

AUTOMATED CLASSIFICATION OF EMOTIO-COGNITION

CROSS-REFERENCE TO RELATED APPLICATIONS

This application claims the benefit of priority to non-provisional Application No. 17/589,512, filed January 31, 2022, claims the benefit of priority to provisional Application No. 63/163,618 filed March 19, 2021, claims the benefit of priority to provisional Application No. 63/163,621 filed March 19, 2021, claims the benefit of priority to provisional Application No. 63/162,987 filed March 18, 2021, and claims the benefit of priority to provisional Application no. 63/143,730 filed January 29, 2021, the entire contents of which are incorporated herein by reference.

BACKGROUND

FIELD OF THE INVENTION

[1] The present disclosure relates generally to monitoring affect, and in particular classifying and tracking intensity of emotio-cognition in natural language content.

DESCRIPTION OF THE RELATED ART

[2] Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects. Affective computing is a multidisciplinary field that brings together linguistics, statistics, human factors and computer science. One aspect of affective computing is to enable bots and other computer applications to respond intelligently to natural human emotional feedback. In the case of text, affective computing includes emotion detection from text. More often, a form of emotion detection known

as sentiment analysis is used to classify text as positive, negative, or neutral. Just about every major company that develops computer software and hardware, as well as university research, and several startups have development projects that include some form of tools for sentiment analysis. The popularity of sentiment analysis stems from the need to better understand sentiment in reactions to news media and various customer comments that are widespread in social media, customer product comments, and interactions with chat bots.

[3] In practice, sentiment analysis is the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective emotio-cognition states and subjective information. Sentiment analysis has been accelerated in part due to the availability of large data sets of human dialog, which are obtained from such sources as various social media platforms, recorded conversations, and other outlets for textual expression. However, sentiment analysis must deal with the evolving nature of natural language. For example, sentiment analysis must deal with subtle distinctions or variations in meaning between words, or even whole phrases. Some phrases may appear to indicate the same thought, but may indicate a difference in sentiment. Sentiment analysis must deal with words or phrases that may have different meanings depending on the context.

[4] Despite significant recent advances in technologies used for natural language processing, sentiment analysis suffers from being tied to training sets, which typically have been manually classified, and is thereby subjective. In particular, annotation of big training datasets of text is performed manually. Training sets from manual classification methods tend to be slow, poor-performing, and expensive. Additionally, financially competitive methods of obtaining raters, primarily Mechanical Turk, suffer from non-native speakers incentivized to rush through classification tasks, resulting in low-quality, conflicting results, with attempts at prevention of

these effects limited to cumbersome ID-scanning and unreliable IP-address filtering. Subtle emotion detection is difficult and error prone.

[5] Moreover, training sets used for machine learning do not afford for creativity in language. Human beings have an apparent infinite ability to generate novel sentences through speech and writings, never before written or spoken. Indeed, a necessary property of language is precisely this allowance for such creativity, which current state of the art systems are unable to effectively accommodate.

[6] State-of-the-art technology machine learning models for natural language processing (BERT (Bidirectional Encoder Representations from Transformers), GPT2 (Generative Pre-trained Transformer 2), GPT3), which are seemingly robust tools that can hold so much in memory and effectively look bi-directionally, are no match for an evolving natural language. Statistical models rely on strong statistical, often probabilistic components. Supervised machine learning models predict things they have seen before or relationships they've seen reoccur. There are countless phrases and sentences to be made in the future that cannot be encapsulated by sentences that have come before, including elements like portmanteaus, slang, jargon, metaphor or invented words.

[7] In addition, there is still a semantic deficit in sentiment analysis; this is in part due to a lack of effective methods for measuring the intensity of emotions, the use of culled and unrepresentative datasets for training purposes. Additionally, overreliance on lexicon-centric or token-based solutions prevents such solutions from ultimately obtaining staying power, as linguists and engineers contend with the dynamic nature of language, including semantic shifts, obsolescence, and various other linguistic changes over time.

[8] As such, sentiment analysis suffers from several major issues; namely, lack of gold-standard datasets with objectively rated or labeled data for training, limitations of n-gram based solutions, lack of the ability to determine bonafide intensity, difficulty in parsing hashtags, and lack of rigorous validation for results. Additionally, while like-scale affective ratings are subjectively applied, no sound means exists within the industry or academia to validate classification results.

[9] While the occasional attempt to quantify pragmatic factors (predominantly via brainstormed enumeration, and occasionally using n-gram selection with high token: type ratios) surfaces in the sociolinguistic literature, it is the study of sociolinguistics that largely focuses on fMRI studies, social or real-world experiments, intuitive analyses, and close examination and comparison of intuitive, pragmatic examples. Specific, but limited, syntactically-driven theories exist within the field, largely in individual constructions such as Andrews construction (adjectival and adverbial phrases with the construction “X knows,” e.g., “God [only] knows,” “Who knows”) or somewhat more comprehensively, the semantically rich, complex but verb-centered seminal analysis of construction grammar, focused on specific grammatical constructions for object relationships, known as argument structure, dealing by nature with arguments (objects) of verbs.

[10] Preferably, to be a construction, a piece of language has to be permutable and modular. By nature, this creates a focus not just on grammatical rules, but on common usage. Sociolinguistics have focused on pragmatics, the science of usage in the real world, analyzing specific word usage in a magnified view. However, analysis of constructions has been focused on argument structure, and verb-focused analysis of form-meaning pairings. There is a need for

more efficient, robust and accurate detection of cognition, emotion, and emotio-cognition, which bridges cognitive science, social-linguistics and semantics.

[11] The foregoing “Background” description is for the purpose of generally presenting the context of the disclosure. Work of the inventors, to the extent it is described in this background section, as well as aspects of the description which may not otherwise qualify as prior art at the time of filing, are neither expressly or impliedly admitted as prior art against the present invention.

SUMMARY

[0012] According to an embodiment of the present disclosure, an aspect is a method for automatically augmenting natural language content with emotio-cognition by processing circuitry, the method can include receiving, via an input device, the natural language content as a textual input; searching, by the processing circuitry, for matches between a plurality of linguistic rules for a given emotio-cognition and components of the textual input, wherein instances of the linguistic rules have at least one human dimension; activating, by the processing circuitry, the matched linguistic rules, and evaluating the at least one human dimension of the activated matched linguistic rules; scoring, by the processing circuitry, each human dimension to obtain a prototypical profile of dimension scores for the given emotio-cognition; aggregating, by the processing circuitry, the dimensions in the obtained profile of dimension scores to obtain an intensity indication for the given emotio-cognition; and displaying, by a display, the natural language content augmented in a manner that relates the matched linguistic rules to the given emotio-cognition and signals the respective intensity indication of the given emotio-cognition.

[0013] Further, according to an embodiment of the present disclosure, a further aspect is an electronic reader, that can include a touchscreen display; processing circuitry; and a memory, wherein the touchscreen display is configured to display text of an electronic book; the

processing circuitry is configured to scan and tag the text using rules that upon being triggered, detect emotio-cognitive states, and determines intensity with which the emotio-cognitive states have occurred; the processing circuitry is configured to generate and display one or more sidebars for listing dynamics and emotio-cognition-intensity information based on detected components of the displayed text; the touchscreen, when touched at a position in the display, is configured to select a dynamic or emotio-cognition-intensity; and the processing circuitry is further configured to generate and display color-coded highlighting that designates an occurrence of the selected dynamic or emotio-cognition-intensity.

[0014] Further, according to an embodiment of the present disclosure, a further aspect is a system for mitigating a psychological disorder, that can include a mobile device having processing circuitry and memory; and a peripheral device having a communications device and one or more actuators, wherein the memory of the mobile device stores program instructions, which when executed by the processing circuitry of the mobile device, cause the mobile device to perform a method including: receiving, via an input device, natural language content as a textual input; searching, by the processing circuitry, for matches between a plurality of linguistic rules for a given emotio-cognition and components of the textual input, wherein instances of the linguistic rules have at least one human dimension; detecting, by the processing circuitry, the matched linguistic rules to obtain an intensity indication for the given emotio- cognition; and when the intensity indication for the given emotio-cognition reaches a negative emotio-cognitive intensity that exceeds a first threshold, transmitting a first activation signal that identifies the emotio-cognitive intensity; and the peripheral device is configured to receive, via the communications device, the transmitted first activation signal; and activate the one or more actuators to create a sensory distraction to mitigate the psychological disorder.

The foregoing general description of the illustrative implementations and the following detailed description thereof are merely exemplary aspects of the teachings of this disclosure, and are not restrictive.

BRIEF DESCRIPTION OF THE DRAWINGS

[15] The accompanying drawings, which are incorporated in and constitute a part of the specification, illustrate one or more embodiments and, together with the description, explain these embodiments. The accompanying drawings have not necessarily been drawn to scale. Any values or dimensions illustrated in the accompanying graphs and figures are for illustration purposes only and may or may not represent actual or preferred values or dimensions. Where applicable, some or all features may not be illustrated to assist in the description of underlying features.

[16] The characteristics and advantages of exemplary embodiments are set out in more detail in the following description, made with reference to the accompanying drawings. In the drawings:

[17] FIG. 1 is a block diagram of a system for automated classification of belief, opinion, sentiment, and emotion in accordance with exemplary aspects of the disclosure;

[18] FIG. 2 is a block diagram of a computer system in accordance with an exemplary aspect of the disclosure;

[19] FIG. 3 is a system block diagram for automated classification of emotion in accordance with an exemplary aspect of the disclosure;

[20] FIG. 4 is a diagram of a training architecture in accordance with an exemplary aspect of the disclosure;

- [21] FIG. 5 is a diagram of adaptive operation of the emotion classification system in accordance with an exemplary aspect of the disclosure;
- [22] FIG. 6 is a diagram showing types of linguistic rules in accordance with exemplary aspects of the disclosure;
- [23] FIG. 7 is a bottom-up stack for layers of the rules engine in accordance with exemplary aspects of the disclosure;
- [24] FIG. 8 is a flowchart of a method of operation of a computer system in accordance with an exemplary aspect of the disclosure;
- [25] FIG. 9 is a flowchart for steps for evaluating using linguistic rules in accordance with an exemplary aspect of the disclosure;
- [26] FIG. 10 is a flowchart for detecting rules in accordance with an exemplary aspect of the disclosure;
- [27] FIG. 11 is a flowchart for scoring in accordance with an exemplary aspect of the disclosure;
- [28] FIG. 12 is a flowchart for detecting rules in accordance with an exemplary aspect of the disclosure;
- [29] FIG. 13 is a flowchart for determining numeric value for a token proximity rule in accordance with an exemplary aspect of the disclosure;
- [30] FIG. 14 is a flowchart for classifying in accordance with an exemplary aspect of the disclosure;
- [31] FIG. 15 is a flowchart for hybrid multi-model learning in accordance with an exemplary aspect of the disclosure;

- [32] FIG. 16 illustrates an electronic reader in accordance with an exemplary aspect of the disclosure;
- [33] FIG. 17 is a flowchart for operation of an electronic reader in accordance with an exemplary aspect of the disclosure.
- [34] FIG. 18 is a flow diagram of the system for a Multimedia Audio Book or Visio-Spatial Data Sentiment Classifier in accordance with an exemplary aspect of the disclosure.
- [35] FIG. 19 is a block diagram of a multi-media rules engine in accordance with an exemplary aspect of the disclosure;
- [36] FIG. 20 is a flowchart for a rules discovery engine based on HUNCHes in accordance with an exemplary aspect of the disclosure;
- [37] FIGs. 21A, 21B is a flowchart for rule discovery in audio media in accordance with an exemplary aspect of the disclosure;
- [38] FIG. 22 is a graph of a speech signal pattern;
- [39] FIG. 23 is a flowchart for a method of real time emotion classification in a stream of video/audio in accordance with an exemplary aspect of the disclosure;
- [40] FIG. 24 illustrates a display device in accordance with an exemplary aspect of the disclosure;
- [41] FIG. 25 is a system diagram of adaptive operation of the emotion classification system in accordance with an exemplary aspect of the disclosure;
- [42] FIGs. 26A, 26B, 26C is a schematic diagram of an electronic bracelet in accordance with an exemplary aspect of the disclosure;
- [43] FIG. 27 is a circuit diagram for an electronic bracelet in accordance with an exemplary aspect of the disclosure;

[44] FIG. 28 is a system diagram of user interface features for sociolinguistic data in accordance with an exemplary aspect of the disclosure; and

[45] FIG. 29 is a flow diagram of a sociolinguistic engine pipeline in accordance with an exemplary aspect of the disclosure.

DETAILED DESCRIPTION

[46] The description set forth below in connection with the appended drawings is intended as a description of various embodiments of the disclosed subject matter and is not necessarily intended to represent the only embodiment(s). In certain instances, the description includes specific details for the purpose of providing an understanding of the disclosed embodiment(s). However, it will be apparent to those skilled in the art that the disclosed embodiment(s) may be practiced without those specific details. In some instances, well-known structures and components may be shown in block diagram form in order to avoid obscuring the concepts of the disclosed subject matter.

[47] As used herein any reference to “one embodiment” or “some embodiments” or “an embodiment” means that a particular element, feature, structure, or characteristic described in connection with the embodiment is included in at least one embodiment. The appearances of the phrase “in one embodiment” in various places in the specification are not necessarily all referring to the same embodiment. Conditional language used herein, such as, among others, “can,” “could,” “might,” “may,” “e.g.,” and the like, unless specifically stated otherwise, or otherwise understood within the context as used, is generally intended to convey that certain embodiments include, while other embodiments do not include, certain features, elements and/or steps. In addition, the articles “a” and “an” as used in this application and the appended claims are to be construed to mean “one or more” or “at least one” unless specified otherwise.

[48] Referring now to the drawings, wherein like reference numerals designate identical or corresponding parts throughout several views, the following description relates to a system and method for automated classification of belief, opinion, sentiment, and emotion. The method optimally includes a linguistic rules engine as an input layer to a probability layer, and a layer for determining intensity.

[49] As mentioned above, language is perpetually novel, and even robust tools that can hold so much in memory and effectively look bi-directionally (i.e., BERT) are no match for an evolving natural language. There are countless sentences to be made in the future that cannot be encapsulated by sentences that have come before, including elements like portmanteaus, slang, jargon, metaphor or invented words. Focusing on permutable constructions and mining them for extractable belief, opinion, sentiment, and emotional dimensions allows for more efficient, robust and accurate detection.

[50] Also, in natural language processing, probability is a poor indicator of verbal intensity, because frequency does not necessarily equal intensity. As such, in disclosed embodiments, probability is used as an indication that an emotion is present in a specified portion of a natural language input. Intensity of the emotion is separately determined.

[51] Various techniques may be used for analyzing text in an effort to understand the sentiment, emotion, opinion, or belief that may be expressed or implied by the text. Sentiment may be defined as an attitude, thought, or judgment prompted by feeling. Kin to sentiment is emotion, which may be defined as a strong feeling, such as love, anger, joy, hate, or fear. Emotion may include a conscious mental reaction subjectively experienced as strong feeling and accompanied by physiological and behavioral changes in the body. Opinion may be defined as a belief, judgment, or way of thinking about something. Belief may be something that is accepted,

considered to be true, or held as an opinion. For purposes of this disclosure, the term “emotio-cognition” will be used as a term to portray each of sentiment, opinion and belief, emotion, according to its ordinary meaning, judgment, as well as feelings (affect / desires, emotional or sexual bonding), interpersonal / social forces (affinity, community, bonds, influence), cognitive elements (thoughts, opinions, beliefs, stances) and the sentimental space in between (aspirations, values, motivations, regrets).

[52] Disclosed embodiments utilize lexical rules having semantic-syntactic constructions, pre-scored across numerous dimensions, and containing building blocks for semantic sentimental logical operations. Rule-searching measures make tagging easier, faster, and more empirical, and thus reduce the need for GPU-fine-tuning (i.e., fine tuning a pre-trained transformer, such as BERT, GPT2, GPT3), agreement calculations, or high RAM operations. Rule suggestion via dimensional pattern spotting, sentimental occurrence-tracking, and sequence-spotting can also save a tremendous amount of resources tagging, retraining, or using resources to add epochs for accuracy increase or multiple models to solve ambiguity issues. Logical derivation of other sentimental phenomena via aggregation / processing of dimensions allows for simple search-and-count processing per-line instead of heavy calculation, making way for novel calculations (detection of mental health symptoms) without need for a new or specialized training set, new task or added layer.

[53] FIG. 1 is a block diagram of a system for automated classification of emotio-cognition in accordance with exemplary aspects of the disclosure. The system 100 includes a text input 102 which receives text from various sources, including a continuous data stream, social media dialog, documents, and whole books. The text received from the text input 102 undergoes a data cleaning and data normalization process 104. Various tools are available for cleaning and text

normalization, and generally involve stripping text data of unwanted characters and standardizing words. The choices of which characters are unwanted are user dependent. For example, in some cases punctuation marks may be unwanted. In some embodiments, specific punctuation marks are not removed, but instead may be used in later processing. Specific punctuation marks may include commas, quotation marks, and exclamation marks. Punctuation marks that may be removed may include the at (@) symbol, hashtag (#), dollar (\$), percent (%), carrot (^), ampersand (&), and asterisk (*). In some embodiments, markups such as HTML tags may be removed. In some embodiments, emoticons may be left intact. In addition, text may be converted to lower case. The cleaned and normalized data is then pre-processed 106, including tokenization, part-of-speech tagging, stemming, and lemmatization. Tokenization splits text into individual elements (e.g., split cleaned text at their whitespaces). Part-of-speech tagging attaches labels to word tokens to identify their part of speech. Stemming is a process of transforming a word into its root form. Lemmatization is a process of obtaining the canonical forms of individual words. Another task may be to remove stop words. The pre-processed data may be formatted for an unsupervised learning process 108, a rule-based system 110, and a supervised learning process 112. A typical method for formatting pre-processed words is to use Google's word2vec algorithm.

