reduce classification errors for our framework implementation, each Cultural Feature has its own support vector machine. Thus, each Cultural Feature response — for our initial implementation a *positive* *orientation* and *negative orientation* – requires training. Our implementation contains two distinct features, but there is no limit to the number a SVM can handle.

Essentially, a document is transformed into a feature vector where each vector index represents a token and vector values correspond to the frequency of that token appearing in the document. In training, a set of vectors and corresponding labels (in this case, the feature identifier) are fed into the trainer, creating a pattern associated with the label. Following training, a model with the different patterns is available for predictions. In prediction mode, a document is again transformed into a feature vector and sent to the SVM, which then attempts to match the vector with the trained patterns.

Fig. 6 shows the parsing and preprocessing steps required for SVM training. The parse documents step is responsible for loading a set of training documents and extracting the text for each Cultural Feature. For our implementation, each Cultural Feature has two training sets, one for the *positive orientation* in support of the qualifying statement, and one for the *negative orientation* in opposition to the statement.

The create document representation is responsible for taking parsed text and creating a representation that the support vector machine can use. Tokenization is the separation of text into individual tokens, or the individual words (minus punctuation, whitespace, etc.) that compose the text. Stop word removal is the removal of very common words such as: of, a, the, she, and it. Stemming is the process of transforming a word into its root form. For example, a stemming algorithm would reduce fishing, fished, fish, and fisher to the root word fish. Feature Normalization calculates the Term Frequency-Inverse Document Frequency (TF-IDF) score for each stemmed token. This returns a weighted value which is used in the feature vector. TF-IDF is a calculation that measures the relative impact of a stem on that document, using the entire corpus to calculate how often the stem is seen in all documents. Support vector machines typically require a label and a feature vector. The Format for SVM transforms the processed output into a format understood by the SVM. The feature vector is a vector where each index is a term, or stem, and the value is the TF-IDF of that stem for the document.

Once the proper format is available, the Train SVM step is merely a function call to train the SVM. Classification of a document undergoes roughly the same sequence. However, rather than using the support vector machine's training mode, the prediction mode is used (there is no additional updating of the classifications).

(3) Bag of Words Classifier

This approach uses positive and negative word lists to classify a document as positive or negative. The initial implementation uses the positive and negative lists from the Harvard General Inquirer category lists. Words which are considered subjective from negative and positive word lists are used to compile this lexicon. Their lexicon consists of roughly 3620 words – 1620 positive and 2010 negative.

Unfortunately, a *bag of words* approach is unable to account for many semantic aspects of language. For instance, phrases such as "not all that good" or "what was supposed to be a horrible" can alter the orientation of the sentence from the strict definition of any single word. Therefore, there exists an opportunity for missing the underlying semantics and possibly circumventing the true expression of the text.

IV. CULTURAL MODELS

As mentioned, our framework is designed to work independent of any specific cultural modeling technique. Existing literature provides the calculations and definitions for the Cultural Features and corresponding Cultural Trait values. Although it is envisioned this framework could work with virtually any models, we briefly provide a few examples of some of the better known cultural models which can be incorporated within our cultural response framework.

(A) Individualism and Collectivism

One of the most popular dimensions of cross-cultural psychology is the continuum between individualism and collectivism. Broadly, individualism refers to the philosophy that one's self is most important and decisions are made which focus on the best individual outcome. Collectivism is a worldview which incorporates one's in-groups and bases decisions on what will benefit the groups in addition to the self. In Mary Douglas' discussion of Cultural Theory, she suggests collectivists are a combination of hierarchists and egalitarians [11]. Political conservatism can be described as a combination of both individualism and hierarchy.

