ISSN: 2321-7782 (Online)
Volume 1, Issue 7, December 2013
International Journal of Advance Research in Computer Science and Management Studies
Research Paper
Available online at: www.ijarcsms.com

Treating Questionnaire-based inputs for Extraction of Affect Features

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Abstract: Affect recognition systems deal with identification of affects, like sentiments and opinions, from various input sources that are related directly or indirectly to human subjects, whose behaviour needs to be identified or analysed. This paper discusses the limitations of automated psychoanalysis through processing of questionnaire inputs. The paper also proposes a method to improve the automated affect identification process based on heuristics designed to mine the different forms of text inputs that are questionnaire-based.

Keyword: affect mining; sentiment analysis; data mining; artificial intelligence; psychoanalysis; cognitive engineering.

I. INTRODUCTION

Affect recognition systems deal with mining various forms of inputs looking for affect data and analysing its semantics for different applications. Such systems necessarily output the analysis results in the form of sentiment polarity, summarised affects and their intensity values, or psychological summaries that are further used as input to cognitive systems like psychoanalysis for treatment of mental or cognitive disorders and, e-learning applications[1].

The input-types to such systems may vary in the form of text, speech, images or videos. Often more than one form of input is given to such systems, in which case these systems are referred to as multi-modal sentiment analysis systems. For instance, videos of customers, giving product reviews on the company's website, are segregated into sequence of images, speech, and text. The text from these videos is obtained by capturing speech from the videos and converting it to text form. These modalities (text, speech and videos/images) are separately represented and processed to find the affect meaning to the input.

Interactive affect analysis systems provide frequent questionnaire to users or human subjects, the answers to which are rated by experts to form an evaluation. This type of input is necessarily text-based and rated based on the answers to objective questions. The analyses of intricate and complex disorders through processing of such questionnaires seem straight-forward. But, rather it depends on the mining algorithm to extract hidden affects from the objective answers of the human subject. Secondly, the design of the questionnaire should be intelligent enough for the mining algorithm to work consistently well on the questionnaire answers provided to it. The major challenge in these systems is that the emotions or affects expressed in the input are not usually explicit. It is hidden in indirect word formations on which strong mining algorithms need to be executed in order to find the hidden affects.

As far as providing affect data to affect analysis systems is concerned, there are two points to be taken care of:

1. Extracting content words related to affects from the text input (*in this case, answers*)
2. Representing the extracted data in optimised dimensionality using appropriate data model for further mining

The major challenges that are faced in affect data representation systems include the following:

- Converting the unstructured input into structured form
- Combining and relating the affect data received from temporally ordered inputs
- Deciding the optimal number of data values for the analysis and deciding the dimensions for the data representation
- Dealing with inconsistencies in self-reports from different observers for similar events observed. (These inconsistencies need to be normalised by considering whether the observer type is a domain expert or a layman)
- Deciding the level and type of inter-dependencies between different affect states in human subjects [2, 3]. *For e.g.* affect states for '*irritability*' and '*mania*' are strongly related to each other.

The paper proposes a method to identify affect data features extracted from text-based questionnaire results. The novel technique proposed in this paper can be easily extended to generate a semantic network of affect states that can be used for future analysis during the treatment of psychological disorders or similar applications. The scope of this paper however is restricted to the feature extraction technique and hence does not cover the treatment pattern prediction methods.

The paper is organised as follows. Section II, discusses the related work in the field of affect recognition systems; Section III explains the steps for the extraction of affect features from questionnaire inputs; Section IV discusses the application of the method for generation of a semantic network model representation for the proposed system; finally Section V describes the applications of the proposed system and gives the conclusion.

