Towards World Models in AI and Natural Language Processing Applications: Emotion, Creativity and World Knowledge

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Abstract

With Emotion, as a prerequisite for Creativity, mirroring human behavior and human values, the modelling of world knowledge for behavior and emotion functioning as a "roadmap" of key-parameters in the language(s) and/or domain(s) concerned contributes to the creation of world models for applications (i.e. Sentiment Analysis, voice user interfaces - VUIs) and training data, including Large Language Models (LLMs). World models reflecting human behavior and human values in the real world can be based on world knowledge - Collective Intelligence –integrated in analysis and processing strategies from text types such as political and journalistic texts, containing socio-cultural elements and involving essential information for understanding human behavior, emotion and, ultimately, the human mind. This complex information can be processed in respect to a "three-level" framework with distinct, identifiable features, comprising the User-Group Level, the Pragmatic Level and the Prosodic -Paralinguistic Level.

Emotion as an Element of Creativity and its Integration in World Models

Emotion is defined as the major driving force of almost all types of creativity (Gu et. al. 2018), even if it is not consciously evoked (Gu et. al. 2018) with the type of emotional state often affecting creative performance (Akinola and Mendes 2008). The link between Creativity and Emotion is underlined in the possibility of emotions playing a key-role in thought processes expressed with novel features that are of meaning and value to the recipients ("instrumentally creative" emotions) (Deonna and Teroni 2025). The link between Creativity and Emotion is also underlined in the relation of emotions to values, where emotions are defined as "constitutively creative", because of their key-role in understanding values and because they partly constitute value properties (Deonna and Teroni 2025). In other words, Emotion, as a prerequisite for Creativity (Deonna and Teroni 2025), mirrors human behavior and human values, which, in turn, correspond to the framework (and hence, ontology or model) of socio-cultural features of the communication context concerned.

With the link between Emotion and Creativity, world models containing world knowledge for Emotion may also contribute to a better understanding of the element of Creativity for its integration in AI applications and/or for the evaluation of AI applications.

In other words, if the target is to create world models with the successful integration of real-world human emotions and other features related to the human mind, AI applications may play the role of tools complementing human Creativity and may even co-evolve with human intelligence.

From research concerning human behavior and human emotion (Caruso and Salovey 2004) (Davaei et. al. 2022), it can be observed that:

- Emotion can contribute to evaluation and decision-making tasks, since emotions inform cognitive processes (Caruso and Salovey 2004) (1).
- People from different cultures react and behave differently (Caruso and Salovey 2004) (2).
- A person (speaker, evaluator) who may be diligent in communication and interactions in one's own culture may not be equally diligent in respective cases concerning situations and people from other cultural backgrounds (Davaei et. al. 2022) (3).

The creation and maintenance of better world models in applications with Large Language Models (LLMs) involving human behavior and emotion remains a challenge despite remarkable achievements in recent research. The in-depth and correct understanding of human behavior and human emotion and its complexity factors contributes to the successful and efficient integration of real-life situations and world knowledge in AI and Natural Language Processing

(NLP) applications and, subsequently, to the creation of robust world models. Specifically, the efficient integration of in-depth world knowledge concerning language and culture-specific and/or domain-specific information is an essential requirement for the creation of robust world models.

In other words, the efficient integration of human and machine intelligence in world models may provide in-depth, correct information in regard to the broad range and diversity of human behavior, including Emotion. The efficient integration of human and machine intelligence in world models may contribute to the creation or upgrading of applications targeting to filter out misinformation for decision-making or recommendation (i.e. Sentiment Analysis) or targeting to be human-compatible, geared towards human behavior and/or human well-being (i.e. voice user interfaces – VUIs).