[54] The unsupervised learning process 108 may classify the data, including classification of emotio-cognition. The unsupervised learning process 108 does not require labeled data, but instead may cluster pre-processed data into classes. The pre-processed data input and resulting classification may be used for feature/rule suggestion 114. Suggested rules and feature selection 120 may be performed to generate future linguistic rules.

[55] The rule-based system 110 includes predetermined linguistic rules. The predetermined linguistic rules may be organized by categories of emotio-cognition.

[56] The supervised learning process 112 requires labeled data. The labeling of emotio-cognition may be performed manually. The supervised learning process 112 may be used for machine classification of emotio-cognition 118. Errors in classification may be adjusted/corrected 122 in order to improve later classifications. The supervised learning process 112 generates neural models to perform their own classification, which assigns a probability. The neural models also are trained on the rules themselves. They locate similar cooccurrence vectors, similar POS-patterns, and similar n-grams, and suggest these as potential Rules / Suggested Features.

[57] Tabulation and scoring 116 may be applied to the results of the unsupervised learning process 108 and supervised learning process 112. Both the unsupervised learning process 108 and the supervised learning process 112 may output a probability for each class (e.g., using the softmax function).

[58] In one implementation, the functions and processes of the system 100 may be implemented by a computer 226. Next, a hardware description of the computer 226 according to exemplary embodiments is described with reference to FIG. 2. In FIG. 2, the computer 226 includes a CPU 200 which performs the processes described herein. The process data and instructions may be stored in memory 202. These processes and instructions may also be stored on a storage medium disk 204 such as a hard drive (HDD) or portable storage medium or may be stored remotely. Further, the claimed advancements are not limited by the form of the computer-readable media on which the instructions of the inventive process are stored. For example, the instructions may be stored on CDs, DVDs, in FLASH memory, RAM, ROM, PROM, EPROM,

EEPROM, hard disk or any other information processing device with which the computer 226 communicates, such as a server or computer.

[59] Further, the claimed advancements may be provided as a utility application, background daemon, or component of an operating system, or combination thereof, executing in conjunction with CPU 200 and an operating system such as Microsoft® Windows®, UNIX®, Oracle® Solaris, LINUX®, Apple macOS® and other systems known to those skilled in the art.

[60] In order to achieve the computer 226, the hardware elements may be realized by various circuitry elements, known to those skilled in the art. For example, CPU 200 may be a Xenon® or Core® processor from Intel Corporation of America or an Opteron® processor from AMD of America, or may be other processor types that would be recognized by one of ordinary skill in the art. Alternatively, the CPU 200 may be implemented on an FPGA, ASIC, PLD or using discrete logic circuits, as one of ordinary skill in the art would recognize. Further, CPU 200 may be implemented as multiple processors cooperatively working in parallel to perform the instructions of the inventive processes described above.

[61] The computer 226 in FIG. 2 also includes a network controller 206, such as an Intel Ethernet PRO network interface card from Intel Corporation of America, for interfacing with network 224. As can be appreciated, the network 224 can be a public network, such as the Internet, or a private network such as LAN or WAN network, or any combination thereof and can also include PSTN or ISDN sub-networks. The network 224 can also be wired, such as an Ethernet network, or can be wireless such as a cellular network including EDGE, 3G and 4G wireless cellular systems. The wireless network can also be WiFi®, Bluetooth®, or any other wireless form of communication that is known.

[62] The computer 226 further includes a display controller 208, such as a NVIDIA® GeForce® GTX or Quadro® graphics adaptor from NVIDIA Corporation of America for interfacing with display 210, such as a Hewlett Packard® HPL2445w LCD monitor. A general purpose I/O interface 212 interfaces with a keyboard and/or mouse 214 as well as an optional touch screen panel 216, or haptic device on or separate from display 210. General purpose I/O interface also connects to a variety of peripherals 218 including printers and scanners, such as an OfficeJet® or DeskJet® from Hewlett Packard®. The I/O Interface 212 may also connect to a microphone for voice input and speakers and/or headphones for sound output. The microphone and/or headphones may be connected to the I/O Interface 212 by way of an input port, including USB, HDMI, or other peripheral input connection.

[63] The general purpose storage controller 220 connects the storage medium disk 204 with communication bus 222, which may be an ISA, EISA, VESA, PCI, or similar, for interconnecting all of the components of the computer 226. A description of the general features and functionality of the display 210, keyboard and/or mouse 214, as well as the display controller 208, storage controller 220, network controller 206, and general purpose I/O interface 212 is omitted herein for brevity as these features are known.

[64] FIG. 3 is a system block diagram for automated classification of emotion in accordance with an exemplary aspect of the disclosure. The system 300 includes a multi-media classification engine 312. Multi-media can include video, audio, and text. The multi-media can include scripted or subtitled multimedia, such as audio books, visio-spatial multimedia like movies, TV shows, augmented reality, or virtual reality, which are transcribed and scanned into the system 300. Textual and transcribed media is received as input text 302. The input text 302 is processed in the pre-processing engine 304 in order to transform the text data into a form necessary for

matching with rules 306, 308, 310, or for input to machine learning models 320. In some embodiments, the pre-processed text data is run through the Natural Language Rules (306).

When rules match textual or transcribed media, the rule is said to be fired. Visio-spatial rules 310 can include rules for visual cues. Audio-speech rules 308 can include rules for speech signals.

[65] The Emotio-Cognitive Sensor (314) processes input on a sentence-, paragraph-, passage-, scene-, or chapter-level, and classifies each with a given emotion, cognition, sentiment, state- or dynamic- or trait-based tag. When a rule is triggered, an emotion is detected. Also, linguistic rules have ratings based on Dimensions. In some embodiments, dimension values for a rule are stored as a vector. Emotions can be deduced from the “shape” of the dimensions. Features of emotions include the shape of a vector of the dimensions, the values of the dimensions, and the difference from or similarity to derived calculations from other vectors associated with the rule. The output of the Natural Language Rules 306 is fed to the Emotio-Cognitive Sensor 314 and Intensity Rating Sensor 316, allowing otherwise qualitative data to be transformed into quantitative data for population analysis, as in a scientific study or political poll.

[66] The intensity rating sensor (316) determines intensity ratings for each detected emotion based on the Dimensions. In some embodiments, the Intensity Rating Sensor (316) assigns objective intensity ratings based on subcomponents of each cognitive, emotional, social, interpersonal or state-based element, as the Dimensions.

[67] The Emotio-Cognitive Tagging Engine (318) tags the textual data with the assigned emotion class. Emotion and intensity of emotio-cognition can be associated with metadata, such as demographic information, online profile features, time stamps, sources, geo-locations. A result for aggregate emotio-cognitive states for a sample of the population and labeling of emotio-cognitive states are returned in the Emotio-Cognitive Tagging Engine 318.

[68] A rules discovery engine 326 can generate new rules, also referred to as rules suggestion. The machine learning models 320 can be trained on the rules themselves. The trained machine learning models 320 can locate similar co-occurrence vectors, similar POS-patterns, and similar n-grams, and suggest these as potential new Rules. In addition patterns of emotions as they are detected in the Emotio-Cognitive Sensor (314), as well as dimension patterns may be used to generate new rules.

[69] The machine learning models engine 320 can include any machine learning model or models from among transformer models, such as BERT, RoBERTa, support vector machine, word2vec, KNN model, Long Short-Term Memory model, Convolution Neural Network model.

[70] A statistical models engine 322 can include one or more statistical models. Statistical models can include any statistical model or models from among k-means model, Bayes model, document search models, logistic regression model, linear regression model, polynomial regression model, recommendation matrix, random forest model, and n-gram language model. Each statistical model is used as a classifier.

[71] A lexical engine 324 provides lexicons that can be used in the system 300. Sources of lexicons include NRCLEx, Harvard Inquirer, MPQA, sentiwordnet, textblob, VADER, and other lexicons not specifically listed.

[72] In some embodiments, the aggregate emotio-cognition ensemble classifier 328 can output a final answer, such as an emotion. Random Forest can be used as an ensembling classifier, using one-hot coding. In another embodiment, Logistic Regression can be used for ensembling. In a further embodiment, a neural layer can be used as an output of the ensembling. An output can include association of sentiment and intensity of emotio-cognitive sentiment with metadata, such as demographic information, online profile features, time stamps, sources, geo-locations. An

output can be a pictorial or graphical representation of a user's, brand's, business's, celebrity's, organization's, topic's, word's or phrase's emotio-cognitive summary over a period of or point in time, using a color-based geometrical representation. Optionally, the output can include a report, at any given time or over time, of dimensions, emotions, dynamics, or societal currents for a demographically or otherwise segmented or aggregate sample. Optionally, the output can include generation and display of the distribution of emotio-cognitive state for a given time period, for a single or aggregate users' emotio-cognitive states over time or at a point in time.

[73] FIG. 4 is a diagram of a training architecture in accordance with an exemplary aspect of the disclosure. In order to accommodate an evolving natural language, the training architecture 400 uses a machine learning models engine 320 to train machine learning models to generate rules. The machine learning models also are trained on the rules themselves. They locate similar co-occurrence vectors, similar POS-patterns, and similar n-grams, and suggest these as potential new Rules.

[74] The linguistic rules model 310 begins with a set of preprogrammed linguistic rules that may be applied to natural language phrases and sentences. Detection can involve potential comparison of these rules, recognition of similarity, and creation of rules that use concatenation of the rule potential elements (rule types). Creation of rules may occur through identification of strings with sufficient similarity via a threshold, then creation of tuples of each word with word, part of speech, dependency, stem, and lemma, and matching among similar items based on index position to find the coordinating part of each tuple. The results can then be concatenated, with optional parts, or wildcards, or nearness calculations, as necessary into a concatenated formulaic rule.

[75] The training architecture 400 includes a text input 302 for accessing, via processing circuitry and memory, multiple natural language data items. The multiple natural language data items may be read from a data repository, or may be directly input as a stream of text. The text may include captured, transcribed, or translated text that has originated from human speech input, text databases, documents, or other text data sources.

[76] The training architecture 400 includes a pre-processor 304 for performing various preliminary processes that are typically performed on text for natural language processing. The pre-processor 304 may utilize any of known software libraries for data normalization, tokenization, part-of-speech tagging, dependencies, stemming, and lemmatization to generate multiple preprocessed natural language data items. An example of software libraries is the Natural Language Toolkit (NLTK). The NLTK includes text processing libraries for classification, tokenization, stemming, tagging, and parsing. The NLTK includes a WordNet Lemmatizer having a lemmatize function, as well as a variety of other lemmatizers. Normalization may be performed as canonical normalization.

[77] In some embodiments, the training architecture 300 may involve labeling the multiple preprocessed natural language data items as emotion and an intensity of the expressed emotion. The labels and associated natural language data items may be used to train a supervised learning model.

[78] The training architecture 400 provides the multiple preprocessed natural language data items in parallel to machine learning models engine 320 and a linguistic rules model 306. The training architecture 400 performs training, in parallel, of the machine learning models engine 320 and the linguistic rules model 306 in multiple training epochs to identify, in the natural language data, emotion and to determine an intensity of the emotion. Each training epoch of the

machine learning models engine 320 may, based on a decision 412, generate feature or rule suggestions 326 for subsequent training epochs of the linguistic rules engine 306. After each training epoch of the linguistic rules engine 306, subsequent epochs of the machine learning models engine 320 are tabulated and scored (provided as probabilities of each class). In 414, an output representing the trained machine learning models engine 320 and the trained linguistic rules 306 is stored in a non-volatile memory.

[79] FIG. 5 is a system diagram of adaptive operation of the emotion classification system.

The rule discovery engine 326 can generate new rules while presenting emotion and intensity information as an output.

[80] In order to assist in operation, the operation of the emotion classification system will be described in terms of an example. The example is simplified for ease of understanding. The present disclosure is by no means limited to this example. In the example, a hashtagged text “Why am I the one who ‘needs’ to take out the trash? #NOTANEED” is input 302 by reading the text from a file, or as a continuous stream that is entered into the computer system. The text input is processed by Pre-processing Engine 304, which performs functions including tagging the Input text with index positions, tokenizing the Input text, and separating out the Input hashtag. In some embodiments, the hashtag is a component that has an associated emotion. The index position can be an integer number that indicates a position relative to an overall text, for example a sequential number that is generated by a counter or within a tokenized input’s array. Alternatively, the index position can be an index such as a vector position, line number, or some input number that identifies where in a sequence of hashtagged text, the current text input occurs. The tokenizing function may selectively separate out punctuation marks, such as “?” as tokens, and may delete others. In the example, the quote marks around “needs” may be preserved in

order to indicate an emphasis. The hashtag may be separated out from the other text so that it can be treated as an identifier, rather than as an emotional expression. In some embodiments, the hashtag may be used as an auxiliary indication of the emotion. In this example, the hashtag may indicate that the input text is a sarcasm. Hashtags can also be used to indicate emphasis, commentary / asides, subtweets, organization, continued expression, humor, context, emotions, marketing, protest.

[81] The natural language engine has a function of searching among natural language rules 306 for a rule, or rules, that matches the input text. A rule may indicate a text pattern, with some required words or phrases, mixed with syntax. In the example, a Rule, such as “[why]”[...] + being verb + “the one who” + verb is pattern matched and triggered.

[82] Rules are grouped by emotions and cognitive terms, and emotio-cognitive blended terms. The Emotio-Cognitive Sensor 314 has a function of applying a Emotio-Cognitive Label (ANGER) based on the triggered rule.

[83] The Intensity Rating Sensor 316 has a function of activating Dimensions for that triggered rule, which can include 3 dimensions with scores - positive, negative, neutral, or null, the dimensions being for example, respect, ego, blame. The values of dimension scores are not limited as such and can include numeric values, in a predetermined range. The Intensity Rating Sensor 316 has a function of aggregating Dimension scores to obtain an intensity score. The Intensity Rating Sensor 316 assigns the intensity score to the Emotio-Cognitive Label and compares the intensity score against a predetermined threshold. The predetermined threshold may be a fraction value, such as .6, an integer in a range, such as 6 in a range of 0 to 10, a percentage, such as 60%, that is common across all emotions, or may be set for each Emotio-Cognitive Label. In this example, according to the threshold, the emotional intensity level is

labeled (ANGER -- MEDIUM). In some embodiments, the intensity score may also be relative to the speaker, if the speaker's baseline is known.

[84] The Meta-Emotio-Cognitive Aggregator 328 has a function of assessing an Emotio-Cognitive Label and combining the label with other surrounding labels to form a pattern of Emotio-Cognitive Labels, e.g., ANGER__PEACE.

[85] In a next level, a Dynamics 610 has a function of pattern matching the pattern of Emotio-Cognitive Labels with a Dynamic pattern. The Dynamics 610 assigns a label based on the matched Dynamic pattern, e.g., FORGIVENESS.

[86] FIG. 6 is a diagram showing types of linguistic rules in accordance with exemplary aspects of the disclosure. The types of linguistic rules for sentiment, emotion, opinion, and belief, that are applied to the specified portion of the natural language input can include

[87] a rule that uses part of speech tagging, syntax, or dependency parsing (502), including: e.g., modal and optative verbs, tense notations, declension, conjugation, accents, as well as direct objects, and proper nouns.

[88] a rule that uses string matching, including exact, inexact, masked or wildcarded (504),

[89] a rule that uses distance between tokens (506),

[90] a rule that uses punctuation (508),

[91] a rule that uses lemmatization (510),

[92] a rule that uses stemming (512),

[93] a rule that uses lexicon (514), and

[94] a rule that uses word lookup or dictionary (516).

[95] In some embodiments, rule components may include graphical content, including Emojis, Glyphs, Emoticons, characters, scripts, and any other graphemes. Applying the linguistic rules to

the specified portion of the natural language input results in obtaining the numeric or Boolean value for each of the one or more linguistic rules.

[96] In some embodiments, additional linguistic rule types accommodate other world languages, including Japanese, Korean, Chinese, Vietnamese, and other Asian languages. The additional linguistic rule types can include

[97] a rule that tags dependencies,

[98] a rule, or rules, that detects particles,

[99] a rule, or rules, that detects markers,

[100] a rule, or rules, that detect structural-narrative forces, including topic, subject and predicate,

[101] a rule, or rules, that signifies classes of nouns grouped by commonalities,

[102] a rule, or rules, that detects cases, including nominative, ablative, and others,

[103] a rule, or rules, that detects verbal categories, for verbs,

[104] a rule that detects click transcriptions, for capturing semantic information from clicks, on a mouse, touchpad, touchscreen,

[105] In some embodiments, linguistic rules may incorporate an OR operator, for optional conditions, and a concatenation operator, for combined conditions. In some embodiments, linguistic rules may include intra-rule referents, which refer to other parts of a rule. An intra-rule referent may include doubling or replication: ADJ + NOUN + NOUN, with a condition that the NOUN is an immediately preceding NOUN. An intra-rule referent may include an index for positions in a rule: a placeholder or position Element[0] in a rule.

