HICEM: A High-Coverage Emotion Model for Artificial Emotional Intelligence

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Abstract—As social robots and other intelligent machines enter the home, artificial emotional intelligence (AEI) is taking center stage to address users' desire for deeper, more meaningful human-machine interaction. To accomplish such efficacious interaction, the next-generation AEI needs comprehensive human emotion models for training. Unlike theory of emotion, which has been the historical focus in psychology, emotion models are a descriptive tool. In practice, the strongest models need robust coverage, which means defining the smallest core set of emotions from which all others can be derived. To achieve the desired coverage, we turn to word embeddings from natural language processing. Using unsupervised clustering techniques, our experiments show that with as few as 15 discrete emotion categories, we can provide maximum coverage across six major languages–Arabic, Chinese, English, French, Spanish, and Russian. In support of our findings, we also examine annotations from two large-scale emotion recognition datasets to assess the validity of existing emotion models compared to human perception at scale. Because robust, comprehensive emotion models are foundational for developing real-world affective computing applications, this work has broad implications in social robotics, human-machine interaction, mental healthcare, computational psychology, and entertainment.

Index Terms—Modeling human emotion, basic emotions, emotion theory, statistical clustering, natural language, multilingual emotion models, psychology.

1 Introduction

As far back as Darwin, researchers have studied the subjectivity and universality of human emotions [1]. While such research was primarily confined to academic discussions in university psychology departments, with the rise of in-home social robots and other intelligent machines (*e.g.*, Alexa, Astro), has expanded this subject matter into the field of affective computing where developing an accurate model of human emotion is a stepping stone toward artificial emotional intelligence (AEI) [2]. Here, emotion modeling is a descriptive tool used to ensure that systems being developed have sufficient coverage for a wide range of human-machine or human-robot interactions.

Ideally, a robust model with sufficient coverage means *identifying the smallest core set of independent human emotions from which all other emotions can be derived*. If the emotion model used in an AEI program consists of an excessive number of components, the AEI may struggle to distinguish among these components. Conversely, if the model used is overly simplistic, the AEI may not be able to comprehend human emotions to a level necessary for the intended application. Some researchers used continuous dimensions such as valence, arousal, and dominance (VAD) to circumvent this problem [3]. However, the oversimplification of emotional experiences by continuous emotion models can render the use of them alone unsuitable for many AEI applications, such as emotion classification. Specifically, continuous models are unable to capture the nuances and subtleties of emotions, as exemplified by the frequent overlap of categorical emotions in the VAD space (illustrated later in Figs. 12-15). Additionally, the richness and complexity of emotional experiences cannot be fully captured by a limited number of dimensions. Finally, the substantial inter-individual differences in emotional experiences further underscore the limitations of relying solely on three dimensions.

Developing an optimal emotion model for AEI is a complex problem. Existing models either lack sufficient coverage [4] or incorporate excessive, overlapping labels to describe the space [5], [6], [7]. We provide a visual representation of an emotion model's coverage so the power of different models can be compared (Fig. 5). These are generated by taking the FastText word vectors [8] for 1,720 emotion concepts and projecting them down to two dimensions using Uniform Manifold Approximation and Projection (UMAP) [9] (Fig. 1). This dimensionality reduction technique, similar to t-distributed stochastic neighbor embedding (t-SNE) [10], is designed to preserve global relationships. We then generate the heatmaps using the maximum log cosine similarity between the FastText word vectors for the model and our emotion-concepts list.[1] This step enables us to visualize the coverage of each emotion model relative to our emotion concepts list. More details will be provided later.

To overcome the limitations in existing models and understand the full range of human emotion, we turn to natural language processing (NLP). Language has evolved to be the principal means of human communication and has been shown to influence our perception of the world [11],

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1. Since the distribution of the maximum cosine similarity across the entire list is exponential, the log of this distribution is taken to assist in visualization.

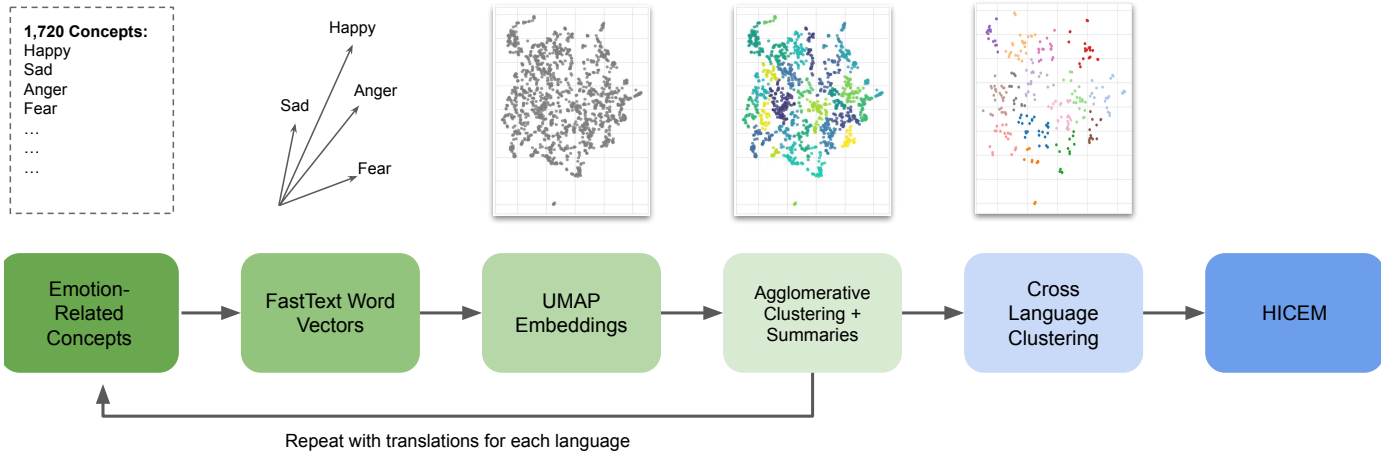

Fig. 1. Our pipeline for generating a cross cultural, high-coverage model of emotion. Starting with our list of emotion-concepts, we generate their FastText word vectors. Then we perform dimensionality reduction and clustering to generate summary words. This process was repeated to create summary words for six major languages. Finally, these were once again clustered to produce our final model, the HICEM.

[12]. By examining emotion-related words across cultures, we can identify trends and develop more robust, universal emotion models for next-generation affective computing applications. Previous work has taken similar approaches by having groups manually annotate existing emotions across continuous affective dimensions such as the VAD space [13]. However, word embeddings popular in NLP can now encode this information automatically. Understanding this advancement, we leverage statistical techniques to identify the minimum number of components that offer maximum coverage across multiple cultures. We propose a new emotion model, the HIgh-Coverage Emotion Model (HICEM), which provides higher coverage with fewer components compared with existing models popular in psychology used for affective computing. Using two separate evaluation metrics and a user study, we demonstrate the effectiveness of HICEM is able to achieve this goal. In support of this assertion, we also analyze the results from recent large-scale emotion recognition datasets to assess the validity and coverage of existing discrete and continuous emotion models.

The **main contributions** of our work include:

- **Creation of two new emotion models:** We provide to the affective computing and AEI communities a new high-coverage emotion model, named HICEM or HICEM-15, which contains more comprehensive information with fewer labels than existing emotion models. An extended version with 25 components, named HICEM-25, is also provided.
- **Evaluation framework for existing emotion models:** We offer a new evaluation framework for emotion models that takes into account their coverage and completeness, and assesses how they perform in real world annotation tasks.
- **Curation of 1,720 emotion concepts:** We provide a curated list of 1,720 emotion concepts for use in future affective computing research.
- **Data-driven validity assessment:** We propose a new data-driven approach that leverages annotations from existing large-scale emotion recognition datasets to assess the validity of existing emotion models in relation to human perception at scale.
- **Global perspective for emotion modeling:** We provide a global perspective in our evaluation by comparing across the six major languages recognized by the United Nations.

The rest of the paper is organized as follows. We cover related work in emotion modeling in Section 2. Section 3 describes our methods for generating a high-coverage cross-cultural model of emotion, the HICEM. The methodology and analysis of existing large-scale emotion recognition datasets are shown in Section 4. We discuss our results and identify future areas of interest in Section 5 and conclude in Section 6.

2 Related Work

There are three competing schools of thought on emotion: basic emotions, continuous models, and componential models. In this section, we briefly discuss these approaches in relation to affective computing and AEI.

2.1 Basic Emotion Theory

Basic emotion theory suggests that humans evolved a set of discrete, independent emotions which when triggered produce a physiological response or action tendency. From these basic emotions, all other human emotions can be derived. As shown in Table 1, these basic emotions are often used as categorical labels in affective computing datasets. More specifically, Paul Ekman's research into basic universal emotions serves as the foundation for most annotation schemes currently used [14], [15], [16], [17], [18], [19]. His original research identified six emotions universally recognizable by their facial expression [4]. They are fear, anger, joy, sadness, disgust, and surprise. However, several studies [20], [21], [22] suggest facial expressions alone are insufficient to differentiate emotions. Since it has been demonstrated that body language cues are also universal across cultures [23], there may exist a subset of emotions that are universal for body language while being indistinguishable in facial expressions alone [24]. Although not shown

TABLE 1
Recent Emotion Recognition Datasets

Dataset	Labeled Samples	Categorical Emotions	Cont. Emotions	Year
BoLD [14]	20k	26†	VAD	2020
DFEW [16]	16k	7‡	-	2020
GoEmotions [7]	58k	28‡	-	2020
MOSEI [17]	23k	6†	Sentiment	2018
OMG-Emotion [18]	0.6k	7‡	VA	2018
Aff-Wild [32]	0.3k	-	VA	2018
EMOTIC [15]	34k	26†	VAD	2017
EmoReact [19]	1.1k	16‡	V	2016

† Contains a subset of Ekman's basic emotions
‡ Ekman's basic + neutral
Continuous Emotion Key: (V)alence, (A)rousal, (D)ominance

to be cross-cultural, analysis by Cowen et al. on perceived emotions from vocalization [25], facial expressions [26], and perceived emotion from video [6] suggests not six but more than 24 emotion categories are required to adequately map the space. However, this list was limited in that the label space was predetermined by the researchers. In attempting to develop an emotion model for text classification, Demszky et al. expanded upon Cowen et al.'s work by using user-submitted labels to augment their emotion model. These labels were then pruned and refined to generate a more annotator-friendly list of 27 emotions and a neutral category [7].

Although Ekman's basic emotions are the most commonly used in affective computing, other models do exist. In taking an evolutionary-inspired approach, Plutchik proposes an alternative to Ekman's model which consists of eight primary affective states arranged to form a wheel of emotion [5]. Each of these affective states has varying degrees of intensity and when combined form more complex human emotions. Although a useful tool, this model is criticized as being too simplistic and hasn't been shown to have a strong empirical foundation [27]. Compared with Plutchik's palette theory, Jaak Panksepp took a biological approach to understanding emotion. His work pioneered the field of affective neuroscience which works to map specific regions of the brain to emotional experience [28], [29], [30]. In his original work, he describes seven affective systems common across mammalian brains which control specific types of behaviours and generate distinct emotional states [31]. He describes these structures as the "core-SELF."[2] Despite its neurological underpinnings, Panksepp's model hasn't been widely used in the affective computing community.

