Lovotics
ISSN: 2090-9888

Jamisola, Lovotics 2016, 4:1
http://dx.doi.org/10.4172/2090-9888.1000115

Case Report | Open Access

# Conceptualizing a Questionnaire-Based Machine Learning Tool that Determines State of Mind and Emotion

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## Abstract

This paper qualifies the creation of a diagnostic tool that determines the state of the mind and emotion based on the answers given to a questionnaire. State of mind and emotion are defined in this paper as feelings, preference, or opinion that gives an indication of the attitude of an individual which can result into his or her behaviour. It is the case when a person will try to give out an answer that is not based on logic or reason, and will start by saying, "I feel...". The idea of this paper is to characterize a general purpose machine learning tool whose method of computation remains the same, but will only be modified according to the type of questions that were asked. This tool can be used to diagnose substance addiction, alcoholism, sexual attraction, HIV status, degree of commitment, activity inclination, etc. This can be used as a supplementary tool to psychologists or to curious individuals to assess a respondent's status according to the information gathered. The purpose of this tool is to come up with a diagnosis, within acceptable ball-park figures, that is comparable to that performed by a psychologist. Machine learning tools, namely, artificial neural network and support vector machine are proposed to determine a true or false or degree of state of the respondent.

**Keywords:** Diagnostic tool; Questionnaire-based; Psychology; Machine learning; Neural network; Support vector machine; Mind and emotion

## Introduction

Machine learning has been widely used as diagnostic tool in health and medicine. It helped characterize genes and viruses [1-3], evaluate tumours and cancer cells [4-6], analyse medical images, [7-10], and assess the health status of patients [11-13]. However, in the area of psychology, including the feelings of love, affection, or preference where interaction between cognition and emotion is not yet fully understood [14], the use of machine learning tools is still to be extensively applied.

This paper attempts to qualify the creation of a machine learning tool to be used in assessing state of mind and emotion of a respondent through the use of a questionnaire. Assessment questionnaires are extensively used in psychology, and are analyse by psychologists. It has been long suggested that machine learning models can provide better classification accuracy than explicit knowledge acquisition techniques [15]. Thus in the past two decades, much research was performed in machine learning and are applied to a wide range of fields of study. However, a more recent study [16] showed that an analytic instrument from empirical psychometric research can also prove to be a valid alternative to machine learning to detect public sentiment. In some cases, machine learning tools are used to solve traditional mathematical computations [17-20] which proved to be comparable to traditional results. Interestingly, the idea of a gaze sensor that has the ability to detect staring, similar to that of humans was first discussed [21].

The author recognized the fact that questionnaire-based diagnosis cannot be very accurate and precise. Issue on accuracy can occur because of the fact that respondents can lie, and precision can arise because of the fact that even the respondent cannot be precise about his or her own feelings [22]. However, the same challenges are faced by questionnaire-based diagnostic examinations, whether automatically or professionally analyse. The overall purpose of this exercise, however, is to approximate, within a ball-park figure, the state of mind and emotion of a respondent that will be comparable to that as diagnosed by a psychologist.

In this work, a machine learning tool is conceptualized that can automatically assess the answers of a respondent and then outputs a judgment. A database of questions is established and its corresponding machine learning model is derived from training and verification. There are some advantages of this automated analysis compared to the human-analysed questions. First, data errors in creating the model can be compensated by a statistically higher number of consistencies in majority of the gathered information. Second, analysis errors are consistent with the model and can be easily corrected by reconstructing the model. Compared to the manually analyse questions, human error can contribute to errors in analysis. And third, updating the model can be fast by removing erroneous data, adding newly gathered data and reconstructing the model.

Figure 1 shows a diagram of Machine Learning (ML) discussion presented in this paper. Data-gathering methods are shown as blocks on the left-hand side: Questionnaire-Based (QB), Data Mining (DM), User Interface (UI), and camera (CA). Possible outputs of machine learning analysis are true (1), false (0) or number range [a] indicating the degree of state of mind and emotion. In the succeeding sections, we present data gathering methods, type of classifications and machine learning classifiers from previous studies to analyse the state of mind and emotion.