[106] In some embodiments, intra-rule referents for linguistic rules may be in the form of patterns. A pattern may include: NOUN -> NOUN, for duplicate, NOUN !+NOUN, for not duplicate.

[107] The linguistic rules are grouped by types of emotion or cognition. In some embodiments, rules may have an order of importance, and the order may be changed, to indicate precedence over rules below it, and under rules above it. Each linguistic rule has one or more dimensions and a value for each dimension. In one embodiment, dimensions may include sentiment, emotion, Emotio-Cognitive attitudes, values, social mores, mindsets, outlooks, aspects, responses, traits, beliefs, opinions, perspectives, motivations, biases, states, manners, approaches, dynamics, personality trait, emotional approach, emotional choice, reaction, disposition, temporary state, change of state, cognitive aspect, behavioral aspect, internal condition, external condition, feeling, emotion, proposition, attitude, propositional attitude, directed attitude, undirected attitude, self-directed attitude, conscious emotio-cognition, unconscious emotio-cognition. In one embodiment, dimensions can include emotional affects of: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust (from NRCLEx). In another embodiment, dimensions can include, but are not limited to, facets, components, and aspects of emotio-cognition, such as: ego, blame, conformity, sacredness, kindness, respect, time (future), (self) favor, approval, sincerity, vulnerability, judgment, separateness, purpose, formality, minimization, specificity, force, action (activeness), agency, curiosity, clarity, intention, emphasis, energy, certainty, interest, engagement, shock / surprise, tension, speed, nuance, logic, paranoia, trust, distance, identification w/, esteem (self), esteem (other), objectification, attachment, empathy, and patience.

[108] In some embodiments, dimensions may be grouped into categories, such as personality trait, belief, opinion, perspective, aspect, motivation, bias, state, emotional approach / choice, manner, reaction, interpersonal dynamic.

[109] The inventors have found that even entirely accurate classification can still yield very limited semantic information. For example, “accuracy rates” do not always reflect useful semantic information when it comes to affect detection. Labels for affects can be too vague (trying to force more than 25 emotions into six labels). Classification may still lack useful subtextual information and may lack orientation toward the cognitive state of the speaker. Classification does not provide hints as to why a feeling is present. Sentences, phrases, or constructions remain poorly classified for specific affect and deep semantic value, parsed on the sentence-level, oftentimes forced into a single class where multiple labels should apply, or unable to be accurately understood by machine algorithms, due to the complexity and depth of human emotion. Additionally, while conversation can be mined for further information, discursive text value has been limited to contextual clues approaches such as Named Entity Recognition and speaker-specific information, yielding little about affective states.

[110] Despite the existence of state-of-the-art technology such as transformers, these have only historically excelled at prediction and translation tasks, rather than semantic interpretation (in part, due to poorer general performance on semantic tasks). Transformers are ultimately limited in their semantic capacity, due to the gap between human and machine interpretative ability. Among the semantic limitations, particularly with interpreting extemporaneous speech and text, are the ability to identify mixed emotions, complex emotions, figurative expression and insincere emotional expressions (such as sarcasm, irony, politeness, and passive aggression). Disclosed embodiments are an approach to handling range and depth of human emotion and cognition.

[111] FIG. 7 is a bottom-up stack for layers of the rules engine. "Dimensions" (702) are elements of emotio-cognitive expression and the feeling and thoughts behind them. In some embodiments, the system is implemented using object-oriented programming and emotions are a class having a set of dimensions as attributes of the class. Intensity is a method of the emotion class and is used to determine an intensity value based on the presence of dimensions. Intensity values can be stored in a structured or unstructured database. The emotion class has prototypical values for each of the attributes/dimensions. The values of dimensions are tiny valences with trinary values (+1 positive force, -1 negative force, 0 neutral force, and $\emptyset$ not present / not applicable; the latter 2 of which are not equivalent). In some embodiments, the values for dimensions include layers of Boolean, such as (1) TRUE-FALSE (Neutral vs. Not), (2) TRUE-FALSE (True vs. False), (3) Potentially similarly with null. The values may be in the form of floating point numbers or integers.

[112] For each data line, these dimensions receive ratings every time a rule is triggered. So, for instance, for the example

("[why / how come] + BEING-V + PRON + [TIME-HYPERBOLE] + "the one/s who" + VERB"), which denotes a construction with:

an optional Word List item (of 2 items: "why" or "how come") +

a being verb plus a pronoun ("are you" / "am I" / "are they" / "are we" / "is he" / "is she," etc.) +

an optional Word List item for Time Hyperbole ("always", "never", "constantly", etc.) +

fuzzy (inexact string) ("the ones who", "the one who") +

virtually any verb ("sits up front", "pays for everything", "brings up problems", "gets the easy job", etc.) The rule uses those parts that are modular, and covers some degree of permutation.

[113] The system detects a given emotion's core dimensional profile. Different rules find distinct and partial but strongly matching configurations, which represent various expressions of emotional states. In other words, emotions are mental states. Primal emotions are pure and unreasoning (e.g., fear, anger, happiness, sadness). Complex emotions are more social and cognitive (e.g., grief, depression, shame, insecurity, admiration). Complex emotions occur when cognitive states and emotional states co-occur, or when multiple emotions are co-occurring. When rules are activated, they provide an indication of when such emotional states are occurring.

[114] The more dimensions that match a particular emotion, the higher the intensity of that emotion. Subsequently, the measure of intensity is an objective measure and represents a degree of intensity. In some embodiments, if the same construction happens twice in an input text, the matching construction is counted both times. In measuring intensity, Dimension scores are normalized over the number of words. Thus intensity values are density-based.

[115] In an example embodiment, there are 50 dimensions. In some embodiments, there are a greater number of dimensions. Each rule has ratings across the entire set of dimensions.

[116] Each rule 704 includes one or more Dimensions. For the above rule, one example dimension is Ego. Ego can be absent from a given construction (have nothing to do with it — null value), be neutral (there is an ego component, but it is very even and fair), be positive (egotistical, condescending), or negative (admiring, supplicant, self-loathing, etc.). Ego is a dimension that is rated for this rule. Another dimension is curiosity. This construction detected by this rule is proactively curious, so it receives a +1 rating.

[117] Rules 704, once activated, indicate detected Emotions. Once the Emotions have been detected (in the portion of the sentence they exist; tagging is performed via index position instead of simply sentence- or passage- level, which allows for greater distinction and

clarity), complex emotions 706 can be identified, and these usually are comprised of simultaneous emotions. For instance, contempt is a combination of pride /condescension and anger. In addition, emotio-cognitive states can overlap.

[118] Once complex and primal Emotions have been activated in place, patterns of emotions 708 can be assessed, as emotions naturally shift to other emotions, in particular situations. In addition, emotions can progress, escalate, or resolve. Patterns of emotions 708 are formed by concatenating emotions into an ordered array, or a string, of emotions (e.g., HOPE + EXPECTATION + SURPRISE + SADNESS). These patterns can be assessed somewhat like a skip-gram model with limited possibilities. Patterns for shifting emotions, progressing emotions, escalating emotions, and resolving emotions are stored as recognizable emotional patterns.

[119] The patterns of emotions can be used to predict flows of Emotion: excitement turning to acceptance to calm; anger shifting to confusion, realization, and back to love as understanding arises and empathy or forgiveness develop, etc.

[120] The Emotional Patterns build to Dynamics 710. Dynamics 710 are descriptive labels for major emotional events that summarize patterns of emotion. For example, a Dynamic of “DISAPPOINTMENT” is a label for an emotional pattern of HOPE + EXPECTATION + SURPRISE + SADNESS. Dynamic can happen within the Self - this is usually the complex emotion. Next, the Dynamic can happen with the Other / interpersonally - this might be a phenomenon like Forgiveness. In such case, FORGIVENESS is a label for an emotional pattern of ANGER + REALIZATION + LOVE.

[121] A layer above Dynamics 710 may include a Societal currents 712, which are meta-results of strong emotional dynamics *en masse*, often brought to a head by the pressure of major events or mass movements – such as unrest or innovation. Major events can include impending real-

world events (anger explosion, coup, uprising, pop-culture or societal trend, stock market event such as the GameStop stock buy-up, the “canceling” of a public figure, breaking point into violence, etc.) These societal currents can also be present for smaller societal groups, such as with domestic violence breaking points, falling in love, an anger explosion, etc. Detection of Societal Currents enables reaction / prevention or capitalization, or at least passively monitoring / identification. Such events can be correlated with specific, prior such real-world events with these Societal Currents, enabling speedy reaction, prevention of, or capitalization upon if similar events are able to be quickly detected or predicted in the future. Computation of emotio-cognitive states, Dimensions, Dynamics, and Societal Currents, from natural language from one or more user, via the Natural Language Rules 306.

[122] In some embodiments, each level of Emotional /Cognitive flow can be predicted for these layers based on historical data, stored as the classification system is being used.

[123] FIG. 8 is a flowchart of a method of operation of a computer system in accordance with an exemplary aspect of the disclosure. One embodiment relates to a process of tracking nuanced psychological affect in natural language content. The method first applies linguistic rules for emotion to natural language constructions, phrases, or sentences, each rule having one or more dimensions. The results from applying the linguistic rules are used to detect emotion and determine intensity of emotion. A machine learning model is used to suggest new linguistic rules, and thus serves to augment the application of the linguistic rules. The process may be performed in a device having a textual and/or voice input and a textual, speech, and/or graphical output. A computer program includes instructions stored on a computer-readable storage medium, which when executed by a computer system, as in FIG. 2, performs steps as shown in the flowchart.

[124] In S802, the computer 226 is configured to receive the natural language content as text, which may be derived from the textual and/or voice input. The natural language content may be read from a file stored in the disk storage 204, or may be read from a stream of data received at network controller 206, or from text input at a keyboard 214, or from text from voice input via a microphone. In addition, input can include aggregation of data, from an online or offline database, query, taken from a historical archive or corpus, or scraped from a website, such as a social media or user review website. Input can be unprompted or prompted and can concern a topic, person, brand, organization, concept, word, or group of words. Input can include interview data, transcribed or otherwise obtained from participants in surveys, market research, or academic studies. In some embodiments, the input may include time stamps, which may be read in conjunction with the natural language content.

[125] For large sections of text that may exceed the size for an input text that is handled by the natural language rules engine 306 or machine learning models engine 320, one approach is to read the input using a sliding window of fixed size. In optional step S804, the computer 226 is configured to apply a scanning window of fixed length to the natural language content. The length may be a number of characters. The scanning window may overlap by a certain number of characters between successive movements of the scanning window. In step S806, the computer 226 is configured to evaluate the natural language content using the linguistic rules for each emotion in order to obtain linguistic features for human dimensions of emotion. As described above, linguistic rules are patterned matched with the natural language content.

[126] In S808, the computer 226 is configured to score each human dimension for presence, neutrality, level or absence as dimension scores for each matched rule.

[127] In S810, the computer 226 is configured to aggregate the dimension scores for each emotion to obtain an intensity score for the respective emotion. The aggregated scores represent intensity of an emotion. In some embodiments, the starting index and ending index in the natural language content for the emotion is determined for each particular dimension. In some embodiments, the indexed natural language content and corresponding dimension may be forwarded to the machine learning models engine 320. In some embodiments, the top dimension for emotion may be forwarded to the machine learning models engine 320 together with a respective numerical (dimension score) or mapped descriptor. Patterns of emotion including the starting index and ending index may be stored for an entire passage having several constructions, phrases and sentences.

[128] In S812, the computer 226 is configured to classify the natural language content as an emotion class based on the dimension scores. In some embodiments, the classifying may generate a probability for each emotion class.

[129] In S814, the computer 226 is configured to label the aggregated value as an emotion and determine a context of the label, such as a pattern of emotion labels, for the natural language content.

[130] In S816, the computer 226 is configured to output the classification and pattern of emotion labels as the textual, speech, and/or graphical output.

[131] In S818, the computer 226 is configured to track the pattern of emotion labels and associated components in temporal sequence over the natural language content in order to track the emotion labels over time. Each emotion label can be assigned an ordered index number to identify their order in sequence. In the case of natural language content that includes time stamps, each emotion label may be assigned a time stamp of the associated components.

[132] FIG. 9 is a flowchart for steps for evaluating using linguistic rules in accordance with an exemplary aspect of the disclosure. The evaluating using the plurality of linguistic rules of S806, includes the following steps.

[133] In S902, the computer 226 is configured to detect rules using rule pattern matching; and

[134] In S904, the computer 226 is configured to evaluate the human dimensions of each detected rule.

[135] FIG. 10 is a flowchart for detecting rules in accordance with an exemplary aspect of the disclosure. The detecting of rules of S902, includes

[136] S1002, detecting presence or absence of constructions in the natural language content having components related to an emotion.

[137] FIG. 11 is a flowchart for scoring in accordance with an exemplary aspect of the disclosure. The scoring of S808, includes

[138] S1102, evaluating each dimension to determine the dimension scores.

[139] FIG. 12 is a flowchart for detecting rules in accordance with an exemplary aspect of the disclosure. The detecting rules, among the plurality of linguistic rules, of S702, includes

[140] S1202, determining numeric values for

[141] a part of speech tagging or syntax rule,

[142] a string matching rule, exact, inexact, masked or wildcarded,

[143] a token proximity rule,

[144] a punctuation rule,

[145] a lemmatization rule,

[146] a stemming rule,

[147] a lexicon rule, and

[148] a word lookup or dictionary-based rule.

[149] FIG. 13 is a flowchart for determining numeric value for a token proximity rule in accordance with an exemplary aspect of the disclosure. The determining the numeric value for a token proximity rule includes accessing all tokens having a distance of fewer than n tokens from a specified point in the natural language content, wherein n is an integer.

[150] FIG. 14 is a flowchart for classifying in accordance with an exemplary aspect of the disclosure. The computer 225 is configured to perform the classifying of S812 using a machine learning method, including any of supervised learning, unsupervised learning, and a rule-based system.

[151] FIG. 15 is a flowchart for machine learning in accordance with an exemplary aspect of the disclosure. The machine learning of S1402, including

[152] S1502, receiving a plurality of natural language data items from a data repository;

[153] S1504, normalizing and tokenizing the plurality of natural language data items using a preprocessing engine to generate a plurality of preprocessed natural language data items, which may include pre-sorting data lines into Positive, Negative and Neutral, in order to save computing power and time in classification;

[154] S1506, labeling the plurality of preprocessed natural language data items with an expressed sentiment, emotion, opinion, or belief and an intensity of the expressed sentiment, emotion, opinion, or belief;

[155] S1508, providing, in parallel, the plurality of preprocessed natural language data items to an unsupervised learning engine, a rule-based engine, and a supervised learning engine;

[156] S1510, training, in parallel, the unsupervised learning engine, the rule-based engine, and the supervised learning engine in multiple training epochs to identify, in the natural language data, an expressed emotion, and to determine the scalar measure as an intensity of the emotion.

[157] Each training epoch of the unsupervised learning engine provides feature or rule suggestions to subsequent training epochs of the rule-based engine, and each training epoch of the rule-based engine provides tabulation and scoring data to subsequent epochs of the unsupervised learning engine and the supervised learning engine.

[158] In S1512, an output is generated representing the trained unsupervised learning engine, the trained rule-based engine, and the trained supervised learning engine.

[159] In S1514, human dimensions present within the natural language data are matched by matching the human dimensions to existing dimensional arrays, with and without wildcards or pattern skips, in order to suggest new rules for the rule-based engine.

[160] The system allows for deduction or recognition of the points and levels (intensities) at which feeling turns to action (as described within, and detected by, the text). The system allows for the recognition of dynamics within the self alone, on a bipersonal (one-on-one), interpersonal / multi-personal or family, or society (community, country, region, or world). The system allows the tracking of intensity of emotion as it fluctuates throughout the sentence, item / paragraph and passage. The system allows for the identification of large, important shifts in perception, such as a sharp turn in aggregate self-image (via ego dimension), which may indicate a problem or significant change has arisen. The system can reveal the relationship between important factors, via correlation, such as the relationship between self-esteem / self-image and general optimism.

[161] Numerous modifications and variations are possible in light of the above teachings. It is therefore to be understood that within the scope of the appended claims, the invention may be practiced otherwise than as specifically described herein.

[162] Thus, the foregoing discussion discloses and describes merely exemplary embodiments of the present invention. As will be understood by those skilled in the art, the present invention may be embodied in other specific forms without departing from the spirit or essential characteristics thereof. Accordingly, the disclosure of the present invention is intended to be illustrative, but not limiting of the scope of the invention, as well as other claims.

[163] Example Implementations

[164] ELECTRONIC READING DEVICE

[165] Embodiments of the present invention include an electronic reader. An electronic reader can be a dedicated device that incorporates specialized firmware and a display that is configured to optimally display text with high clarity (commonly referred to as an Ebook Reader), or can be a general purpose computing device, such as a tablet computer or smartphone, that is configured with software for text reading, typically in the form of a mobile application (App). An electronic reader has a display screen that is generally 10 inches diagonal or less, and has limited computer processing capability and memory. In most cases, the electronic reader can communicate with a web service via an Internet connection, typically by way of a WiFi connection. Some electronic readers include a communications module for communication by way of cellular transmission.

[166] The system 300 having a multi-media classification engine 312 can be performed in a device with limited processing power and memory, as most of the processing is based on execution of the natural language rules engine 306. The machine learning models engine 320 may be performed off-line in a separate computer, or in a cloud service.