II. Related Work

A. Types of Questionnaire

The extent of most of the psychiatric disorders are identified through behavioural analysis rather than tracking anatomic changes. Since there are no medical diagnostic tools that directly identify behavioural cues, questionnaires are preferably used to identify the psychiatric problem. Often the questionnaires are designed specific to the type of disorder to be analysed. For example, people suffering from *depression* and those being analysed for *subjective happiness* might be given totally different sets of questions with varying answer during diagnosis and analysis of the ailment [4, 5 and 6]. The design of the question-set for affect evaluation depends on multiple factors. The most important ones are mentioned as follows:

- Questions are answered by: The psychoanalyst (or domain expert), an observer/informant (may not be an expert) or the subject himself [2]
- Purpose of the Affect Recognition: General Affect (like social behaviour correction), to study neural deficiencies leading to learning disability or impaired motor functions, acute disorders leading to depression, violence, etc [7]
- Questionnaires with simple yes/no type answers, Likert-scale rating (of the type 1 to 5; 1= feature absent ....4= feature highly visible or ones with descriptive textual answers [8].
- Type of analysis: Whether every answer is separately analysed or if the behaviour is identified by aggregating all the answers and then analysing it. For the analysis, in the first case, we apply the mode, frequencies and chi-square tests on the answers while for the latter case, mean, standard deviation, Annova and regression techniques are used [8].
- Maintaining the time-ordered analysis of the questionnaire-answers to track the progress in the patient [9].

The figure below illustrates the sample formats of various types of questionnaires.

Sample Question for Anxiety
Questionnaire Type A: Likert-Scale Based
(Filled in by the physician/psychiatrist)

Rating Scale: None=0; Mild=1; Moderate=2; Severe=3; Severe and grossly disabling=4
Tension Indicator: Unexplainable Restlessness, Fatigue, constant startling at minor stimulus

Score	Explanation
0	Absent
1	Occasional occurences
2	Above symptoms occur over minor matters and does not affect the patient's day-to-day life
3	Above symptoms depicted over major matters that may occur in future; sometimes affects the patient's day-to-day life
4	Above symptoms occur very frequently; greatly affects the patient's day-to-day life

(Score =)

Fig 1 Likert-scale Based Question Sample(filled by psychoanalyst)

Sample Question for Subjective Happiness Scale
Questionnaire Type B: Likert-scale
(Filled in by the subject)
Rating Scale: Given below individual questions

Q1: Comparative Happiness: As compared to the people around me, I consider myself quite joyful, enthusiastic, optimistic and happy

1	2	3	4	5
Not at all	**Sometimes**	**Depends**	**Most of the time**	**Always**

(Score = _____)

: : : : :
: : : : :

Q5: Approach: I face some or the other personal, professional or social issues, that upsets me

1	2	3	4	5
Always	**Most of the time**	**Depends**	**Sometimes**	**Not at all**

(Score = _____)

Total Score: Mean of scores of all the individual scores = __________

Fig 2 Likert-scale Based Question Sample(filled by subject)

Sample Question for Social Behaviour
Questionnaire Type C: Subjective
(Filled in by the subject)

Q1: Empathetic Concern(EC): A colleague of yours can never say 'no', if someone else inappropriately assigns work to him/her. How do you feel about this?

Possible Answer of Person with high EC: I have a healthy relationship with all my colleagues. If such a thing would with any one of them, I would feel the urge to help them. I would go ahead and try sharing part of the work to ease their load.

Possible Answer of Person with medium EC: I do feel concerned about my colleagues. But one should learn to deny work that is out of their league. In such cases, I will always advise my counterpart to be outspoken.

Possible Answer of Person with low EC: I really do not interfere in my colleagues matters, nor do I care.

Fig 3Subjective-type Sample Question (filled by subject)

This paper discusses a model for feature extraction from objective questionnaires. Method for the processing of subjective answers is beyond the scope of this paper.

B. *Affect Models*

The circumplex model of affect is built on two reference axes namely, pleasure- displeasure and degree-of-arousal (two-dimensional representation). It is based on rating emotions on the perimeter of the circle with two orthogonal axes [3]. Though this model works well on twenty eight basic emotions, it may not be a suitable one for analysis of psychological behaviour because it only rates the current emotion and its correlation with others. On the other hand, psychological behaviour can be treated better, if certain history of events or progressive traits is recorded in sequence of time along with consideration of earlier diagnosis and medication, if any, in the order of time.

