Novel Data Science Approach for Emotion Analytics: from Machine Learning to Quantum Cognition

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In the field of People Intelligence, Emotion Analytics is one of the emerging and growing challenges. A prominent study field is analyzing an individual's emotional state from textual data, as well as recognizing emotions from audio and video recordings. Current Artificial Intelligence approaches for Emotion Analytics based on machine and deep learning and neural networks based on classic data science approaches assume rational people's decision-making process. People's decision-making is irrational. As a result of recent quantum cognition advancements, we show that emotional judgments from one modality may be incompatible with judgments from another, and they cannot be assessed together to produce a final judgment. As a result, the cognitive process exhibits "quantum-like" biases that classical AI approaches based on probability models challenged to analyze. As a result, we offer an emotion analytics approach based on the quantum data science method for predicting people's emotions by a fundamentally novel assessment method.

Keywords: Emotion Analytics, Quantum Cognition, Machine Learning, Deep Learning

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1 Introduction

Emotion is a multidisciplinary field that includes psychology, computer science, and other disciplines. In psychology, emotions are defined as a psychological state associated with thoughts, feelings, behavioral responses, and a level of pleasure or dissatisfaction [1]. Computer science can capture emotions from audio, video, and text documents. Emotion analysis from text documents appears difficult because textual expressions do not usually employ emotion-related words explicitly but rather result from understanding the meaning of concepts and interactions of concepts expressed in the text content.

In interpersonal relationships, emotional reactions are the most important type of communication. It can be conveyed as a neutral joy, surprise, anger, sadness, and disgust [2]. Positive emotions include happiness, excitement, and pride, whereas negative feelings include sadness, hate, anxiety, and depression. In this way, emotions are communicated in various ways. A rich amount of textual information is gathered via social networking, where people spend most of their time posting and expressing their emotions [3]. It is possible to determine an individual's emotional intensity by looking at the textual data available on social networks.

Emotion analytics is an implementing field that combines cognitive science and artificial intelligence (AI) [4]. It investigates how a person's emotion is represented through many modalities, such as linguistic, visual, or audio. Effective modality fusion strategies are in place at their core. Emotion analytics is an intrinsically complex decision-making process that involves the fusion of decisions from different modalities and cognitive biases [5]. Cognitive science research has discovered that human decision-making can be very irrational. Such behavior does not always follow probability and utility theory [6]. As a result, one modality's emotion assessment may be incompatible with another's, i.e., the order matters, and they cannot be evaluated together to create a final decision. Thus, classical probability models cannot qualitatively represent the cognitive process of emotion analytics based on a traditional data science methodology. We analyze existing emotion analytics studies state based on traditional probability-based data science models. Most studies consider people's emotional states as rational decision-making processes independent of cognitive ability, and they presume that their behavior is rational. Most of them are founded on traditional probabilistic data science approaches [7]. To characterize human behavior, inference, measurement, and projection still require a convincing and potent cognitive model fully and accurately [8]. Human behavior is frequently irrational and frequently defies Markov characteristics or known parameter distributions based on classical probability theory [9]. Empirical evidence demonstrates that human bounded rational behaviors, particularly irrational behaviors, including human decision-making, tend to deviate from the probability-based standard assumption of behavior theory [10]. However, due to a lack of understanding of the significance of cognitive "fallacies," "irrational" decision making, and unexpected utility, these models are now far from fulfilling their full potential [7].

On the other hand, the Quantum mathematic method has been proved to be capable of addressing the dilemmas of classical probability theory in describing human cognition [7]. Quantum cognition contradicts the concept that the cognitive states that support decisions have pre-determined values, which a measurement records. The cognitive system is fundamentally indeterminate and indefinite. The measurement would then produce an actual state and cause the system's state. Correct reasoning, estimation, and prediction require non-classical probabilistic cognitive theories [11]. We believe that formalizing Quantum Emotion Analytics (QEA) based on the quantum data science method could improve predicting people's emotional judgments, as inspired by recent developments in quantum cognition. As a result, we offer a quantum-based data science method QEA for anticipating people's emotional assessments that are radically new. We express utterances as quantum superposition states of positive and negative emotion assessments and uni-modal classifiers as fundamentally incompatible observables on a Hilbert space with positive-operator valued measures. The model demonstrates theoretically that the concept of incompatibility allows for therapeutic intervention of all combination patterns, including those that all uni-modal classifiers predict incorrectly.