Haitham Khoury proposed an Individualist/ Collectivist (I/C) factor solution in a 2006 thesis [12]. This thesis drew together multiple I/C measures from various researchers (Hofstede, Triandis & Gelfand, Singelis, Ho & Chiu) to obtain the most meaningful subset of factors which contribute to I/C scoring. The most relevant components (based on a factors analysis) are given below for each of the 5 defined factor areas relevant to individualism and collectivism. Khoury describes the five factors [12]:

Upon reviewing the item content of each factor … it became apparent that the derived factors were somewhat different from those originally theorized by Ho and Chiu (1994). The first factor concerns issues of responsibility. For example, *I think people should be held responsible for their own actions* and *I must pay for the consequences of my actions* illustrate this dimension. The second factor concerns the idea of one's affiliation, and how that influences the formation of an identity, contrasting the focus of the identity between the individual and the group. For instance, *The group I belong to is a significant part of who I am* and *I feel it is important to belong to a social group* exemplify this idea. Factor 3 is primarily focused on the idea of social welfare and whether the group or the individual is the primary source of that. For example, *Society is obligated to help those who cannot help themselves*} and *I think members of a group should care for each other's welfare*. Factor 4 relates to religious beliefs and the idea of religiosity being group-focused or individual focused, as illustrated by *Religious beliefs and practices are private*} and *My religion concerns only me*. Finally, factor 5 concerns the idea of achievement or accomplishment. For example, *It is more efficient to work alone than to work in a group* and *I do things best when I work alone*.

In summary, Khoury categorized I/C measures into factors of responsibility, identity, social welfare, religious beliefs, and achievement, providing an additional method of quantizing individualism and collectivism based on multiple existing cultural models.

(B) Hofstede

Geert Hofstede pioneered much of the seminal cross-cultural research and analyses, stemming from survey-based measurements within industry employees. His Personnel employment within IBM provided an opportunity to obtain and analyze data from hundreds of IBM employees working in a variety of countries. Hofstede's data and analysis brought initial cross-cultural questions to the forefront of the research arena with his 1980 publication Culture's Consequences. Though the original four categories were expanded to five, the basics of Hofstede's cultural factors have been seen time and time again through various researchers [13]. Hofstede defines five cultural dimensions [14] labeled:

1. **Power Distance**, related to the different solutions to the basic problem of human inequality;
2. **Uncertainty Avoidance**, related to the level of stress in a society in the face of an unknown future;
3. **Individualism versus Collectivism**, related to the integration of individuals into primary groups;
4. **Masculinity versus Femininity**, related to the division of emotional roles between women and men;
5. **Long Term versus Short Term Orientation**, related to the choice of focus for people's efforts: the future or the present and past.

(C) GLOBE Dimensions

The GLOBE study examined a variety of factors for cultural distinction [15]. House, et. al. expanded Hofstede's five dimensions to nine, maintaining some of the core Hofstede dimensions such as Power Distance and Uncertainty Avoidance, but not identical meanings. GLOBE attempts to add additional categorical classifications such as splitting Collectivism into Institutional Collectivism and In-Group Collectivism, and Masculinity-Femininity into Assertiveness and Gender Egalitarianism. Long Term Orientation became Future Orientation and two additional dimensions were added: Humane Orientation and Performance Orientation. The nine dimensions were covered by 78 survey questions, half asking respondents to describe their culture "as is" and the other half to judge how it "should be." A brief summary of each of the nine House dimensions is provided below (see [15] for more complete descriptions and discussion).

- **Performance Orientation**: The degree to which a collective encourages and reward group members for performance improvement and excellence.
- **Future Orientation**: The extent to which a collective encourages future-oriented behaviors such as delaying gratification, planning and investing in the future.
- **Gender Egalitarianism**: The degree to which a collective minimizes gender inequality.
- **Assertiveness**: The degree to which individuals are assertive, dominant and demanding in their relationships with others.
- **Institutional Collectivism**: The degree to which organizational and societal institutional practices encourage and reward collective distribution of resources and collective action
- **In-Group Collectivism**: The degree to which individuals express pride, loyalty and cohesiveness in their organizations or families.

- **Power Distance**: The degree to which members of a collective expect power to be distributed equally.
- **Humane Orientation**: The degree to which a collective encourages and rewards individuals for being fair, altruistic, generous, caring and kind to others.
- **Uncertainty Avoidance**: The extent to which a society, organization, or group relies on social norms, rules and procedures to alleviate unpredictability of future events.