For the automated diagnosis of behaviour and treatment pattern, Markov Decision Processes (MDPs) have been implemented [9, 10]. MDPs are a kind of variation on dynamic decision trees that are represented as a collection of belief states and action states. The belief states correspond to the status attained by a patient during the course of treatment. These belief states are driven by action states and previous state of the patient. A combination of previous belief state (patient ailment status and action state (chosen treatment) gives the predicted improvement in the patient, i.e. the resultant belief state and outcome. A sequence of such states and transitions represent temporal sessions of the patient-expert consultation/interaction. Such a model predicts the treatment pattern depending on a particular patient's initial condition and decision on the type of treatment chosen. Such models help estimate the time required for the patients' complete recovery and the probable costs for treatment. Since this model is organized in time-ordered directed trees, certain events like non-adherence to treatment of missing data values are not reflected in the model. Secondly, back-tracking on wrong decisions taken are non-deterministic leading to increased complexity in the prediction model. Some systems set the value missing data parameters as 'absent' that may induce inaccuracy in the inference. For e.g. For the parameter corresponding to allergies, am empty field, may either mean, "no allergies" or "no data available". The inferred result would depend on the probability of the truth of the assumption made.

Directed Acyclic Graph with probabilities (Bayesian Network) and Tree Augmented Network works only on discretized variables. The continuous variables in psychiatric data need to be sampled at regular intervals, converted into discrete value and then appropriately rounded before it is converted into a Bayesian Network Model [11]. Secondly, electronic health records

(EHRs) tend to have numerous fields with missing values at random. This leads to inaccuracies in the evaluation of probability distribution of related parameters that further induces errors in the Bayesian Network model. Also, the immensely massive databases are quantified by evaluating probability distributions and then forming nodes from the distribution table. This probability distribution gets complex with increasing number of parameters. Often affect analysis systems are require to process symptom parameters as many as seventy.

There are few works related to using ontology for the semantic abstraction of affect states. The ontology has been used to define classes for all possible affects that can be represented directly. The ontology is more or less organised in a hierarchy of the affect classes following a taxonomical structure with specific affect states (classes) derived from general ones [13]. The taxonomical structure however does not accommodate overlapping features that may depict multiple-related ailments at the same time. For instance, weightloss and tremor are features that both may relate to affect states, 'schizophrenia' and 'hyper-thyroid-ism', but cannot be represented in the same taxonomical ontology, since they both represent ailments of varying criticalities.

III. EXTRACTING AFFECT-FEATURES FROM QUESTIONNAIRE INPUT

The experimental set-up for the proposed design is :

- Input: Objective-type questionnaire answers
- Output: Identified Psychiatric Disorder with evaluated intensity
- Database Support:

1. An affect database, SentiWordnet, that will be used to find the valence and polarities of the short-listed affects [16]
2. A local lookup-database (LDB), that is populated with the possible symptoms and its related affect state mapping. The LDB will be referred to extract the intensity values for the features as key values.

TABLE I
Excerpt of the Look-up Database (LDB)

Symptom	**Indicator**	**Criticality (Intensity)**	**Affect-feature**	***(key, val)***	**Possible Disorder**
Sadness, Hopelessness, Helplessness, Worthlessness	Direct-Vocal	Low- 0	Depressive Mood	(Depressive Mood, 0)	{Depression, Anxiety}
Sadness, Hopelessness, Helplessness, Worthlessness	Spontaneous Vocal	Medium-2	Depressive Mood	(Depressive Mood, 2)	{Depression, Anxiety}
Sadness, Hopelessness, Helplessness, Worthlessness	Facial(Non-verbal)	High-4	Depressive Mood	(Depressive Mood, 4)	{Depression}
: :	: :	: :	: :	: :	: :
Resistance to commands	Body Gestures	High-4	Delusional	(Delusion, 4)	(Schizophrenia}
: :	: :	: :	: :	: :	: :

The affect data will be extracted from the text in the questionnaire. The method of feature extraction depends on the abstraction depicted through the question contents, its structure, and the predefined mapping of the various possible affects expressed through the answers.

The first level of feature extraction involves converting the Likert-type or the Likert-scale answers to representative affect features. This is be done by a mapping module that connects the selected answer-rating to the variations of the affect being measured. For instance, the rating of the answers to questions related to Insomnia (sleeplessness), can be strongly related to psychiatric disorders at the level of anxiety and/or depression.