[167] FIG. 16 illustrates an electronic reader in accordance with an exemplary aspect of the disclosure. An electronic reader 1600 includes a display screen, or touchscreen display 1602. When the display 1602 is displaying text of a book 1604, the display may include scrolling functions displayed as scrollbars (not shown), and page turning functions, displayed as buttons 1606.

[168] FIG. 17 is a flowchart for operation of an electronic reader in accordance with an exemplary aspect of the disclosure. In S1702, the system 300 may assess a written fiction or nonfiction work for emotional, cognitive, interpersonal or social dynamic, motivation, belief, opinion, or psychological elements, by multi-media classification engine 312. In S1704, text in an electronic book is scanned and tagged with rules that trigger, emotional, cognitive or otherwise states that are identified, and the intensity with which they have occurred.

[169] In an embodiment, in S1706, the system 300 may generate and display color-coded highlighting that designates occurrence of certain emotional or cognitive or sociological or interpersonal dynamics and/or states. In an embodiment, in S1708, the system 300 may generate and display one or more sidebars for dynamics 1610 and emotion-intensity 1620. The sidebars may summarize the emotional, psychological, cognitive, sociological, or interpersonal dynamics or states that occur within the text 1604, with added context where available. In S1710, each dynamic 1612 or state 1622 can be interacted with by selecting 1630 (via touch, mouse, keyboard, etc.) allowing the electronic reader 1600 to be presented with examples 1632 within the text of that given dynamic or state.

[170] MULTIMEDIA AUDIO BOOK or VISIO-SPATIAL DATA SENTIMENT
CLASSIFIER

[171] The system 300 having a multi-media classification engine 312 can be performed in a device with limited processing power and memory, as most of the processing is based on execution of the natural language rules engine 306. The system 300 performs emotion classification for sentences, phrases, and constructions, and can perform the emotion classification in real time as text is being received. The machine learning models engine 320 may be performed off-line in a separate computer, or in a cloud service.

[172] FIG. 18 is a flow diagram for a Multimedia Audio Book or Visio-Spatial Data Sentiment Classifier in accordance with an exemplary aspect of the disclosure.

[173] Scripted or subtitled multimedia, such as audio books, or visio-spatial multimedia like movies or TV shows, can be scanned into the system and transcribed into text.

[174] In 1802, textual and transcribed media is run through a Natural Language Rules Engine (306), matching to rules.

[175] The Emotio-Cognitive Sensor (314) processes input on a sentence-, paragraph-, passage-, scene-, or chapter-level, and classifies each with a given emotion, cognition, sentiment, state- or dynamic- or societal-based tag. Stray, short or partial strings and select individual words, known as High Use Non-Construction Hooks (HUNCHes) with partial dimensions are detected within the text and matched.

[176] The Intensity Rating Sensor (316), analyzes text and assigns objective intensity ratings based on subcomponents of each cognitive, emotional, social, interpersonal or state-based element, known as Dimensions.

[177] The Emotio-Cognitive Tagging Engine (318) tags the textual data with the assigned class.

[178] The Temporal-Positional Coordination (1804) makes timing-based associations between the textual information's tagged classes and the coordinated sections of auditory or visio-spatial

data and signals, which are then classified and sent to the Emotio-Cognitive Tagging Engine (318) to be tagged.

[179] The systems 300 scans for further instances of matching audio or visual patterns, both absolute and relative to the Speaker's audio or visual baseline, and adjusted for gender, age, class, race, accent, locale and other demographic information, and situational information, automatically tagging them with Emotio-Cognitive classes associated with the pattern in question.

[180] Text coordinated with auto-tagged emotional classes in the prior step become automatically flagged in the text as matches to, or flagged as high-likelihood for, the Emotio-Cognitive classes now borne by the audio or visual data.

[181] FIG. 19 is a block diagram of the multi-media rules engine. Textual, visio-spatial and audio data are compared and re-processed as Multi-Media Rule Suggestions and sent back to the Natural Language Rules Engine (310), Visio-spatial Rules Module (306), and Audio-Speech Rules Module (308).

[182] Subsequent audio or visual input exhibiting similar, opposite, partial-matching or exhibiting an otherwise mathematically significant ratio or relationship in audio or visual signals and patterns will receive tags indicating likelihood of the Emotio-Cognitive class.

[183] Comparison of likeness, differences, opposites, and other measurements of each Multi-Media Rule Engine's 312 Rules and suggested rules will improve the rule-suggesting ability, and highlight modular components of each rule.

[184] In one embodiment, HUNCHes are used as hooks, allowing the system to analyze surrounding text, suggesting potential new rules back to the Multi-Media Rules Engine (312).

Dimensional patterns must match Positive and Negative Dimensions or be noncontradictory to the rule pattern.

[185] In particular, the HUNCHes are non-construction based partial pieces (such as 1-2 words, or partial phrases), which carry their own dimensions. Feeding these into the system 300 allows the neural models 320 to "match" these partial-dimensional patterns and use them as hooks for finding indicators of emotion. In an example, an ANGER rule lies undiscovered, but has Ego +1, Impatience +1, Force +1, etc. A hook (like "I won't") may only have Ego +1 and Force +1, but if it looks enough like it could fit with anger, the surrounding text will be examined. To do this, it must have 0 contradictory dimensions, and it must have its existing dimensions matched. This allows permutations of rules to be detected (where both are true), or potentially new rules (where not contradictory, but where the dimensional profile looks enough like anger). Through this technique, a new ANGER construction is found such as "I [won't / am not going to / am not gonna] take it ["one more time", "again", "anymore", "at all"], etc., which might distill down to a rule like "[IP PRON] + ([AUX VERB] + [NEGATION]+ ("GOING") + [INFINITIVE-VERB] or [FUTURE-VERB]) + ((D-OBJECT-PRON))* + [WordList: Time-Phrase] + "!", with asterisked portions optional, yielding, for example:

I'm not going to take it anymore!

I'm not going to serve you again!

We will not bow anymore!

For some emotions and some dimensions with respect to a given emotion two or more values may be acceptable. For example, anger can be blunt or nuanced so could receive either score.

[186] In some embodiments, depending on the emotion and the dimension, more than one value may be acceptable. For example, Anger can (and must be either) ego-neutral or ego-positive. In

other cases, it must be one valence for a dimension. For example, Anger must be forceful; anger must be specific. Consecutive HUNCHes together might match an emotion dimensional array. They also might not, if emotion shifts.

[187] FIG. 20 is a flowchart for a rules discovery engine based on HUNCHes in accordance with an exemplary aspect of the disclosure. The process is performed in the rules discovery engine 326.

[188] In S2002, dimensions associated with HUNCHes may be scored.

[189] In S2004, HUNCHes are matched against profiles for emotio-cognitive states. To be matched with a possible emotio-cognitive state, they cannot have contradictory elements or dimensions to that state. Empty dimensions that do not contradict can potentially be matched.

[190] In S2006, Negative or Positive dimensions must likely match unless flagged as otherwise.

[191] In S2008, Emotio-Cognitive states are suggested.

[192] In S2010, new string matches and surrounding text are suggested back to the Natural Language Rules Module 306.

[193] In S2012, audio or visio-spatial data corresponding with new strings is fed into the corresponding Multi-Media Rules Engine 312.

[194] FIGs. 21A, 21B is a flowchart for rule discovery in audio media in accordance with an exemplary aspect of the disclosure.

[195] In S2102, audio media (or sound from visual media) is transcribed to text and inputted. Optionally, Closed-Captioning transcripts or scripts may become input. In some embodiments, gasps, noises, gestures, and other non-textual audio may be transcribed as annotations in order to capture more features of the audio media.

[196] In S2104, rules are applied to incoming text to detect emotion (as well as cognition and other elements).

[197] In S2106, index positions in the input where rules have been successfully applied are noted

[198] In S2108, rule dimensions are calculated to determine intensity on a phrase-, sentence-, passage-, and chapter- level.

[199] In S2110, passages are annotated with the corresponding Emotion (and/or other elements) and respective intensities and attributes.

[200] In S2112, corresponding soundwaves or visio-spatial data are coordinated, by time, to the index position of the words in the passage.

[201] In S2114, actual audio characteristics and relative relationships between the speaker's baseline audio or visio-spatial profile and a given specific Emotio-Cognitive profile of theirs are calculated and stored.

[202] In S2116, when similar, derivative, opposite or otherwise related audio fragments appear, they are matched to the Emotio-Cognitive label in question. Subpassages or strings that trigger the same rule for different emotions are fed into learning algorithms. Similar sound or visio-spatial fragments detected in data are pre-tagged with suggested Emotio-Cognitive states, based on similar audio's or visio-spatial data's existing tags. Similar fragments detected in audio or visual-spatial data are fed back into the Natural Language Rules Module 306.

[203] FIG. 22 is a graph of a speech signal pattern. In one embodiment, the speech signal pattern 2210 for a text input 2202 is indexed 2204 with the text input 2202 and is used to mark the beginning time and ending time (2208) for an emotion 2206.

EMOTIO-COGNITIVE DYNAMIC DISPLAY

[204] Historically, certain subsets of the population have experienced various barriers to understanding emotional, cognitive, social, belief-based, interpersonal, or metacognitive, meta-emotional, or decision-making cues or dynamics in spoken or written text. In particular, people who are non-neurotypical (e.g., neurodivergent), with conditions such as autism, encounter problematically high rates of misunderstanding or missing social cues, emotions, and other dynamic elements present in the language. Non-native speakers of a given language may also encounter these difficulties. Media consumed by these populations can be confounding, confusing, misleading, and sometimes lead to disconnection, interpersonal conflict or alienation, shunning, and isolation when social norms are not understood and/or transgressed. Enjoyment of media may also be reduced, or less able to be spoken about for social bonding reasons.

Entertainment companies can also lose or experience reduced viewership because audiences do not pick up on the emotional, interpersonal, belief-based, or cognitive dynamics at hand.

[205] Analyzed and annotated subtitles can be fed into machine learning algorithms, for greater efficacy as new situations, dynamics, emotions, cognitive states and social aspects, currents, and dynamics evolve or are introduced. Theory of mind modules can be updated with additional iterations, to adjust to a given society, gender, religious, belief, age, topic, or culture or subculture, for accuracy.

[206] Training data can be partially automated due to the robust information retrieved and matched to incoming media.

[207] Media can be created using the training data, and written, collected, spliced, compromised or mimicked using the annotations on prior data.

[208] Training data can be auditory, visual, textual, multisensory, or a combination of all types.

[209] One type of training data includes the GoEmotions dataset, with the following modifications: Elimination of the Desire class; Elimination of the Neutral label, and instead, the use of the neutral label in deriving a Surety Score of: $1 - \text{Neutral probability score} = \text{Surety Score}$.

[210] Training data is sourced from locations where sentiment such as but not limited to emotions, cognitions and other dimensions are necessarily or with above-threshold necessity logically required to be the case, and/or where the author self-proclaims their own emotion, effectively providing tags, and allowing for empirical labels.

[211] An embodiment of the system 300 for automated classification of emotion is an Emotio-Cognitive Dynamic Display. The dynamic display can insert subtextual data of emotion in real time which allows neurodivergent users to learn and refine their social, emotional, interpersonal and theory of mind skills as they go.

[212] The natural language rules engine 306 is configured with rules consisting of construction-based, high-use, and/or permutable phrases allowing for quick determination of linguistic patterns in textual information made available by subtitles. Hashtags are broken up by contextual, and corpus, unigrams and other present n-grams derived from the input, instead of merely made available via lexicon(s), providing for more accurate, more relevant natural language processing and sentiment analysis. Similar, partial or opposite dimensional patterns are used for detection of sentiment. Rules are created to encode dimensions that can be used to detect mental health symptoms in each rule-triggering construction.

[213] The emotio-cognitive engine 314 is configured to score subcomponents ("dimensions") for each rule allowing for fast and increasingly-accurate recognition of motivation, influence, emotion and cognition and similar subcomponents which aggregate in distinct patterns and

combinations to identify transient and enduring emotive, cognitive, belief-based, opinion-centered, social and personality states. Emotions are deduced from the “shape” of the dimensions. Features of emotions can include the vector of the dimensions, the values of the dimensions, and the difference from or similarity to derived calculations from these parts.

[214] The emotio-cognitive tagging engine 318 is configured for tagging and tracking of development of subtextual information over the course of subtitles and speech using the emotional, cognitive, belief, motivational and opinion state subcomponents. Once emotions are tagged, Aggregate Emotio-Cognition Ensemble Classifier 328 tags meta-emotional states, shifts, and combinations based on emotional patterns.

[215] The rules discovery engine 326 is configured to identify, utilize, deduce from and infer gapped emotional states, trends, dimensional transitions, and other sentimental states and shifts to suggest potential new rules, which are then fed back into the system 300. Emotional patterns and Meta-emotional shifts, states, and combinations are deduced from gaps within patterns of emotion, cognition, or other sentimental components. The rules discovery engine 326 is configured with affective logic that is used to deduce missing sentimental states and shifts in the data, or to solve semantic, cognitive, emotio-cognitive or otherwise sentimental ambiguities. The rules discovery engine 326 is configured to control training of the machine learning models engine 320 on the “edge” of the classes, such as between near-emotional states, like Grief and Sadness, or Sadness and Anger, for more adept, finer, and faster differentiation.

[216] The display 210 is configured to display juxtaposed subtextual cues against visual and auditory (auditory tone and speech) data to enable richer information, and situational awareness. Subtextual data is displayed to inform users and viewers and augment and/or clarify social situations and complex emotional and cognitive states depicted or described in the media.

[217] The rule discovery engine 326 is configured to work with the machine learning models engine 320. Analyzed and annotated subtitles can be fed into the machine learning models engine 320 as new situations, dynamics, emotions, cognitive states and social aspects, currents, and dynamics evolve or are introduced. Training data can be obtained from information retrieved and matched to incoming media. Training data can be auditory, visual, textual, multisensory, or a combination of all modes.

[218] In one embodiment, training data includes the GoEmotions data set. In the embodiment, the GoEmotions dataset is modified by deleting the Desire class. The Neutral label is replaced with a Surety Score that is derived from the neutral label, as: $1 - \text{Neutral probability score} = \text{Surety Score}$.

[219] In some embodiments, training data is obtained from sources where sentiment such as but not limited to emotions, cognitions and other dimensions are necessarily or with above-threshold necessity logically required to be the case, and/or where the author self-proclaims their own emotion, effectively providing tags, and allowing for empirical labels.

[220] FIG. 23 is a flowchart for a method of real time emotion classification in a stream of video/audio in accordance with an exemplary aspect of the disclosure. The method is performed with a display device, including a tablet computer, smartphone, smart TV, that receives streaming audio and/or video, and that includes its own built-in computer with memory.

[221] In S2302, a scene from a movie or television show or streaming show or captured theatre play or animated video source is received together with coordinated textual transcription.

[222] In S2304, rule matching of the textual data is performed by the rule-based engine 306 emotio-cognitive engine 314, intensity rating sensor 316, and emotio-cognitive tagging engine

318, which tags emotional, cognitive, and other such states, with intensity ratings, in the textual transcription.

[223] In S2306, the aggregate emotio-cognition ensemble classifier 328 determines contextual clues based on word co-occurrence, discursive elements, and topic elements.

[224] In S2308, the emotio-cognitive sensor 316 optionally marks individual strings or n-grams with trinary dimensional scores.

[225] In S2310, the visio-spatial rules engine 310 and audio-speech rules engine 308 detect and enter augmented information (AugI) and situational elements (SE) apparent in visual data or tone elements apparent in auditory data into a separate, but time-coordinated, source for the media.

[226] In S2312, the emotio-cognitive sensor 314 performs juxtaposition (coordination and divergence, and degree of each) from the context-oriented semantic information (contextual clues) and AugI and SE data, creating context scores for each scene.

[227] In S2314, bracketed emotional data is returned inline and inserted into the textual transcript for display in the display device 210 so that the viewer may have an easier time correctly identifying emotional, cognitive or social elements of the media.

[228] FIG. 24 illustrates a display device in accordance with an exemplary aspect of the disclosure. An example display device 2400 includes a display screen 2402 for displaying a scene from a movie or television show or streaming show or captured theatre play or animated video source together with coordinated textual transcription 2412. In this example screen, bracketed emotional data 2414 (e.g., Emotion-Intensity pair, "ANGER-MEDIUM") is returned inline and inserted into the textual transcript 2410 and displayed in the display device 2400. It is noted that although the Emotion-Intensity pair is shown as a pair of terms, the Emotion-Intensity pair 2414 may be displayed in other formats, including Intensity as a numerical value, or a

graphical symbol that depicts a relative quantity (Low, Medium High), such as a bar of a certain relative size and/or color, or a set of colored dots that vary in length. Also, an Emotion-Intensity pair 2414 may be displayed in a graphical container, such as inside a circle or rectangular shape, or in a comment balloon-like shape. In addition, although a single Emotion-Intensity pair 2414 is illustrated, the number and/or sequence of Emotion-Intensity pairs is dependent on the contents of the textual transcription 2412. For example, the Emotion-Intensity pairs 2414 may be displayed as a pattern.

[229] BORDERLINE PERSONALITY DISORDER SOOTHING DEVICE

[230] FIG. 25 is a diagram for the emotion classification system with sensory distraction in accordance with an exemplary aspect of the disclosure.