(D) Grid-Group

Cultural Theory refers to the late Mary Douglas's work with concepts of Grid and Group [16]. There are references to the work of Basil Bernstein and Émile Durkheim sprinkled throughout [16] and the original presentation of Grid and Group loosely reflects Bernstein's restricted speech code [16] and Durkheim's classifications of suicide [17]. The Grid-Group concept is a continuum of values, spread across two dimensions, which is intended to classify all cultural characteristics into a small set of measures (4-5 distinct classifications). Douglas's original concept contained four classifications, one for each of the four quadrants. This yields combinations of High Grid and High Group, High Grid and Low Group, Low Grid and High Group, and Low Grid and Low Group. Grid and Group each have distinguishing characteristics and each Grid-Group combination has unique characteristics as well. After reviewing a variety of cultural theorists, Thompson, Ellis, and Wildavsky [17] modeled the Grid-Group concept with an additional fifth classification with both neutral Grid and neutral Group labeled "The Hermit."

Thompson, Ellis, and Wildavsky's analyses allowed for a neutral type (Hermit) which neither influenced nor was influenced by societal factors as the other Grid-Group classifications were. This model hints at the difficulty in distinguishing between each of the classification categories. With such a multidimensional, continuous measure, it can be difficult to determine where a certain Grid-Group ranking fits in with relation to the quadrants. Gross and Rayner [18] include an indeterminate visualization (Fig. 7) which indicates the quadrants are separated by regions of ambiguity. This more accurately reflects the modeling in that the classification into the predetermined categories best fits those individuals wholly and strongly situated in the quadrant. While Fig. 7 allows for the same classifications, there is an underlying caution in classifying mid-ranged rankings. Gross and Rayner's work [18] also attempts to operationalize the collection of identifying characteristics to automatically calculate Grid and Group values similar to the indirect information gathering of our framework. While the process Gross and Rayner described to calculate Grid and Group values required near-omnipotent knowledge, additional methods provide quantitative measures of the Grid and Group dimensions (see [19-22]). [23] provides a comprehensive background and overview of Cultural Theory.

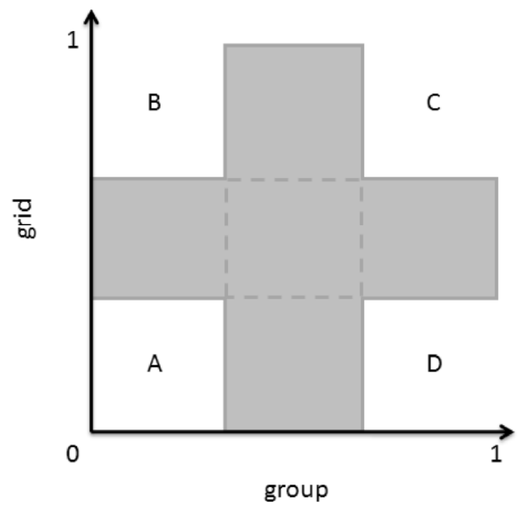

Figure 7: Grid and Group Quadrants shown with Ambiguity

(E) Quantification Difficulty

Clearly there is ambiguity even with these quantifiable measures, as they are based on potentially subjective soft science theories. The inherent difficulty is the need "to make judgments about matters of degree, not just about presence or absence" [18]. Gross and Rayner's brief warning also seems relevant here:

> Some readers might be suspicious of attempts at pursuing numerical precision in a qualitative social science such as anthropology or history. Perhaps it will allay their fears to know that the authors do not seek to reduce the whole range of human experience to numbers or spots on a graph. On the contrary, we see our efforts as a humanistic enterprise, developing a comparative device for social systems. Our method is capable of illuminating and appreciating the complex connection between the formative pressures exerted by a social environment and the culture-creative responses of individuals to those pressures.