In section 2, the state of the art of emotion analytics models is discussed. In section 3. In Section 3, novel QEA is established and theoretically demonstrated. Finally, the conclusion, research limitation and future research is discussed in section 4.

2 Emotion Analytics – State of the Art

2.1 Current AI Research for Emotion Analytics

Existing AI-based emotion analytics research focuses on text, audio, and image signals. Various studies demonstrate emotion analytics by applying Machine Learning (ML) methods. Among these, different researchers utilized a Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), and conditional random field (CRF) approaches while applying supervised or unsupervised ML for emotion detection from textual data sets. These studies achieved a wide spectrum of results accuracy: 59.2% on SVM [12], 64.08% on combined SVM and NB, 72.60% on NB [13], 75% on SVM [14], 83% on NB [15], 90% on combined SVM, NB and DT [16]. Emotion recognition was also tested using voice data sets in other experiments. A recent study shows that using the SVM technique, voice emotion identification may be done with 72.52% accuracy [17]. Current classical probability-based research on the behavioral intentions of human cognition implicitly assumes total rationality and mutual independence. They all use a cognitive theory based on classical probability, which is incompatible with people's emotional decision-making in reality.

Other recent studies have concentrated on Deep Learning (DL), a subset of ML in which programs learn by comprehending and experiencing the hierarchy of concepts. Simpler concepts describe each concept. This methodology helps a program learn complex ideas by building them on simpler concepts [18]. Several research papers address the DL model as long short-term memory (LSTM). The cyclic neural network (RNN) known as the long short-term memory (LSTM) is a type that has found widespread use in the field of behavior prediction due to its exceptional capacity for information mining and deep representation while addressing issues of motivation assessment and specific provision with temporal characteristics. The best result among existing papers presented 99.22% average precision, 98.86% of average recall, and 99.04% F1-score applying LSTM to classify seven emotions (anger, fear, joy, love, sadness, surprise, and thankfulness) [20]. Additional research demonstrated similar results for emotion detection by applying LSTM approach on textual data sets: 94.1% [21], 79.59% [22]. In most studies, we also found that the best performances were obtained for the class "Sad" and the worst for "Happy" emotion. Recent research conducted emotion recognition from voice dataset, utilizing LTSM, accuracy improves by 73.98% and 5.77%, respectively, when using various datasets [22].

Additional research suggests a hybrid approach for a higher likelihood of outperforming the other approaches individually, leveraging the approaches' strengths while attempting to conceal their corresponding limitations. A recent study proposed a combinational framework for emotion detection in implicit texts based on three subsystems. The first subsystem is a machine learning algorithm. The second is a mathematical method based on a vector space model (VSM), and the third is a keyword-based sub-model with an information fusion component to aggregate the main system's final output. If the test text is otherwise abandoned and all three subsystems agree on the same emotion type, their conclusions are aggregated and used to annotate it. The proposed method outperforms the machine learning subsystem by 9.13 percent, VSM by 16.6 %, and the keyword-based method by 23 % [23].

Nevertheless, due to RNN's shortcomings in simulating cognition correlations, different approaches, such as a deep neural network framework different from the RNN framework, are frequently utilized to compensate for RNN's shortcomings. In recent years, Convolutional Neural Networks (CNN) and unsupervised learning methods have been applied for Emotion Detection. For example, recent research combined CNN and LSTM to obtain high performance. The highest F1 score for joy is 93.2 and 89.8, and for sad, 92.3 and 89.4 [24]. The study of Perikos Used Naïve Bayes, maximum entropy, knowledge-based tool, and ensemble classifier [25] and obtained 77%, 85%, 80%, and 87%, respectively.
Emotion analytics cannot be successfully explained using statistical observations alone due to the limited sample efficiency of purely data-driven methodologies. As a result, the prediction's generalization ability or interpretability is poor.

2.2 Challenges of Emotion Analytics

People's behavior entails processing information and making decisions, which are cognitive processes. Hence they must be studied from a cognitive perspective [26]. Cognitive biases are one of the cognitive processes that may play a role in people's behavior. People may not follow logical or normative decision-making models, and biases can influence choice results negatively [27]. Emotion is a component of people's cognitive states, so cognitive bias exists. A cognitive bias refers to a thinking inaccuracy when people receive and interpret information from their environment, influencing their behaviors and perceptions.