[231] Borderline Personality Disorder (BPD) is a mental health disorder that impacts the way one thinks and feels about oneself and others, causing problems functioning in everyday life. It includes self-image issues, difficulty managing emotions and behavior, and a pattern of unstable relationships. Treatment for BPD includes learning to manage emotions that feel intensely overwhelming and can lead to self-harm. Disclosed embodiments include a peripheral device for giving feedback based on certain emotions and pattern of emotions, especially intensity of emotion.

[232] A patient diagnosed with Borderline Personality Disorder (BPD) can be provided with a microphone equipped device or an input device that can accept input from a keyboard, other text input device, such as a voice recorder with transcription, or device with a text input function, such as a touchscreen equipped device having a text input screen. Speech signals may be converted/transcribed into text. Text may be directly inputted (302) to a device. The device is preferably a portable/mobile computing device that the patient may carry. In some embodiments,

the portable/mobile computing device may be a device that facilitates digital communication with a cloud service.

[233] The textual input is processed by the Natural Language Rules Module (306), which then provides Emotion labels, and passes the input to the Emotio-Cognitive Sensor (314).

[234] The Intensity Rating Sensor (316) computes dimensions for each input and assigns an objective intensity rating.

[235] Running averages and aggregate scores are computed in the Aggregate Intensity Module (2504).

[236] Instantaneous intensity scores are computed in the Instant Intensity Module (2502).

[237] When the running Negative Emotional Intensity in the Aggregate Intensity Module (2504) reaches a high enough threshold, the system may optionally proactively dispense a sensory-soothing aid (2506) via a peripheral device, configured for Dialectical Behavioral Therapy (DBT), in order to create a sensory soothing distraction for the patient, including, but not limited to: Dispensation of spicy candies, Vibration of Bluetooth bracelet, Heating of Bluetooth bracelet.

[238] When any given data point in the Instant Intensity Module (2502) reaches a Negative Emotional Intensity over a Danger threshold, the system proactively activates periphery device 2506 to create a sensory distraction.

[239] Intensity monitoring of language or speech resumes via both the Intensity Rating Sensor (316) and the Emotio-Cognitive Sensor 314. When aggregate or data-point intensity reaches a first threshold, a different randomized sensory soothing distraction is activated.

[240] Once the Aggregate Intensity Module (510)'s running average and the Instant Intensity Module's (2504) ratings have not risen above the threshold for 30 or more minutes, a diary card

is dispensed (2508) by the central unit for the patient to fill out and record the experience, for personal or therapeutic use.

[241] In other embodiments, the emotion classification system with sensory distraction has application beyond BPD. Optionally, a user overcoming their addiction to alcohol, drugs or compulsive behavior is monitored in an aftercare rehabilitation program or sober living home, for Emotio-Cognitive signs preceding, or of, relapse, and provide textual or transcribed input (302) to a device. Optionally, a worker's or manager's professional communications are monitored for signs of particular emotio-cognitive states, such as stress or anxiety, and inputted (302) to a device. Optionally, when the running Negative Emotional Intensity in the Aggregate Intensity Module (2504) reaches a high enough threshold, the system alerts the facility, rehabilitation program, or sober living home, or the employer that the user is at risk of relapse, or extreme stress or anxiety.

[242] FIGs. 26A, 26B, 26C is a schematic diagram of an electronic bracelet in accordance with an exemplary aspect of the disclosure. The electronic bracelet 2600 may be in the form of a ring 2612 having embedded electronic components.

[243] Wires:

The wires 2610 are a bundle of multiple insulated wires. Individual wires are either positive '+' or negative '-'. The wires 2610 are preferably nichrome (nickel chromium), but may be made of other wire materials.

[244] The bracelet 2612 may include an embedded communications chip (connected to a microprocessor chip 2620), configured for wireless communication. The wireless communication is preferably a short range communication for transmitting and receiving signals

from the portable/mobile device. In one embodiment, the communication chip performs wireless communications using Bluetooth, or Bluetooth low energy (BLE).

[245] A sliding window feature 2614 is glass or plastic. The sliding window 2614 exposes a dispenser 2616, which is single aperture. The sliding window 2614 is motorized with a micro solenoid step motor 2602. (< 5mm).

[246] The device 2600 is powered by an embedded microprocessor 2620. The microprocessor includes seatings for the wires and components using assembly board-type technology.

[247] A micro electromagnetic eccentric motor 2622 is an actuator that generates vibration via an imbalanced load.

[248] A copper plate 2608, seated in silicone, provides heat.

[249] The device is powered by a Lithium-ion rechargeable battery 2604. The rechargeable battery 2604 has an associated recharging interface 2606.

[250] Indicator lights 2630 on the band 2612 exist for pairing with the portable/mobile device.

[251] The band 2612 is translucent and can change color via LED lights depending on the emotion detected. This may be useful for people with BPD experiencing aversive tension, in a heavily activated state, to communicate their emotions with caregivers or loved ones.

[252] An adaptation of the device 2600 may also be useful for grounding people with PTSD amid panic attacks, and transmitting emotional information to loved ones and caregivers when triggered.

[253] In the above description, any processes, descriptions or blocks in flowcharts should be understood as representing modules, segments or portions of code which include one or more executable instructions for implementing specific logical functions or steps in the process, and alternate implementations are included within the scope of the exemplary embodiments of the

present advancements in which functions can be executed out of order from that shown or discussed, including substantially concurrently or in reverse order, depending upon the functionality involved, as would be understood by those skilled in the art.

[254] EMOTIO-COGNITIVE PROFILER

[255] In an example embodiment, emotio-cognitive classification may be implemented as a profiler.

[256] Text input is spoken or otherwise entered into the Natural Language Rules 306 for analysis. Input may be about the user, another person, or a topic. Optionally, a user may video-capture themselves answering randomized job prompts. Optionally, OCR or audio transcription transcribes written and video or audio encapsulated (respectively) textual information to plain text.

[257] Text is analyzed by the Emotio-Cognitive Sensor 314 for sentimental content.

[258] Emotio-cognitive sentiment is labeled by the Emotio-Cognitive Tagging Engine 318 after classification.

[259] The intensity of sentiment is calculated via dimensions within the Intensity Rating Sensor 316.

[260] A profile is generated with Personality Traits, Expression Traits, Cognitive Traits, and Emotional Traits as well as Values and Biases, within the Emotio-Cognitive Profiler.

[261] Demographic information is associated with profile information in the Emotio-Cognitive Profiler.

[262] The Aggregate Emotio-Cognition Ensemble Classifier 328 makes predictions about the type of candidate who will make a strong fit for the date, job, or jury. Optionally, the user inputs, such as by survey or questionnaire, information about the type of personality traits, values, cognitive traits, emotional traits, values and decision points their ideal candidate would exhibit.

[263] Recommendations are made to dating site users, jury consultants, or hiring managers to recommend a given person as a match, rating desirability and fit.

[264] The profiles compiled by the Emotio-Cognitive Profiler are retained and stored for future use by the Machine Learning Models Engine 320.

[265] EMOTIO-COGNITIVE INFORMED TEXTING/COMMUNICATION

[266] In an example embodiment, emotio-cognitive classification may be implemented as a pre-text application, including, among other things, phone banking, or text banking.

[267] The user submits textual or transcribed input into the system for emotio-cognitive guidance to inform the user about healthy, empathetic, positive, and socially- and / (sub)culturally-aligned communication techniques and psychology.

[268] Optionally, the relationship in question may be: sales relationship; customer service relationship; workplace relationship; academic relationship; counseling / coaching relationship; romantic relationship; friendship; family relationship; former or proposed relationship; estranged relationship; relationship in crisis; acquaintance relationship; or other human relationship.

[269] When unhealthy, inappropriate, insensitive, confusing, or perspective-limited responses are detected in the user or the user's text, the user is prompted to develop their communication skills to learn about stronger communication approaches, via games, modules, tutorials or other

teaching devices. Whether or not the user opts for a learning game or module, the user is asked if they would like to input more context about the situation.

[270] The user is asked if they would like to try the communication again.

[271] If the user chooses to add context, they can answer a series of questions that help assess emotio-cognitive states and the emotional or social situation. If the user declines to provide extra context, the user can opt to be asked further questions to assess his or her own emotio-cognitive state.

[272] Optionally, users can select from a list of worries, issues, problems and hopes for the communication or relationship.

[273] The user is given the opportunity to change their communication technique and input a new communication that incorporates the user's new knowledge and awareness, or reflects their changed emotio-cognitive state.

[274] Users are prompted to start fresh.

[275] DYNAMIC/ADAPTIVE EMBODIMENT

[276] Spontaneous user textual or transcribed input is entered into a computing device, app, gaming console, phone, or tablet.

[277] Text goes to the Pre-Processing Engine 304 and analyzed by Natural Language Rules 306 and then analyzed by the MultiMedia Classification Engine 312.

[278] Overtly stated (explicit) and subtextually detected (implicit) emotio-cognitive states are assessed in the Emotio-Cognitive Sensor 314 and degree of mental states are scored in the Intensity Rating Sensor 316.

[279] User inputs receive labels in the Emotio-Cognitive Tagging Engine 318.

[280] The system provides a crafted, selected, generated, edited, or otherwise transformed response and / or adapted to the user's emotio-cognitive state, providing a customized, interactive, discursive experience for the user. Optionally, the discourse may involve more than one computer-generated and / or guided bot or character. Optionally, the discourse may occur during the course of a traditional, virtual reality, or augmented reality video game. Optionally, the discourse may involve one or more additional human agents. Optionally, the discourse may involve a therapeutic bot providing psychotherapeutic-, counseling-, crisis- or sobriety help to the user or groups. Optionally, the discourse may involve a virtual friend or assistant providing companionship or help to the user. Optionally, the discourse may involve one or more automated sales or customer support bots.

[281] Optionally, environmental controls such as complexity, difficulty, volume, speed, color scheme, interventions, plotlines, mini-games and/or side quests, options, questions, characters, alerts, commentary, dialogue, capacities or offered choices, and other such customizations and custom activities adapt with user response to the most recent and aggregate bot-driven language replies.

[282] Past responses from the user/s are stored in a database, paired with respective iterated prompts, for future reference during current and future user sessions.

[283] SOCIOLINGUISTICS

[284] PROBLEM:

[285] Historically, sociolinguistics studies up-close attitudes, beliefs, opinions, and sentiments of individuals, classes of individuals, people groups, races, genders, socioeconomic groups and other people groups via observation and/or analysis of their spoken, written or gestured words.

[286] Sociolinguistics is a subdiscipline of semantics that assesses text in relationship to societal factors, including subcultures, differences among races, genders, sexes, subclasses of people, regions, and more. Sociolinguistics has long since studied the context of language, including cultural norms, cooperations, expectations, issues of identity, interpersonal interactions, and social context.

[287] Researchers in the humanities and social sciences, as well as natural language processing (NLP) engineers in the computer science field, perform analysis of spontaneous and crafted text and speech. Historically, these researchers and professionals have had to deploy computer code in order to parse, clean, tag, annotate and analyze words to garner insights.

[288] These shortcomings have alienated Researchers from the Humanities and Social Sciences (such as Psychology, Sociology, Applied Behavioral Science, Anthropology, Communications, Rhetoric, Women's Studies, Ethnic Studies and Political Science), depriving society of rich commentary on everyday language use and its significance. Furthermore, the general lack of integrated computational solutions for sociolinguistic and cognitive language assessment have prevented acceleration of social progress in an era where textual and speech communications are increasingly rapid, vital and centered for societal advancement, equity and comprehension.

[289] Furthermore, natural language, cognitive and sociolinguistic pipelines themselves have generally required difficult installations, dependence on pre-made data flows and their constraints, or incompatible solutions that create difficulty and delay to coordinate.

[290] PRIOR APPROACHES:

[291] Previous attempts to automate sociolinguistic research and analysis of digital, scanned, transcribed or translated text has required a succession of multiple tools, each requiring technical know-how to classify and integrate. Available corpora often suffer from limitations of scope,

accessibility and size, and additional corpora are difficult and expensive to curate. Few user-friendly scraping engines exist, offer only basic parsing, such as and do not integrate with fine-grained linguistic and natural language tools, allow for observer or tagging insights in the native environment, classification of human sentiment, belief, opinion or emotion have centered on supervised learning (often with Bayesian probability), unsupervised learning (such as neural networks).

[292] No existing solution integrates state-of-the-art social research tools that cover the entire study pipeline from top-level study design; survey skip-pattern design; volunteer recruitment; consent form integration; polling, surveying, interviewing, or data contribution; data intake and ingestion, study supervision, and query creation. Similarly, no existing solution provides a suite of modern, custom statistical analysis tools that span linguistic, computational, aggregation, cloud integration and machine learning training, testing, and use.

[293] Existing solutions also do not provide a seamless way to download, disseminate, collect, comment upon research and academic datasets, statistical sets, relevant code, and results papers. Finally, existing solutions do not allow users to contribute datasets back to the general public or academic peers for use in further research.

[294] METHOD

[295] This sociolinguistic pipeline is needed and wanting as technology advances, expanding reach of sociolinguistic studies, as well as amplifying humanities and sciences research outside of the linguistics field to incorporate textual, auditory, and visual historical, subculture, population, geographical and meta-data for the advancement of research, as well as society.

[296] Currently, sociolinguistics is performed on curated, narrower datasets. Computational tools for the professional tools for the professional or academic sociolinguist are wanting, with

existing solutions as overly fundamental, less fine-grained, and with a high technical barrier to entry. The very few user-friendly solutions for sociolinguists tend to be incomplete pipelines, allowing for basic curation, simple search and top frequency phrase calculations, export, and little else.

[297] This pipeline is novel and valuable for continuous, wide computational linguistic analysis on a range of topics, for commercial use in reputation management, advertisement and marketing assessment, viral topic tracking, as well as propaganda and “fake news” detection and associated ratings.

[298] In general, datasets’ performance often varies by type and task. Existing solutions show POS-tagging, n-grams, collocations, and frequency and relative frequency, and allow for scraping and basic language, term or linguistic analysis. However, existing solutions do not provide robust and dedicated, discipline-driven sociolinguistic tools, centralized academic, research, and nonprofit-driven tools for sociolinguistic research in the humanities and sciences, as well as study design and deployment tools throughout the life cycle of research studies.

[299] This method also includes optional geolocation tools, word and term comparison tools, discourse analysis and social interactions tools, as well as sociolinguistic sentiment analysis. Juxtaposed over time, language shifts indicating population value detection and attitudinal change are also novel, and can be leveraged for social problem and societal value tracking.

[300] Advocacy groups, nonprofits, and academic researchers currently have no comprehensive sociolinguistic pipeline to handle these needs fully, as well as digital means to design and create robust sociolinguistic, short-term, near-term and longitudinal studies end-to-end. Public policy could benefit from the digital application of the sociolinguistic pipeline to other disciplines, and commercial brands could also benefit from messaging tracking and analysis, market research,

product development, focus group testing, and sociolinguistic, automated sentiment analysis over time.

[301] Evaluative uses could also be applied to this pipeline, including national security analysis, law enforcement or police brutality monitoring, psychological and social behavioral studies, social program evaluation, legal analysis, fair and effective hiring practices, and risk management.

[302] Finally, mental health and physical health care as well as vaccine, pharmaceutical and therapist and physician care greatly needs a comprehensive, integrated-research analytic sociolinguistic pipeline for mass assessment of health care issues, adverse drug reactions, and disease monitoring. Financial markets are also currently vulnerable to movement by mass social media expression, and would benefit from a means to assess, track and monitor social media expression through a technical lens.

[303] FEATURES OF METHOD

[304] The Sociolinguistic Engine provides the following features:

- Integration of automated semantic tools available for sentiment analysis, including positive-negative-neutral (PNN) polarity-based measurement, specific affect detection with multiple emotional labels.
- Seamless data processing flows able to be set up hierarchically by the user, to completely automate a custom pipeline for textual data processing.
- Integration of connotative tools that establish, detect and allow for notation and prediction of latent and subtextual inferential information, word embeddings, sentence embeddings, cognitive linguistic features, structure-semantic mappings and markers for deductive and inductive reasoning.
- User-defined measurable dimensions, including but not limited to linguistic features and morpheme, phoneme, lexical, sentence-level and paragraph-level

structural components, with user-distributed weights for algorithm creation.

- Optional integrated threshold determination and weighting for categorization of specific, predefined or layered semantic information.
- Selectable and tuneable Machine Learning integration, including seamless deployment of 0 to n models of supervised, semi-supervised and unsupervised learning onto the dataset.
- GUI graphical user interface)-guided wizards that allow nontechnical users to make study design selections to set parameters for Research Project observers, annotators, subjects and raters for subjective labeling of textual or transcribed data.
- Calculation of dataset statistical averages, moving averages, and other methods of central tendency, historical emotion and sentiment scores linked to user-defined themes, corpora or search queries, connotations scores for each user-defined dimension for user-defined themes, corpora or search query, and statistics about other user-defined syntactic, phonological, morphological, cognitive linguistic, sociolinguistic and semantic linguistic dimensions of text.
- Intensity: Our classification model is the only one we are aware of that classifies emotion, connotation or lexical frame *intensity* instead of probability (of a classification) offered as a proxy for intensity.

[305] MODEL

[306] This invention describes a sociolinguistic pipeline that enables researchers from social science, computer science, and humanities disciplines and subfields to analyze spoken and written language, garnered online and offline, and create analyzable datasets analyzed by machine learning and procedural code to yield insights to the user, without the need for computer programming knowledge required.