Complexity Factors in Emotion – Perception, Interpretation and Processing

As observed in recent research (Weidinger et. al. 2021), data-driven and Large Language Model (LLM)-based approaches are not always synonymous with data quality, resulting to a wide range of issues, from ethical to practical. In the case of understanding and processing human behavior and human emotion, limitations in language resources and text types -less resourced languages and/or text types, among others (Alexandris 2024), often result to a restriction of specific ways of expression that does not reflect real life and conditions, especially across a variety or user groups. Furthermore, features for processing user group information and behavior mostly do not extend beyond information such as the detection of stress levels, frustration or moods (i.e. in affective computing) or census-type data such as age, gender and occupation, . The focus (and restriction) in regard to these information categories is typical even in recent research involving deploying LLMs on big data with remarkable degrees of granularity in emotion detection for enhancing Collective Intelligence (i.e. (Kadiyala et. al. 2025)).

For example, depending on the situational context concerned and the related to socio-cultural norms, in texting or even in spoken interaction in voice user interface (VUI), the same word may contain - imply more information to one user/group than to another user/group and trigger different responses or reflexes. Furthermore, words and expressions may also reflect concepts and definitions (including values and principles) that are often socio-culturally determined and vary across language, cultural and social groups. Additionally, complications in the correct perception, interpretation and processing of Emotion may also interfere with any attempts of expressivity within a communication context and, hence, Creativity. Moreover, the expression of complex and subtle emotions is often the subject in Literature-Poetry and the Arts, namely creative forms of expression.

In regard to ways of expression and emotions, intense emotions - easily detected and processed in AI – NLP applications, are not typically encountered in most types of discourse and transactions in the real world. In particular, we note that complex emotions recognizable within a (socio-culturally determined) context, such as "contempt" and "disapproval" are located in the outer circles of the Plutchik Wheel of Emotions (Plutchik 1982).

Complex emotions are often elusive or ambiguous, since they are usually not expressed by a single word (i.e. "disappointed") or a word group and often involve parameters from different levels of linguistic analysis (i.e. Morphosyntax and Pragmatics) and/or prosodic (Prosody) and paralinguistic features. In contrast, the inner circles of the Plutchik Wheel of Emotions comprise "concretely" (and universally) identifiable emotions – including intense and universally recognizable emotions, such as "rage" and "grief". Therefore, subtlety of emotions constitutes a crucial complexity factor in emotion perception, interpretation and processing:

Complexity Factor: Subtlety: Intense and universally recognizable emotions, are typically easily detected and processed by current practices in Sentiment Analysis and Opinion Mining (Alexandris 2024). However, intense emotions are not typically encountered in most types of discourse and transactions in the real world.

An additional complexity factor in natural languages is the degree of the actual intensity of an emotion. Specifically, culture-specific parameters or "unwritten" rules may determine whether emotions perceived as intense might be actually less intense or whether subdued, understated emotions might actually be stronger (Complexity Factor: Intensity).

The type of existing forms of expression as a manner of expressing emotion constitute an additional complexity factor. The types of phenomena linked to emotion and opinion (or even their existence) may vary across languages. For example, Irony and Silence as a form of expression encountered in interaction may be phenomena that are common in some languages, less common or even non-existent in other languages (Complexity Factor: Manner).

The existence or the degree of language-related and socio-cultural interference in expressing emotion is observed to be an additional factor, especially when international users (or speakers) are concerned. Regarding the degree of language-related and socio-cultural interference in expressing emotion, special attention is required in commonly used languages (lingua franca) such as English. In the case of English speakers / users of the international community may occasionally or habitually integrate features of their own native language and/or misuse or misinterpret words and expressions (Complexity Factor: Interference). This Complexity Factor usually results in incorrect perception, interpretation and processing of information.

Interference and Creativity

On the other hand, in some cases, Interference may also result to novel ways of expression (Deonna and Teroni 2025) in a given language, especially in communities with significant multinational elements and backgrounds, contributing to Creativity. Here it may be noted that Creativity can be linked to blending distinct, identifiable features, in this case, socio-culturally determined expressions of Emotion and emotional stimuli.

