LXIO: The Mood Detection Robopsych[1][2][3]

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Abstract

Words and languages are the direct representations of our thoughts and perceptions. Accordingly, the only access to an individual's thoughts and psyche is through the language that he/ she speaks or writes [1]. Psychological disorders and mood states such as depression and PTSD therefore, can be identified and predicted by continuously analyzing a patient's discourse. In doing so, we utilize the method of predictive linguistics [2], which determines cognitive mood states by computationally modeling the notions of 'mind axiology' and 'emotional states'. Our proposed system expresses cognitive states in terms of axiology, i.e., the system of positive and negative values associated with concepts that are universally accepted. Axiological notions provide more insights about the various cognitive states because a patient's words are only intelligible if axiological elements like conception, perception, and intention are taken into consideration. The framework for our analytics engine consists of multiple modules responsible for coherently and systematically retrieving, parsing and processing a patient's discourse. The backbone of this system relies on a learning algorithm that accounts for various valuation criteria such as time-based, intrinsic, consequent and contextual value analysis, while also building a nested network of mood states and their dependencies. By executing this mechanism and correlating our computational data to results calculated by a psychological assessment testing, we are better positioned to classify a patient's mood states – e.g., as being depressive or not. This work will have implications in the area of cognition research and practical applications such as automated neurological and psychiatric assessments, advanced human – computer interaction (HCI), as well as others.

Keywords: MDA, predictive linguistics, depression, axiology, LXIO

1 Introduction

Understanding a patzient's discourse by examining their selection of words, their value, and the instances of which they used them in will paint a clear picture of their current state of mind. After all, language is the container of our intent [3] and focusing on such attributes will allow real-time mood analysis that can prove effective and essential in treating disorders. This psycholinguistic analysis is to link verbal expressions to psycho-cognitive states. Analyzing a person's words (both oral and written) highlights the underlying positive or negative language values over time and/or space [7].

[1] Language axiological input / output system for detection of mood states towards the design of a robot psychiatrist

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Our proposed system deciphers language in written formats (speech to text is also applicable) and passes its data to a Parser which breaks down each sentence into multiple words and creates a data structure for these particular phrases within specific time frames. These structures are generated based on the properties and characteristics of each word. They grow in capacity and connectivity depending on the relativeness between previous and currently processed data. After the features of each word are extracted, they are then passed through a processing framework that includes multiple independent modules based on time-oriented, axiological, contextual, and consequent criteria. Initially, each word is exposed to the time-oriented engine that dynamically looks up the tenses for each word and logs its results. This iteration is followed by a direct comparison function that fetches the values for relevant words within the Mind State Axiology.

Accordingly, each sentence is then passed into the consequent and contextual modules and their results are logged for further examination. Additionally, this framework serves as a sandbox where various combinations of these criteria are examined and new outputs are generated. The output of this system defines a modified object for the sentence values, which can then be further analyzed by a learning algorithm within various proximities to project a mental state that most likely presents a patient's mood and is verified by practicing physicians.

2 Experimental Paradigm and State Modulations

2.1 Patients

A wide range of patients participated in a study conducted at the University of Geneva where axiology-based values were extracted based on a patient's mood and feelings regarding different words and sentence phrases.
These lists of words were presented to each patient and accordingly their value (+ or -) was then individually retrieved based on each patient's perception. Common word values were then identified from the wide variety of collected data and then stored in a database referred to as mind default axiology database [2].

2.2 Mind Default Axiology (MDA)

A database of axiology words with multiple dimensions that are based on the frequency of the word-value used along with the cultural/traditional usage of the word and not only its intrinsic value. Using this database as a main lookup source helps assign the initial state value for each word, which has significant effect on the projected value of a given statement.