2.2 Continuous Models

Recognizing the limits of discrete labels for human emotions, some researchers have worked to define continuous dimensions to measure a person's affective state. As shown in Table 1, annotations along continuous dimensions are often used together with basic emotions. In the simplest case, such annotations simply mean labeling a sample based on how positive or negative it is. This dimension is usually described as the sentiment, pleasure, or valence of the sample. Expanding beyond one dimension, the Circumplex of Affect by Russel considers arousal (relaxed vs. aroused) and valence (pleasant vs. unpleasant) as the two fundamental dimensions which together provide a mapping for the discrete emotions [33]. There is strong support for the two-dimensional approach of the Affective Circumplex. These two dimensions appear across a wide range of studies [34], [35], [36]. Similar to Panksepp's mapping of discrete emotions, there has also been a considerable amount of work mapping valence and arousal to processes in the human brain [37], [38], [39], [40].

For three dimensions, another popular model comes from the researchers Mehrabian et al. who described the emotion space across pleasure-displeasure, arousal-nonarousal, and dominance-submissiveness (PAD[3]) [13]. This mirrors earlier work by Osgood et al., who considered the closely related concept of control instead of dominance [41]. Here, control can be thought of in terms of both the feelings of power or weakness in addition to interpersonal dominance or submission. With regards to the PAD model, other proposed dimensions include anticipation-expectation, anxiety-confidence, boredom-fascination, frustration-euphoria, terror-enchantment, and intensity (how far the person is from a state of pure, cool rationality) [42], [43], [44].

2.3 Componential Models

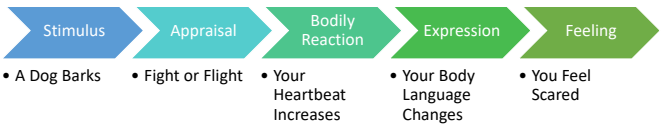

Fig. 2. An example of the processes within the componential model of emotion according to Scherer [45].

In contrast with discrete basic emotions and the previously described continuous models, there has also been some work in developing componential models derived from the appraisal theory of emotion [43], [45], [46], [47]. This is the dominant theory for describing how emotions are generated [48]. Under this framework, emotion is not a state but a dynamic process thought to result from a person's repeated evaluation (appraisal) of their circumstances [49], [50]. This process is broken down into several components including appraisal, action tendency, bodily reaction, expression, and feeling [45]. An example of this process is shown in Fig. 2. To generate emotions, a person first evaluates the scenario they are in. Subsequently, their central nervous system prepares a reaction (e.g., a fight or flight response). Bodily symptoms present themselves such as changes in heartbeat, shivers, or blushing. Similarly, there are changes in motor expression such as shifts in speech, body language, or facial expressions [51]. The final stage involves the manifestation of these changes as a feeling,

2. These include SEEKING (expectancy), FEAR (anxiety), RAGE (anger), LUST (sexual excitement), CARE (nurturing), PANIC/GRIEF (sadness), and PLAY (social joy).

3. Valence and pleasure are often used interchangeably and sometimes referred to as VAD for valence, arousal, and dominance.

TABLE 2
UMAP's Effect on Similarity

Emotion Pairs	Synonyms	Cosine Similarity				
		Raw Word Vector	PCA	SVD	t-SNE	UMAP
Happiness, Sadness		0.43	0.38	0.65	0.88	**-0.97**
Happiness, Anger		0.16	0.02	0.39	0.75	**-0.92**
Happiness, Fear		0.13	0.05	0.39	0.82	**-0.80**
Happiness, Contempt		0.06	0.61	0.70	0.82	**-0.78**
Happiness, Disgust		0.10	0.12	0.56	0.89	**-0.98**
Happiness, Surprise		0.18	0.98	0.93	0.89	**-0.55**
Happiness, Joyous	✓	0.23	-0.37	-0.87	0.37	**0.45**
Happiness, Gladness	✓	0.39	**0.99**	0.89	0.63	**0.99**
Happiness, Bliss	✓	0.42	0.82	0.54	**0.99**	**0.99**

PCA, SVD, t-SNE, and UMAP results are in two dimensions

which can be described in terms of its intensity, duration, valence, arousal, and tension [45].

An advantage of componential models over descriptive models that leverage basic emotions or continuous dimensions is that they provide an explanation for why an emotion presents itself. However, because these models rely heavily on subjective experience [43], [52], outside of lab-constrained experiments [53], [54] they have not been widely adopted for use in affective computing.

3 Cross Cultural Word Embeddings

NLP provides an interesting avenue for research into emotion modeling. By examining how current annotation schemes relate to other emotion-related words, we can take a quantitative approach toward identifying gaps in existing models. In this section, we outline our methods for generating HICEM from NLP word embeddings.

3.1 Generating a List of Emotion-Concepts

As shown in Fig. 1, we first compiled a list of emotion-related concepts from various models [1], [4], [5], online sources [55], [56], [57], and the Semantic Atlas of Emotional Concepts [58]. This list is then passed through a pre-trained Word2Vec model [59], which encodes the semantic meaning of a word into a 300-dimensional vector, enabling us to perform algebraic operations across these embeddings to reveal semantic relationships between words. A popular example of this process is

$$\overrightarrow{\text{king}} - \overrightarrow{\text{man}} + \overrightarrow{\text{woman}} \approx \overrightarrow{\text{queen}} .$$

That is, if we take the vector for "king," subtract the vector for "man," and then add the vector for "woman," the resulting output vector is approximately equal to "queen." For each pairwise combination of words in this list, we append synonyms based on the cosine similarity of the average of their Word2Vec vectors. For example, given "happy" and "sad" we would be able to identify "bittersweet" because its vector is approximately the average of the two. That is,

$$\text{average}(\overrightarrow{\text{happy}}, \overrightarrow{\text{sad}}) \approx \overrightarrow{\text{bittersweet}} .$$

This expanded set was manually pruned to remove adverbs (words with an *-ly* suffix) and words unrelated to a person's emotional state. For example, words such as "terrorist" and "terrorism" are closely related to the pairwise combination "terror" and "anger". However, these have little to do with emotion so they are removed from the final expanded list. More generally, if a word did not adequately fit the format "I feel {candidate word}", then it was excluded from the list. Likewise, there was a small subset of words typically used in religious contexts (e.g., 'glee', 'woe', 'joy', 'awe') which had an extremely high cosine similarity between their word vectors. This had an adverse effect on clustering so they were removed. However, alternate forms used in different contexts were kept (e.g., 'gleeful', 'woeful', 'joyful', 'awed'). Because the objective of this study was to identify gaps in existing emotion models for affective computing tasks, we took a more inclusive approach and kept words that may not qualify classically as emotions but are still concepts and dispositions (e.g., pain) that influence a person's expressions [30], [60]. In total, the final list contained 1,720 emotion-related keywords. [4]

3.2 UMAP Reduction

Using the list of 1,720 emotion concepts, a pre-trained FastText model [61] is used to encode the semantic meaning of the word. FastText is a variant of Word2Vec that operates at the n-gram level which allows for the use of subword information to improve the quality of the embeddings [62]. Trained on Common Crawl and Wikipedia, this model provides a 300-dimensional embedding for each word. FastText was chosen over more advanced techniques such as BERT [63] due to its location invariance and its use of the same methodology to generate vectors for multiple languages [8]. BERT embeddings vary based on the location of the word within the text. In our testing, BERT produced poor results when feeding individual words to the model.

Since word embeddings are generated based on their local context, antonym word pairs (*e.g.*, Happiness/Sadness) which are commonly used in the same context may have high cosine similarities relative to their perceived similarity. To mitigate this issue, we use UMAP [9]. UMAP relies on a set of neighbors to generate an embedding, and if a word possesses more true synonyms than similar-context

4. The full emotion-concept word list and project code are available at http://github.com/Mars-or-bust/HICEM . The word list is also included in the Supplementary Material.

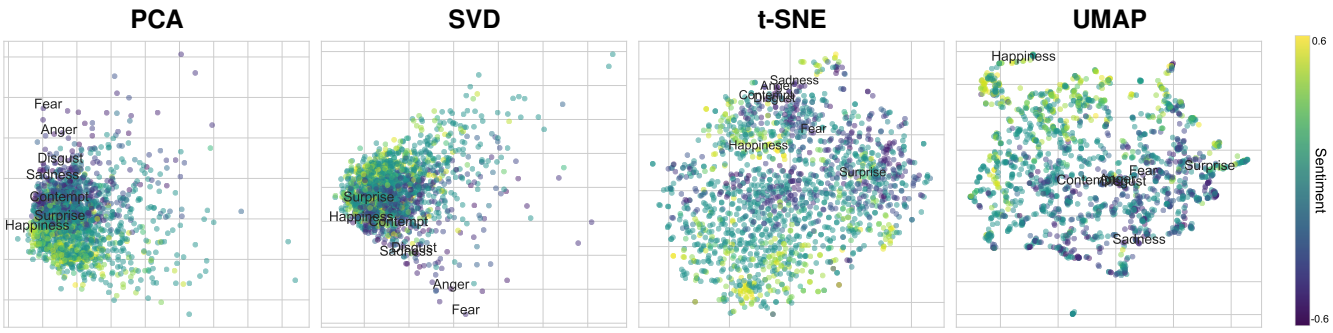

Fig. 3. We compare four different dimensionality reduction methods using sentiment as a heuristic. Unlike t-SNE [10], UMAP [9] is able to separate and organize positive and negative emotion concepts. Compared with other methods, when we plot Ekman's basic emotions [4] in the UMAP embedding space the separation between "Happiness" and the negative basic emotions is increased. This result is also shown in Table 2 where we compare the cosine similarity between the raw FastText [8] word vectors and UMAP embeddings across synonyms and antonyms for "Happiness."

antonyms, UMAP will draw the synonyms closer to each other while distancing antonyms from each other. This effect is evident in Table 2, where UMAP increases the similarity between synonyms while pushing antonyms away. Despite having quite different semantic meanings, "Sadness" has the highest cosine similarity with "Happiness" in the raw vectors. Other dimensionality reduction techniques such as principal component analysis (PCA), singular value decomposition (SVD), and t-SNE do not produce accurate cosine similarities between synonyms and antonyms after reduction.

In Fig. 3, we visualize the different embeddings with respect to the sentiment for each word using the Python Natural Language Toolkit (NLTK) [64]. Although we don't use any sentiment information when generating the embeddings, all dimensionality reduction techniques successfully create a separation between positive and negative emotions. However, t-SNE only achieves local separation and lacks consistent global separation. Similar to the outcome in Table 2, when we plot Ekman's basic emotions, we see much clearer separation between "Happiness" and Ekman's negative basic emotions in UMAP embeddings than in other techniques.

3.3 Hierarchical Clustering

Agglomerative clustering [65], [66] was used to programmatically select emotion words with the highest coverage. We preferred agglomerative clustering over other methods because it mirrors the hierarchical nature of basic emotions [31], [67]. Ward's Method was used as a linking metric for agglomerative clustering to minimize the variances of the clusters being merged [68]. The optimum number of clusters was determined using the elbow method [69], which identifies the "elbow" or "knee" corresponding to where diminishing returns are no longer worth the additional cost [70]. Finally, we summarize the contents of each group by finding the word embedding closest to the centroid of the embeddings of each cluster. The results of this stage are shown in Fig. 4.

To construct our cross-cultural model, we repeat this process by translating our list of emotion-related concepts from English into the other official languages recognized by the United Nations (i.e., Arabic, Chinese, French, Spanish, and Russian) using Google's Translation API.[5] We then once again proceeded with Facebook's FastText models, which have been trained on Common Crawl and Wikipedia for each of these languages [8].