## Data-Gathering Methods

In this section, we present data gathering techniques that were used

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**Received** April 23, 2016; **Accepted** June 06, 2016; **Published** June 10, 2016

**Citation:** Jamisola RS (2016) Conceptualizing a Questionnaire-Based Machine Learning Tool that Determines State of Mind and Emotion. Lovotics 4: 115. doi:10.4172/2090-9888.1000115

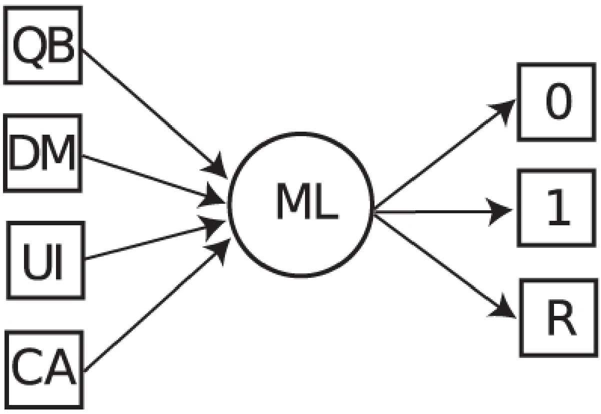


**Figure 1:** A diagram of the discussion presented in this paper. The center circle represents the machine learning (ML) method used for classification. Inputs discussed are questionnaire-based (QB), data mining (DM), user interface (UI), and camera (CA). The output of classification can be true (1), false (0), or a number range (R) representing a degree of state.

| Method | Purpose | Technique | Output | Ref. |
|---|---|---|---|---|
| Quest based | Conjoint analysis | Bayes, SVM | Consumer Feedback | [23] |
| | Tutoring student classification | CLARISSE | Categorized Students | [24] |
| | Open answers questionnaires | Rule Learning, Cor. Analysis | Classification Rules, Association Rules | [25] |
| | Acquire effcient decision rules | Sim. Breeding, Ind. Learning | Decision Rules | [26] |
| Data mining | Opinions on travel destinations | Naive Bayes, SVM, N-Gram | Sentiment Classification | [27] |
| | Personalized adaptation hypertext | Con. Clustering, Ind. Algorithm | Dynamic User Profile | [28] |
| | Tracking navigation patterns | Neural Network, Markovian | Navigation Classification | [29] |
| User int. | Give feedback to ML systems | Rule Learning, Naive Bayes | Suggested Features | [30,31] |
| | Prediction learner's emotion | ID3 | Emotional Classification | [32] |
| | Determine learner's preference | dec. trees, HMM | Customized Interface | [33] |
| | Detecting human emotion | *k*-n.n., SVM Bayesian net., reg. tree | Emotion Classification | [34] |
| | Detect eight emotional states | *k*-n.n., max. a posteriori | Emotion Classification | [22] |
| Camera | Emotion by facial expression | LDA, SVM | Emotion Classification | [35,36] |
| | Facial expression database | Bayesian net., dec. trees, SVM | Emotion Classification | [37] |
| | Facial expression recognition | SVM, LBP | Emotion Classification | [38] |
| | Facial expression from video | Neurofuzzy, Markovian, Naive Bayes | Emotion Classification | [39,40] |
| | 3D Facial expression | LDA | 3D Facial Database | [41] |

**Note:** [a]Definitions for abbreviated words: Ref: References; Quest: Questionnaire; Cor: Correspondence; Sim: Simulated; Ind: Inductive; Con: Conceptual; Int: Interface; Dec: Decision; N.N: Nearest Neighbor; Net: Network; Reg: Regression

**Table 1:** Data-gathering methods used in machine learning diagnostic tools *a*.

by previous studies related to judging or classifying the respondent from the gathered information. A quick-glance summary of the data-gathering methods used is shown in Table 1.