From a mathematical standpoint, axiological value defines truth within a general cognitive knowledge system, often referred to as axiomatic. Therefore, value is a starting point within a logical system that can be chosen at random. However, the relevance of the axiomatic calculation depends on the relevance of its values and their interpretation [7]. Axiological values are the basis of all formal cognitive processes. Here is a simple calculation that includes values and follows a rule of internal composition (+):

the value 0 exists
All values X are followed by succ(X)
X+0 = X
Succ(X) + Y = X = succ(Y)

Using these values and defining 1, 2, 3 as *succ(0)*, *succ(succ(0))*, *succ(succ(succ(0)))*, respectively, then: *succ(X) = X + 1*; and:

1 + 2 = 1 + succ(1)	Abbreviation extension (2 = succ(1))
1 + 2 = succ(1) + 1	Axiom
1 + 2 = 2 + 1	Abbreviation extension (2 = succ(1))
1 + 2 = 2 + succ(0)	Abbreviation extension (1 = succ(0))
1 + 2 = 2 + 1 = succ(2) + 0 = 0 + succ(2)	Axiom
1 + 2 = 3 = 0 + 3	Use of the abbreviation (succ(2) = 3)
0 + 1 = 1 + 0 = 1	Axiom
X+ succ(X) = succ(X) +X	Axiom

All assertions that cannot be inferred from the values and whose negation also cannot be inferred from them can logically be added as axioms [7]. Axiological attribution is based on mathematical logic that attempts to assign a temporal value to language, such that the meaning given to a word is the consequence of its temporal value in relation to its meaning. The goal is to find the best possible axiological value amongst many possibilities [7].

2.3 State Projections

We can treat the process of generating sentence values in terms of state instances. These states vary based on the various measurement criteria we mentioned previously. With that in mind, a given word might pass through different instances and its value could change depending on the stage level of interaction within a given statement.

3 Framework Analysis

Figure 1 highlights the main structure of our proposed system. For the sake of simplicity, we will not fully expand our description of each segment, but we will present a concise and accurate depiction of functionality and usability. Figure 1 describes the higher-level design of the analyzer. Many parts of this architecture can be freely interchanged or grouped based on testing apparatus conducted by scientists and researchers. This unique feature allows us to adjust and fine-tune our system to compensate for errors resulting from a patient's inaccurate descriptions or words that have a particular and unique sentimental value to the patient being examined.

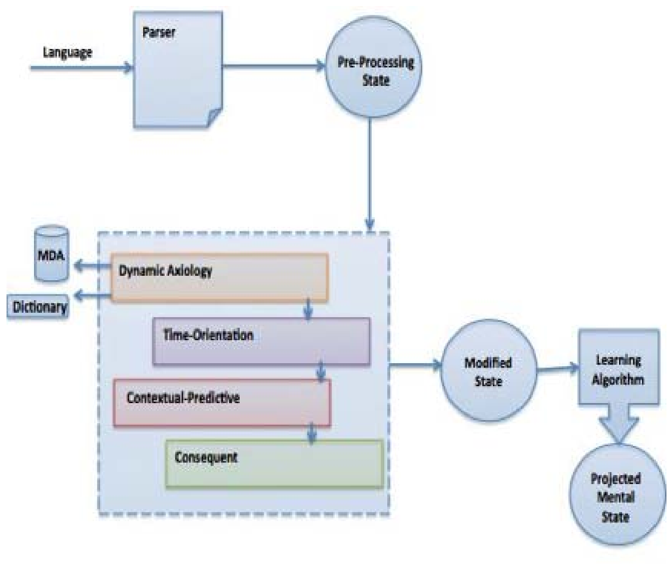


Figure 1: Overall System Structure

The system also takes into account various forms of linguistic expressions regardless of the language or dialect it was described in. By inputting the axiological database of specific languages and applying an accurate parser we can account for differences in language and structure.

Initially, our approach was to use a parser that simplifies the representation of each clause and by simply assigning negative values to words presented in the past and positive values to words presented in the future. Consequently, we would have a plain depiction of word's effect on the patient. This technique does not, however, take into account the effect of words upon one another and the context of when these words were used. There are many other factors that contribute to how a word is used, perceived or emphasized, which led us to the following state analyzer architecture that compensates for such criteria.

3.1 Parser Transform

In this segment we used a parser developed at Massachusetts Institute of Technology (MIT) called the START parser. This parser allows us to retrieve the main building blocks of each word use and consequently understand its grammatical structure.