[307] Researchers, nonprofits, and other users can use the Sociolinguistics Engine to deeply analyze speech and text corpora. Text can be time-sliced to be tracked over time, or constrained for time-bounded analysis.

[308] Preprocessing includes part of speech tagging (as well as an option to create POS-grams), n-gram generation, frequency and relative frequency calculations, Named Entity Recognition, collocations, skip-grams, bootstrapped n-grams, bootstrapped and other lexicons, and other NLP data preparation features.

[309] TECHNICAL DETAILS

[310] The Core Sociolinguistics Engine System flow incorporates the following essential and discretionary customized steps:

- I. The system begins by saving, ingesting, scraping, and otherwise cataloguing text posted, generated by and within, and replied to, digitized, transcribed, or resident on the Internet (including but not limited to audio or video spoken words ["speech"], plain text, marked up text and emojis, annotated, hyperlinked or augmented text, transcribed text or translated text). Selections are scraped, cleaned and placed into structured and unstructured (respectively) databases for storage.
- II. Meanwhile, the Sociolinguistics Engine performs continuous corpus collection and aggregation, including but not limited to social media posts, forum posts, Q&A site replies, internet comments, advertisement copy, instructional copy, works of written or spoken art, and legal text. If applicable, automated tagging commences, with continuous Data formatting, indexing, and processing / enriching, including but not limited to, storage and tracking of beliefs, opinions, emotions, and stances on and triggered by a

range of themes and topics for a given individual or group, in continuous sentiment analysis deployment. Data then undergoes indexing for future searches.

- III. Next, the administrator receives the options to deploy sentiment analysis on the dataset, allowing the data to be processed for emotion, sentiment, belief, and opinion by employing semantic analytical tools and methods, including, but not limited to: neural network, random forest algorithm, clustering algorithm, principal component algorithm, matrix factorization algorithm, Bayes classification algorithm, rule-based engine, search engine.
- IV. Once automatic tagging is completed, users can access a graphical user interface on personal computers, smartphone, tablet, or mobile handheld device, to create and administer surveys, create new data, or tag stored data through surveys.
- V. Users may access a graphical user interface to create new cognitive-linguistic component tagging rules that can be applied to existing data and future data.
- VI. Users can access a graphical user interface to create query-driven Custom Views on the data, to answer research questions, including but not limited to: academic and scientific research questions, business intelligence, marketing intelligence, stock market analysis, insights for political campaign.
- VII. Finally, surveys, tagged data, and new user-generated corpora and sub-corpora, can be incorporated in the data store, to allow new queries to be performed on it.
- VIII. Similarly, new, user-created automated tagging rules, query-driven Custom Views, visual representations of data, and machine learning models, and their tuneable thresholds, parameters and hyperparameters can be incorporated into the Automated Tagging Engine, to tag and index new incoming data for future access, querying.
- IX. The two previous steps represent an inclusion of data-feedback loops for improvement of data analysis statistical and machine learning performance.
- X. A graphical user interface allows exporting of selected datasets, with select features, components and parameters for analysis.
- XI. Contribution of data to an open-source data storehouse upon publication or project completion.

[311] EXEMPLARY EMBODIMENTS

[312] A sociology professor wants to conduct a study of words for disease used over time in online discourse since 2002.

[313] Previous methods would primarily allow results of top word, phrase or topics to be calculated, marked in the data and reported. FIG. 28 is a system diagram of user interface features for sociolinguistic data. FIG. 29 is a flow diagram of a sociolinguistic engine pipeline. The sociolinguistics pipeline is novel and non-obvious for its ability to take free-form spontaneous expression and turn it into quantifiable, calculable data.

[314] Previously, qualitative researchers were primarily able to focus on impressions that were both subjective and aggregate. The datasets could only be parsed by metadata, such as age, cancer stage, location, or marital status.

[315] The sociolinguistics pipeline is also novel for its ability to facilitate correlations, operations, machine learning statistical, data- analytical, class-based or predictive classifications from partially or purely qualitative data.

[316] The professor inputs URLs into the engine's Corpus builder, which aggregates, normalizes, and merges scraped data into a single textual dataset.

[317] Next, the user imports audio files collected by the sociology department the last 5 years by students with tape recorders.

[318] The audio files are transcribed into text and added to the meta-corpus. Each subcorpus includes a field that distinguishes its source.

[319] The professor enters queries with the purpose of analyzing historical trends in words for disease.

[320] Audio files are automatically tagged for responses to open-ended questions that previously could not have been quantified, such as:

[321] “Could you tell me a bit more about what happened then?”

[322] “How do cope with that?”

[323] “Did you get support from anyone at the time?”

[324] “What do you think you learned from this experience?”

[325] “How have you applied what you’ve learned to another life situation?”

[326] For each of these questions, the sociolinguistic pipeline can now quantify dimensions (as well as their respective subcomponents), such as but not limited to:

[327] Emotions

[328] Issue Stances

[329] Personality

[330] Beliefs

[331] Perspectives

[332] Sentiment

[333] Perception

[334] Opinions

[335] The professor and her team conducts 8 90-minute audio-recorded interviews over the course of 2 years, with patients and their primary caregivers, including 4 interviews throughout the chemo process, with a follow-up once chemo is completed.

[336] Audio from remaining interviews is transcribed and ingested into the sociolinguistic pipeline, where the PI can simply upload the audio interviews using the data-preprocessing tools.

[337] The professor receives an email notification once the files are processed and transcribed into text.

[338] The pipeline's Data Import Wizard allows researchers to declare names of relevant fields, input metadata, or merge datasets.

[339] The professor can then run the data through linguistic sentiment NLP, statistical or semantic tools, such as, but not limited to: tokenization (receiving top terms words and phrases used by cancer patients in the interviews), collocations to discover important terms surrounding terms queried from the interviews, correlations, emotional scores to track feeling, opinion, or belief or stance at each interview checkpoint and/or follow-up.

[340] The professor can opt to run comparison metrics to compare language and/or sentiment used by patients with respect to time, geographical location or other metadata, and/or receive measures of centrality for the dataset and further statistical interventions, measures and points of correlation (which otherwise would be unavailable for qualitative interviews).

[341] Additionally, the professor can make conclusionary comparisons with similar studies of cancer patients undergoing different or similar treatments, unify qualitative interview datasets with post-interview follow-up surveys in written form, export datasets for further analysis in statistical programs, perform machine learning (groupings, clustering users, predict well-being, assessing which features matter for well-being.)

[342] If the study generates new data, the professor can train machine learning algorithms of their choice on the new data, and/or contribute it back to the Data Store for use by others.

[343] If the professor wishes, they can study or discover patterns in the data, for further conclusions.

[344] Additionally, patients can be clustered, cases can undergo a T-test or other measures for anomaly detection.

[345] The professor can opt to use further tools to highlight significant features, such as but not limited to Random Forest.

[346] Using machine learning, the professor can detect cancer patients at lowest well-being levels, their associated features, and/or those at the highest risk for suicide.

[347] Once the research paper has been published, the professor can contribute her datasets to a general knowledge pool via the Data Store, approve use of them in select or entire conditions, and point to her research papers for categorization and use by other researchers.

[348] While certain embodiments have been described, these embodiments have been presented by way of example only, and are not intended to limit the scope of the present disclosures.

Indeed, the novel methods, apparatuses and systems described herein can be embodied in a variety of other forms; furthermore, various omissions, substitutions and changes in the form of the methods, apparatuses and systems described herein can be made without departing from the spirit of the present disclosures. The accompanying claims and their equivalents are intended to cover such forms or modifications as would fall within the scope and spirit of the present disclosure. For example, this technology may be structured for cloud computing whereby a single function is shared and processed in collaboration among a plurality of apparatuses via a network.

[349] SEMIOTIC LINGUISTIC POLITICAL ANALYSIS

[350] PROBLEM

[351] No sentiment analysis system exists that can enumerate political stance with reliable accuracy, including political party affiliation and its psycholinguistic subcomponents.

Additionally, no semantic system exists that can capture subtextual fine-grained signals of political belief in transcribed, translated or authored text or (audio) speech with inclusionary semantic framing.

[352] No machine learning solution has captured these implicative and connotative nuances of political speech in granular, valence-based quantified format. These are increasingly important functions as difficult-to-iterate speech and text communications have marked effect on the public and interest in their prevention (such as the January 6, 2021 insurrection on the US Capitol).

[353] Machine learning has not been applied to these cognitive linguistic elements with precision measurements of subcomponents of belief systems, valence of self and others, or intra-messaging discursive turns in ways that create robust personal profiles, clusters, and relationships of political stance and its sub-parts within communities, parties, and people groups.

[354] Affect (emotion) detection both in the delivery of political communications — as well as the induced and incited emotional reactions within the collective and individual audience — are necessary for the protection of society, understanding of and preservation of political discourse and free speech, as well as the warding off of future potential political violence.

[355] Furthermore, a normalized rating and classification set of systems are needed in order to further classify and detect other aspects of sentiment implied and connoted in textual and spoken political speech, such as but not limited to opinion, beliefs and stances.

[356] Attempts to measure and improve shifts in societal belief systems, reduction of hate crimes, reduction of political violence between parties, and other pro-social, peacekeeping

outcomes require a set of systems for measuring online, cellular, digital, and analog communications, their implications, nuances and effects.

[357] Finally, measurement of positions along the political spectrum is necessary to detect political extremism or domestic or foreign terrorism.

[358] PRIOR APPROACHES

[359] Automated classification of political stance has lacked fine-grained, enriched micro-information about belief, opinion and feeling (sentiment). No single system has been able to reliably predict political stance shiftings, swing-voter type and inclinations, and likelihoods to change opinions and parties, all at once.

[360] Furthermore, theoretical cognitive linguistic elements which can capture nuances of political beliefs have not been reliably quantified in a normalized way that allows for comparison points across sectors of societies.

[361] In the wake of political interferences by foreign entities, such a system is needed. Additionally, the use of political language, video and speech in ways that have marked emotional and cognitive effects on citizens have risen to public attention in recent months and years. A system for detection of nuanced messages and effects upon audiences during and after political communication is made is sorely needed.

[362] Furthermore, the rise of subcultures such as white supremacists and other extremist groups on respective sides of the political spectrum, as well as their societal influence and rising violence, requires that a set of systems for quantifying, identifying and predicting emotional escalation and rises towards political violence is necessary.

[363] Prior solutions to this problem have been able to predict violence itself, but not tie it to implicature and connotation in specific elements of communication.

[364] Previous solutions to this problem have not addressed sub-elements of cognition, linguistics, emotion, intellectual processes and assumptions, as well as micro-placements across the political spectrum beyond the major parties.

[365] Classification of opinion, belief, sentiment and emotions in this area is vital for a peaceful society, threat detection, public discourse, incitement prevention, and insight into political audiences as applied to both human and computing arenas.

[366] METHODS

[367] Ingestion of websites or otherwise digitized text, transcribed audio, and their linguistic preprocessing and subsequent linguistic analytical measurements to aggregate multi-dimensional scores, valence, polarity and deixis.

[368] Conversion of multi-dimensional author, speaker, party, and news media or content source to a single score Political Lean Score (PLS), with sub-dimensions for attitudinal readings with respects to governmental, constitutional, ideological and societal issue tracking.

[369] Continuous updates of content and media scores as new datalines are ingested.

[370] Detection and classification of datalines in regards to Swing Voter Likelihood Scores (SVLS), measuring party loyalty thresholds, rates of variance in sequential stances over time or political event communications, as well as the degree to which they change with respect to time or event, and severity and intensity of the event.

[371] Classes of swing voter that can be detected, according to central cause and major factors, for their political ambivalence, openness, flexibility, impressionability, malleability and motion along political spectrum and related sub-axes.

[372] Ability to be leveraged in national security efforts, human-robot interactions, educational applications and experiments, emotional modeling for social robots, and other affect detection security interactions.

[373] APS3 score measures loci such as power, control, reform, directionality, nature, action and status relations as represented in linguistically computed constructions and strings.

[374] Ability to integrate and perform translation to robot-readable measurements of social psychology, including group dynamics, intergroup relations, prejudice or stereotyping, and organizational psychology.

[375] Computed and transmitted integrations of cognitive emotive linguistic elements such as, but not limited to, Power valences, Enacted Virtue Score (EVS), Comparative Value Score (CVS), Auto-Positioning Social Subcomponent Score (APS3) and their respective subdimensions.

[376] Measurements of feature components in multidimensional space, resistance, religion, locality score, ironic construction, rhetorical device type, speech acts, dynamic psycholinguistic state change.

[377] User attribute scorings and valence derivations on subcomponents such as bravery, curiosity, authenticity, vulnerability, emotional quotient score (EQS), compassion, judgment, and learnability as they relate to political locations and positions.

[378] FEATURES OF THE MODEL

[379] Profiles of prototypical users of a given cluster, collectively and individually, to identify micro-divisions of political stance and position along associated sub-axes.

[380] Inclusion of micro-labels and sub-axes for political stance, breaking down political and party affiliation into fine-grained sentiment-based sub-parts, with opinions on but not limited to

financial, moral, social assistance, economic, governmental reach, civil liberties, constitutional position, and other political sectors of sentiment able to be parsed, collected, and arranged for mathematical, statistical and vector-based classification.

[381] Theoretical components of cognitive linguistics, including but not limited to framing, conceptual metaphor, literary device, metaphor, conceptual blending, mental spaces, lexical semantics, frame semantics, force dynamics, and other cognitive linguistic subcomponents have been measured and incorporated, where they previously have not in a unified set of systems that measures subcomponents for quantification and computation of these emotive effects through language.

[382] Incorporation of theoretical cognitive linguistic elements centered on meaning, applied to the inputted data in quantifiable form, via conversion to statistical and machine learning elements, labels, matrices and inputs, to capture rich semantic political information about stance, political lean and belief.

[383] Heuristics for flagging social media comments in response to audio (such as podcasts), visual (such as videos and imagery), and textual or speech (including but not limited to speeches, commentaries, interviews, news stories, comments, posts, e-mails, and other inputs) that do not agree with the observed or witnessed posted content.

[384] Our model has the singular ability to combine machine learning (supervised and unsupervised learning) with a rule-based set of systems that provides more empirical classification of sentiment, emotion, belief, and opinion, stronger profiling of the parties using language, more effective classification, and more flexibility around datasets.

[385] Use of meta-information, synchronized streams, model deployment, partitioning, baseline comparisons against perceptual results, and valence computations to detect political sector and emotive reasoning.

[386] TECHNICAL DETAILS

[387] Gathering ability for labelled data is done by using heuristics, filtering, location-based and rule-based proxies for political affiliation, and stance on a predefined list of sub-axes, themes, topics and lexical frames.

[388] Gathering integration for signature n-grams associated to a person, website, location, or period of time, by statistical and machine learning approaches, including but not limited to: n-gram count and measure of specificity to said person, website, location or period of time in comparison to other such entities.

[389] The systems start by identifying characteristic sub-axes, themes, topics and lexical fields and frames specific to a particular politicians, public figures, through text-mining of top n-grams, and topic modelling of user-generated data in various forms, including but not limited to: tweets, transcribed speech.

[390] These systems also can identify characteristic sub-axes, themes, topics and lexical fields and frames specific to particular social media user, through text-mining of top n-grams, and topic modelling of user-generated data in various forms, including but not limited to: tweets, reddit posts, transcribed speech from social media interactions, photos, liked content, and audio if available.

[391] These systems also can identify characteristic sub-axes, themes, topics and lexical fields and frames specific to particular social media outlet, through text-mining of top n-grams, and topic modelling of user-generated data in various forms, including but not limited to: articles,

posts, transcribed speech from videos, social media interactions for the official outlet account, photos, liked content, and audio if available.

[392] These systems can then define a final list of issues on which to measure users' stance, based sub-axes on pre-defined and discovered through statistics and machine learning.

[393] These systems can then identify user stance on each issue and sub-axis with a certainty score, using machine learning including but not limited to the following approaches: rule-based indicators such as viral signature n-gram adoption, dominant theme identification through word, n-gram, skipgram and part-of-speech (POS) gram co-occurrence and specialized collocations, Bayesian classifiers, collaborative filtering, matrix factorization, clustering algorithm, LSTM neural network, fine-tuned Transformer neural network, identified through text-mining and topic modelling. These systems then associate this data to mined user-metadata, which can indicate age, ethnic group, socioeconomic status.

[394] These systems can then predict user-similarity, based on stance-similarity on the elicited list of sub-axes, using machine learning approaches, including but not limited to: neural network, Bayes classifier, k-nearest neighbor algorithm, clustering algorithm, logistic regression, SVM, random forest.

[395] These systems can then predict political affiliation, using user-stances as input features, with machine learning approaches, including but not limited to rule-based indicators, Bayesian classifiers, LSTM neural networks, fine-tuned Transformer neural networks trained on political data and public response.

[396] Gathering of user information can be integrated regarding discovered and pre-defined dimensions, including but not limited to: compassion, stubbornness, likelihood of mutability of political stance, tendency towards violence, etc.

[397] These steps can then be repeated for any specific point in time, and analysis of changes in the data allows to track of political movement and identify trends in political stances over time, for a single user, a specific group of users, or on the dataset of all users as a whole.

[398] By cross-referencing user-generated data with exposure to propaganda, advertisement, and other identified sources of influence, these systems can quantify the degree of change in stance on any identified sub-axis.