V. RESULTS

Our framework was implemented using Grid and Group as initial Cultural Traits with Cultural Features for each trait using the general Grid-Group model from [24]. The choice of Grid and Group for initial Cultural Traits allows usage of readily available data and includes a large set

Table 1
Individual Analysis of Grid Components

Variable (Cultural Characterizers and Features)	*Average Error Without Variable*	*Average Error With Variable*	*Difference*
Raised religiously	0.214	0.254	0.040
Justifiable: divorce	0.216	0.256	0.040
Future changes: Greater respect for authority	0.217	0.254	0.037
# Children	0.219	0.253	0.034
Social Class	0.219	0.250	0.031
How important is God in your life	0.221	0.250	0.029
Job Status	0.220	0.248	0.028
Age	0.222	0.250	0.028
Education Level	0.221	0.248	0.027
Justifiable: prostitution	0.221	0.248	0.027
Justifiable: abortion	0.224	0.247	0.023
Older people should be forced to retire	0.226	0.244	0.018
Men should have more right to a job than women	0.226	0.243	0.017
Profession	0.226	0.243	0.017
A woman has to have children to be fulfilled	0.229	0.243	0.014
Justifiable: homosexuality	0.228	0.241	0.013
Sex	0.232	0.238	0.006
Town Size	0.234	0.237	0.003
Religion important in life	0.236	0.234	-0.002
Married	0.236	0.234	-0.002
Following instructions at work	0.242	0.228	-0.014

Table 2
Individual Analysis of Group Components

Variable (Cultural Characterizers and Features)	*Average Error Without Variable*	*Average Error With Variable*	*Difference*
Education Level	0.184	0.238	0.054
Management	0.187	0.230	0.043
# Children	0.188	0.230	0.042
Friends Important in life	0.192	0.231	0.039
Social Class	0.192	0.230	0.038
Hard Work Brings Success	0.190	0.228	0.038
Profession	0.193	0.228	0.035
Trusting Others	0.195	0.226	0.031
Town Size	0.194	0.223	0.029
Age	0.196	0.224	0.028
Less Importance Placed on Work	0.197	0.222	0.025
Private vs State Ownership of Business	0.197	0.219	0.022
More Emphasis on Technology	0.199	0.221	0.022
Government Responsibility	0.200	0.218	0.018
Less Emphasis on Money/Possessions	0.202	0.217	0.015
Fairness - Secretary Pay	0.202	0.216	0.014
Family Important in life	0.203	0.216	0.013
Job Status	0.205	0.214	0.009
Respect and Love for Parents	0.206	0.214	0.008
Sex	0.207	0.212	0.005
Married	0.214	0.204	-0.010

of Cultural Features to highlight effects of incomplete data within the subsequent analyses while still maintaining ties to well-accepted individualist-collectivist theories. World Values Survey (WVS) data from Wave 3 (1995) and Wave 4 (2000) of the 4-wave integrated questionnaire [25] was used to populate Grid and Group's corresponding Cultural Feature data. Additional demographic data was incorporated as Cultural Characterizers including gender, age, town size, and marital status, among others. Data consistency was ensured across the two data sets using the WVS equivalences tables and the two waves were not differentiated individually thereafter.

Two inference engines were trained to calculate Cultural Traits of Grid and Group scores using Cultural Characterizers and Cultural Features from Table 1 and Table 2, respectively. Following the training phase, a variety of tests were run to obtain an understanding of performance predictions for various conditions. For the first test, all data with complete information were tested for error between the known Grid and Group scores and the Inference Engine prediction. A second test tested the situations when all but 1 of the inputs was known. The remaining tests were designed to simulate real-world conditions where a much larger portion of data might be unavailable. For the main random input testing, a variety of random input selections were generated to determine which inputs would be included. These tests were created using a fixed probability Bernoulli trial which loosely maintained a uniform distribution on the number of times each variable was used and produces a binomial distribution over the number of input variables in the resulting configurations. Following the random input testing, additional test cases were constructed as necessary to fill in data gaps to cover the entire range of the number of variables used in Grid and Group Inference Engine testing. All tests processed each known datum which had all included inputs available, and the average resulting error was recorded and aggregated over all data for each input.