TABLE 3
Recommended Number of Clusters from the Elbow Method

Language	# Clusters (Elbow)
English	14
Arabic	14
Mandarin Chinese	15
French	11
Spanish	13
Russia	14
Cross-Cultural	15

The translated UMAP embeddings for Chinese and Russian required adjustments due to certain limitations in translation. In the case of Chinese, the embeddings initially formed two distinct clusters, which was caused by the inclusion of the nominalization particle "的" that converts nouns or noun phrases into adjectives (*e.g.*, "快乐" or happiness → "快乐的" or happy). An equivalent example in English would be the use of the suffix "-ness" such as in "happiness." This suffix converts the adjective "happy" into a noun. Since FastText uses subword information to generate its word vectors, the semantic meaning of this character influences the final word embedding. When UMAP is run on these embeddings, the inclusion of this character creates enough separation between the word vectors that all words containing this character get clustered separately from the rest of the emotion-concepts list. A similar separation was observed in the Russian where one cluster exclusively comprised abstract nouns ("happiness" from the example above) formed by the addition of suffixes such as "-ность", "-ость", "-ия", or "-ие" to the root word. To resolve the divide, these clusters were excluded from the analysis since the primary clusters were significantly larger and already contained a superset of Ekman's basic emotions.

With the translated word vectors, we once again apply the process of agglomerative clustering for each language.

5. https://cloud.google.com/translate

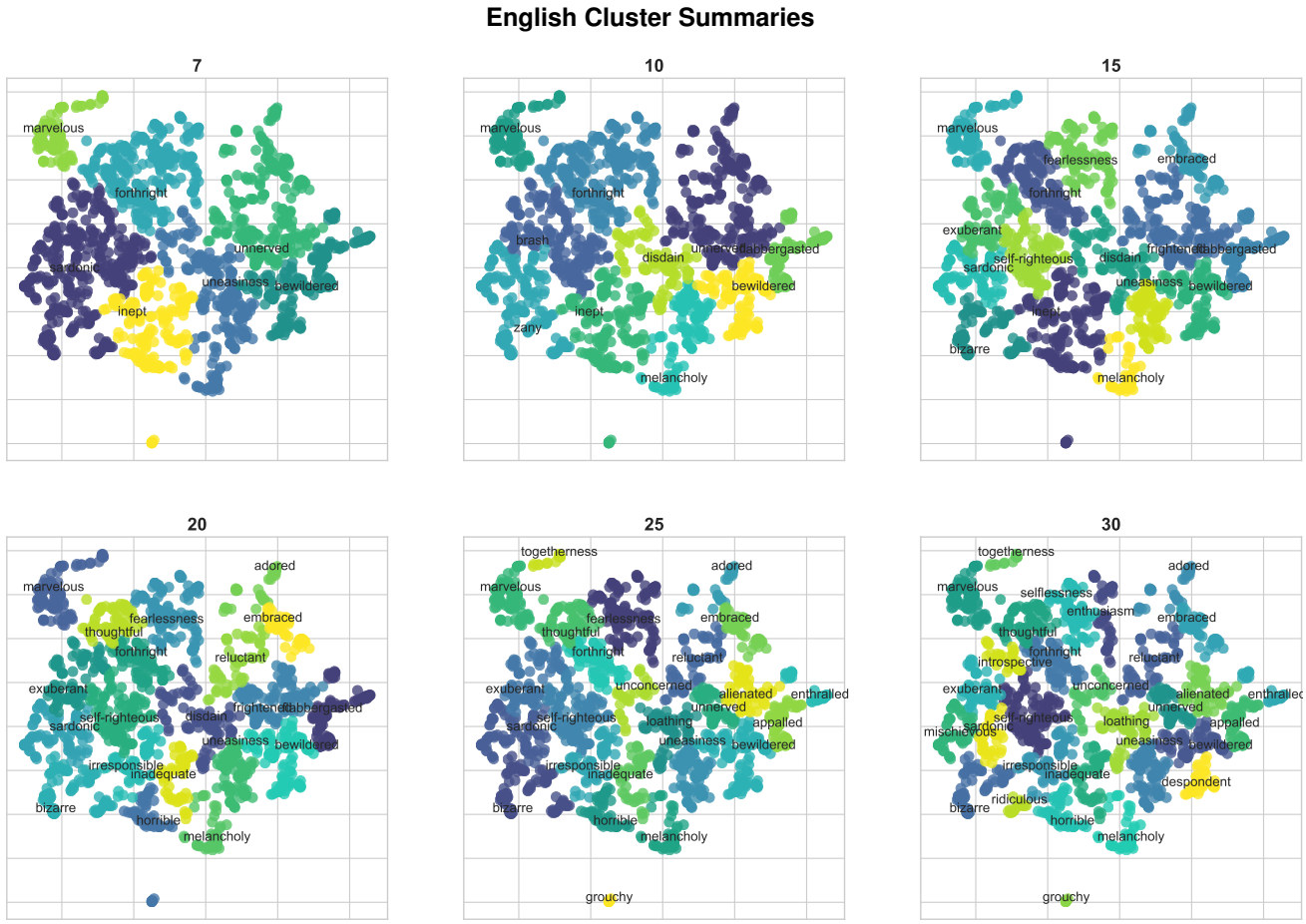

Fig. 4. Cluster summaries for English for the number of clusters, k, increases from seven to 30. As k increases, we are able to generate more complete models of human emotion. Since UMAP maintains global relationships among samples, we can visualize the relationships among different emotions.

As this process combines the two closest centroids in each iteration, it can handle situations where one-to-one translations do not exist. As shown in Table 3, we begin to experience diminishing returns in all languages at around 15 clusters. This result provides quantitative evidence that all other emotion-related words can be embedded into the semantic space of roughly 15 dimensions.

An notable finding arising from our analysis is that the identified clusters broadly capture the fundamental emotions described by Ekman, namely fear, anger, happiness/joy, sadness, disgust, and surprise, across multiple languages. Likewise, the clusters exhibit discernable themes of humor, abnormal behavior, friendliness, anxiety, and confusion. To ensure our model has coverage across cultures, we select the top 50 cluster summary words from each language and subjected them to further agglomerative clustering. Through the application of the elbow method, we determine that the optimum number of clusters is 15 (i.e., k=15), yielding a list of 15 cross-cultural summary words. As a final step, we engage native speakers of each language to replace rare or outdated words with more commonly used terms. This process provides us with the final list of 15 high-coverage emotion concepts, as shown in Table 4. Our novel emotion model can be referred to as HICEM-15, or simply as HICEM. Furthermore, we conducted an additional round of the final agglomerative clustering step for 25 clusters (with the generated model labeled as HICEM-25) to facilitate comparison with emotion models of comparable size.

3.4 Assessing Performance

In the following, we evaluate HICEM through two custom evaluation metrics and a user study conducted on Amazon Mechanical Turk.

3.4.1 *Comparisons using Recoverable Information*

A qualitative assessment of the quality of this list can be performed by projecting it onto the English embeddings, as illustrated in Fig. 5. Because this list is uniformly distributed throughout the space, it is reasonable to assume that there is minimal overlap among its labels. Additionally, we introduce a new metric, Coverage, to provide a quantitative assessment of the quality of each model. This metric is derived from cosine similarity between the words in the model and our emotion list, and is defined as follows:

$$\text{Avg. Coverage}(M) = \frac{1}{n}\sum_{i=1}^{n} \max_{m \in M} \text{CosSim}(m, w_i)\ , \qquad (1)$$

and

$$\text{CosSim}(a, b) = \frac{a \cdot b}{\|a\|\|b\|}\ . \qquad (2)$$

TABLE 4
HICEM-15 and HICEM-25 Components in Six Major Languages

	English	Arabic	Mandarin	French	Spanish	Russian
	affable	ثمد	和蔼可亲	affable	afable	приветливый
	affection	ەفطاع	喜爱	affection	cariño	привязанность
	afraid	فئاخ	害怕	peur	asustado	боюсь
	anger	بضغ	愤怒	colère	enfado	злость
	apathetic	يلابمرغ	冷漠	apathique	apático	апатичный
	confused	رئاح	困惑的	confus	confundido	смущенный
	happiness	ةداعس	高兴	bonheur	felicidad	счастье
15	honest	قداص	诚实的	honnête	honesto	честный
	playful	بوعل	顽皮的	enjoué	juguetón	игривый
	rejected*	ضوفرم	被拒绝的	rejeté	rechazado	отклоненный
	sadness	نزح	悲伤	tristesse	tristeza	грусть
	spiteful	دقاح	恶意的	malveillant	malévolo	злобный
	strange	بيرغ	奇怪的	étrange	extraño	странный
	surprised	شەدنم	惊讶	surpris	sorprendido	удивлен
	unhealthy	ضرم	不健康的	maldif	malsano	нездоровый
	accepted	لوبقم	被接受的	accepté	aceptado	принято
	despondent	سئاي	沮丧的	découragé	abatido	подавленный
	enthusiasm	سامح	热情	enthousiasme	entusiasmo	энтузиазм
	exuberant	ريزغ	精力充沛的	exubérant	exuberante	буйный
	fearless	عاجش	无所畏惧	sans peur	audaz	бесстрашный
25	frustration	طابحإ	挫折	frustration	frustración	разочарование
	loathed	رقتحم	厌恶	détesté	odiado	ненавидел
	reluctant	ددرتم	不情愿的	réticent	reacio	вынужденный
	sarcastic	رخاس	讽刺的	sarcastique	sarcástico	саркастический
	terrific	عئار	了不起的	formidable	fantástico	потрясающий
	yearning	قوت	渴望	aspiration	anhelo	тоска

* is replaced by "loathed" in HICEM-25

In Eq. (1), M denotes the collection of FastText word vectors present in an emotion model, and $W - M$ is the set of vectors representing words from the set of 1,720 emotion concepts (denoted by W) excluding the components of the emotion model (i.e., M). Let $n = |W - M|$ be the cardinality of the set $W - M$. We have opted for the maximum cosine similarity, i.e., Eq. (2), to gauge the strength of the top synonym for a given emotion model and emotion-concept ($w_i \in W - M$) pair. As seen in Table 5 and Fig. 6, our model provides a higher coverage with fewer components compared with the previous models.