[399] Results of analyses for specific user and time period can be visualized in a GUI, including but not limited to: website, browser plugin, smartphone app.

[400] These systems can also be applied to assess the stance of a user on a single or restricted data point, such as a single post, video, or any form of incoming text, audio, video.

[401] PREJUDICE, DISCRIMINATION AND BIAS DETECTION

[402] These methods are unique for their recognition of covert and overt bias, with granular linguistic features specifically extracted from and applied to prejudice and discrimination-based expressions in natural language, which can be applied and fine-tuned to instances of racism, sexism, ageism, homophobia, transphobia, xenophobia, sexual harassment, classism and ableism in spontaneous or crafted speech or text, by private and public figures and entities, nonprofits, publications, websites and other media sources and their mediums of communication.

[403] PROBLEM

[404] Detection of discrimination against, prejudices held against, and otherwise negative or biased sentiments held in regards towards a given people group, protected class, minority, disempowered or disadvantaged population have not easily been unifiedly quantified in computational linguistics. No formalized system has been put forth that can be applied across time, texts and biases, reliably, as detection as of this writing remains overly dataset specific.

[405] Additionally, as sociolinguists, sociologists, psychologists, and ethic, women's, and queer studies (and their equivalent humanities and science studies) have examined language up-close, few reliable sets of rules and cues have been developed as a standard for detecting racial bias.

[406] As a result, there has been no unified measure against which to assess natural language or spontaneous speech. Because of this, a consistent, relative degree of bias and prejudice has not been established, making it difficult to exert accountability and promote more rapid social change.

[407] This has created a society where minority suffering is "invisible," with special populations effectively gaslit by lack of definitive, unified proof in the language. This effect has also made it difficult for organizations and corporations to measure their performance and responsiveness as collective entities when it comes to implicit bias.

[408] Finally, real-world outcomes need set of systems of measure to be correlated with from a lens of implicit bias and discrimination, so that public and private individuals, entities and systems can be held accountable, assessed and improved (as well as interventions designed for improvement of such systems, individual communications, and entities' performance in equitable treatment). Society requires a solution for bias prediction and degree, as handled by these systems, to identify, prevent and detect probability of individual or mass violence from or against a people group, in general, as well as at any given time or location.

[409] Subtle forms of bias, such as "othering" (treating minorities and oppressed classes as if they are outside the norm of whiteness, heteronormativity, cisgenderedness, or other majority status), "white knighting" (treating minorities or oppressed classes as if they need to be rescued, with the majority status members centered as saviors), or "microaggressions" (small, hidden, and

easy-to-miss slights frequently unconscious but collectively bringing psychological harm) are difficult to enumerate, anticipate, and quantify.

[410] As such, there have been no standardized methods for quantification of bias and discrimination until now.

[411] FEATURES

[412] Computational efficiency of discrimination detection due to implementations of indices in all integrated algorithms herein.

[413] High clarity and precision due to time- and text-slicing techniques to pinpoint emotional and bias reactions during interviews, observations and communications inputted into the systems.

[414] Further computational efficiency of accessing results (query speed), due to implementation of indices in the algorithms included.

[415] Integration of multi-sensory inputs into a single bias-detection systems that outputs a set of normalized scores and a Bias Master Score indicating the presence and degree of prejudice, bias, discrimination or uneven favorability in perception and action of a given input.

[416] Ability to tie discriminatory and bias ratings and inputs to real-world outcomes, including but not limited to judicial decisions, fair housing assessment, police brutality allegations, employment discrimination, media bias, persuasion and marketing outcomes, commercial ROI (results on impression, both literally on web, tablet and smart phone entities, as well as other conversions from prospects to sales on other media), and social norm assessments.

[417] Dexterity in assessing the implicit bias of observers in witnessing and internally processing multi-sensory data, as well as the implicit bias resident in the media consumed itself,

and the actors therein, allowing for correlations and statistical connections to be made between the two.

[418] Fine-tunable applications that can be fitted to parameters for discriminatory orations and linguistic expressions, and applied beyond traditional classifications of bias, to fine-tuned features for intersexism bias, national origin discrimination, pregnancy discrimination, religious discrimination, parental or partner status and socioeconomic class.

[419] Use of meta-data and computational linguistic assessments together with other sensory inputs, to create profiles of geographical, socioeconomic, political and social stance, age-related, and other features for prediction of entities and individuals likely to carry bias, for effective interventions.

[420] Ability to monitor interventions against a timeline and location track, for adjustment, improvement and grant purposes.

[421] Base State Detection (BSD) markers, allowing for automated data line identifiers copied to the data store and sorted according to markers instantiated for gender, race, socioeconomic class, sexual orientation, physical degree of ability, and incorporative dimensions for poverty or socioeconomic index conversion.

[422] Computation of comparative signals between data with BSD marker attachment and incoming data flow, allowing the AI to improve efficiency in processing time in subtextual channels, garnering reduction in both training rounds and systems' resources.

[423] METHOD

[424] These systems of bias and prejudice detection quantifies discriminatory stances and negative attitudes towards protected, minority, disadvantaged, or particular classes of people.

These systems elucidate the detection of discriminatory language via detection and measurement

of subtextual linguistic cues by feature presence and placement within the sentence and by measuring instance(s) (of range $[0, n]$); intrasentence relative position (IRP); a plurality of syntactic sequence, fuzzy or exact string matching or a combination thereof; microdimensional comparison (MDCs) of any type the following categories of linguistic constructions and distinguished sociolinguistic features and their associated points of measurements:

1. Minimization
2. Scapegoating
3. Issue Reframing as Non-prejudicial
4. Dismissals
5. Otherizing
6. Fear-based Descriptors
7. Threat-based language
8. Accusations of lawlessness
9. Discriminatory denials
10. Animal language
11. Deflective language
12. Strawmanning and hyperbolic mockery
13. Justifications of bias
14. Invalidation of suffering (
15. Extremist framing
16. Insubordination language
17. Victim-blaming
18. Silencing
19. Overt threats
20. Dominance techniques
21. Honorific insistence
22. Shoulding
23. Defensive techniques
24. Patronizing Explanation Formats (mansplaining, whitesplaining, etc.)
25. Disqualification of victims
26. Stereotyping
27. Exclusive language
28. Class-based language
29. Virtue-questioning
30. Class-based Character-judgments
31. Smear campaigns
32. Double-standards
33. Linguistic mimicry
34. Erasure and posturing

35. Exoticizing
36. Pre-equality nostalgia
37. Micro-insults
38. Majority-trait perception praise
39. Loaded questions
40. Model minority praise
41. Paternalizing
42. Appropriate language
43. Criminalization Language
44. Moralizing
45. Dehumanizing language
46. Purity speech
47. Intrusion/Invasion/Takeover language
48. Fraud/Social Service Abuse allegations
49. Allegations of Societal Spoiling
50. Assimilation complaints
51. Intelligence language
52. Claims of prejudice as honesty / realism
53. Conservation Terminators
54. Awareness as Special Treatment fallacy
55. Prejudiced prejudice-denial preambles / Qualifiers before a racist comments
56. Prejudice cloaked as humor
57. Using targets for social validation
58. Invalidation of caused trauma
59. (Faulty / flattening) Generalization (“one of those,” “someone like that”)
60. Indefinite pronoun of the demonstrative pronouns
61. Gaslighting
62. Dehumanization
63. Normalization of Bias
64. Bandwagon Fallacy
65. Instructions to Ignore Bigotry
66. Allegations of minority status as leverage / privilege
67. Bootstraps mythologies
68. Freudian Slip justifications
69. Trivialization
70. Racialization
71. Restorative Justice as Double-Standard Assertions
72. Backhanded compliments
73. Menacing Minority language
74. Single data point fallacy
75. Dominating language / Assertions of Power
76. Reminders of Lower Societal Status
77. Victims as agitators (claim of deserved harm/force)

- 78. Claims of uncivilization
- 79. Infantilizing language
- 80. Diminutives
- 81. Objectifying
- 82. Sexualization
- 83. Fetishization
- 84. Majority-Oriented language
- 85. Accusations of Dishonesty
- 86. Accusations of Lack of Virtue
- 87. Justification by Token Presence or Success
- 88. Assumption of Majority-race, Majority-ethnicity, Gender in Power, Majority-Sexual-Orientation, Able / non-Disabled, or otherwise societally privileged advantages
- 89. Semantic Frame-implied slights or accusations
- 90. Implicit Oppressor Education Demands

[425] EMBODIMENT

[426] These elements are distinguished amid the language by ensembling one or more of the following linguistic features:

1. Discover discriminative and prejudicial linguistic markers, of 0 to n, from the feature list, where each linguistic marker represents a second linguistic embedding of cognitive component measurements (CCMs) that contribute to the overall bias score and discriminatory label.
2. Available enumeration of skip grams of phrases in the corpus that may highlight differences between treatment of people groups, as well as computed cognitive linguistic features associated with prejudice, bias, or discriminatory viewpoints or practices towards a given people group, minority, or protected class, according to their presence or absence, intensity and degree.
3. Optional assembly of a corpus of sound, images and videos, as well as social media data and metadata, to be observed by human beings as well as analyzed and rated by machine learning algorithms, to assess implicit bias, discrimination, and prejudice through microexpression analysis, sound wave analysis and computation in all of its aspects, as well as speech transcription, from authorized access, uploads, live video, audio or camera capture.
4. Additional optional capture of input from observers themselves, through images, video, audio, written or transcribed or translated text, survey data, interviews, or comments from live, website or social media interactions as well as any corresponding metadata.

5. Perform natural language package deployment where indicated on the text corpus, generating part of speech (POS) tags for each word in context in the corpus, and creation of mappings of each word to its corresponding part of speech.
6. If appropriate, deploy further linguistic enumeration, notation and tagging, including but not limited to structural dependencies, and collocations.
7. Identification and preprocessing of any facial images, including but not limited to: semantic segmentation, reframing and normalization.
8. Identification and preprocessing of relevant, timed, user-produced audio snippets which can indicate user emotion, intent, opinion.
9. If applicable to the input, train selected models on curated corpora or prototypical texts that display bias, discrimination, prejudice, favoritism against, a given people group, protected class or minority, as well as on transcribed, translated, inputted or scraped natural language texts, gesture inputs, facial expressions or spontaneous speech.
10. If applicable to the input type, train computer vision emotion detection models on gathered, and preprocessed facial data.
11. If applicable to the input, Train audio emotion-recognition models on gathered, identified and preprocessed sound, speech produced by the user.
12. Optionally use facial emotion prediction to predict an emotion label for the image(s), and associate that label to existing text for the user. This enables additional elicited data to tag the images and text data with the level of believability, trust, guilt-assumption, truth-assumption and favorability of their responses.
13. Optionally use sound emotion prediction to predict an emotion label for the image(s), and associate that label to existing text for the user. This enables additional elicited data to tag the sound and text data with the level of believability, trust, guilt-assumption, truth-assumption and favorability of their responses.
14. Enumerate part-of-speech grams (POS-grams) that potentially highlight differences between treatment of people groups.
15. List and examine frequency for POS-grams and skip-grams resident in the data.
16. Using one or more statistical approaches, discover skip grams and part-of-speech grams that potentially highlight or emphasize differences between treatment of people groups.
17. As necessary, augment the data using human- or machine-generated word lists including an array of sociolinguistic indicators of bias in a plurality of contexts towards a given

people group, control group or the general population.

18. Apply data augmentation methods as appropriate to generate similar synograms (semantically similar n-grams) to use as features.
19. Augmentation of frequent n-grams as required by replacing each word with an array consisting of respective words or sequence of words that have similar semantic meaning, valence, sentiment label, sentiment cluster, semantic association or polarity to the identified word.
20. Expand any augmentation of the list of frequent n-grams with k-nearest neighbors in the Word2Vec embedding space, additionally sorting antonyms and synonyms from the list, respectively.
21. For indicated cases, compare skip-grams differentiated by two or more terms or words that respectively have a significant difference, distance and directionality in polarity, sentiment, valence, cluster, or semantic association or meaning.
22. Detect the presence of enumerated and augmented features in the inputted, corpus-based, scraped, translated or transcribed text or speech, distinguishing features that are indicators of bias.
23. Compute scores for data line for each applicable label based on the features detected, including but not limited to text facial image features.
24. Train machine learning methods on any augmented data and selected features from inputs including but not limited to LSTM, transformers, CNN, KNN, clustering, random forest, linear regression, and Bayesian probability to quantify bias.
25. Use image and text data to output and grade Implicit Bias, Discrimination Score, Prejudice Score, Believability score, Truth score, Guilt-Assumption Score, and Favorability score.
26. Use the ensuing trained model to predict bias, discrimination, or prejudice in any video, image or sound wave file associated with given speech or text input.
27. Assessment of audio, text, computer vision reactions to similar or same communication by different and distinct people groups by analyzing ratios, points in time or passage demarcations, or number of words, of favorable, unfavorable and neutral facial, textual, or auditory expressions and reactions (as well as their subdimensions and specific emotions) with regards to other people group communication, gesture, images, voices, or profile data.

[427] The above disclosure also encompasses the embodiments listed below.

[428] (1) A method for automatically augmenting natural language content with emotio-cognition by processing circuitry. The method including receiving, via an input device, the natural language content as a textual input; searching, by the processing circuitry, for matches between a plurality of linguistic rules for a given emotio-cognition and components of the textual input, wherein instances of the linguistic rules have at least one human dimension; activating, by the processing circuitry, the matched linguistic rules, and evaluating the at least one human dimension of the activated matched linguistic rules; scoring, by the processing circuitry, each human dimension to obtain a prototypical profile of dimension scores for the given emotio-cognition; aggregating, by the processing circuitry, the dimensions in the obtained profile of dimension scores to obtain an intensity indication for the given emotio-cognition; and displaying, by a display, the natural language content augmented in a manner that relates the matched linguistic rules to the given emotio-cognition and signals the respective intensity indication of the given emotio-cognition.

[429] (2) The method of feature (1), in which the human dimensions include one or more of emotional affects of sentiment, emotion, Emotio-Cognitive attitudes, values, social mores, mindsets, outlooks, aspects, responses, traits, beliefs, opinions, perspectives, motivations, biases, states, manners, approaches, dynamics, personality trait, emotional approach, emotional choice, reaction, disposition, temporary state, change of state, cognitive aspect, behavioral aspect, internal condition, external condition, feeling, emotion, proposition, attitude, propositional attitude, directed attitude, undirected attitude, self-directed attitude, conscious emotio-cognition, unconscious emotio-cognition, anger, anticipation, disgust, fear, joy, sadness, surprise, trust, ego, blame, conformity, sacredness, kindness, respect, time, favor, approval, sincerity, vulnerability, judgment, separateness, purpose, formality, minimization, specificity, force, action , agency,

curiosity, clarity, intention, emphasis, energy, certainty, interest, engagement, shock or surprise, tension, speed, nuance, logic, paranoia, distance, identification, esteem, objectification, attachment, empathy, and patience, in which each dimension has a value being one of +1 for positive force, -1 for negative force, 0 for neutral force, and Ø for not present or not applicable, and in which the scoring, by the processing circuitry, each human dimension includes scoring human dimensions for all matching rules.

[430] (3) The method of features (1) or (2), in which the step of searching using the plurality of linguistic rules further includes detecting constructions based on the linguistic rules; and evaluating the human dimensions of each detected construction.

[431] (4) The method of any of features (1) to (3), in which the step of scoring including comparing the intensity indication to thresholds for the given emotio-cognition to obtain an emotional intensity level.

[432] (5) The method of feature (3), in which the step of detecting constructions further includes detecting a presence or an absence of constructions in the natural language content having components related to the given emotio-cognition.

[433] (6) The method of any of features (1) to (5), further including determining, by the processing circuitry, a pattern of emotio-cognitions that includes the given emotio-cognition by concatenating with other emotio-cognitions detected by other linguistic rules and identifying the pattern of emotio-cognitions as a dynamic emotio-cognition; and tracking the given emotio-cognition and the other emotio-cognitions together with associated components in a temporal sequence over the natural language content.

[434] (7) The method of feature (3), in which the step of detecting the constructions further comprises determining a numeric value for one or more of a part of speech tagging or syntax

rule, a string matching rule that is exact, inexact, masked, or wildcarded, a token proximity rule, a punctuation rule, a lemmatization rule, a stemming rule, a lexicon rule, and a word lookup or dictionary-based rule.

[435] (8) The method of feature (7), in which the step of determining the numeric value for the token proximity rule comprises accessing all tokens having a distance of fewer than n tokens from a specified point in the natural language content, wherein n is a positive integer.

[436] (9) The method of any of features (1) to (8), further including generating new linguistic rules by a machine learning engine that performs at least one of supervised learning and unsupervised learning.

[437] (10) The method of feature (9), further including receiving a plurality of natural language data items from a repository; normalizing and tokenizing the received plurality of natural language data items using the preprocessing to generate a plurality of preprocessed natural language data items; labeling the plurality of preprocessed natural language data items with an expressed emotio-cognition and an intensity of the expressed emotio-cognition; providing, in parallel, the plurality of preprocessed natural language data items to an unsupervised learning engine and a supervised learning engine; training, in parallel, the unsupervised learning engine and the supervised learning engine in multiple training epochs to identify, in the natural language data, a particular emotio-cognition, and to determine an intensity of the particular emotio-cognition, wherein each training epoch of the unsupervised learning engine provides rule suggestions to subsequent training epochs of the rule-based engine, and each training epoch, the rule-based engine provides tabulation and scoring data to subsequent epochs of the unsupervised learning engine and the supervised learning engine; and providing an output representing at least one of the trained unsupervised learning engine and the trained supervised learning engine.