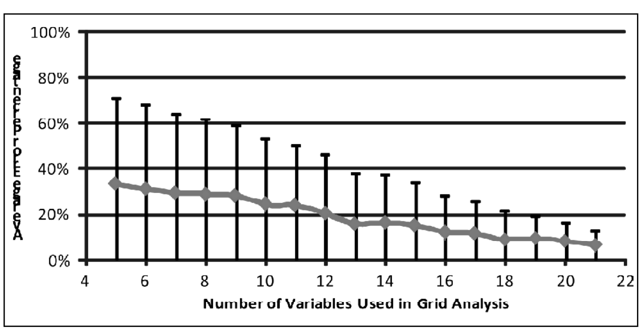

Figure 8: Grid's Average Error and Standard Deviation with Different Input Lengths

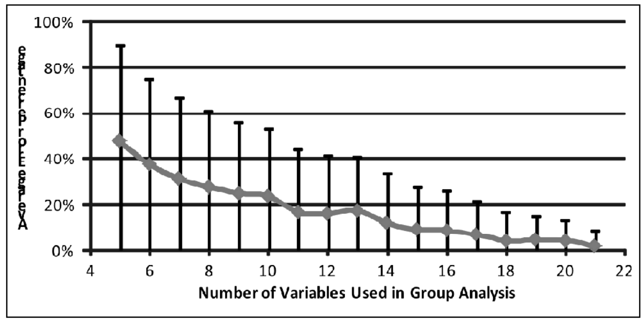

Figure 9: Group's Average Error and Standard Deviation with Different Input Lengths

For the main random input testing, Grid was tested with 327 random input settings with each input variable occurring in approximately half of the input settings (50% ± 5%). Table 1 shows the average error over all data for all input settings where each variable was (and was not) included. This provides one measure of each variable's importance and decrease (or, potentially, increase) in resulting error given the Characterizer or Feature included as input over all tested input settings. Group random input was tested in a similar manner with 290 random input settings with each input variable occurring in approximately half of the input settings (50% ± 6%) with results shown in Table 2.

The number of variables used throughout the entire testing process ranged from complete information (21 data inputs) to as few as 5 inputs in the random-input tests. Fig. 8 and Fig. 9 plot the average error aggregated over all available input settings of a given length for Grid and Group, respectively. The average standard deviation of data within each input setting is also showed for each input length within each figure.

VI. CONCLUSION

With such a variety of data and research on various cultural aspects, it would seem that each cultural modeling technique may be best suited for specific niches or certain behavioral predictions. Haitham Khoury's thesis capitalized on the differentiation of multiple Individualist/Collectivist measures [12], showing that each cultural theory should bear consideration (and may impact cultural analyses in different ways). We have provided a framework which allows these different cultural models to be captured and used natively without preexisting bias toward any theory. Our framework captures the cultural characteristics inherently within the machine learning ARTMAP algorithm, naturally bringing out the characteristics which influence each facet of the cultural response prediction. We have begun implementation of our framework and have included some preliminary analyses of Inference Engine 1 using Grid and Group as initial Cultural Traits based on data availability, breadth of variables used in these calculations, and the relationship with existing Individualist/Collectivist measures.

Additional empirical testing and validation will incorporate additional models and analyses, such as taking into account applicability and scoping issues such as those discussed in [19, 26]. A refined variation of this framework including additional distinction between cultural and behavioral models was presented in [27].

ACKNOWLEDGMENT

This material is based upon work supported by the Office of Naval Research (ONR) under Contract No. N00014-08-C-0273. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of ONR.

REFERENCES

[1] R. Xu and D. Wunsch, *Clustering*, IEEE Press / Wiley, 2008.

[2] G. A. Carpenter, S. Grossberg, and J. H. Reynolds, "ARTMAP: Supervised Real-Time Learning and Classification of Nonstationary Data by a Self-Organizing Neural Network," *Neural Networks*, **4**, 1991, 565–588.

[3] G. Carpenter, S. Grossberg, N. Markuzon, J. Reynolds, and D. Rosen, "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Analog Multidimensional Maps," *IEEE Transactions on Neural Networks*, **3**, 1992, 698–713.

[4] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs Up?: Sentiment Classification Using Machine Learning Techniques," *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Morristown, NJ: 2002, pp. 79–86.