Miller's review [28], which focuses on the reasons and thinking processes that people employ when choosing an explanation, such as causality, abnormality, and the use of counterfactuals, is the only systematic treatment of psychological phenomena applicable to machine learning [29]. According to this authoritative review, there is currently no research examining cognitive biases in picking explanations for machine learning approaches.

The importance of bias mitigation in machine learning has lately been recognized, with researchers focusing on biases that apply to machine learning and proposing unique debiasing strategies for each [30]. Kliger et al. study focuses on cognitive biases as psychological processes that might alter the interpretation of machine learning models if not adequately accounted. The disjunction fallacy was one of the most significant issues. It refers to a decision that defies the disjunction rule, which states that the probability Pr(X) cannot be greater than the probability Pr(Z), where Z is the result of combining events X and Y (i.e., XY). Configural Weighting and Adding theory [31], applying quantum cognition principles [32], and inductive confirmation theory [33] are only a few of the recent explanations for disjunctive fallacies.
For Emotion Analytics, we use the quantum cognition theory since it supports the prospect of improved accuracy and outcomes explainability of cognitive state.

2.3 Quantum Cognition

Over the course of the past two decades, quantum theory, which was initially developed within the domain of physics, has contributed significantly to the development of a wide variety of non-physical fields, such as mental function, decision making, information exchange, data processing, and so on [7]. It has not only developed into a more mature theoretical framework, but it has also become more frequently applied. The earliest quantum indication in the scope of human cognition, which is most closely related to cognition state detection, enables to perceive the promise and possibility of using quantum theory to solve the cognitive difficulties of emotion analytics. This is because cognition state detection is the area of human cognition that is most closely related to quantum inkling. The theory of quantum mechanics provides a fresh viewpoint on the illogical and unpredictable aspects of human decision-making [32]. The topic of this work that needs to be investigated and solved is how to correctly grasp the uncertain behavior and interaction of human emotions based on quantum theory and how to make correct interactive behavior decisions based on this. This work is currently waiting to be explored and solved.

Scientists in the area of cognition have discovered that quantum mechanics' interference and entanglement and the interaction of human cognition share many similarities and help develop the mathematical formulation of quantum mechanics. The cognitive domain is introduced to quantum probability to use unique traits to construct a cognitive model of quantum mechanics to explain complex difficulties in human cognition that classical probability cannot explain. The slow emergence of quantum cognitive decision theory based on quantum probability [34]. Von Neumann, a famous mathematician, proposed quantum logic by defining occurrences as a subspace in Hilbert space [32].

Quantum logic is a generalized Boolean logic that lacks many of the constraints of Boolean logic, has more flexibility and unpredictability, and is more suited to understanding human judgments and decisions [35]. Quantum cognitive decision theory has produced several advancements in human cognition during the last ten years, and it has been recognized as a new technique to investigate human cognitive science [32].

3 Novell Quantum Emotion Analytics Method

3.1 Hilbert Space for Quantum Cognition

Quantum cognition uses Hilbert space H, an infinite complex-valued vector space in which a quantum system's state is represented as a unit-length vector. Quantum probability events, unlike classical probability, are characterized as orthonormal basis states. A projective geometric structure establishes relationships between states vectors and basis states [39,40]. Different sets of orthonormal basis states can represent the same Hilbert space, and the same state can be specified over different sets of orthonormal basis states.

We embrace the widely-used *Dirac Notations* for the mathematical framework of Quantum Cognition in accordance to Quantum Mechanics (QM). The key quantum cognition concepts [43,44,36] are required to build the proposed model.
One of the essential ideas in Quantum Mechanics is quantum superposition, which describes the uncertainty of a single particle. A particle, such as a photon, can be in numerous mutually exclusive basis states with a probability distribution in the micro universe. A general pure state $|\psi\rangle$ is a vector on the unit sphere, represented by $|\psi\rangle = w_1|e_1\rangle + \cdots + w_n|e_n\rangle$. Where $|e_1\rangle, \dots, |e_n\rangle$ are *basis states* forming an orthogonal basis of the Hilbert Space, and the probability amplitudes $w_1, \dots, w_n$ are complex scalars with $\sum_{j=1}^{n}\left|w_j\right|^2 = 1$, when $|\cdot|$ stands for the moduls of a complex number. $|\psi\rangle$ is a *superposition state* when it is not equal to one of the basis states. Specifically, in a Hilbert Space H_2 of two-dimensions (also known as the Bloch sphere), which is spanned by the basis states $|0\rangle$ and $|1\rangle$, a pure state $|\psi\rangle$ is defined by

$$|\psi\rangle = \cos\frac{\theta}{2}|0\rangle + e^{i\phi}\sin\frac{\theta}{2}|1\rangle$$

Where $\theta, \phi \in [0, \pi]$ and i is the imaginary number. Notice that the above equation expresses any pure state on H_2 in a unique way.