[438] (11) The method of any of features (1) to (10), further including generating new linguistic rules by the processing circuitry that performs matching human dimensions present within the natural language content by matching the human dimensions to existing dimensional arrays, having wildcards or pattern skips, to identify new rules for the rule-based engine.

[439] (12) The method of any of features (1) to (11), in which the receiving step further comprises continuous reading of a streaming live video or animated video source together with coordinated textual transcription, and the method further including determining contextual clues based on word co-occurrence, discursive elements, and topic elements; marking individual strings or n-grams with trinary dimensional scores; detecting and entering further information apparent in visual data or tone elements apparent in auditory data into a separate, but time-coordinated, source for the video; and performing juxtaposition from the contextual clues and further information, to create context scores for each scene in the video.

[440] (13) The method of feature (12), in which the displaying step includes displaying the textual transcription in a manner that the given emotio-cognition and respective intensity indication is bracketed and inserted inline adjacent to the components.

[441] (14) The method of any of features (1) to (13), further including generating new linguistic rules by a rules- discovery engine, and in which the method further includes detecting, by the processing circuitry, hook words or pairs of words in the natural language content; evaluating one or more human dimensions associated with the detected hook word or pairs of words to determine if the hook words or pairs of words indicate a possible emotio-cognition; when a possible emotio-cognition exists, extracting a predetermined window of words surrounding the hook words or pairs of words; scoring, by the processing circuitry, the one or more human dimensions to obtain a profile of dimension score for the hook word or pairs of words; and when

the profile of dimension score is above a majority, constructing a new rule for the possible emotio-cognition based on the hook word or pairs of words and extracted surrounding words.

[442] (15) The method of any of features (1) to (14), further including identifying index positions in the textual input at positions where linguistic rules are matched.

[443] (16) The method of feature (15), further including annotating the textual input with an emotio-cognition and a respective intensity indication at the index positions.

[444] (17) The method of any of features (1) to (16), in which the receiving step further comprises receiving, via the input device, the natural language content as a audio input and transcribing the audio input into text input, the method further including matching a fragment of the audio input with a stored rule for a similar sound fragment, and assigning the audio fragment with an emotio-cognitive label of the stored rule.

[445] (18) An electronic reader, including a touchscreen display; processing circuitry; and a memory, in which the touchscreen display is configured to display text of an electronic book; the processing circuitry is configured to scan and tag the text using rules that, upon being triggered, detect emotio-cognitive states, and determine intensity with which the emotio-cognitive states have occurred; the processing circuitry is configured to generate and display one or more sidebars for listing dynamics and emotio-cognition-intensity information based on detected components of the displayed text; the touchscreen, when touched at a position in the display, is configured to select a dynamic or emotio-cognition-intensity; and the processing circuitry is further configured to generate and display color-coded highlighting that designates an occurrence of the selected dynamic or emotio-cognition-intensity.

[446] (19) A system for mitigating a psychological disorder, including a mobile device having processing circuitry and memory; and a peripheral device having a communications device and

one or more actuators, in which the memory of the mobile device stores program instructions, which when executed by the processing circuitry of the mobile device, cause the mobile device to perform a method including receiving, via an input device, natural language content as a textual input; searching, by the processing circuitry, for matches between a plurality of linguistic rules for a given emotio-cognition and components of the textual input, wherein instances of the linguistic rules have at least one human dimension; detecting, by the processing circuitry, the matched linguistic rules to obtain an intensity indication for the given emotio-cognition; and when the intensity indication for the given emotio-cognition reaches an emotio-cognitive intensity that exceeds a first threshold, transmitting a first activation signal that identifies the emotio-cognitive intensity; and the peripheral device is configured to receive, via the communications device, the transmitted first activation signal; and activate the one or more actuators to create a sensory distraction to mitigate the psychological disorder.

[447] (20) The system of feature (19), in which the program instructions, which when executed by the processing circuitry of the mobile device, further cause the mobile device to perform the method, including continuing to receive, via an input device, the natural language content as a further textual input; and when the intensity indication for the given emotio-cognition reaches an emotional intensity for a negative emotion that exceeds a second threshold, transmitting a second activation signal that identifies the emotional intensity for the negative emotion; and the peripheral device is further configured to receive the transmitted second activation signal, and activate the one or more actuators in order to create a different randomized sensory distraction to mitigate the personality disorder.

[448] (21) The method of feature (1), further including highlighting words in the natural language content based on the intensity indication; transmitting, the natural language content

with the highlighted words to the display; and displaying the natural language content with the highlighted words as an augmented reality display on the display during a course of a video streaming session.

[449] (22) The electronic reader of feature (18), further including detecting a presence or an absence of constructions in the text having components related to the emotio-cognitive states; and displaying, when a user touches text displayed on a touchscreen, representations of the emotions and cognitions of the text, wherein the representations are color heat maps.

[450] (23) The electronic reader of feature (18), further including annotating the text with the emotio-cognitive states and a respective intensity at index positions where shown when the electronic reader is touched during reading.

[451] (24) The system of feature (19), further including in response to the detecting of the matched linguistic rules, the mobile device is configured to transmit electrical signals or short radio waves, in order to trigger, based on the linguistic rules, a color-coded lighting of the peripheral device.

[452] (25) The system of feature (19), in which the peripheral device further comprises a colored, geometric display configured to activate an LED according to the intensity indication for the given emotio-cognition.

[453] (26) The system of feature (19), in which the method performed by the mobile device further includes comparing the intensity indication to thresholds for the given emotio-cognition to obtain an emotional intensity level for a cognition-emotional state; and the peripheral device comprising color-emitting diodes and a vibrator, and is configured to broadcast the cognition-emotional state, via the color-emitting diodes, and vibrate, via the vibrator, when the intensity indication is over a threshold.

[454] (27) The system of feature (19), in which the method performed by the mobile device further includes determining a pattern of emotio-cognitions that includes the given emotio-cognition by concatenating with other emotio-cognitions detected by other linguistic rules and identifying the pattern of emotio-cognitions as a dynamic emotio-cognition; and the peripheral device comprising LED lights and a vibrating device that vibrates in coordination with pulsing of the LED lights, to shift as the emotio-cognitions shift.

[455] (28) The system of feature (19), in which the method performed by the mobile device further comprises identifying index positions in the textual input at positions where linguistic rules are matched during audio conversations received and transcribed when spoken by a wearer of the peripheral device.

CLAIMS

What is claimed is:

1. A method for automatically augmenting natural language content with emotio-cognition, by processing circuitry, the method comprising:
 - receiving, via an input device, the natural language content as a textual input;
 - searching, by the processing circuitry, for matches between a plurality of linguistic rules for a given emotio-cognition and components of the textual input, wherein instances of the linguistic rules have at least one human dimension;
 - activating, by the processing circuitry, the matched linguistic rules, and evaluating the at least one human dimension of the activated matched linguistic rules;
 - scoring, by the processing circuitry, each human dimension to obtain a prototypical profile of dimension scores for the given emotio-cognition;
 - aggregating, by the processing circuitry, the dimensions in the obtained profile of dimension scores to obtain an intensity indication for the given emotio-cognition; and
 - displaying, by a display, the natural language content augmented in a manner that relates the matched linguistic rules to the given emotio-cognition and signals the respective intensity indication of the given emotio-cognition.
2. The method of claim 1, wherein the human dimensions include one or more of emotional affects of sentiment, emotion, Emotio-Cognitive attitudes, values, social mores, mindsets, outlooks, aspects, responses, traits, beliefs, opinions, perspectives, motivations, biases, states, manners, approaches, dynamics, personality trait, emotional approach, emotional choice, reaction, disposition, temporary state, change of state, cognitive aspect, behavioral aspect,

internal condition, external condition, feeling, emotion, proposition, attitude, propositional attitude, directed attitude, undirected attitude, self-directed attitude, conscious emotio-cognition, unconscious emotio-cognition, anger, anticipation, disgust, fear, joy, sadness, surprise, trust, ego, blame, conformity, sacredness, kindness, respect, time, favor, approval, sincerity, vulnerability, judgment, separateness, purpose, formality, minimization, specificity, force, action, agency, curiosity, clarity, intention, emphasis, energy, certainty, interest, engagement, shock or surprise, tension, speed, nuance, logic, paranoia, distance, identification, esteem, objectification, attachment, empathy, and patience,

wherein each dimension has a value being one of +1 for positive force, -1 for negative force, 0 for neutral force, and Ø for not present or not applicable, and

wherein the scoring, by the processing circuitry, each human dimension includes scoring human dimensions for all matching rules.

3. The method of claim 1, wherein the step of searching using the plurality of linguistic rules further comprises:

detecting constructions based on the linguistic rules; and
evaluating the human dimensions of each detected construction.

4. The method of claim 1, wherein the step of scoring comprises:

comparing the intensity indication to thresholds for the given emotio-cognition to obtain an emotional intensity level.

5. The method of claim 3, wherein the step of detecting constructions further comprises:

detecting a presence or an absence of constructions in the natural language content having components related to the given emotio-cognition.

6. The method of claim 1, further comprising determining, by the processing circuitry, a pattern of emotio-cognitions that includes the given emotio-cognition by concatenating with other emotio-cognitions detected by other linguistic rules and identifying the pattern of emotio-cognitions as a dynamic emotio-cognition; and

tracking the given emotio-cognition and the other emotio-cognitions together with associated components in a temporal sequence over the natural language content.

7. The method of claim 3, wherein the step of detecting the constructions further comprises determining a numeric value for one or more of

- a part of speech tagging or syntax rule,
- a string matching rule that is exact, inexact, masked, or wildcarded,
- a token proximity rule,
- a punctuation rule,
- a lemmatization rule,
- a stemming rule,
- a lexicon rule, and
- a word lookup or dictionary-based rule.

8. The method of claim 7, wherein the step of determining the numeric value for the token proximity rule comprises accessing all tokens having a distance of fewer than n tokens from a specified point in the natural language content, wherein n is a positive integer.

9. The method of claim 1, further comprising generating new linguistic rules by a machine learning engine that performs at least one of supervised learning and unsupervised learning.

10. The method of claim 9, further comprising:

- receiving a plurality of natural language data items from a repository;
- normalizing and tokenizing the received plurality of natural language data items using the preprocessing to generate a plurality of preprocessed natural language data items;
- labeling the plurality of preprocessed natural language data items with an expressed emotio-cognition and an intensity of the expressed emotio-cognition;
- providing, in parallel, the plurality of preprocessed natural language data items to an unsupervised learning engine and a supervised learning engine;
- training, in parallel, the unsupervised learning engine and the supervised learning engine in multiple training epochs to identify, in the natural language data, a particular emotio-cognition, and to determine an intensity of the particular emotio-cognition, wherein each training epoch of the unsupervised learning engine provides rule suggestions to subsequent training epochs of the rule-based engine, and each training epoch, the rule-based engine provides tabulation and scoring data to subsequent epochs of the unsupervised learning engine and the supervised learning engine; and

providing an output representing at least one of the trained unsupervised learning engine and the trained supervised learning engine.

11. The method of claim 1, further comprising generating new linguistic rules by the processing circuitry that performs matching human dimensions present within the natural language content by matching the human dimensions to existing dimensional arrays, having wildcards or pattern skips, to identify new rules for the rule-based engine.

12. The method of claim 1, wherein the receiving step further comprises continuous reading of a streaming live video or animated video source together with coordinated textual transcription, and

the method further comprises

determining contextual clues based on word co-occurrence, discursive elements, and topic elements;

marking individual strings or n-grams with trinary dimensional scores;

detecting and entering further information apparent in visual data or tone elements apparent in auditory data into a separate, but time-coordinated, source for the video; and

performing juxtaposition from the contextual clues and further information, to create context scores for each scene in the video.

13. The method of claim 12, wherein the displaying step includes displaying the textual transcription in a manner that the given emotio-cognition and respective intensity indication is bracketed and inserted inline adjacent to the components.

14. The method of claim 1, further comprising generating new linguistic rules by a rules-discovery engine, and

wherein the method further comprises:

detecting, by the processing circuitry, hook words or pairs of words in the natural language content;

evaluating one or more human dimensions associated with the detected hook word or pairs of words to determine if the hook words or pairs of words indicate a possible emotio-cognition;

when a possible emotio-cognition exists, extracting a predetermined window of words surrounding the hook words or pairs of words;

scoring, by the processing circuitry, the one or more human dimensions to obtain a profile of dimension score for the hook word or pairs of words; and

when the profile of dimension score is above a majority, constructing a new rule for the possible emotio-cognition based on the hook word or pairs of words and extracted surrounding words.

15. The method of claim 1, further comprising identifying index positions in the textual input at positions where linguistic rules are matched.

16. The method of claim 15, further comprising annotating the textual input with an emotio-cognition and a respective intensity indication at the index positions.

17. The method of claim 1, wherein the receiving step further comprises receiving, via the input device, the natural language content as an audio input and transcribing the audio input into text input, the method further comprising:

 matching a fragment of the audio input with a stored rule for a similar sound fragment, and assigning the audio fragment with an emotio-cognitive label of the stored rule.

18. An electronic reader, comprising:

 a touchscreen display;

 processing circuitry; and

 a memory, wherein

 the touchscreen display is configured to display text of an electronic book;

 the processing circuitry is configured to scan and tag the text using rules that, upon being triggered, detect emotio-cognitive states, and determine intensity with which the emotio-cognitive states have occurred;

 the processing circuitry is configured to generate and display one or more sidebars for listing dynamics and emotio-cognition-intensity information based on detected components of the displayed text;

 the touchscreen, when touched at a position in the display, is configured to select a dynamic or emotio-cognition-intensity; and

 the processing circuitry is further configured to generate and display color-coded highlighting that designates an occurrence of the selected dynamic or emotio-cognition-intensity.

19. A system for mitigating a psychological disorder, comprising:

a mobile device having processing circuitry and memory; and
a peripheral device having a communications device and one or more actuators,
wherein the memory of the mobile device stores program instructions, which when
executed by the processing circuitry of the mobile device, cause the mobile device to perform a
method including:

receiving, via an input device, natural language content as a textual input;
searching, by the processing circuitry, for matches between a plurality of
linguistic rules for a given emotio-cognition and components of the textual input, wherein
instances of the linguistic rules have at least one human dimension;
detecting, by the processing circuitry, the matched linguistic rules to obtain an
intensity indication for the given emotio-cognition; and
when the intensity indication for the given emotio-cognition reaches an emotio-
cognitive intensity that exceeds a first threshold, transmitting a first activation signal that
identifies the emotio-cognitive intensity; and
the peripheral device is configured to receive, via the communications device, the
transmitted first activation signal; and activate the one or more actuators to create a sensory
distraction to mitigate the psychological disorder.

20. The system of claim 19, wherein the program instructions, which when executed by
the processing circuitry of the mobile device, further cause the mobile device to perform the
method, including

continuing to receive, via an input device, the natural language content as a further
textual input; and

when the intensity indication for the given emotio-cognition reaches an emotional intensity for a negative emotion that exceeds a second threshold, transmitting a second activation signal that identifies the emotional intensity for the negative emotion; and

the peripheral device is further configured to receive the transmitted second activation signal, and activate the one or more actuators in order to create a different randomized sensory distraction to mitigate the psychological disorder.

21. The method of claim 1, further comprising:

highlighting words in the natural language content based on the intensity indication; transmitting, the natural language content with the highlighted words to the display; and displaying the natural language content with the highlighted words as an augmented reality display on the display during a course of a video streaming session.

22. The electronic reader of claim 18, further comprising:

detecting a presence or an absence of constructions in the text having components related to the emotio-cognitive states; and

displaying, when a user touches text displayed on a touchscreen, representations of the emotions and cognitions of the text, wherein the representations are color heat maps.

23. The electronic reader of claim 18, further comprising annotating the text with the emotio-cognitive states and a respective intensity at index positions where shown when the electronic reader is touched during reading.

24. The system of claim 19, further comprising:
in response to the detecting of the matched linguistic rules,
the mobile device is configured to transmit electrical signals or short radio waves, in order to trigger, based on the linguistic rules, a color-coded lighting of the peripheral device.

25. The system of claim 19, wherein the peripheral device further comprises a colored, geometric display configured to activate an LED according to the intensity indication for the given emotio-cognition.

26. The system of claim 19, wherein the method performed by the mobile device further comprises

comparing the intensity indication to thresholds for the given emotio-cognition to obtain an emotional intensity level for a cognition-emotional state; and

the peripheral device comprising color-emitting diodes and a vibrator, and is configured to broadcast the cognition-emotional state, via the color-emitting diodes, and vibrate, via the vibrator, when the intensity indication is over a threshold.

27. The system of claim 19, wherein the method performed by the mobile device further comprises

determining a pattern of emotio-cognitions that includes the given emotio-cognition by concatenating with other emotio-cognitions detected by other linguistic rules and identifying the pattern of emotio-cognitions as a dynamic emotio-cognition; and

the peripheral device comprising LED lights and a vibrating device that vibrates in coordination with pulsing of the LED lights, to shift as the emotio-cognitions shift.

28. The system of claim 19, wherein the method performed by the mobile device further comprises identifying index positions in the textual input at positions where linguistic rules are matched during audio conversations received and transcribed when spoken by a wearer of the peripheral device.