## Questionnaire-based

An extensive number of studies aimed at getting information from individuals are through the use of a questionnaire, also known as a survey. This is the usual method used in getting feedback from users or consumers of a particular product.

One study used choice-based conjoint analysis that builds models of consumer preferences over products with answers gathered from questionnaires [23]. This is a marketing research technique that is used to determine the required features of a new product based on feedback from consumers. Two machine learning tools were used: hierarchical Bayes analysis and Support Vector Machine (SVM). In another study, an adaptive pre-test is used together with a machine learning tool called CLARISSE that categorized students for an intelligent tutoring system [24].

Rule learning and correspondence analysis are used to automatically mine useful information from open answers to questionnaires [25]. The authors argued that answers to open-ended questions often contain valuable information and provide an important basis for business decisions. The mined information should extract characteristics for individual analysis targets and relationships among the targets.

The study in [26] aimed to create efficient decision rules from noisy questionnaire data. It used both simulated breeding (genetic algorithm) and inductive learning techniques. Simulated breeding was used to get the effective features from the questionnaire data and inductive learning was used to acquire simple decision rules from the data. Domain expert opinion showed favourable response on ease of understanding and level of accuracy.

## Online data mining

Online data mining involved automatic gathering of information based on online content. This is normally performed by applications that crawl through online contents and gather information based on keywords found. The mined data from previous studies presented here are based on personal sentiments, opinion, or preferences that are available online.

One study [27] involved sentiment classification of online reviews as a class of web mining techniques that performed analysis of opinion on travel destinations. The authors went through travel blogs to gather information and used three supervised machine learning techniques, namely, naive Bayes, SVM and the character based N-gram mode.

On the basis of a user's browsing history in hypertext, without additional input from the user, a study [28] involved applying machine learning algorithms to generate personalized adaptation of hypertext systems. Conceptual clustering and inductive machine learning algorithms were used. Pre-defined user profiles were replaced with a dynamic user profile-building scheme in order to provide individual adaptation. A superficial evaluation indicated educational effectiveness, but more thorough evaluation showed the positive results may be attributed to other causes.

A homemade access log database is used, together with a number of statistical machines learning models, to compare different classification or tracking of user navigation patterns for closed world hypermedia [29]. Statistical machine learning tools are used for dealing with temporal data: neural network and Markovian models.

### User interface

A user interface data gathering allows the respondent to input his or her reaction to a stimulus, normally through a screen display, by natural language, or physical cues. This type of data gathering allows real-time interaction with the respondent, and allows online machine learning analysis.

One study used respondents to communicate feedback to machine learning systems [30,31], with the purpose of improving its accuracy. Users were shown explanations of machine learning predictions and were asked to provide feedback. These include suggestions for re-weighting of features, proposals for new features, feature combinations, relational features, and changes to the learning algorithm. Two learning algorithms were used: the Ripper rule-learning algorithm and the naive Bayes algorithm. The study showed the potential of rich human–computer collaboration via on-the-spot interactions, to share intelligence between user and machine.

ID3 (Iterative Dichotomiser 3) algorithm is used in machine learning and natural language processing domains. For the study in [32], the learner's emotional reaction in a distant learning environment is inferred using ID3 algorithm.

A user interface has been devised so different learner preferences can be acquired through interaction with the system. Based on this information, user interfaces are customized to accommodate a learner's preference in an intelligent learning environment [33]. User preference is diagnosed using Decision Tree and Hidden Markov Model (HMM) approaches.

A study is performed to detect human emotion from physiological cues using four machine learning methods: *k*-nearest neighbour, Regression Tree (RT), Bayesian network and Support Vector Machine (SVM) [34]. The respondents interact with computers, and their emotions were detected by sensors attached to their bodies. Results showed that SVM gave the best classification accuracy even though all the methods performed competitively.