In addition to analyzing the coverage, we conducted an experiment to assess the amount of emotion information captured by each model. The rationale behind this experiment is that, ideally, we should be able to recover a considerable number of emotional states for a given sample using solely the annotations from a particular model. In contrast to coverage, where we only consider the maximum cosine similarity, here we leverage the additional annotations across all the components to make a prediction on the emotion present. In Eq. (3), we assume the existence of an oracle that, when given an emotion model M, can generate an embedding X for a specific word vector w_i using the cosine similarities between the FastText word vectors of each $m \in M$ and w_i. Formally,

$$X = \text{CosSim}(w_i, M) \ . \tag{3}$$

Then,

$$\hat{w}_i = G(X) \ , \tag{4}$$

where G is a function we pass X through in order to make a prediction on the original word vectors $\hat{w}_i$. Then once again

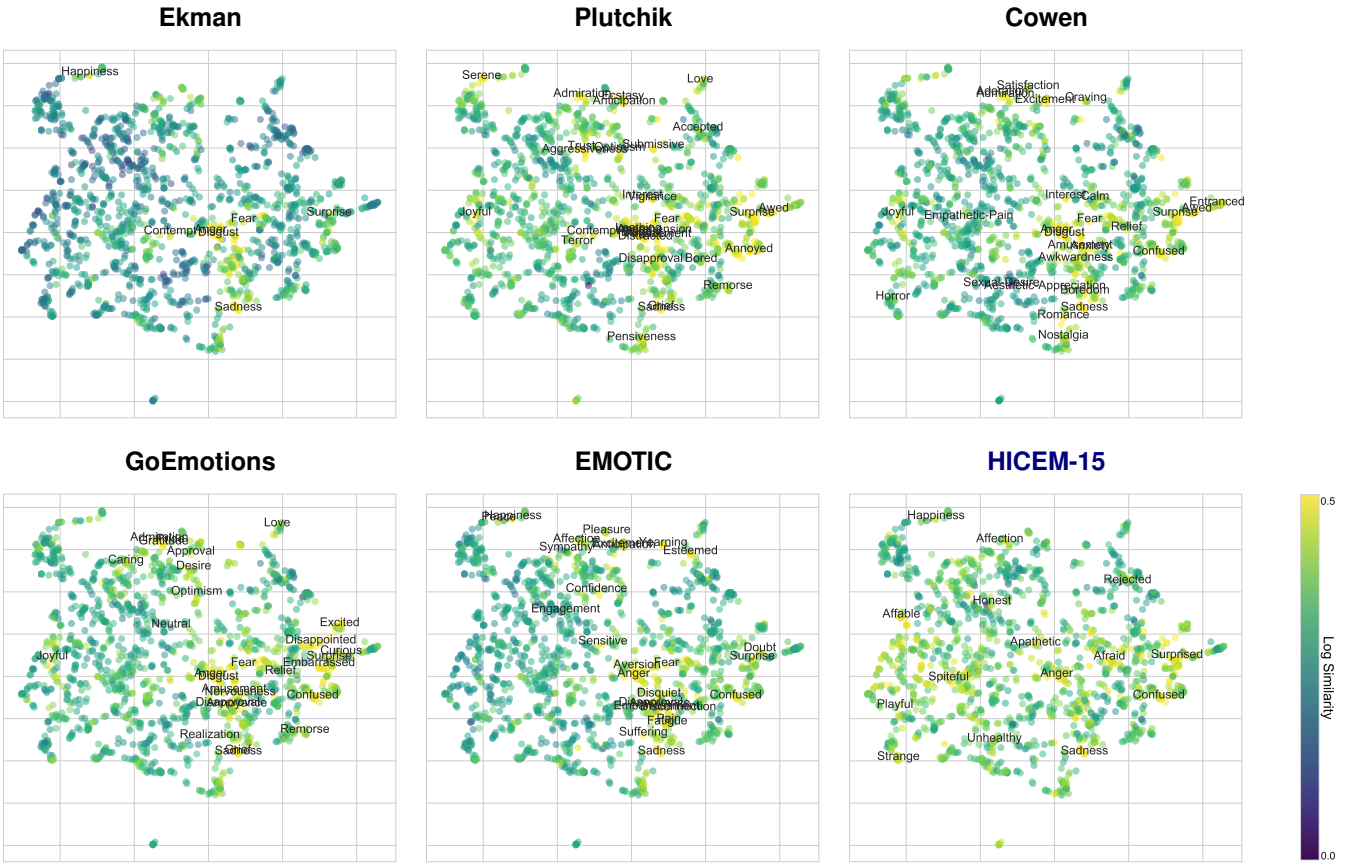

Fig. 5. Conventional emotion models provide incomplete representations across the entire emotion space. Here we visualize the maximum log cosine similarity (with a ceiling of 0.5) between the word vectors of 1,720 emotion concepts and the contents of the model. A higher cosine similarity (indicated in yellow) implies that the contents of the model have a similar semantic meaning to the given concept. For example, in the plot of Ekman's model, the concept of "Afraid" would appear in yellow since it is semantically akin to "Fear," whereas "Engagement" would be displayed in blue as it bears little similarity to any of Ekman's basic emotions. Let k denote the number of labels or components in an emotion model. We observe that Ekman's basic emotions [4] (k=7) are insufficient to capture the full spectrum of emotions. While Plutchik's wheel of emotion [5] (k=32) improves upon Ekman's model, it suffers from substantial label overlap. In contrast, our proposed HICEM-15 model leverages unsupervised techniques to minimize label overlap while offering nearly identical coverage as Plutchik's model, but with half as many components. For comparative purposes, we also include Cowen's emotions identified in video [6] (k=27), the annotation categories for the GoEmotions Dataset [7] (k=28), and the EMOTIC [15] dataset annotation scheme (k=27).

using cosine similarity (Eq. (2)), we compare the original word vector w_i with our recovered prediction $\hat{w}_i$ as follows:

$$\text{Avg. Recovered Information}(M) = \frac{1}{n}\sum_{i=1}^{n}\text{CosSim}(w_i, \hat{w}_i)\ . \tag{5}$$

In practice, if we are to annotate the emotional expression of a character in a video clip using a categorical emotion model, this would be equivalent to a human annotator for the clip assessing the degree of similarity or dissimilarity between the sample (*i.e.*, the character's emotional expression) and the labels of the given emotion model and then using those annotations to recover the ground-truth emotion present in the clip. There is often a level of disagreement among annotators in real-world settings, which adds noise to the oracle's embedding X. Nevertheless, the assumption of a perfect oracle establishes a theoretical upper bound on the amount of recoverable information, which we can leverage for comparative purposes.

In our experiment, we use the Ridge regression [71] for G and a 50/50 train-test split on the list of 1,720 emotion concepts. We then train on the similarity embeddings for

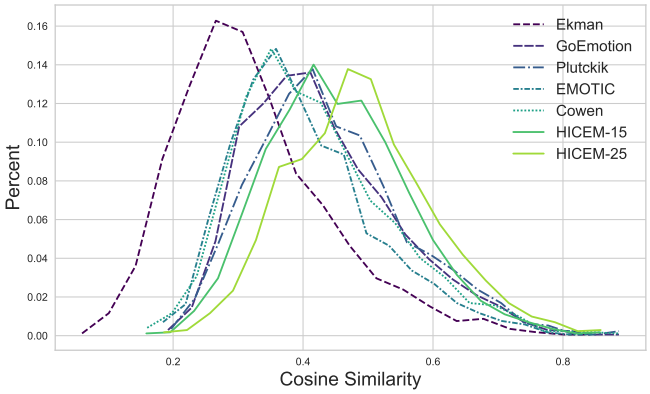

Fig. 6. In this histogram of coverage by cosine similarity across English word vectors, we show that our HICEM-15 model is able to provide higher coverage with fewer labels compared to other models of emotion popular in psychology [4], [5], [6], [7], [15], [42]. In English, our model achieves an average similarity of 0.45. This result is equivalent to the similarity between "happiness" and "calmness," "merriment," or "euphoria" (0.45 ± 0.01).

TABLE 5
Coverage across Languages and Emotion Models

Emotion Model	# Components	Average Coverage ↑						
		English	Arabic	Mandarin	French	Spanish	Russian	Total
Ekman	7	0.324	0.273	0.286	0.355	0.333	0.327	0.314
EMOTIC	27*	0.400	0.374	0.332	0.409	0.397	0.437	0.390
Cowen	27	0.432	0.352	0.332	0.443	0.447	0.505	0.415
GoEmotions	28†	0.430	0.362	0.332	0.449	0.448	0.479	0.414
Plutchik	32	0.461	0.365	0.341	0.457	0.475	0.503	0.428
HICEM-15	15	0.458	0.349	0.315	0.455	0.458	0.501	0.416
HICEM-25	25	0.503	0.378	0.337	0.484	0.490	0.528	0.444

* The combined category Doubt/Confusion was split into two labels †27 Emotion labels + Neutral

TABLE 6
Recoverable Information across Languages and Emotion Models

Emotion Model	# Components	Average Recoverable Information ↑						
		English	Arabic	Mandarin	French	Spanish	Russian	Total
Ekman	7	0.370	0.263	0.336	0.328	0.325	0.339	0.327
EMOTIC	27*	0.585	0.470	0.502	0.515	0.534	0.528	0.522
Cowen	27	0.577	0.414	0.497	0.512	0.545	0.529	0.512
GoEmotions	28†	0.592	0.473	0.504	0.540	0.544	0.552	0.534
Plutchik	32	0.620	0.485	0.525	0.552	0.573	0.562	0.552
Random-7	7	0.372	0.312	0.346	0.332	0.340	0.386	0.348
Random-15	15	0.507	0.393	0.435	0.442	0.468	0.497	0.457
Random-25	25	0.597	0.468	0.477	0.522	0.544	0.550	0.526
Random-30	30	0.625	0.492	0.491	0.550	0.566	0.564	0.548
HICEM-15	15	0.520	0.412	0.426	0.464	0.473	0.494	0.464
HICEM-25	25	0.591	0.451	0.482	0.537	0.548	0.556	0.528

* The combined category Doubt/Confusion was split into two labels †27 Emotion labels + Neutral

TABLE 7
Annotation Task User Study Results

Emotion Model	# Components	Median Time (seconds) ↓	Mean Annotations per Video	Average Majority in Agreement ↑	Mean Percentage in Agreement ↑
Ekman	7	120	1.09	0.7	.299
EMOTIC	26	375	1.21	0.9	.168
COWEN	27	287	1.16	0.5	.162
GoEmotions	28†	305	1.42	0.5	.157
Plutchik	32	383	1.12	0.5	.150
HICEM-15	15	123	1.18	0.9	.232
HICEM-25	25	499	1.22	0.8	.183

†27 Emotion labels + Neutral

each model to make a prediction on the original embedding. To provide a baseline, we randomly select subsets of words from the emotion-concept list of varying sizes. As shown in Fig. 7 and Table 6, HICEM-15 and HICEM-25 are the only emotion models that outperform a random subset of the same size. There are several possible explanations for this finding. First, this model's success could be influenced by the presence of redundant or overlapping labels in the random subsets. Second, because the random subsets were selected using a random uniform distribution, they are more likely to sample across the entire emotion concept space, thereby providing a greater amount of unique information. Lastly, our models benefit from being biased toward the emotion-concept list they are being tested against. Although other models touch on concepts such as craving [6] and pain [14], [15], these types of concepts have only recently been included in the discussion of emotion [60], [72], [73]. As they are included in the list of 1,720 emotion concepts, our models can better represent them since they are derived from this same list.

It is important to consider that in practice, there exists a trade-off between the size of the emotion model and the amount of information the annotators will give for any sample. As emotion models become more complex and include increasingly abstract concepts, the agreement between annotators decreases substantially. This reduction can be observed in the levels of inter-annotator agreement across several large-scale datasets that reported this information.

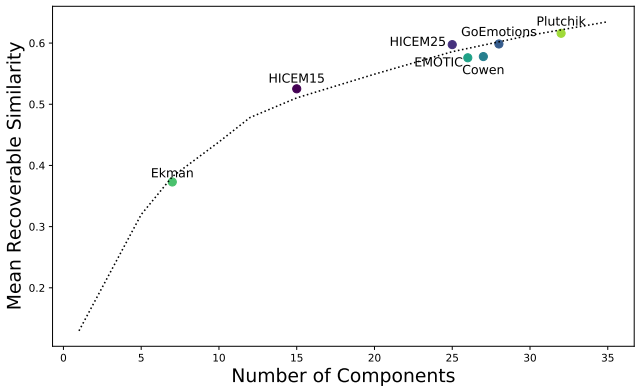

Fig. 7. In this plot of recovered cosine similarity vs. the number of components using English word vectors, the only models which outperform a uniform random sample of words (*i.e.*, the dotted line) are HICEM-15 and HICEM-25.