Possible Solutions in Data-Driven Processing Approaches in Emotion and Sentiment Analysis

As far as processing approaches are concerned, the complexity factor of human emotion remains a challenge, even in recent, sophisticated approaches. For example, a characteristic recent data-driven approach for Sentiment Analysis involves knowledge graphs targeting to capture the complex and nuanced relationships between words and aspects based on the combination of relational representations generated by knowledge graphs using Node2Vec and BERT's contextual embeddings (Katat et. al. 2025). Experiments were performed comparing and contrasting embeddings, such as GloVe, Word2Vec, BERT, and Node2Vec, also in combination with various basic knowledge graph structures. The research involves sentiment polarity annotations used by all knowledge graph versions deployed and focuses in understanding and classifying sentiment at the aspect level, especially in complicated relationships between words, aspects, and sentiments, also referred to as "sentences with intricate syntactic structures and multiple sentiments" (Katat et. al. 2025).

However, in the real world, human emotions often manifest themselves beyond the framework of sentiment polarity and the "positive" – "negative" axis (Complexity Factor: Subtlety). Furthermore, for some languages – or in the case of an interfering native tongue in a commonly used language (Complexity Factor: Interference), multiple "sentiments" within an utterance or phrase may correspond to a distinct type or nuance of emotion (Complexity Factor: Manner).

Despite the above-described challenges, according to recent research, reinforcement of knowledge-graphs (KGs) may provide insights for the explainable processing of complex information such as emotion and account for the Complexity Factors of Subtlety, Intensity, Manner and Interference.

In particular, the combination of Knowledge Graphs (KGs) with LLMs and subgraphs is introduced (Susanti and Färber 2025) for the domain of Chemistry and Medicine. The possibility of subgraphs containing world knowledge concerning language and culture-specific and/or domain-specific information, including emotion is an option for further investigation (Approach A: KG-Subgraphs).

Likewise, the possibility of the integration of ChatGPT and other forms of AI-generated data with Knowledge Graphs (KGs) for the enrichment with language and culture/domain-specific world knowledge and emotion is an additional option for research and evaluation. Specifically, an integration of ChatGPT with KGs is proposed in the case of customer segmentation (demographic, psychographic, behavioral, geographic customer data), targeting to bridge the gap observed in "post-hoc explainability (...) inspite of the promising applications of the integration of knowledge graphs and LLMs in various domains" (Hu et. al. 2024) (Approach B: Additional Resources). Additional Resources also include multimodal data containing prosodic and paralinguistic information. The ability of comprehensive knowledge systems to interpret visual and auditory data in addition to processing textual information is stressed in recent research (Hu et. al. 2024), targeting to make KGs "more versatile and robust in handling complex, multimodal data environments" (Hu et. al. 2024).

In regard to spoken language and interaction, recent research involving KGs accounting for additional dimensions of spoken words – and paralinguistic features also concerns the detection and processing of emotion. Specifically, the "Context" relation (Alexandris 2023) connects KG nodes with information types implied by unspoken linguistic or paralinguistic features, co-occurring with the spoken word in the utterance (Approach C: "KG Context" Relations). The "Context" relation is differentiated between language-specific and socio-culturally determined "inherent" implied linguistic information (w-lang – context) and paralinguistic (p-lang – context) information and implied linguistic (w–context) and paralinguistic (p–context) information that is not language-specific and socio-culturally determined. The KGs are created (Alexandris 2023) (Alexandris et. al. 2022) for their subsequent use in vectors and other forms of training / seed data. They are targeted to function as a dataset for training a neural network (Wang et. al. 2021) (Mountantonakis and Tzitzikas 2019) (Tran and Takashu 2019) (Mittal et. al. 2017) in NLP applications (i.e. in Graph Neural Networks, (Ye et. al. 2022)).