3.2 Pre-processing State

At this state, the server breaks up sequences of sentences and sends back a sequence of clauses associated with each sentence. There are two types of clauses, which are relevant to the computation of word values. These are "has_tense" and "word_root" clauses. Initially, if the verb is not in our MDA (Mind Default Axiology) it will be counted as "+" for present/future tense, and "-" for past tense. In order to count "has_tense" clauses, we leverage the fact that "word_root" clauses always come after "has_tense" clauses. As such, when the server is processing a "has_tense" clause, it first looks up the word in the dictionary. Then, if the word is found, the sentence value is left unchanged (since the value of the word will be appropriated added later when the corresponding "word_root" clause is processed), and if the word is not found, the sentence value is incremented or decremented according to the tense. In the latter case, the verb is stored to a list variable "tense_counted" so that they can be rendered properly in the front end.

3.3 Modular Engine

This engine consists of several modular constructions joined by logical data dependencies where each plays a significant role in evaluating a given discourse.

The framework is divided into the following:

3.3.1 Dynamic Axiology Module:

The data here is compared to a mind default axiology (MDA) database and a given pre-defined dictionary. The role of this module is to identify and retrieve the value associated with identical words.
The processing of "word_root" clauses in this module is simple, if the word is looked up in the database or dictionary, and if its value is found, it is counted, else it is not counted. The value of the word is determined either by the lookup, which has just occurred, or by the previous counting of a "has_tense" clause, which can be found in the list "tense_counted."
The resultant of such lookup will be stored at the given module. This mechanism will iteratively continue until the whole sentence has been processed. Labeling each word with its value enables us to compute and update sentence values in linear time. From Figure 2, both the MDA and dictionary contribute to the value for each word string.

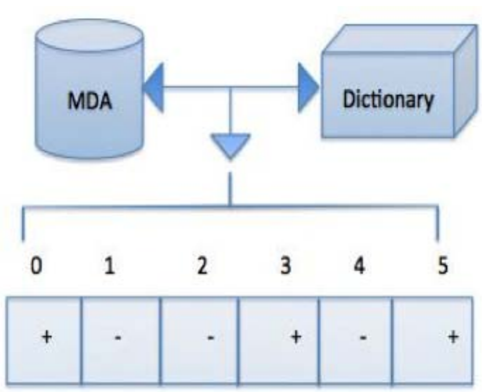


Figure 2: A String of Words Labeled from 0 to 5 each with a Different Computed Value

```
set axiology_value (set mda, set dictionary)
    {
 int i;
for (i=0; i <= sentence_length; i++) {
    axiology_value = mda ^ dictionary ;
    }
return axiology_value;
```

This pseudo computes the axiology value of the word based on AND'ing the values from both the MDA and dictionary. Using this logical operation we can account for the values retrieved from both databases while outputting the desired result. A straightforward string-matching algorithm [5] is implement to identify matching word patterns.

```
Int findmatch (char *p , char *t)
{
int i, j;                    /* counters */
int m, n;           /* string lengths */
 m = strlen(p);
 n= strlen(t);
for (i=0; i<=(n-m); i=i+1) {
j=0;
while ((j<m) && (t[i+j]==p[j]))
j=j+1;
if (j==m) return (i);
}
return (-1);
}
```

3.3.2 Time-Based Module:

This module accounts for time orientation. Time is very essential in analyzing a patient's mood. Research suggests that individuals will separate their personal experiences, the basis of memories, into the psychological time frames of past, present, and future [4]. These memories, good or bad, have different implications on current behavior and future directions. Psychologist Phil Zimbardo maintains that individuals with a more future-based time perspective, for example adopting goals to achieve, exhibit greater psychological satisfaction than those who do not [4]. Hence, a tense that represents the past is considered to be negative, while a tense representing the future is considered positive. Many sentences carry their own representation of the tense as a whole in which case we need to account for such tenses. Therefore, the module examines the tense of a given word and verifies its time projection.