The mapping module will aggregate the mappings of other related answer-ratings to automate the feature extraction process along with the prediction of the measure of the disorder. Considering, the disorder related to anxiety as well as depression, there are some common features (symptoms) and some distinct features. The symptoms that are distinct between two disorders could be commonly occurring to other types of disorders. For e.g., though uncommon in depression, the dyspnea feature may occur for both anxiety disorders and mania. The inter-relations between affect features and disorders can get intricate with multiplicity and varying strength of relations between different affect pairs. Considering the semantic complexity in associating a feature with multiple affect states, it proves difficult to use the traditional models like Bayesian Network model, decision trees and vector-based probabilistic models for the affect data representation [10, 12]. Ontologies may have been employed for the same, but the added complexity is that the model also requires storing the strength of the relationship between features (symptoms) and particular affects [13].

Table I illustrates an excerpt of the relationships and their intensities defined for various psychiatric ailments. The authors have performed a manual mapping of major eight disorders, namely, mania, hypo- and hyper- thyroid-ism, schizophrenia, depression, anxiety, Parkinsonism and, dementia.

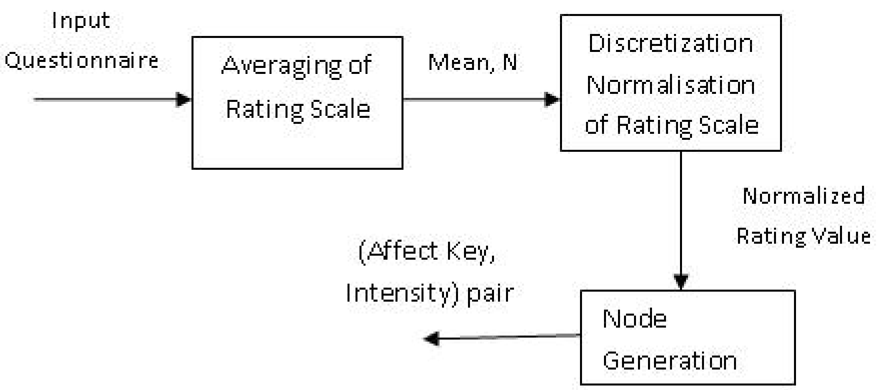

Fig 4: Affect Feature Extraction from Questionnaire Input

The preprocessing of the input data has been explained in the following steps:

1. **Averaging:** The ratings scale of the objective answers may vary depending on the number of possibilities for the question. Some answer-ratings may range say, from 1 to 4 in steps of 1 and some other ratings may have options between 0 to 5 in steps of 1. For. e.g the *di-urnal variation* may have three possible outcomes (0= No variation; 1= worse in mornings; 2=worse in evenings). In the same questionnaire, *psychological anxiety* may be expressed as one of five possible outcomes. Therefore to leverage the questions, first the ratings of the scale are normalised to the mean over the number of rating options for all the questions. Thus, in a given input questionnaire with 'n' questions, if, xi is the number of options on the 'i'th question,

   N, is the normalised number of ratings given by,

$$N = \sum_{i=1}^{i=n} xi/n$$

2. **Discretization-Normalization of Rating Scale:** The actual option chosen (before normalization) is then converted to the rating as per the normalised scale by evaluating the proportionality of the chosen option and then performing the discretization to convert the original rating to the normalized rating without altering the intensity level of the original rating. The discretized value may be a real number that is retained to avoid cumulative error in the aggregation phase.

   The rate-interval for Question 'i' is now calculated as

   Rate_Interval(Qi)= Current_Max_Scale (Qi)/ N

Assuming that the initial rating scale had 'k' range, the rating-scale is then discretized to

Current_Min_Scale(Qi) + j Rate_Interval(Qi)*

3. **Affect-state Generation:** The normalized and discretized rated value of the answer now represents the intensity of the symptom or feature related to the question. This feature and the intensity is combined to form a *key-value* pair, *(ki, vi)*, to represent one feature node [17]. The *key-value* pair is then searched for in the look-up database to find all the related affect classes. A given key (feature), (e.g. *worthlessness*) may have multiple entries in the *look-up database (LDB)*, depending on its possible combinations with various intensity values. In the previous example, the *'di-urnal variation'-key* will be associated with three intensity values, while the *anxiety-key* will have five possible intensity values.