The proposed approach is compatible to recent implementations combining KGs and neural networks to resolve issues ranging from practical problems across disciplines and professional domains (Antaris et. al. 2021) (Yerramsetti and Yerramsetti 2023) to issues in multilingual data and applications (Tam et. al. 2022), even in spoken dialogue systems (Deng et. al. 2023). Furthermore, Approach C (KG "Context" Relations) is compatible to observations regarding the higher performance of models with additional information regarding nodes (attributes, types) relationship types and "prior knowledge" (Wang et. al. 2021). At the same time, the small and shallow set of nodes of Approach C results to their easier training (Antaris et. al. 2021) (Yerramsetti and Yerramsetti 2023) (Tam et. al. 2022). Apart from a stand-alone knowledge graph-based processing strategy, Approach C (KG "Context" Relations), accounting for additional dimensions of spoken words and paralinguistic features (Alexandris 2023), can also be used as a customized subgraph (Approach A).

The integration of (customized) subgraphs and / or additional resources in KG-based approaches combined with LLMs for processing emotion may contribute to the enrichment of existing resources and strategies. The subgraphs (Approach A and Approach C) and/or additional resources (Approach B) can function as language/culture or domain-specific "plug-in" customization and/or refinement processing levels with the appropriate world knowledge (and, subsequently, world model) data and information.

Other Approaches

For the processing of complex information concerning human behavior and emotion, ChatGPT and other forms of AI-generated data may not constitute an efficient solution in the case of less resourced languages and/or text types. Furthermore, the creation of appropriate knowledge graphs (KGs) may not be always possible due to limited time and/or human resources. If (additional) resources are either unavailable or not suitable, there is the default strategy of creating a set of appropriate and efficient seed data (and annotation) (for example, as in traditional Sentiment Analysis approaches – (Jurafsky and Martin 2025)) or rule based parameters for applications such as chatbots and spoken dialogue systems (Approach D: Default Strategy).

Integration of Behavioral and Emotional World Knowledge in Models and Applications: Empirical Research as "Collective Intelligence" from Processing Political and Journalistic Texts

Insights from the analysis and processing of written and spoken monolingual and multilingual political and journalistic texts (linguistic research and empirical data) may contribute to the definition of key-parameters for the integration of world knowledge – as a form of "Collective Intelligence" - and, subsequently, world models, at least in relation to linguistic and paralinguistic aspects.

In particular, written and spoken political and journalistic texts are considered complex text types often including socio-linguistic/-cultural elements and content that may encompass several domains and, possibly, various types of target audiences – including the international community (Alexandris 2020). These written and spoken text types provide examples and insights in how emotions inform cognitive processes and how people from different cultures react and behave differently to the same situation or information (Caruso and Salovey 2004). Journalistic panels and political speeches (i.e. in the United Nations (Hatim 1997)) may even provide insights on how people may not always be diligent in interaction in a foreign language with elements unfamiliar to one's cultural background (Davaei et. al. 2022).

Insights from empirical data (professional journalists (i.e. (Alexandris 2020) (Alexandris et. al. 2022) and the social media - i.e. (Alexandris et. al. 2024)) and the above-mentioned research (i.e. Linguistics and Psychology) may constitute a form of Collective Intelligence (Baltzersen 2022) from the domain of Politics and Journalism. This information can be channeled into a processing framework for gaining accurate, detailed and user-group –specific data and results.

In particular, complex information in written and spoken (monolingual and multilingual) political and journalistic texts is analyzed and processed in relation to a "three level" framework for a world knowledge model, providing distinct, identifiable features: the User-Group (Audience) Level (I), the Pragmatic Level (II), the Prosodic -Paralinguistic Level (III) (Alexandris 2020). The User-Group (Audience) Level determines parameters of the Pragmatic Level and the Pragmatic Level and is, in turn, connected with the Prosodic -Paralinguistic Level (Alexandris 2020). In the "three level" framework for written and spoken (monolingual and multilingual) political and journalistic texts, the Pragmatic Level (II) plays a pivot role where all information detected and processed – especially implied and connotative features including Emotion – is evaluated within (domain-specific or language-specific parameters of) Speech Act types (Searle 1969) and the Gricean Cooperative Principle (Grice 1975). The violation of the Gricean Maxims of Quantity, Quality and Manner of the Gricean Cooperative Principle are connected to Irony and other "non-neutral" implied content including Emotion (Grice 1975) (Hatim 1997).