3.3.3 Contextual-Predictive Module:

Based on sentence analysis, this module is responsible for identifying words that can affect the value of succeeding words. Therefore, some words that can be linked to others will affect their values. The module takes into account these combinations and creates a database that identifies them in various languages. Hence, contextual words are either negative or positive. For example, "my life" is positive, "life" is intrinsically positive and "my" is positive since it is linked to it.
There are several algorithms to represent this mechanism, perhaps one of which is the use of the nearest-neighbor heuristic. This approach not only allows us to identify the nearest words within a sentence but it can also be used to correlate those words that have a contextual connection within different sentences.

3.3.4 Consequent Module:

This module is used to allocate words that carry a meaning in themselves. Many compound nouns such as 'nothing', 'nowhere', 'somebody', etc. have either a positive or negative value based on what they represent. For example, the word nothing is opposite to something, which has a positive value, hence nothing is negative. After all of this, modules have computed the values for each word, logs are generated per each stage and at each level of a given paragraph. Therefore, if we were to trace two words throughout the whole modular process we can witness the following. For example, the sentence: "my life is good" then "my" and "life" are presented as Figure 3 demonstrates. In this example, word values are computed for each module separately. The value from each modular iteration is then convoluted with the value from the other module.

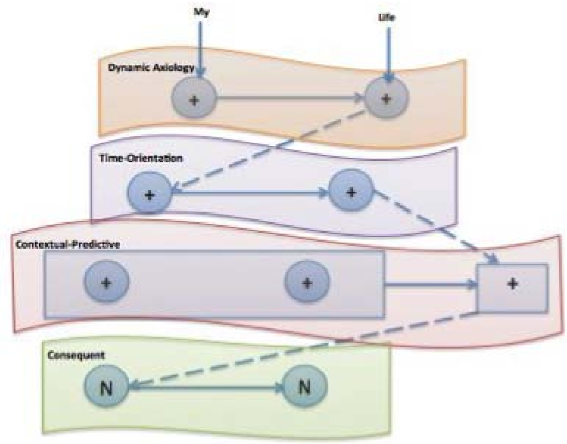


Figure 3: Consequent Module Tracing "my" and "life"

3.4 Modified State

This is the initial state representing the resultant mood value based on the modular architecture. This value is the approximate representation of each mood state, however it is still dependent on the history of the patient and their different word representations.

3.5 Project Mental State

We are applying a learning algorithm that looks at various instances and tracks a patient's word analysis history. This algorithm takes into account the resultant modified state and redefines the word values based on the history of the patient.
Once every word is clearly defined or calculated, the mood state is represented based on the unary summation of the words forming the full sentence. To further explain this notion it is important to look at how this unary system behaves.

4 Unary System Topology

The unary system can identify mental mood states by analyzing abstract structures of an individual's mind [7]. Positive or negative mental states are defined by the formation of new concepts, which are in part or aggregately created by various forms of activations (electrical, chemical and biological) throughout the brain [7]. These activations in a series or sequence establish an activation set.

For each activated region in the brain an activation set constitutes a connected framework, defined as a node [7]. A node's circumference adjusts based on an activated region's duration, and the reflexivity of a node is a result of varying instances of region re-activation. Nodes, representing forms of activation, can be linked to each other. The nodes' connections vary in shape and time orientation, while the actual segment that forms the connection itself represents time orientation [7]. A new activation set is created once this connected structure of nodes is formed. The new activation set can also be connected with other activation sets, forming a concept set. Based on unary system calculation, nodes in the same set are added together in terms of waveform signals that are weighted by a statistical coefficient to produce axresultant active node [7]. A concept set, formed from connected activated sets, generates an axiological value. This axiological value, after being projected on a positive and negative plane, designates a mood state. The activation set with the higher positive value defines the value of the concept set [7]. Hence, the dominant activation set subsides the effect of other activation sets. The value of a concept set ranges on a scale from positive infinity to negative infinity; after projection the value becomes a unitary positive or negative.