For example, despite several quality-control measures implemented during data collection and the post-processing done to filter unreliable annotators in the BoLD dataset [14], the average Fleiss' Kappa [74] across emotion categories is $\kappa = 0.173$ [14]. Intuitively, less complex emotions such as "Happiness" have higher levels of agreement, which are comparable to objective tasks performed at the time of data collection, such as determining age or ethnicity. Conversely, more abstract concepts, such as "Yearning" and "Sensitivity," exhibit almost no agreement among participants. This finding is consistent with the results from the EMOTIC [15] and GoEmotions [7] datasets. This comparison is significant, as increasing the size of the emotion model is likely to result in the inclusion of more abstract emotion concepts. Not only do additional components have diminishing returns in terms of the information they provide, but since emotion is subjective, they also suffer an agreement penalty during the annotation process, further limiting their effectiveness. One potential solution to mitigate this issue is to select more concrete emotion concepts as the foundation for emotion models. This approach was not considered when generating the random models in Table 6. Although they seem to outperform existing models in terms of recoverable information, the abstractness of their labels would severely constrain their real-world effectiveness.

3.4.2 User Studies

To measure the performance of HICEM in real-world annotation tasks, a study was conducted on Amazon Mechanical Turk. Participants were presented with short video clips, lasting between 6 to 10 seconds, and were instructed to select from a dropdown menu all emotions exhibited by by the subject in the scene. To ensure sufficient variability of the videos, ten of the most expressive samples were manually selected from the BoLD dataset [14] to provide coverage across all of BoLD's 26 emotion categories. For each emotion model, ten different participants annotated each of the ten videos, resulting in 700 annotations in total across the seven models. The base pay rate for this task was set at \$0.24 per video annotated (\$15 per hour) based on a preliminary test run, during which participants took approximately a minute per video.

Using this annotation task, we measure each model's performance across several metrics including median time to complete the task, mean annotations provided per video, average majority agreement, and mean percent agreement. Average majority agreement represents the number of times on average that at least 50% of the annotators selected the same emotion for a video. Similarly, mean percent agreement is the mean inter-rater agreement in terms of percent agreement across all emotion annotations for a video. For instance, a mean percent agreement of 0.3 would indicate that annotators agreed on the presence of a particular emotion roughly 30% of the time.

As shown in Table 7, there is a significant reduction in the median time required to annotate a video with HICEM-15 compared to larger existing emotion models. Likewise, both HICEM-15 and 25 show higher agreement between annotators in terms of mean agreement and the average number of labels with majority agreement. This suggests HICEM produces annotations of higher quality in less time than existing emotion models.

4 Large-Scale Data Analysis

To gain a deeper insight into how people consciously perceive emotion, we also examined annotations from two large-scale emotion recognition datasets: EMOTIC [15] and BoLD [14]. These are both in-the-wild datasets annotated for the same 26 categorical emotions as well as valence, arousal, and dominance [13]. Although the categorical emotions were not based on any pre-existing emotion models, there is enough overlap with these emotion models, enabling us to assess their validity. Additionally, as EMOTIC consists of images and BoLD consists of videos, the two datasets provide valuable insights into how humans perceive emotions in different modalities.

To provide a visual representation of the relationships between the annotated emotions, we projected them onto the VAD space, as illustrated in Figs. 9 and 10. In general, the categorical emotions share similar distributions for both datasets. However, looking at the plots for valence vs. dominance, there is a distinct cluster in the BoLD dataset for high-dominance, low-valence emotions such as "Anger," "Disapproval," "Aversion," and "Annoyance." Because these are all high arousal emotions, this difference between datasets may be attributed to the additional motion information present in video samples compared to static photos. Aside from this cluster, a strong correlation between dominance and valence is apparent, confirming previous findings that these dimensions are not completely orthogonal [76]. The collected annotations from these two datasets seem to confirm this finding. Even with the distinct clustering off the mainline dominance/valence plot, this can be accounted for by their separation in the arousal dimension. The scatter plots in Fig. 8 indicate that the only categorical emotion outside the "Anger" cluster that really benefits from the inclusion of dominance is confidence, as its heatmap appears uniformly distributed across the valence axis while decreasing from high dominance to low dominance. Similar to the linear relationship between valence and dominance, in the raw valence-arousal projections in Fig. 9, we also

Fig. 8. Categorical emotions plotted against valence and dominance for the BoLD dataset. Horizontal delineation suggests valence and vertical delineation suggests dominance as the discriminant factor. In these scatterplots of categorical emotions according to their valence and dominance ratings, there appears to be a gap (*i.e.*, blank space) for low-dominance, high-valence emotions. Looking at the few samples present in this area; these seem to represent guardian-child type relationships where one subject takes on the role of the protector and the other takes on the role of the child. We suggest the lack of samples in this area is due to some bias in the original data collection and not necessarily due to a limitation of the continuous VAD dimensions.

observe a collapse along the arousal dimension. This observation suggests changes in valence are the primary discriminative factor for differentiating emotions. This "valence focus" observation is consistent with previous studies [75]. Nevertheless, when the labels from the BoLD dataset are projected onto the unit circle based on the mean valence and arousal for each emotion, the outcome broadly aligns with the affective circumplex [33], [77].

In addition to the simple VAD embeddings (Fig. 12-16), we also once again produce UMAP embeddings [9] of the space as shown in Fig. 11. We performed this analysis on both datasets. However, due to the large imbalance in the EMOTIC dataset as well a lack of data cleaning similar to BoLD's annotator reliability analysis, we limit the following analysis strictly to BoLD. First, it is important to note that although the dimensions are not meaningful, we can assign some meaning to them by also looking at the continuous VAD annotations in the same embedding space. In general, valence corresponds to the horizontal axis with arousal on the vertical. Similar to their correlation in the 2D VAD embeddings, dominance closely follows valence by generally increasing from left to right. For each individual categorical emotion, we then generate a heatmap so we can see where it exists in these embeddings. The discreteness of these heatmaps provides insights into how fundamental each of these emotions is. For example, in Fig. 11, it is clear that "Happiness" and "Anger" occupy their own distinct clusters separate from the main grouping. Likewise, Ekman's other basic emotions (Sadness, Fear, Surprise) also have relatively discrete clusters, suggesting that they are a

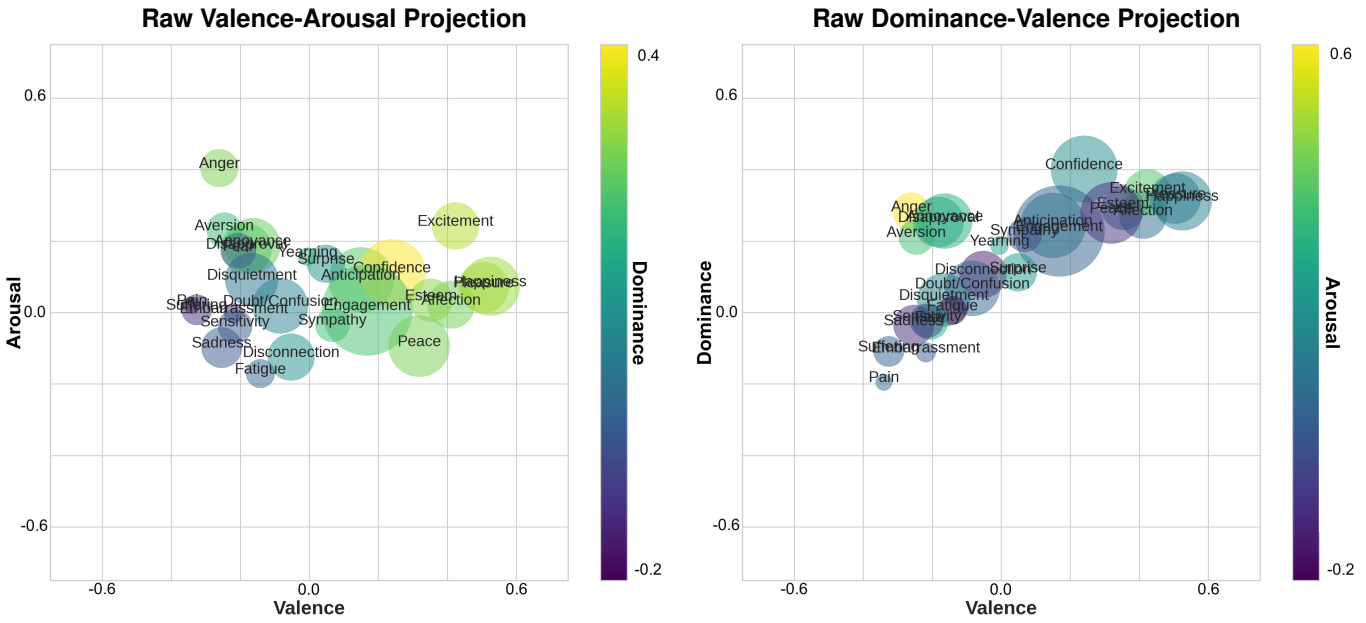

Fig. 9. Projections of BoLD categorical labels across continuous dimensions. **Left:** The relationship between raw Valence-Arousal dimensions is visualized. These are colored by Dominance. The circle size is based on the number of samples for that label within the BoLD dataset. The compression of emotions along the Arousal dimension is in line with previous experiments [75]. **Right:** Similar to previous work [76], the Dominance-Valence projection shows a strong linear relationship between these two dimensions.

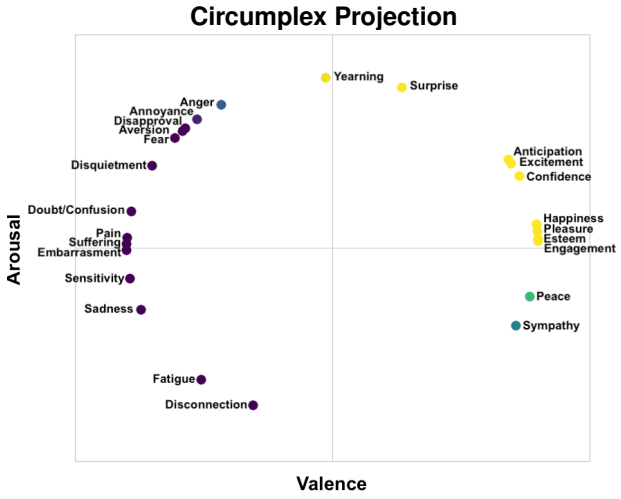

Fig. 10. Projections of BoLD categorical labels across continuous dimensions. When the BoLD labels are projected onto the unit circle for valence and arousal, the locations of the emotions broadly line up with the Affective Circumplex [33].

fundamental building block for more complex emotions. On the opposite end of the spectrum, "Anticipation" and "Engagement" appear almost randomly dispersed throughout the embedding space, indicating that they are more complex in their expression and present themselves in a wider range of scenarios.

5 Discussion

Through the use of word embeddings, we were able to demonstrate how existing models of human emotion in psychology either lack comprehensive coverage or contain redundant and overlapping labels. We used agglomerative clustering techniques to derive 15 components that minimized overlap and maximized coverage across different cultures. This model, HICEM-15, was able to provide nearly as much coverage as existing emotion models but with half the number of labels. Notably, the only basic emotion described by Ekman that was absent in HICEM was "Disgust." The combination of "Anger" and "Disgust" in our analysis is similar to previous work on biologically basic emotions [78].