The User-Group (Audience), Pragmatic and Prosodic-Paralinguistic levels, functioning as world knowledge parameters in human emotion and human behavior, can be integrated in all three above-described processing approaches, namely "Approach A: Subgraphs", "Approach B: Additional Resources", Approach C: "Context" Relations and the default "Approach D: Default Strategy".

Application – specific and language-specific implementation pathways and parametrization strategies are not analyzed here. However, we present characteristic cases-examples as "fragments" of deep emotion modelling processes.

User-Group Level and Pragmatic Level

In particular, the User-Group Level (I) as a world knowledge factor, is directly related to the Pragmatic Level

(II), where complex emotions and emotional information in interaction can be determined and evaluated and issues concerning the above-presented Complexity Factors can be resolved. For example, a wide range of LLM-based (Large Language Model - LLM) research focuses on syntax-related "linear" forms of information such as Contradiction in regard to Irony (i) or sentences containing words and expressions with different or even contrasting emotions (ii) in regard to sentiment analysis (i.e. (Zeng and Li 2022) (Katat et. al. 2025)) (Case-Example 1). However, both cases (i) and (ii) are not universal and are restricted to language-specific (and hence user-group specific) data. In the first case (i), Contradiction as a form of Irony is a more commonly occurring phenomenon in some languages (i.e. English) in comparison to others. In the second case (ii), a sentence containing words and expressions with different or even contrasting emotions, in some languages, can be identified as a distinct sentiment category in itself, such as a "lukewarm" positive or a "mild" negative, depending on context. These language-specific cases of Irony may constitute modelling and data parameters concerning the User-Group Level (I) and the Pragmatic Level (II). Their specification and integration in KGs – subgraphs (Approach A, Approach C), additional resources (Approach B) or "traditional" approaches such as rule-based approaches (i.e for VUIs) (Approach D) may contribute to the rigorous and correct detection, evaluation or modeling of Emotion, by-passing issues concerning the Complexity Factors, primarily the Complexity Factor of Manner.

Another example of the connection of the User-Group Level (I), as a world knowledge factor, to the Pragmatic Level (II) are language-specific linguistic features functioning as pragmatic elements within the discourse structure in written and spoken texts such as discourse particles (Paltridge 2012). Specifically, beyond their function in discourse structure, discourse particles may also play a key-role in setting the emotional tone of text input (Case-Example 2). For example, in some languages (i.e. German) discourse particles may also substitute information in the Prosodic and Paralinguistic Level (i.e. discourse particles used to subtly emphasize or "soften" the information transmitted) (Alexandris 2020). The language-specific role of linguistic elements such as discourse particles may be integrated in customized KGs – subgraphs (Approach A, Approach C), in language-specific additional resources (Approach B) or used in annotation and/or dialog modeling in "traditional" approaches (Approach D). Depending on their appropriate evaluation and/or integration, language-specific linguistic features such as discourse particles may contribute to resolve issues concerning the Complexity Factors, primarily the Factor of Subtlety.

The determination of the User-Group Level (I) as a world knowledge factor may also play a key-role in processing subtle, implied information "hidden" in seemingly "neutral" expressions and terms. In regard to Emotion, some generally "neutral" terms may also have a positive or a negative connotation according to socio-cultural norms or specific domain, as observed in Sentiment Analysis (i.e. "waiter" – negative in restaurant reviews) (Jurafsky and Martin 2025). Sometimes, these distinctions are not always evident. For example, in American English, expressions, jargon and terminology from the domain of Business are often integrated in a non-business context, also for expressing opinion and emotion (Case-Example 3). In other languages and cultures, the usage of terms from the domain of Business in a non-business context may be considered unusual or even offensive.