A study by [22] used physiological signals to gather data from a single subject over six weeks. A computer controlled prompting system called "Sentograph" showed a set of personally-significant imagery to help elicit eight emotional states, namely, no emotion (neutral), anger, hate, grief, platonic love, romantic love, joy, and reverence. Transforming techniques used sequential floating forward search, Fisher projection, and a hybrid of the two. Classifiers used *k*-nearest-neighbour and maximum a posteriori.

### Camera

The last method discussed in the paper for data gathering is through the use of a camera. This method can perform a real-time observation of bodily movements or facial expression, or can be non-real-time through a video recording, which the machine learning method then analyzes to output a judgment. One disadvantage on relying on face or voice to judge a person's emotion is that we may see a person can be smiling or hear that her voice sounded cheerful, but this does not mean that she was happy [22]. But because human emotion is greatly displayed by facial expression, its detection by camera is extensively studied.

One study that used camera to detect facial expression [35,36] utilized AdaBoost for feature selection prior to classification by Support Vector Machine (SVM) or Linear Discriminant Analysis (LDA). The system obtained 93% correct generalization to novel subjects on the Cohn-Kanade expression dataset, and was applied to fully automated recognition of facial actions) with a mean accuracy of 94.8%.

Facial expressions in video is analysed in a study in [37]. It developed authentic facial expression database where the subjects showed natural facial expressions based on their emotional state. Then it evaluated machine learning algorithms for emotion detection including Bayesian networks, SVMs, and decision trees.

Local Binary Pattern (LBP) is used for facial expression recognition. A boosted-LBP is used to extract the most discriminant LBP features, and the results are classified via SVM. It was claimed that the method worked in low resolutions of face images and compressed low-resolution video sequences captured in real-world environments [38].

Extraction of appropriate facial features and identification of the user's emotional state through the use of neurofuzzy system is studied [39], which can be robust to variations among different persons. Facial animation parameters are extracted from ISO MPEG-4 video standard. Neurofuzzy analysis is performed based on the rules from facial animation parameters variations both at the discrete emotional space and 2D continuous activation–evaluation.

A 3D facial expression recognition is shown in [40,41] that has developed 3D facial expression database. It has created a prototypical 3D facial expression shapes and 2D facial textures of 2,500 models from 100 subjects. LDA classifier is used to classify the prototypic facial expressions of sixty subjects.

Multi-level architecture of a hidden Markov model layer and a Markov model layer is shown in [40] for automatically segmenting and recognizing human facial expression from video sequences. Classification of expressions from video used naïve Bayes classifiers, and learning the dependencies among different facial motion features used Gaussian tree-augmented naïve Bayes classifiers.

## Types of Classifications

It has been observed that there is a strong link between cognition and emotion, and that the interaction between them is not yet fully understood [14]. The types of classifications presented in this section are the classifications performed by previous studies and are grouped here accordingly. Table 2 showed the summary of classifications.

### Classification of preference

Previous studies showed classification of preferences on services

| Classification | Purpose | References |
|---|---|---|
| Preference | Consumer product | [23,42] |
| | Travel destinations | [27] |
| | Ranking of preferences | [43] |
| | Learner's preference on online tutorial | [33] |
| | Dynamic browsing profile | [28] |
| | Tracking of navigation patterns | [29] |
| | Feedback to machine learning systems | [30,31] |
| Grouping | Dynamic preference in adaptive hypermedia | [44] |
| | Adaptive pre-test to categorize students | [24] |
| | Likelihood prediction of student response | [45] |
| | Identifying off-task behavior | [46] |
| | Model formation to predict future actions | [47] |
| | Gaming-detection model for tutoring behavior | [48] |
| Emotion | Eight emotion classifications | [22] |
| | Learner's emotion in distant learning | [32] |
| | Emotion derived from web content | [49] |
| | Detect emotion from physiological cues | [22,34] |
| | Emotion detection from speech | [50,51] |
| | Facial expression from direct camera output | [35,36,39] |
| | Facial expression from video sequences | [37,38,40] |
| | 3D facial expression | [41] |
| Rules | Open answers to questionnaires | [25] |
| | Effcient decision rules from noisy data | [26] |
| | Learning casual relationships and word meanings | [52] |
| | Production rules from independent searches | [53] |
| | Construct psychology to refine knowledge base | [54] |