The (key, value) pair search in the LBD returns a vector of affect states. This vector will consist of only one value if the LDB contains many to one mapping of the (feature, intensity) to affect state combination. The feature is represented as a node, that is assigned a unique identifier and a *color* attribute. The range of the feature (mapped affect) intensity depends on the value of N calculated in the normalization phase and it is considered as the node weight. In our model we have assumed a maximum value of N as 6 (i.e. maximum possible range between 0 and 6).

The generated affect node is then populated with an appropriate color value corresponding to the evaluated intensity (weight) of the affect represented by the node.

The (intensity, color) ranges defined in the system are as below:

TABLE II
Values of color atributes corresponding to the intensity values

Affect Node Intensity (Weight)	Assigned Color
0	Violet
1	Dark Blue
2	Light Blue
3	Green
4	Yellow
5	Orange
6	Red

IV. EXTENSION OF NODE GENERATION TO SEMANTIC-NETWORK MODEL FOR AFFECT DATA REPRESENTATION

A. Connecting Individual nodes for Affect Analysis:

Each question-answer in the input questionnaire is fed to the feature extractor (explained in the previous section), that produces at least one affect node each. There may be more than one output nodes generated for each question answer-rating, if feature-key has multiple matching entries, found in the LDB. Hence, one entire

The graph nodes contain the following descriptors:

- NodeID- unique node identifier
- NodeName- Label of the mapped affect state
- NodeWeight- color intensity (The color is assigned as per the affect mapping specified in Table II)

To form one single network, the nodes that are generated as discussed in the previous section, are associated with each other with links defined by the following descriptors:

1. LinkID- unique link identifier
2. Attributes-(BeginNodeID, EndNodeID, LinkWeight), where BeginNodeID and EndNodeID represent the nodes at the source position and target position of the link. The LinkWeight parameter is assigned a weight proportional to the type

of relativity of two affect nodes. The value of the link weight assigned is derived from the architecture as illustrated in fig.4 [15]. For instance, if Question M generates the indifference affect node and Question K generates the Sadness affect node, then the algorithm establishes a link between the two states, assigning a high link weight, since sadness indicates a primary emotion leading to a high intensity rating.