For example, if we were to think of "Sky" as a concept set and in order for us to determine what it's axiological value is we need to follow the current procedure. The concept "Sky" is a resultant of various activation sets in which each contribution was based on the level of its activation within a specific time frame and orientation. If we were to consider another concept such as "Dark" most likely the same computation applies but a negative axiological value would be assigned. At another point in time and according to the same patient the concept "Morning" can be formed based on these two concepts and it will result with a positive axiology since a "Dark Sky" might resemble the end of a day and hence announcing the coming of the "Morning". This axiological value is valid within these time-division constraints and it might change if the constraints were to change, similarly for other patients. Therefore, the use of a learning algorithm will enhance our computational accuracy while reducing evaluated errors for specific patients.

5 Unary Algebraic Topological Framework

Below is an introduction to a mathematical framework for Unary Topological Axiologies describing mental states [8]. The structure highlights a continuous signal representation: Let's begin with a set S (uncountably infinite) representing brain regions, which may be activated by some means. We introduce a σ-algebra A on this set, and call the elements a ϵ A activation sets (by definition a ⊂S). Now introduce a second set W whose elements are labeled concepts in the brain, which correspond to words. For some subset $\mathcal{A} \subset A$ there is a mapping $P: a' \in \mathcal{A} \mapsto w \in W$ called the concept activation mapping. The elements a' of A are action potentials. Let $\tilde{P}: w \in W \mapsto \tilde{a} \in \tilde{A}$ be a mapping we call the brain activation mapping. Let μ be a measure on S, and let $F: A \longrightarrow \{+,-\}$ be a parity mapping. An axiology is a mapping $\Xi: W \rightarrow \{+,-\}$ generated by computing:

$$f(w)=\int_a F(s)d\mu$$

with

$$a=\tilde{P}(w)$$

and the projecting

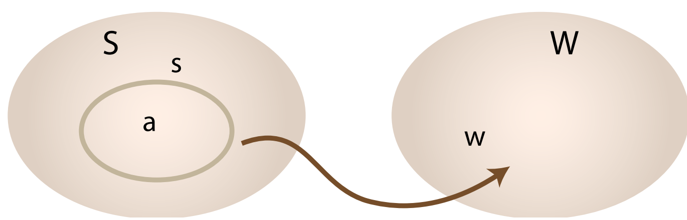
$$\Xi(w)= sign(f)$$

Symbol Definitions [6]:

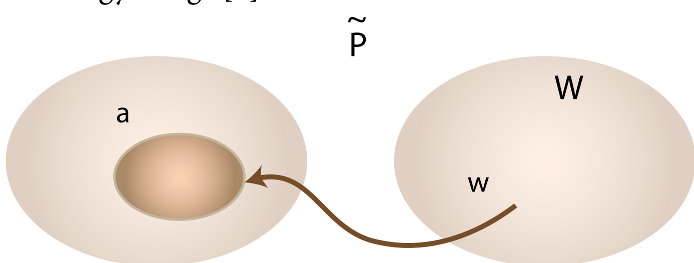
Symbol	Description	Properties
S	Brain regions	
A	Activation sets	$a \in A \Rightarrow a \subset S$
$\mathcal{A}$	Concept activation sets	$\mathcal{A} \subset A$
W	Concepts	
P	Concept activation mapping	$P: a' \in \mathcal{A} \mapsto w \in W$
Ξ	Axiology	$\Xi: W \rightarrow \{+,-\}$

F	Parity mapping	
µ	Weight mapping	

Algebra Image [7]:



Axiology Image [7]:



Conclusion

The cognitive mood analyzer (LXIO) is essential in identifying a patient's state of mind. The fundamental framework for such an analyzer depends highly on axiological values, time-orientation and the inter-relation between the words forming a discourse. This architecture offers a unique interface to how words are represented and the method to evaluate their values. However, some characteristics such as facial and gesture analysis would also increase accuracy and estimation of a patient's mood state. We would further investigate the possibility of using other methods to utilize the experience and knowledge acquired by psychologist's conducting assessment tests. By allowing the clinician's to adjust our modular framework according to their personal analysis of a patient we would hence improve the robustness of our mood projections.

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