Quantum cognition also includes the concept of measurement, which is used to calculate quantum probabilities. Projection-Valued Measure (PVM) in QM transforms an uncertain system state into a specific event by projecting a state to its equivalent basis state. In the lack of measurement, the state is uncertain since it takes all possible measurement values simultaneously.

The state collapses to a certain basis state after measurement. Since subsystems of a larger system can not be represented via PVMs, one can use the Positive-Operator Valued Measure (POVM), which tackles this problem by assigning a positive probability to each measurement outcome while ignoring the post-measurement condition [41]. In other words, POVM is an extension of PVM that provides mixed state information for the entire ensemble of subsystems. Mathematically, a POVM is a set of Hermitian positive semi-definite operators $\{E_i\}$ on a Hilbert space H that sum to the identity operator $\sum_i E_i = 1$. For a pure state $|\psi\rangle$ we can calculate its density matrix $\rho = |\psi\rangle\langle\psi|$. The probability with respect to E_i is computed as $P(i) = Trace(E_i\rho) = \langle\psi|\, \mathrm{E_i}\, |\psi\rangle$ and $\sum p(i) = 1$.

Incompatibility is a concept that applies to a Hilbert space solely. Each basis state, defining a probability event, has a projector to evaluate the event. The conjunction of two events is not necessarily commutative [42]. In quantum cognition, the joint probability distribution of two events A, B equals the product of the two projectors Π_A, Π_B corresponding to the basis state which is the intersection between them. If $\Pi_A \Pi_B = \Pi_B \Pi_A$, then the two events are called *compatible*. Otherwise, then their product is not a projector, and the two events do not commute, i.e., they are *incompatible*. Incompatibility indicates that the two measurements can't be obtained simultaneously without interfering with each other. Classical probability, assuming that measurements are always consistent, cannot capture such a disturbance. However, quantum probability's mathematical framework enables both compatible and incompatible measurements to exist [40] by generalizing the probability theory as we know it.

3.2 Process phases and classes of emotions

Complex exponent $e^{i\phi}$ is periodic function repeating itself after every 2π radians. This defines the phase dimension's circular topology, suited for mapping process-causal relationships between contexts [37]. In this scheme, contexts are mapped to the azimuthal phase dimension. Their subjective association does the mapping with particular functional classes according to the basis decision alternative. Six basic classes are defined as follows:

1. **Sensing** $\frac{11\pi}{6} < \phi < \frac{\pi}{6}$

The contexts that describe the circumstances and observations that lead to the basic decision alternative.

2. **Novelty** $\frac{11\pi}{6} < \phi < \frac{\pi}{6}$

The contexts that describe a specific novel factor (surprise, issue, or problem) addressed by the considered decision.

3. **Goal-plan** $\frac{11\pi}{6} < \phi < \frac{\pi}{6}$

The contexts that set objectives regarding the novelty and describe plans for its achievement.

4. **Action** $\frac{11\pi}{6} < \phi < \frac{\pi}{6}$

The contexts that describe efforts for implementation of the plan, including preparation of the resources and building process with all the associated activities.

5. **Progress** $\frac{11\pi}{6} < \phi < \frac{\pi}{6}$

The contexts that describe intermediate advances which provide feedback for the action.

6. **Result** $\frac{11\pi}{6} < \phi < \frac{\pi}{6}$

The contexts that describe the final results and consequences of the decision

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Novelty, Action, and Result are an iconic trio of process stages recognized in the traditional story and screenplay frameworks, cybernetic control loops, and a number of life-cycle models [37]. This triple has a minimal closed semantic structure in which Novelty arises from prior Results and necessitates Action, Action is a transition from Novelty to the result, and result is a result of previous Action and a possible source of future Novelty.

Goal-plan, Progress, and Sensing account for less expressive, but distinct parts of the behavioral cycle enabling transitions between three main stages. The resulting six-stage process taxonomy is considered optimal for behavioral control due to matching with a normal capacity of human attention, which enables to capture at most seven items simultaneously [38].