**Table 2:** Classifications in determining state of mind and emotion.

or products. In this type of classification, an individual liking can be determined that will give insight to his her type of personality or psychological condition. Such information can be used to diagnose an individual to certain aspects of their being that needs special attention. In this case, the diagnostic tool will give insight of an individual's preferences in terms of activity inclination, substance addiction, or sexual tendency.

Two studies used conjoint analysis to build models on consumer preferences [23,42]. This is normally used by private companies to gain feedback on new products or services. In some cases, sentiment classification [27] is studied by automatically crawling through online information on services of travel destinations. Preferences determinations were also performed through learning the mapping from instances to rankings of preference [43].

In the case of a user interface, this can be modified according to the learner's preference which was acquired by the interaction of the learner to the system [33]. Through a browsing history, a dynamic user profile-building scheme was introduced [28] in order to provide individual adaptation to hypertext systems. The same approach can be utilized by tracking of user navigation patterns for closed world hypermedia [29].

And lastly, preferences can also be conveyed by directly communicating feedback to machine learning systems [30,31]. In this previous work, the machine learning systems gained suggestions in terms of improving itself from interaction with its users, which can include re-weighting of features, feature combinations, proposals for new features, or changes to the learning algorithm.

### Classification by grouping

This type of classification groups individuals according to preparedness to perform assigned tasks. For the most part, this was used in previous studies to classify students on online tutoring systems based on students' background. The types of lessons can then be modified according to the determined level of the student. Arguably, this created a personalized tutoring system for students.

One of such studies used to model concept drift in student preference of an adaptive hyper-media educational system [44], and in an adaptive pre-test [24] that categorized student abilities. The ability to answer in mathematics tutoring was shown [45] such that it can predict the time the student will generate a response as well as predicting the likelihood the student response was correct. Another method assessed abilities of students in intelligent tutoring systems by identifying off-task behaviours [46]. In user modelling, training examples in a machine learning system are used to form a model designed to predict future actions [47]. Gaming-detection models were developed [48] to investigate underlying factors to enable students to systematically exploit tutor behaviour in order to advance through a curriculum quickly and easily.

### Classification of emotion

Eight types of emotion classification has been studied in [22], namely, no emotion (neutral), anger, hate, grief, platonic love, romantic love, joy, and reverence. This subsection presents previous studies that considered classification of an individual's emotion. And because a person's face is one of the most easily detectable displays of his or her emotions, a considerable number of studies are dedicated to this end.

One study detected emotion from the learner's reaction in a distant learning environment [32], and of feelings of people derived from web content [49]. Another study detected human emotion from physiological cues [34], and through the use of physiological signals [22] gathered from a single subject over six weeks. Emotional state can also be represented and automatically detected in speech [50], as well as by extracting emotional information where linguistic processing is problematic [51].

Some studies involved detecting emotion of a person's face by extracting images as seen directly from the camera [35,36,39] and immediately processing them. In some cases, the facial images were extracted from video sequences [37,40], which sometimes can be compressed and low-resolution [38]. The facial images can also be stored and processed as 3D facial expressions [41].

### Classification of rules

Lastly, we consider classification that creates rules or policies in dealing with certain situations. Open answers to questionnaires [25] often contained valuable information which can become important basis for business decisions. In some cases, possibly creating efficient decision rules can be derived from noisy questionnaire data [26], or through learning from word meanings, un-observed properties, causal relationships, and many other aspects of the world [52]. Production rules may require independent searches for different portions of the rule [53]. In other cases, knowledge is acquired from personal construct psychology [54] to help construct, analyse, test and refine knowledge bases.