Another consideration in the construction of comprehensive emotion models is the inclusion of general wellbeing/pain as well as a neutral affective state in the model. Although these are not classically thought of as emotions, their inclusion in HICEM is justified because wellbeing/pain is expressed through facial expressions and body language similar to other emotions, and "Neutral" affective states also contain a variety of information useful for filtering out functional movements (*e.g.*, walking) that are common in everyday life. In addition to this, recent work taking inspiration from componential models of emotion has looked to relate other physiological systems to affective states. Factors such as hunger, thirst, sleepiness, and stress have been shown to be connected to emotion [60], [79]. These factors can be added to the components found in HICEM to provide complete coverage across both physiological processes and emotion.

Although quantitative analysis shows diminishing returns after around 15 clusters, qualitatively the completeness of the model seems to peak between 25 and 30 emotion concepts, as previous studies have also found [6], [25]. Thus, it may be more advantageous to proceed with more than 15 base components in future dataset creation to ensure maximum completeness. Likewise, if specific areas of the emotion space are particularly relevant to a given domain, the hierarchical nature of our model allows for additional dimensions to be easily incorporated while maintaining max-

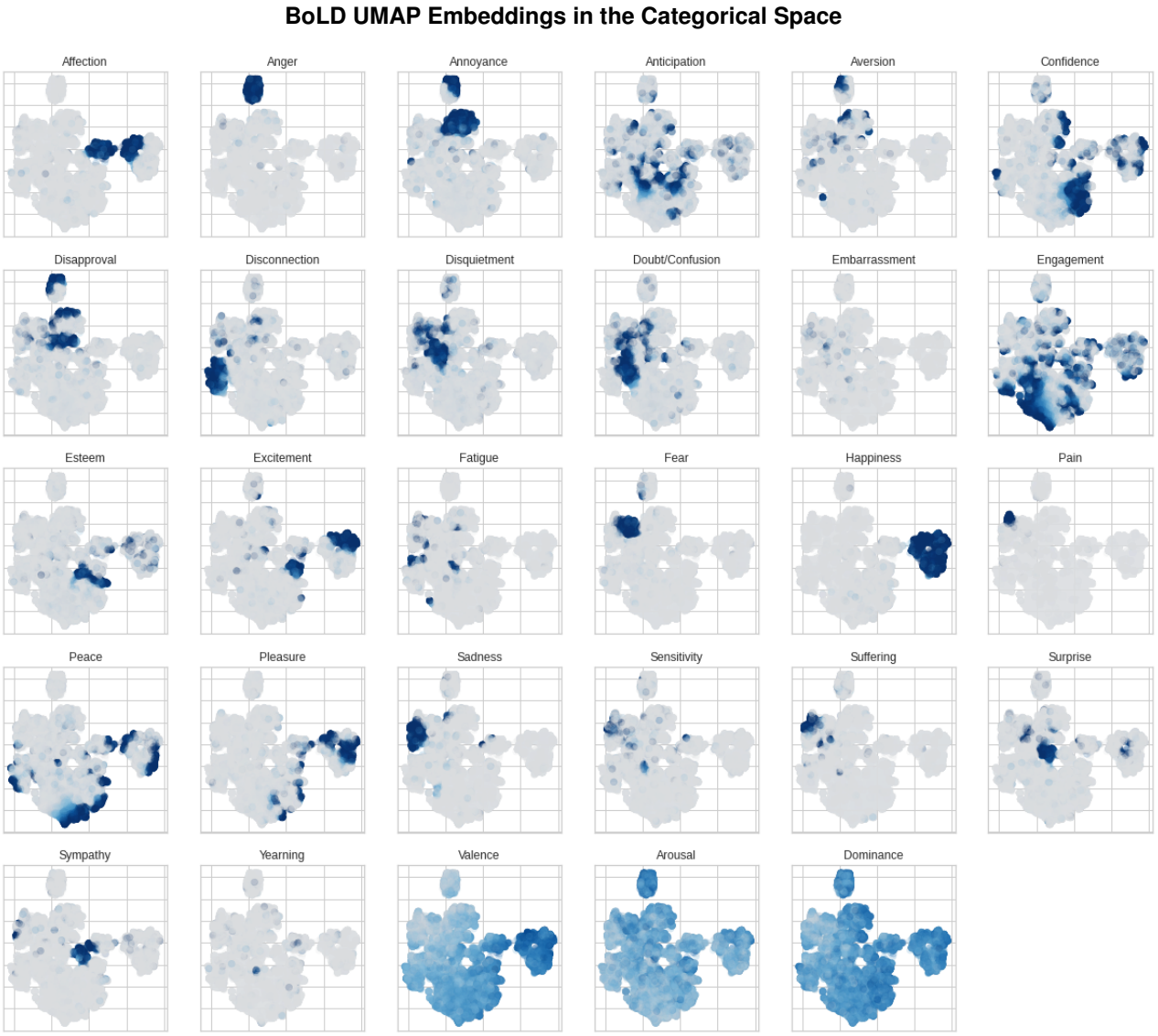

Fig. 11. Heatmaps for each of the 26 categorical emotions in the BoLD dataset based on their categorical UMAP embeddings. The blue areas represent where that emotion exists within this embedding. Ekman's basic emotions form concrete clusters suggesting they are the building blocks for more complex emotions such as Annoyance or Pleasure. Similarly, other higher-order emotions such as Anticipation and Engagement appear to spread out throughout the embeddings representing the wide range of scenarios in which they present themselves. Although the axes are meaningless, by projecting the continuous VAD dimension in this space (last three images) we can roughly correlate Valence and Dominance to the X-axis and Arousal to the Y-axis.

imum coverage. An example of this might be the inclusion of abnormal emotional states for mental health diagnoses. If we consider the clustering in Fig. 4 for 15 components, instead of using "bizarre" as a label, we can examine the two clusters that formed it and split the label into "zany" and "nonsensical."

Finally, similar to previous work, it is recommended that HICEM should be used in tandem with continuous affective dimensions (*i.e.*, VAD) to provide a holistic representation of the emotion space. Given the relationship between valence and arousal in existing large-scale datasets, it is recommended to eliminate dominance as a dimension in future data collection to reduce redundancies and costs associated with the data collection. Instead, other dimensions such as certainty or effort may be included. A fascinating extension of HICEM would be to explore the latent continuous dimensions of emotion and develop a similar high-coverage model to describe the space.

5.1 Limitations

A significant constraint of our analysis is that HICEM is tailored to our set of 1,720 emotion concepts. Since HICEM is derived from the same list it is being measured against, there is a bias favoring HICEM in our experiments involving coverage and recoverable similarity. The plots in Fig. 5 are helpful in understanding this bias since they show areas where other models under perform compared to HICEM. The user study performed as another point of comparison likewise had limitations in its set-up. A disclaimer was included at the start informing workers that they would be

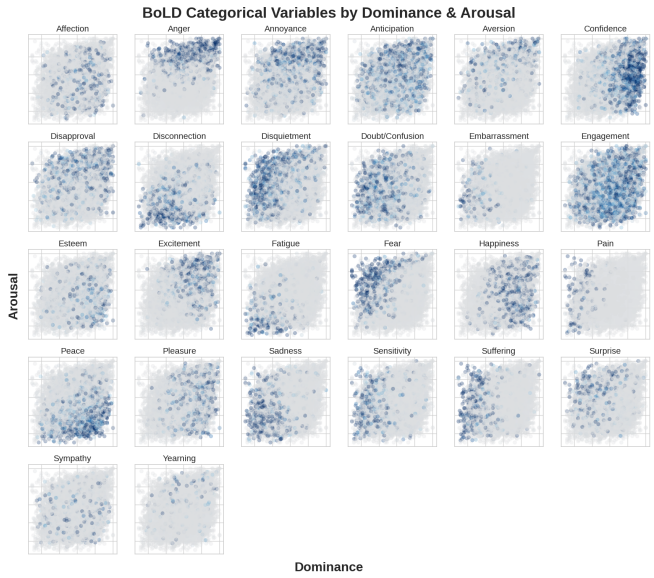

Fig. 12. Categorical emotions plotted against dominance and arousal for the BoLD dataset. Horizontal delineation suggests dominance and vertical delineation suggests arousal as the discriminant factor.

Fig. 13. Categorical emotions plotted against valence and arousal for the BoLD dataset. Horizontal delineation suggests valence and vertical delineation suggests arousal as the discriminant factor.

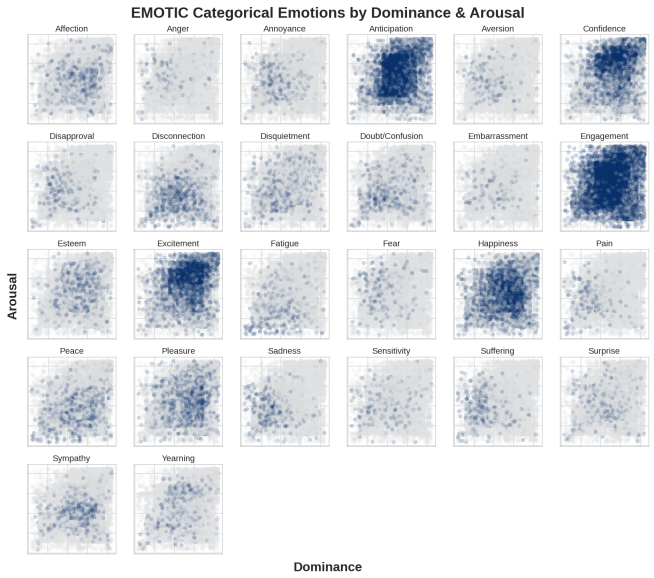

Fig. 14. Categorical emotions plotted against dominance and arousal for the EMOTIC dataset. Horizontal delineation suggests dominance and vertical delineation suggests arousal as the discriminant factor.

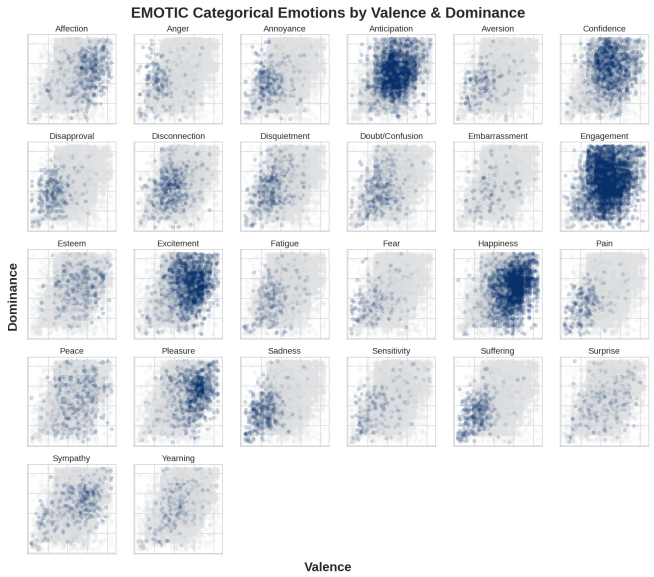

Fig. 15. Categorical emotions plotted against valence and dominance for the EMOTIC dataset. Horizontal delineation suggests valence and vertical delineation suggests dominance as the discriminant factor.

participating in an academic study. Because of this, some worker annotations may not be informative as they know this is an IRB approved task so their responses will not get penalized or rejected.