The process structure holds for both pure and mixed qubit states, which are mapped to the azimuthal circle's circumference and interior, respectively. Circular process dimension associated with the basis behavioral alternative $\{|0\rangle, |1\rangle\}$ is a key difference from classical probability space describing binary uncertainty.

The subject's attribution of causal structure to behavioral contexts is expressed by the arrangement of qubit context representations in the azimuthal phase dimension. The set of relevant contexts would be different for each hypothetical causal structure. As a result, the abstract process cycle serves as an empty semantic template filled up with particular contexts in each decision case based on the subject's causal relations.

The semantics of the qubit space lead to the quantum model of emotions. Its key components are the process-stage map of the qubit's azimuthal dimension and the z-axis of the Bloch sphere, i.e. Θ in the $\cos\frac{\theta}{2}$ and $\sin\frac{\theta}{2}$ terms, encoding subjective context evaluation. Specifically, the context of each process stage is subjectively reflected to a specific class of qubit-emotion states, which are further discriminated to positive ($\Theta > \Pi/2$) or negative ($\Theta < \Pi/2$) valence:

1. **Sensing:** Expectation– Anxiety

Positively, the sensing stage activity is accompanied by calm future expectations, whereas negatively, the expectation takes the form of anxiety and depression.

2. **Novelty**: Surprise – Fear

Positively, new and unexpected information produces wonder and surprising emotions, while negatively it implies worry and fear.

3. **Goal-plan**: Inspiration – Boredom

Positively, setting goals and drawing plans evokes inspiration, passion, and excitement, whereas negatively it experienced as boredom.

4. **Action:** Passion – Rage

Positive emotions of the action stage include ambition, passion, and courage, while negative emotions involve anger, hatred, and contempt.

5. **Progress**: Acceptance – Disgust

Depending on the feedback received at this stage, the contexts of this class are reflected by emotions of acceptance, or disgust.

6. **Result**: Joy – Sadness

This class's contexts provide a positive or negative assessment of the result, which is crucial for behavioral control. Positive emotions about the result are represented by contentment, joy, and happiness, whereas negative emotions about the result are experienced as sadness, sorrow, and misery.

As can be seen from the above list, process stages do not have the same level of emotional expressiveness. Following the division of process stages into main and intermediate triples, novelty, action, and result are emotionally strong, while sensing, goal-plan, and progress are relatively weak. Changes in emotional expressivity are related to changes in activity during the process cycle.
These classes of emotions are located in the Bloch sphere. The equatorial plane is divided into six azimuthal segments of $\pi/3$ radians, each corresponding to one of

the six classes: Sensing, Novelty, Goal-plan, Action, Progress, and Result, with upper and lower hemispheres containing positive and negative emotions, respectively. Polar angles are used to quantify the difference in evaluation between positive and negative emotions in each class.

In practice, connections are represented by mixed qubit-emotional states that occupy the interior of the Bloch sphere and are divided into the same azimuthal sectors. According to the similarity measure, the distinction between different emotions decreases as one moves from the surface to the center of the sphere. For fixed evaluation and azimuthal phase, this change is quantified by the length of the corresponding vector in the Hilbert plane H_2. The vector's length encodes the intensity of an emotional state. It reaches zero at the diameter of the Bloch sphere, representing classical probability space and a non-emotional objective component of cognitive information [37].

4 Conclusion and Research Limitation

A quantum cognitive theory-based Emotion Analytics model is provided, which can account for people's irrational decision-making and marginal events when predicting individual emotional states. We compared quantum data science to classical ML and DL, and found that QEA could account for irrational elements in the interaction process, resulting in a more accurate reflection of true emotional state intention. In a complex-valued sentimental Hilbert space, we defined utterances as states and unimodal decisions as mutually incompatible observables. The incompatibility captures cognitive biases in the decision-making process, which would otherwise be impossible to measure using classical probability. The suggested approach has been proven to be theoretically capable of handling all combination patterns, including circumstances in which all unimodal classifiers made incorrect emotional judgements.

Although the QEA approach positively impacts emotion prediction, it does have certain drawbacks. Further optimization in terms of interpretation, for example, is required, and a more advanced QEA model will be developed in future research work in conjunction with DL or Neuron Networks. Also, to test and improve the correctness of the results, we will undertake an empirical investigation of the proposed QEA approach utilizing open-source validated data sets.

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