## Machine Learning Classifiers

Two machine learning tools are considered: Artificial neural network and Support vector machines. The number of questions will be equal to the dimension of the input space, $n$. For an $i$-th sample, the corresponding answers can be true (1), false (0), or a degree of

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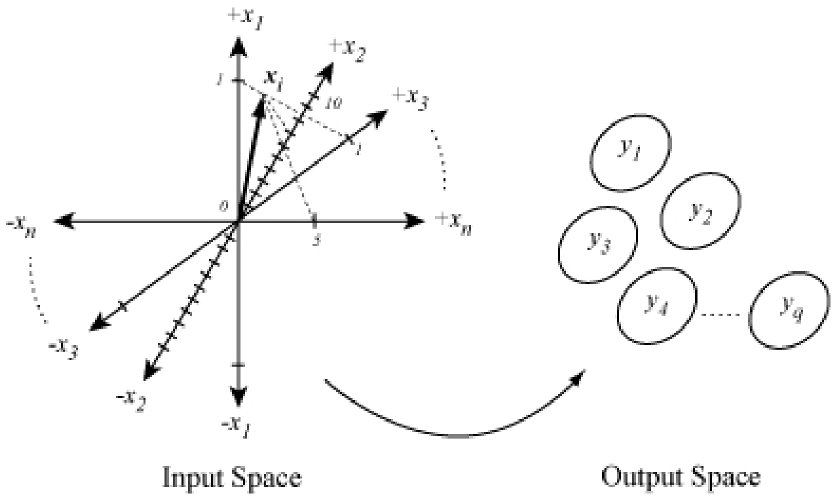


**Figure 2:** The input vector $x_i$ is transformed from the input space to the output space through the use of ANN or SVM. The dimension of the input space $n$ is defined by the number of questions in the questionnaire. The axes $x_1$ to $x_n$ define the input space. The output space consists of $q$ classifications denoted by $y_1$ to $y_q$.

state ([10; 100]). Thus for an input $x_i \in R^n$, a function $f: R^n \rightarrow R$ is defined as

$$y_i = f(x_i) \tag{1}$$

where $y_i \in \{1, 0, [10, 100]\}$ The function $f$ is numerically derived from artificial neural network or support vector machine.

## Artificial Neural Network (ANN)

Artificial neural network (ANN) has been extensively used in many different machine learning applications. Two widely used types are feed forward multilayer perceptron and radial basis function.

For multilayer perceptron, given input layer $i$ and output layer $j$, a weight between layers

$i$ and $j$ is denoted as $wi\ j$, such that for $n$ nodes in layer $w_j \in R^n = [w_{1j}, ..., w_{ij}, ..., w_{nj}]$ An output of a single node in layer $j$ for a given input $x \in Rn$ can be expressed as

$$y_j = \sum_{i=1}^{n} w_{ij} x_i \tag{2}$$

For an input layer $i$, hidden layers $j$ and $k$, and a single node output (output layer $l$), we can recursively apply (2) three times, to get the input-output relations to

$$y_l = \sum_{k=1}^{q} w_{kl} f\left(\sum_{j=1}^{p} w_{jk} f\left(\sum_{i=1}^{n} w_{ij} x_i\right)\right) \tag{3}$$

such that $w_l \in R^q, w_k \in R^p, w_j \in R^n$ and $y = f(.)$ is called activation function.

For radial basis function with one single output, given input x and number of samples $m$, the following equation can be applied

$$y = \sum_{j=1}^{m} w_j \phi\left(\|x - x^{(j)}\|\right) \tag{4}$$

Where $\phi(.)$ is a set of radial basis functions, $X^{(j)}$ is a center of the a radial basis function, and $w_j$ is an unknown coefficient.