The above-described cases-examples (Cases-Examples 1-3) illustrate the language-specific parameters concerning the User-Group Level (I) and the Pragmatic Level (II) as world knowledge factors for expressing emotion and opinion. Their integration in the proposed general processing approaches (Approach A, B, C and D) contribute to the evaluation and decision-making tasks, since emotions inform cognitive processes (Caruso and Salovey 2004), as stated above (1).

Prosodic and Paralinguistic Level

Furthermore, the User-Group Level (I) as a world knowledge factor may define culture-specific parameters in the Pragmatic Level (II) or even in the Prosodic and Paralinguistic Level (III) concerning the Complexity Factor of Intensity. For example, for user groups across various European countries and regions (Northern / Central Europe versus Southern Europe, Western Europe versus Eastern Europe) there may be distinct degrees of acceptable intensity in expressing opinion and emotion in most domains. Sentiment Analysis (intelligence) data may be extracted from a user group where exaggeration -and even dramatization- is a normal way of expression (i.e. as a means of friendliness or for emphasizing ones opinion) (Alexandris et. al. 2024) (Case-Example 4). In this case, the extracted (Sentiment Analysis) data will be examined under a different scope in respect to data from a user group where people tend to use understatements and/or prefer subtle means of expression.

Socio-culturally determined forms of expression and behavior are characteristically evident in the Prosodic and Paralinguistic Level (III) and can be detected and processed in audio -visual data for Sentiment Analysis applications and also in voice user interfaces (VUIs) or chatbots, sensing subtle emotions in user input and generating user-friendly system output. Information concerning the Prosodic and Paralinguistic Level is mostly implied information and may often also be subtle, as another example of the Complexity Factor of Subtlety.

Prosodic and paralinguistic information may complement the information content of the spoken utterance or constitute "stand-alone" information (Alexandris et. al. 2022). For example, the raising of eyebrows (Case-Example 5) is linked to a set of possible (also language and culture-specific) interpretations. The interpretation "I am surprised" [and / but this surprises me] may be indicated in annotation data, VUI output (Alexandris 2020) or KGs (Alexandris et. al. 2022) either as [I am surprised] as a pointer to information content or as a substitute of a spoken response - a "stand-alone" paralinguistic feature [Message /Response: I am surprised]. Alternative (language/culture-specific) interpretations of the paralinguistic feature are "I am listening very carefully", "What I am saying is important" or "I have no intention of doing otherwise" and are linked to the appropriate annotation or message (Alexandris 2020).

The above-described Example 4 and Example 5 illustrate the socio-cultural and language-specific parameters concerning the User-Group Level (I), the Pragmatic Level (II) and the Prosodic and Paralinguistic Level (III) as world knowledge factors- "Collective Intelligence" for expressing emotion and opinion. Their integration in the proposed general processing approaches (Approach A, B, C and D) contribute to the evaluation and decision-making tasks, taking into account that people from different cultures react and behave differently (Caruso and Salovey 2004) (2).