As previously stated, the use of word embeddings comes with a limitation regarding the occurrence of antonyms being used in similar contexts, which may lead to a higher cosine similarity than their synonyms. Although UMAP helps in increasing the distance between these antonyms in our analysis, the context issue can still influence cluster purity because there may be situations where it is difficult to differentiate them. By taking the median vector for each cluster, we minimize this effect when generating our summary words. Another alternative would be to use word-level emotion distributions as described by Li et al. [80] for text classification tasks. In addition to this, the use of Deep Learning (DL) generated embeddings [63] from free text annotations provides an intriguing alternative. These do not rely on local word context to generate their vectors and have shown higher performance in NLP tasks when compared to traditional methods.

In addition to the embeddings, our method is also constrained by translation. We minimized the influence of this by averaging across several cultures. However, better results for each individual language may be achieved by having native speakers generate localized emotion word lists and then using those lists to fine-tune the models. Similarly, although we can generate a consistent set of labels for use across

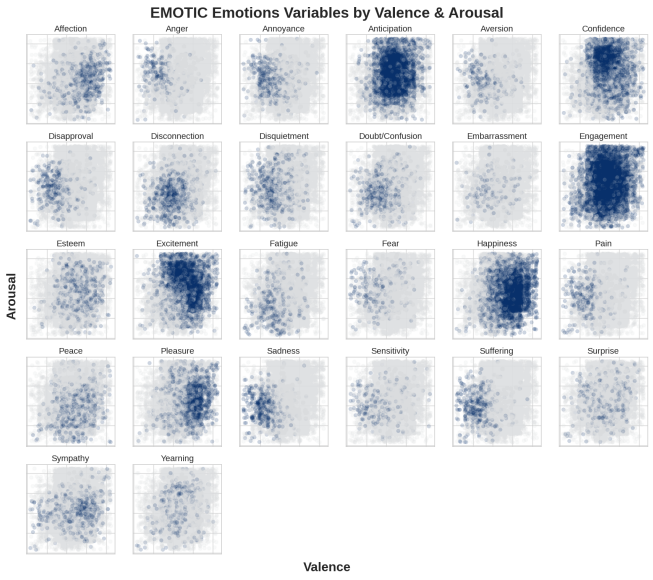

Fig. 16. Categorical emotions plotted against valence and arousal for the EMOTIC dataset. Horizontal delineation suggests valence and vertical delineation suggests dominance as the discriminant factor.

languages, the way people perceive different emotion words varies among cultures. Given that all languages appear to share the same 15 base components, transfer learning and fine-tuning can be performed to adjust machine learning models to better suit their local language context.

5.2 Applications

HICEM is primarily a descriptive tool, so its value comes from its ability to describe large numbers of affective states with relatively few labels. This is ideal for dataset annotation in modern data-driven AI because it maximizes the return on investment in terms of the amount of information gathered from each sample labeled. Although limited to 15 components, HICEM still provides comprehensive coverage of a wide range of human emotions. This advancement means next-generation affective computing or AEI applications leveraging HICEM will allow for more natural human-machine or human-robot interactions.

Furthermore, beyond its utility as an annotation tool, the methodology used to develop HICEM can also be utilized to construct a taxonomy of human emotion that is similar to WordNet [81]. Such a tool could have numerous applications in psychological research, as well as in succinctly describing a patient's emotional state. Because HICEM is limited to discrete emotions, an intriguing extension of this would be to use NLP word embeddings to identify equivalents for the continuous emotion dimensions.

6 Conclusions

While much research has been conducted on computational techniques for recognizing human emotion, little work has focused on examining the actual emotion models that underpin this research. As our analysis shows, existing models of emotion are insufficient for practical, real-world applications. In affective computing, coverage is of greater importance than the completeness of the emotion model due to the challenges associated with data collection and annotation. Through unsupervised techniques, we were able to identify 15 components that exhibit minimal overlap and maximum coverage across 1,720 emotion concepts. Our work presents a more efficient and effective model of human emotion, which represents a significant step toward achieving artificial emotional intelligence.

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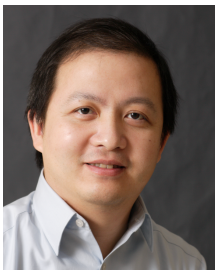

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Supplementary Material for HICEM: A High-Coverage Emotion Model for Artificial Emotional Intelligence

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List of 1,720 Emotion-related Words

A: abandoned, abashed, abhorrent, abominable, absurd, abused, abysmal, accepted, accustomed, acknowledged, acrimonious, acrimony, adamant, adept, adequate, admirable, admiration, admire, admired, adoration, adored, adulation, adventurous, adversarial, affable, affection, affectionate, affirmation, affirmed, affronted, afraid, aggression, aggressive, aggressiveness, aggrieved, aghast, agile, agitated, agonized, agony, agreeable, aked, alarmed, alarmist, alert, alertness, alienated, alienation, aloof, altruism, amazed, amazement, ambition, ambitious, ambivalence, ambivalent, amiable, amicable, amorous, amused, amusement, anemic, angelic, anger, angered, angry, angst, anguish, anguished, animus, annoyance, annoyed, antagonistic, antagonized, anticipation, antipathy, antisocial, antsy, anxiety, anxious, apathetic, apathy, apologetic, appalled, appreciated, appreciation, appreciative, apprehension, apprehensive, approachable, approval, ardent, argumentative, arousal, aroused, arrogance, artful, artistic, ashamed, asinine, assertive, assertiveness, astonished, astonishment, astounded, astute, atrocious, attentive, attentiveness, attraction, attuned, audacious, authentic, authoritative, averse, aversion, aware, awed, awesome, awestruck, awful, awkward, awkwardness

B: backed, bad, baffled, balanced, baseless, bashful, beautiful, bedazzled, bedeviled, bedraggled, befriended, befuddled, beguiled, beleaguered, belligerence, belligerent, beloved, bemused, benevolence, benevolent, besotted, betrayal, betrayed, bewildered, bewitched, bigoted, bitter, bitterness, bittersweet, bizarre, bleak, blessed, blindsided, bliss, blissful, bloodthirsty, blue, bohemian, boisterous, bold, boldness, bombast, boorish, bored, boredom, bossy, bothered, brash, bravado, brave, bravura, brazen, breathless, brilliance, brilliant, brooding, brotherhood, browbeaten, brutal, brutish, bullish, bullishness, bummed, buoyant, burdened

C: calamitous, callous, calm, calmed, calmness, camaraderie, campy, candid, canny, cantankerous, capable, captivated, carefree, careless, caring, cartoonish, catastrophic, catty, caustic, cautious, cavalier, celebrated, celebratory, centered, certain, chaos, chaotic, charisma, charismatic, charmed, charming, chatty, cheeky, cheerful, cheery, cherish, cherished, childish, childlike, chipper, chirpy, chuffed, chummy, circumspect, civilized, classless, classy, clever, closeness, clueless, cockiness, cocky, coercive, cognizant, collaborative, comatose, combative, comedic, comforted, comfy, comical, commendable, commitment, communicative, companionship, compassion, compassionate, compelled, competent, complacency, complicit, composure, compulsive, conceited, concern, concerned, conciliatory, condescension, confidence, confident, conflicted, confounded, confrontational, confused, confusion, congenial, conscientious, considerate, consoled, consternation, constructive, contemplation, contemplative, contempt, content, contented, contentious, contentment, contradicted, contradictory, contrite, controlled, controversial, convenient, convicted, cooperation, cooperative, cordial, cosmopolitan, courage, courageous, courteous, covetous, cowardice, cowardly, coy, crabby, crafty, cranky, crass, crave, craved, craven, craving, craziness, creative, credible, creepy, crestfallen, crippled, cruel, cruelty, crummy, crushed, cunning, curiosity, curious, curt, cuteness, cynical

D: dainty, dalliance, daring, daunted, daze, dazed, dazzled, deadpan, deceitful, decency, decent, deceptive, decisiveness, dedicated, dedication, defeated, defenseless, defensive, deferential, defiant, deflated, degraded, dejected, delight, delighted, delightful, delirious, deluded, delusional, demented, demoralized, demure, deplorable, depraved, depressed, depression, depressive, deprivation, desire, desirous, desolate, desolation, despair, desperate, desperation, despised, despondent, destitution, destructive, determination, determined, detested, devastated, devilish, devoted, diabolical, difficult, dignified, diligence, diligent, directionless, directness, disaffected, disagreeable, disappointed, disappointment, disapproval, disapproving, disbelief, disciplined, discombobulated, discomfited, discomfort, disconcerted, disconnected, disconnection, disconsolate, discontent, discontented, discontentment, discord, discouraged, disdain, disdainful, disempowered, disenchanted, disenchantment, disenfranchised, disgrace, disgraced, disgraceful, disgruntled, disgust, disgusted, disharmony, disheartened, disheveled, dishonesty, dishonorable, disillusioned, disillusionment, disinclined, disingenuous, disinterest, disinterested, disjointed, disliked, dismal, dismay, dismayed, dismissed, dismissive, disorganized, disorientation, disoriented, dispassionate, dispirited, displeased, displeasure, disquiet, disregarded,

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disrespect, disrespected, dissatisfaction, dissatisfied, dissension, dissonance, distaste, distasteful, distinct, distracted, distraction, distraught, distress, distressed, distrust, distrustful, disturbed, diverse, divisive, dizziness, dizzy, docile, dogmatic, doleful, dominant, dominated, doom, doomed, dopey, dorky, doubt, doubted, doubtful, downcast, downhearted, downtrodden, drained, drama, dread, dreaded, dreamlike, dreamy, dreary, driven, droll, dubious, dull, dumb, dumbfounded, dumbstruck, duplicitous, dutiful

E: eager, eagerness, earnest, earnestness, eccentric, ecstasy, ecstatic, edgy, eerie, effervescent, efficiency, effusive, egotistic, egotistical, elated, elation, electrified, elitist, eloquence, eloquent, embarrassed, embarrassment, embattled, embittered, emboldened, embraced, emotionless, empathetic, empathy, empowered, emptiness, enamored, enchanted, encouraged, endorsed, energetic, energized, engagement, engrossed, enigmatic, enjoyment, enlightened, ennui, enraged, enraptured, enthralled, enthused, enthusiasm, enthusiastic, entranced, envied, envious, envy, erotic, erratic, esteemed, estranged, estrangement, ethereal, euphoria, euphoric, evocative, exalted, exasperated, exasperation, excellent, exceptional, excitable, excited, excitement, exemplary, exhausted, exhaustion, exhilarated, exhilaration, expressionless, expressive, exquisite, exuberance, exuberant, exultant

F: fabulous, faith, faithful, faithfulness, fanatical, fantastic, fantastical, farcical, fascinated, fascination, fastidious, fated, fatherly, fatigue, fatigued, faultless, fawning, fazed, fear, feared, fearful, fearless, fearlessness, fearsome, feckless, fed-up, feeble, feisty, ferocious, fervent, fervor, festive, feted, fevered, feverish, fidgety, fiendish, fierce, fine, fixated, flabbergasted, flakey, flaky, flamboyance, flamboyant, flawed, flawless, flexible, flippant, flirtatious, flirty, flummoxed, flustered, focused, fondness, foolish, foolishness, forced, forceful, forgetful, forgiveness, forgotten, forlorn, formidable, forsaken, forthright, fortitude, fractious, frantic, frazzled, freaky, freedom, frenetic, frenzied, frenzy, fretful, fretted, friction, friendliness, friendly, friendships, fright, frightened, frisky, frivolous, frustrated, frustration, fulfilled, fulfillment, fumed, fun, funny, furious, fury