[5] T. Nasukawa and J. Yi, "Sentiment Analysis: Capturing Favorability using Natural Language Processing," *Proceedings of the International Conference on Knowledge Capture (K-CAP)*, Sanibel Island, FL: 2003, pp. 70–77.

[6] T. Mullen and N. Collier, "Sentiment Analysis Using Support Vector Machines with Diverse Information Sources," *Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, D. Lin and D. Wu, eds., Barcelona, Spain: 2004, pp. 412–418.

[7] P. Turney, "Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews," *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics (ACL)*, Philadelphia, PA: 2002, pp. 417–424.

[8] C. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," *Data Mining and Knowledge Discovery*, 1998, pp. 121–167.

[9] V. Vapnik, "An Overview of Statistical Learning Theory," *IEEE Transactions on Neural Networks*, **10**, 1999, 988–999.

[10] J. Lee and D. Lee, "An Improved Cluster Labeling Method for Support Vector Clustering," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **27**, 2005, 461–464.

[11] K. Dake, "Orientating Dispositions in the Perception of Risk: An Analysis of Contemporary Worldviews and Cultural Bias," *Journal of Cross-Cultural Psychology*, **22**, 1991, 61–82.

[12] H. Khoury, "Measuring Culture: The Development of a Multidimensional Culture Scale," University of South Florida, 2006.

[13] G. Hofstede and G. J. Hofstede, *Cultures and Origanizations: Software of the Mind*, New York: McGraw Hill, 2005.

[14] G. Hofstede, "Dimensionalizing Cultures: The Hofstede Model in Context," Bellingham WA: Center for Cross-Cultural Research, Western Washington University, 2006.

[15] R. House, P. Hanges, M. Javidan, P. Dorfman, and V. Gputa, *Culture, Leadership, and Organizations: The GLOBE Study of 62 Societies*, Sage Publications, 2004.

[16] M. Douglas, *Natural Symbols: Explorations in Cosmology*, London: Routledge, 1996.

[17] M. Thompson, R. Ellis, and A. Wildavsky, *Cultural Theory*, Boulder, CO: Westview Press, 1990.

[18] J. Gross and S. Rayner, *Measuring Culture*, New York: Columbia University Press, 1985.

[19] E. Olli, "Cultural Theory Specified – The Coherent, Sequential, and Synthetic Individual Approaches," University of Bergen, 1995.

[20] C. Marris, I.H. Langford, and T. O'Riordan, "A Quantitative Test of the Cultural Theory of Risk Perceptions: Comparison with the Psychometric Paradigm," *Risk Analysis*, **18**, 1998, 635–647.

[21] D. M. Kahan, D. Braman, J. Gastil, P. Slovic, and C.K. Mertz, "Culture and Identity-Protective Cognition: Explaining the White Male Effect in Risk Perception," *Journal of Empirical Legal Studies*, **4**, 2007, 465–505.

[22] D. Braman and D.M. Kahan, "More Statistics, Less Persuasion: A Cultural Theory of Gun-Risk Perceptions," *University of Pennsylvania Law Review*, **151**, 2003.

[23] V. Mamadouh, "Grid-Group Cultural Theory: An Introduction," *GeoJournal*, **47**, 1999, 395–409.

[24] S. Chai, M. Liu, and M. Kim, "Cultural Comparisons of Beliefs and Values: Applying the Grid-Group Approach to the World Values Survey," *Beliefs and Values*, **1**, 2009, 193–208.

[25] European Values Study Group and World Values Survey Association, *European and World Values Surveys Four-wave Integrated Data File, 1981-2004, v.20060423*, Aggregate File Producer: ASEP/JDS, Madrid, 2006.

[26] G. Zacharias, J. MacMillan, and S.V. Hemel, eds., *Behavioral Modeling and Simulation: From Individuals to Societies*, Washington, DC: The National Academic Press, 2008.

[27] M. Gosnell and W. Noll, "Behavioral Prediction from Cultural Measurement," *Huntsville Simulation Conference (HSC)*, 2009.