An example for the categorization of spoken and multimodal input combining the Pragmatic Level (II) with the Prosodic and Paralinguistic Level (III) is the "Sphere" Model presented in previous research concerning Approach C (Alexandris 2023). In the "Sphere" Model, context-specific additional dimensions of individual spoken words may be described as a context-specific information (atmo) "sphere" surrounding the spoken word, or in a more general case, any given form of expression. The concrete meaning – actual semantic content of the word / expression (retrievable and processable in Natural Language Processing-NLP) is surrounded by two context-specific layers, with its context-specific and language-specific dimensions (linguistic parameters and socio-cultural norms) in the inner layer of the sphere (A) and its context-specific and non-language-specific / domain-specific dimensions in the outer layer of the "sphere" (B) (Alexandris 2023). The inner layer of the sphere (A) may also contain paralinguistic information, specific facial expressions, gestures and prosodic features that are language-specific and/or socio-culturally determined (Alexandris 2020). Additionally, it may be noted that the differentiation between context-specific dimensions of a spoken word that are language specific (inner layer A) and non-language-specific (outer layer B) allows a formal differentiation between factors/evidence circumstantial and socio-culturally-biased factors/evidence in data analysis and training data. The "Sphere" Model constitutes the basis of the above-described KG-based approach in Approach C where nodes with information types implied by unspoken linguistic/paralinguistic features, co-occurring with the spoken word in the utterance are connected with distinct "Context" relations (Alexandris 2023). As discussed above, the Model in Approach C can be customized and integrated as a subgraph in KG-based approaches that are combined with LLMs for processing emotion and other complex information.

In all cases and examples described, the User-Group Level (I) constitutes the crucial element in the Approaches (A, B, C and D) and the Complexity Factors concerned. The User-Group Level (I) is not only crucial for determining information – and content involving Emotion – in the Pragmatic Level (II) and the Prosodic and Paralinguistic Level (III), but also for the determining the possibility of the existence of misused, integrated features originating from other languages (Complexity Factor: Interference). The Complexity Factor of Interference is essential for the rigorous and correct detection, evaluation or modeling of Emotion, since as stated above, people may not always be equally diligent in communication within one's own culture and in a foreign or international environment (Davaei et. al. 2022) (3).

The above-presented "three level" general framework for world knowledge and, subsequently, a world model (User-Group (Audience), Pragmatic and Prosodic -Paralinguistic Levels) has the function of managing and channeling complex types of world knowledge – including Emotion- from expert-human (i.e. Linguistics, Psychology) and data-driven (i.e. Journalism, Politics) resources ("Collective Intelligence") and its efficient integration in processing strategies, according to application type. In other words, world knowledge (frameworks/models) targeting to the efficient processing of Emotion may contribute to the creation of world models in AI and NLP and may also lead to insights in understanding aspects of Creativity for AI applications, either for integration or for evaluation, providing a basis for AI tools to co-evolve with the human intelligence.

Understanding (and Processing) Emotion and Creativity: Discussion and Further Research

With Emotion, as a prerequisite for Creativity, mirroring human behavior and human values, the modelling of world knowledge for behavior and emotion functioning as a "road-map" of key-parameters in the language(s) and/or domain(s) concerned contributes to the creation of world models for applications (i.e. Sentiment Analysis, voice user interfaces - VUIs) and training data, including Large Language Models (LLMs). World models reflecting human behavior and human values in the real world can be based on world knowledge - Collective Intelligence –integrated in analysis and processing strategies from text types such as political and journalistic texts, containing socio-cultural elements and involving essential information for understanding human behavior, emotion and, ultimately, the human mind. This complex information can be processed in respect to a "three-level" framework with distinct, identifiable features, comprising the User-Group Level, the Pragmatic Level and the Prosodic -Paralinguistic Level (Alexandris 2020).

This world knowledge framework serves as basis for "plug-in" customizations for language/culture or domain-specific human behavior and emotions – with their complexity factors- either in the form of subgraphs or additional resources (Approaches A, B and C) targeting to upgrade and refine KG-based approaches combined with LLMs. The framework can also contribute to the upgrading of rule-based approaches, annotation and seed data (Approach D) and/or refinement processing levels.

The efficient integration of the proposed world knowledge framework in training data and applications and its ultimate integration in world models remains an issue for further investigation and evaluation. Results from future research may provide further insights on whether the successful integration of real-world human emotions and other features related to the human mind (and society) can result to AI applications complementing human Creativity with a possibility of co-evolving with human intelligence.

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