G: gallant, galled, genial, gentle, gentlemanly, gentleness, genuine, giddy, glad, gleeful, glib, gloomy, glorious, glum, glumness, gluttony, gobsmacked, godly, good, goofy, gorgeous, grace, graceful, gracious, grandeur, grateful, gratification, gratified, gratitude, great, greed, greedy, gregarious, grief, grim, griped, gripped, gritty, groggy, grotesque, grouchiness, grouchy, grounded, groundless, gruff, grumble, grumpiness, grumpy, guilt, guilty, gumption, gutless, gutsy

H: hapless, happiness, happy, harassed, hardy, harmed, harmonious, harried, harsh, hate, hated, hateful, hatred, haughty, headstrong, healed, healthful, healthy, heartache, heartbreak, heartbroken, heartened, heartfelt, heartless, heartsick, heartsore, heavenly, hedonistic, heinous, hellish, helpless, helplessness, heroic, heroism, hesitancy, hesitant, hesitated, hesitation, hilarious, homesick, homesickness, homey, homicidal, honest, honesty, honorable, honored, hope, hopeful, hopeless, hopelessness, horny, horrendous, horrible, horrified, horror, hostile, hounded, hubris, humble, humbled, humiliated, humiliation, humorless, humorous, hurried, hurt, hurtful, hushed, hyperactive, hypnotic, hysteria, hysterical

I: ideal, idealism, idealistic, idleness, idyllic, iffy, ignorance, ignored, ill-at-ease, imaginative, imbalanced, immaculate, immoral, impassioned, impatience, impatient, imperious, impetuous, impolite, impotent, impressed, impressionistic, impressive, impulsive, inadequacy, inadequate, inattentive, incapable, incapacitated, incensed, incisive, incited, inclined, incoherent, incompetence, incompetent, inconsiderate, inconsistent, inconsolable, inconvenient, incredible, incredulous, indecision, indecisive, indefatigable, indifference, indifferent, indignant, indignation, indomitable, industrious, ineffective, ineffectual, inefficient, inept, inexcusable, infatuated, infatuation, inferior, inflamed, influenced, influential, informative, informed, infuriated, injured, innocence, innocent, innovative, inquisitive, insecure, insightful, insincere, insipid, inspired, insufficient, insulted, intelligent, intense, interest, interested, intimacy, intimate, intimidated, intolerable, intolerance, intolerant, intoxicated, intransigent, intrigued, introspective, introverted, intuitive, invective, inventive, invigorated, invited, irate, irked, ironic, irrational, irrepressible, irresponsible, irreverence, irreverent, irritable, irritated, irritation, isolated, isolation

J: jaded, jaunty, jealous, jealousy, jeered, jilted, jittery, jolly, jovial, joyful, joyous, jubilant, jubilation, judgmental, jumpy

K: keen, keenness, kind, kindness, kinship, kitsch, kitschy, kooky

L: lackadaisical, lackluster, laconic, laidback, lame, languid, lawlessness, laziness, lazy, leery, lenient, lethargic, lethargy, liberated, liberation, lifeless, lighthearted, lightness, liked, listless, lithe, lively, livid, loathed, loathing, loathsome, loneliness, lonely, lonesome, longed, loony, loopy, loquacious, lost, lousy, love, loved, lovelorn, lovely, loving, loyalty, ludicrous, lulled, luminous, lunacy, lust, lustful, lusty

M: macabre, mad, magical, magnanimous, magnificence, magnificent, majesty, malaise, malevolent, malicious, mania, maniacal, manic, manipulative, mannered, marginalization, marginalized, marvel, marveled, marvelous, masterful, maternal, mean, meanness, mediocre, meditate, meditative, meek, melancholic, melancholy, mellow, mended, merciful, merciless, merriment, merry, mesmerized, methodical, miffed, mindful, miracle, miraculous, mirth, mirthful, mischievous, miserable, miserliness, misery, misgivings, misguided, misinterpreted, mistreated, mistrust, misunderstood, misused, modesty, molested, moody, morbid, moronic, morose, mortified, motherly, motivated, mournful, mystical, mystified

N: naivete, naivety, narcissism, narcissistic, nasty, natural, naughty, nauseated, nauseous, neat, necessary, negative, neglect, neglected, neglectful, negligent, nervous, nervousness, nervy, neurotic, neutral, nice, nightmarish, nirvana, noble, nonchalant, noncommittal, nonsensical, nostalgia, nostalgic, nuanced, numb, numbed, numbness, nurturing, nutty

O: obedient, objectivity, oblivious, obnoxious, observant, obsessed, obsession, obsessive, obstinate, obtuse, offended, okay, ominous, oneness, openness, opinionated, opposed, oppressed, optimism, optimistic, ornery, ostracized, otherworldly, outrage, outraged, outrageous, outrageousness, outspoken, overbearing, overjoyed, overlooked, overwhelmed, overwrought

P: pacified, pain, pained, painful, panic, panicked, panicky, paralysis, paralyzed, paranoia, paranoid, passion, passionate, paternalistic, pathetic, patience, peace, peaceful, peerless, peeved, peevish, pensive, pensiveness, peppy, perceptive, perfect, perilous, perky, pernicious, perplexed, persecuted, perseverance, persevere, persevered, persistence, personable, persuasive, perturbed, perverse, perverted, pessimism, pessimistic, petrified, phenomenal, piety, pious, piqued, pithy, pitiful, placid, plagued, plaintive, playful, playfulness, pleasant, pleased, pleasure, plucky, poetic, poignant, pointless, poise, polite, politeness, pompous, positive, possessive, potent, powerful, powerless, powerlessness, prayerful, precarious, precocious, prejudice, prejudiced, preoccupation, preoccupied, prepared, pressured, presumptuous, pretension, pretentious, pride, principled, proactive, productive, profane, proper, prosecuted, prosperous, proud, provocative, provoked, prudence, psyched, pugnacious, punished, puritanical, pushy, puzzled

Q: quarrelsome, queasy, questionable, questioned, quick, quickness, quirkiness, quirky

R: rabid, radiant, radical, rage, rambunctious, rancorous, rankled, rapturous, raucous, ravished, reactionary, readied, ready, reassured, rebellious, rebutted, recalcitrant, receptive, reckless, recklessness, recognized, reflective, refreshed, refuted, regret, regretful, reinvigorated, rejected, rejection, rejoiced, rejuvenated, relaxation, relaxed, relentless, relief, relieved, religious, reluctance, reluctant, remarkable, remembered, remorse, remorseful, renegade, renewed, repentant, reproachful, repudiated, repugnant, repulsed, repulsive, rescued, resent, resented, resentful, resentment, resigned, resilient, resolute, resonant, resourcefulness, respect, respectable, respected, respectful, responsive, rested, restful, restless, restlessness, restrained, retaliative, reticence, reticent, revelatory, revered, reverence, reverent, reviled, revitalized, revived, revulsion, ridiculous, righteous, riotous, risque, robust, romance, romantic, rudderless, rudeness, ruffled, ruinous, ruthless, ruthlessness

S: sad, saddened, sadness, safe, sanctimonious, sanguine, sarcasm, sarcastic, sardonic, sassy, satirical, satisfaction, satisfied, saucy, savage, saved, scandalized, scandalous, scared, scary, schadenfreude, scornful, scrappy, scrupulous, scuttled, secluded, secrecy, secretive, secure, sedate, seduced, seduction, seductive, self-righteous, selfish, selfishness, selfless, selflessness, sensational, sensitive, sensual, sensuous, sentimental, serene, serious, sexiness, sexy, shaky, shambolic, shame, shamed, shameful, shameless, shattered, sheepish, shock, shocked, showy, shy, shyness, sick, sickened, silliness, silly, sincere, skeptical, skepticism, skillful, skittish, sleepiness, slighted, sloppy, sluggish, sluggishness, sly, smarmy, smart, smiley, smitten, smug, snappy, snarky, snobbery, snooty, snubbed, sociable, solemn, solid, solitude, somber, sombre, sordid, sore, soreness, sorrow, sorrowful, sorry, soulful, soulless, spectacular, speechless, spellbound, spineless, spirited, spiritual, spite, spiteful, splendid, spontaneous, spooked, spunky, spurned, squalid, stable, stagnant, startled, steadiness, steady, stellar, stiffness, stilted, stimulated, stirred-up, stoic, straightforward, stranded, strange, strangeness, strength, strengthened, stress, stressed, strident, strife, strong, stubborn, stubbornness, stuck, studious, stunned, stupefied, stupendous, stupid, subdued, sublime, submissive, subpar, subservient, substandard, succinct, suffered, suffering, suicidal, sulkiness, sulky, sullen, sullenness, sumptuous, superb, superior, supernatural, supported, supportive, surly, surprise, surprised, surreal, suspenseful, suspicious, swamped, sweetness, sympathetic, sympathy

T: taciturn, talkative, tantalized, tasteless, tearful, tedium, tempestuous, tempted, tenacious, tender, tendered, tenderness, tense, tension, tepid, terrible, terrific, terrified, terror, testy, thankful, thankfulness, thoughtful, thoughtfulness, thoughtless, threatened, thrill, thrilled, thuggish, tickled, timeless, timid, tired, tiredness, tireless, titillated, togetherness, tolerance, tolerant, torment, tormented, tortured, touchy, tough, toughness, tragedy, tragic, tranquil, transparent, trapped, traumatized, tremendous, tremulous, trepidation, tricky, trippy, triumph, triumphant, troubled, trust, trusted, trustworthiness, trustworthy, truthful, truthfulness, turbulent, turmoil, twitchy

U: unabashed, unacceptable, unaware, unbalanced, unbridled, unburdened, uncertain, uncertainty, uncivilized, uncomfortable, uncomplicated, unconcerned, unconscionable, unconvinced, uncooperative, undercut, undermined, understood, underwhelmed, undesirable, undeterred, undisciplined, unease, uneasiness, uneasy, unethical, unfazed, unflappable, unfocused, unfortunate, unfriendly, unfunny, ungrateful, unhappiness, unhappy, unhealthy, unhelpful, unhinged, unhurried, unimpressed, unimpressive, uninformed, uninhibited, uninspired, uninterested, unique, uniqueness, unmoved, unnatural, unnecessary, unnerved, unparalleled, unperturbed, unpleasant, unpleasantness, unpopular, unpredictable, unprepared, unprofessional, unprovoked, unresponsive, unrivaled, unruffled, unsafe, unsatisfied, unsavory, unscrupulous, unseemly, unselfish, unselfishness, unsettled, unspectacular, unstable, unsteady, unsuccessful, unsympathetic, untruthful, unwillingness, unworthy, uplifted, uproarious, upset, uptight, urbane, useful, useless

V: vacuous, valiant, vehement, vengeful, venomous, verdant, vexed, vibrant, vicious, viciousness, victimized, vigilance, vigilant, vigorous, vile, vindicated, vindication, vindictive, violated, violent, vitriolic, vivacious, volatile, vulgar, vulnerable

W: wacky, wanted, wariness, warmhearted, warmth, warned, wary, weak, weakness, weariness, weary, weepy, weird, welcomed, whimsical, whimsy, whiny, wicked, willingness, wily, wistful, witty, woeful, wonder, wonderful, wonderment, wondrous, woozy, worried, worrisome, worry, worshipful, worthwhile, worthy, wowed, wrath, wrathful, wretched, wronged

X: –

Y: yearn, yearning, youthful

Z: zany, zealous, zestful