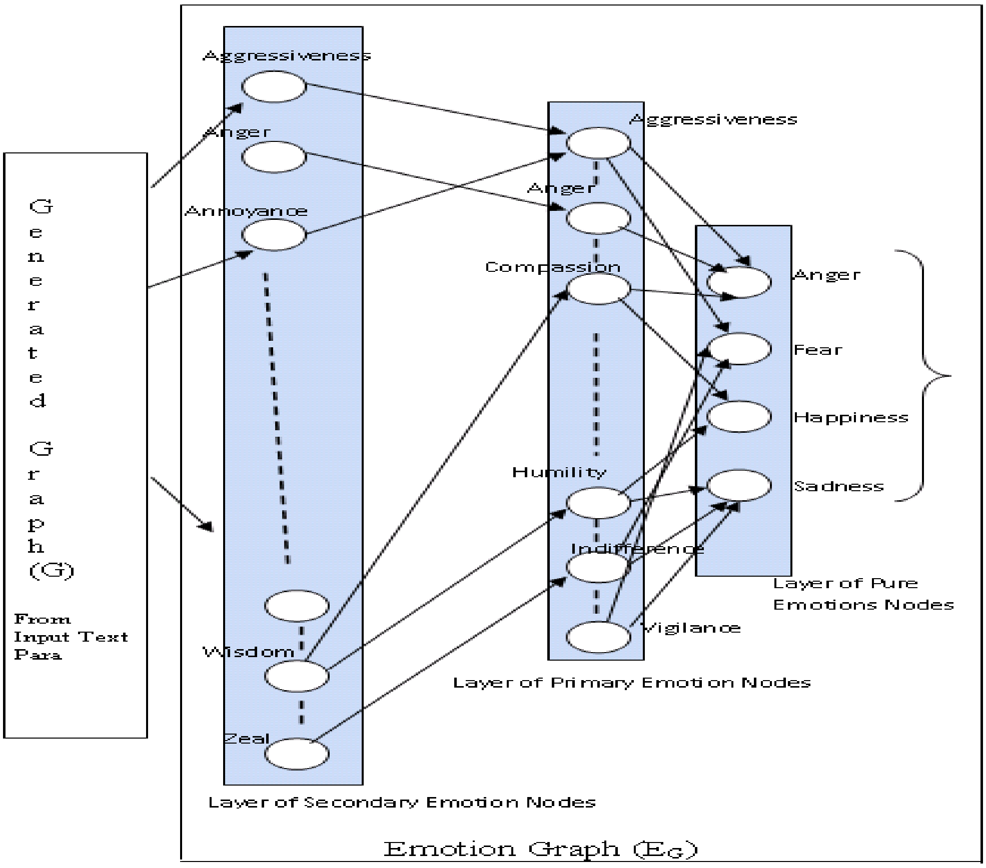

Fig 4: Emotion Framework Adopted for linking of Affect States [15]

B. Analysis of the semantic network:

The individually generated nodes for the given set of questions are integrated to form one semantic network (*as explained in IV-A*). It is required to analyse the entire network to evaluate the associated psychiatric ailment for which the following steps are performed:

1. The edge density for each node in the graph is calculated as a function of the total number of incident edges and the weights on each edge.

$$EdgeDensity(Node) = f(count(Incident\_Edges), vector(e=Incident\_Edge\_Weights))$$

2. The edge density thus evaluated is reflected back on the total weight of the node.

$$NodeWeight(Node) = NodeWeight(Node) + EdgeDensity(Node)$$

3. The updated nodes are first grouped on the assigned color code weights (each color group indicates affect states with similar valence); in each color-group, the affect states are sorted on the node weights. A low color-code indicates less critical symptom while the highest color code indicates the most critical symptom. If the count of nodes are higher in color clusters with higher codes, it indicates a critical psychiatric condition and the condition is named as per the mapping in the LUD.

The proposed design is based on the assumption that all the questions in the questionnaire are of equal importance to contribute in the affect recognition process. It also assumes that the initial rating scale has a uniform interval of value 1.

The model has been prototyped for eight ailments. Since, there are legal issues in getting questionnaire filled by actual patients, the sample questionnaire was provided as well as filled out by one domain-expert from the field of psychiatric counseling, posing as a mentally ailing subject..The results are convincing for questionnaire analysis for *schizophrenia* and *dementia* (approx. accuracy= 82%), *hypothyroidism* (approx. Accuracy= 86%) and *hyperthyroidism* (approx. accuracy= 87%). We obtained little lesser accuracy for *depression* (approx. 53%), *anxiety* (approx. 53%), *mania* (approx. 62%), reason being the number of symptoms were overlapping with the three disorders, due to the rated answers were mostly distributed over as range of intensity values. *Parkinsonism* indicated good results in the feature extraction (approx 83%), but the source of the rated inputs were not convincing, hence this result can be neglected.

V. Applications and Conclusion

Questionnaire-based inputs are primitive but effective form of affect inputs for most affect-analysis systems. The most popular application is the semi-automated psychoanalysis of persons suffering from psychological disorders. The proposed architecture for the mining of such inputs can be extremely used for evaluation of cognitive properties of human subjects. The same can also be useful to treat learning disorders in autistic children [1]. A similar architecture can also be used in intelligent tutoring systems, when the machine-tutor can adapt to the learning and cognitive capabilities of the student to dynamically tailor the course delivery and improve the learning curve.

Rather than the system being dependent only on the initial set of questionnaire answers as input, the novel method discussed in the proposed system will be able to associate the observable states to the hidden affect states to improved affect feature extraction. The attempt described in this paper has been made to experiment with the credibility of the questionnaire system on which most psycho-analysts heavily rely. The result, though from a prototypical model, indicate promising results if the model can be designed on more generalized grounds. The future scope of this work includes extending the current proposed model for affect feature extraction from subjective-type questionnaire-answers.

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