## Support Vector Machine Model (SVM)

Support vector machines (SVM) is derived from statistical learning theory [55]. It has two major advantages over other machine learning tools: (1) it does not have local minima during learning, and (2) its generalization error does not depend on the dimension of the space. Given $m$ samples $(x_i, y_i) = 1$ for an $i$-th sample input $x_i \in R^n$ a scalar offset $b \in R$ and a weighting vector $w \in R^n$, a function $f$ is given as

$$f(x_i) = w.x_i + b \tag{5}$$

A loss function $L$ that is insensitive to tolerable error $\epsilon$ can be expressed as

$$L = \|w\|^2 + \frac{c}{m} \sum_{i=1}^{m} \max\{|y_i - f(x_i)| - \in\} \tag{6}$$

Where $C \in R$ is a regularization constant which can be expressed as an optimization problem in the form

$$\min \ \frac{1}{2}\|w\|^2 + \frac{c}{m} \sum_{i=1}^{m} (\xi_i + \xi_i *) \tag{7}$$

Subject to: $(w.x_i + b) - y_i \leq \in + \xi_i$

$y_i - (w.x_i + b) \leq \in + \xi_i *$

$\xi_i, \xi_i * \geq 0$ *for i=1,.......,m*

## Comparison between ANN and SVM

In this subsection we are going to briefly compare Artificial Neural Network (ANN) against Support Vector Machines (SVM). We will compare the two proposed methods in terms of input data and method of classification. In principle, the two proposed methods will use the same input data and will output the same types of classification, as shown in (Figure 2). The only difference will be on the computation involved in each method.

The dimension of the input space will be determined by the number of questions asked from the questionnaire. As shown in (Figure 2) - Input Space, we assign this number with dimension $n$, such that $x_1$ to $x_n$ are the corresponding axes of the space. Answers to the questions can be "true" or "false" which are converted to numbers 1 or 0, respectively. This answer will then represent a point in the corresponding axis, which in this case, has a graduation of zero and one. In some cases, the answers can have three or more options, and this number of options will determine the graduation of the corresponding axis. Or the answer can be a degree of preference, which again will be reflected in the graduation of the corresponding axis. Thus, for a given respondent of the survey, his or her answers can be represented by input vector $x_i$ as shown in the (Figure 2). The subscript $i$ [1 $m$] represents the number of respondents in the survey. Then ANN or SVM will process the input vector $x_i$, transform it to the output space, and classify it as $y_1$ to $y_q$, depending on the number of desired classifications, denoted by subscript $q$.

The process of ANN development started from a heuristic approach through applications and extensive experimentation before formalizing its theory. However, SVM developed through extensive theoretical development first before extensive experimentation [56]. The most significant advantage of SVM against ANN is that the solution to SVM is global and unique, while ANN solution can have several local minima [57]. In addition, the computational complexity of ANN can depend on the dimension of the input space, but this is not true for SVM. And lastly, ANN can be prone to over fitting but not SVM. In this proposed approach, SVM will be applied to classify several classes, but its original theory was intended to perform binary classification.

When linear decision hyper planes are no longer feasible in some problems, an input space is mapped into a feature space (the hidden layer in ANN models), and this can results into a non-linear classifier [58]. Thus ANN is generally considered in non-linear classifications. However, SVM itself can become a non-linear classifier when it involves a kernel function.

## Conclusion

This paper has characterized a machine learning tool to be used as a diagnostic supplement to psychologists. Such a tool can be used to determine feelings, preferences or opinion of an individual based on his or her response to a questionnaire. This tool will use the same method of computation for all applications, but will vary only on the types of questions asked depending on the individual information to be extracted. This machine learning diagnostic tool must be able to output judgment that is comparable to that performed by psychologists.

### Acknowledgment

The author would like to acknowledge the contribution of Constantine Della of the Department of Psychology, University of the Philippines, Manila for his inputs in the preparation of this manuscript.

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**Citation:** Jamisola RS (2016) Conceptualizing a Questionnaire-Based Machine Learning Tool that Determines State of Mind and Emotion. Lovotics 4: 115. doi:10.4172/2090-9888.1000115