Learning Emotion Representations from Verbal and Nonverbal Communication

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Abstract

Emotion understanding is an essential but highly challenging component of artificial general intelligence. The absence of extensive annotated datasets has significantly impeded advancements in this field. We present EmotionCLIP, the first pre-training paradigm to extract visual emotion representations from verbal and nonverbal communication using only uncurated data. Compared to numerical labels or descriptions used in previous methods, communication naturally contains emotion information. Furthermore, acquiring emotion representations from communication is more congruent with the human learning process. We guide EmotionCLIP to attend to nonverbal emotion cues through subject-aware context encoding and verbal emotion cues using sentiment-guided contrastive learning. Extensive experiments validate the effectiveness and transferability of EmotionCLIP. Using merely linear-probe evaluation protocol, EmotionCLIP outperforms the state-of-the-art supervised visual emotion recognition methods and rivals many multimodal approaches across various benchmarks. We anticipate that the advent of EmotionCLIP will address the prevailing issue of data scarcity in emotion understanding, thereby fostering progress in related domains. The code and pre-trained models are available at https://github.com/Xeaver/EmotionCLIP.

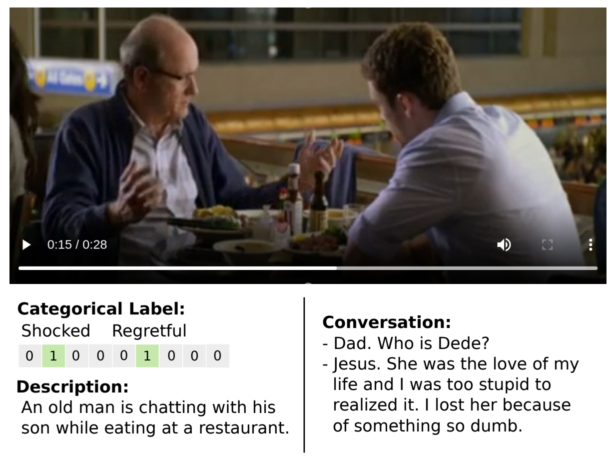

Figure 1. Emotions emerge naturally in human communication through verbal and nonverbal cues. The rich semantic details within the expression can hardly be represented by human-annotated categorical labels and descriptions in current datasets.

1. Introduction

If artificial intelligence (AI) can be equipped with emotional intelligence (EQ), it will be a significant step toward developing the next generation of artificial general intelligence [46, 92]. The combination of emotion and intelligence distinguishes humans from other animals. The ability to understand, use, and express emotions will significantly facilitate the interaction of AI with humans and the environment [20, 48–50], making it the foundation for a wide variety of HCI [3], robotics [11], and autonomous driving [31] applications.

Artificial emotional intelligence (AEI) research is still in its nascency [30, 73]. The recent emergence of pre-trained models in CV [10, 24, 62] and NLP [7, 16, 33, 68] domains has ushered in a new era of research in related subjects. By training on large-scale unlabeled data in a self-supervised manner, the model learns nontrivial representations that generalize to downstream tasks [42, 62]. Unfortunately, such a technique remains absent from AEI research. The conventional approaches in visual emotion understanding have no choice but to train models from scratch, or leverage models from less-relevant domains [27, 66], suffering from data scarcity [29, 45]. The lack of pre-trained models greatly limits the development of AEI research.

Research in neuroscience and psychology offers insights for addressing this problem. Extending from the capabilities that have been coded genetically, humans learn emotional expressions through daily interaction and communication as early as when they are infants. It has been shown that both vision [58] and language [41] play crucial roles in this learning process. By absorbing and imitating expressions from others, humans eventually master the necessary

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feelings to comprehend emotional states by observing and analyzing facial expressions, body movements, contextual environments, *etc*.

Inspired by how humans comprehend emotions, we propose a new paradigm for emotion understanding that learn directly from human communication. The core of our idea is to explore the consistency between verbal and nonverbal affective cues in daily communication. Fig. 1 shows how communication reveals emotion. Our method that learns from communication is not only aligned with the human learning process but also has several advantages:

1) *Our method bypasses the problems in emotion data collection by leveraging uncurated data from daily communication.* Existing emotion understanding datasets are mainly annotated using crowdsourcing [29, 45, 77]. For image classification tasks, it is straightforward for annotators to agree on an image's label due to the fact that the label is determined by certain low-level visual characteristics. However, crowdsourcing participants usually have lower consensus on producing emotion annotations due to the subjectivity and subtlety of affective labels [90]. This phenomenon makes it extremely difficult to collect accurate emotion annotations on a large scale. Our approach does not rely on human annotations, allowing us to benefit from nearly unlimited web data.

2) *Our use of verbal expressions preserves fine-grained semantics to the greatest extent possible.* Limited by the data collection strategy, existing datasets usually only contain annotations for a limited number of emotion categories, which is far from covering the space of human emotional expression [86]. Moreover, the categorical labels commonly used in existing datasets fail to precisely represent the magnitude or intensity of a certain emotion.

3) *Our approach provides a way to directly model expressed emotion.* Ideally, AEI should identify the individual's emotional state, i.e., the emotion the person desires to express. Unfortunately, it is nearly impossible to collect data on this type of "expressed emotion" on a large scale. Instead, the current practice is to collect data on "perceived emotion" to approximate the person's actual emotional state, which inevitably introduces noise and bias to labels.

In general, learning directly from how humans express themselves is a promising alternative that gives a far broader source of supervision and a more comprehensive representation. This strategy is closely analogous to the human learning process and provides an efficient solution for extracting emotion representations from uncurated data.

We summarize our main **contributions** as follows:

- We introduce EmotionCLIP, the first vision-language pre-training paradigm using uncurated data to the visual emotion understanding domain.
- We propose two techniques to guide the model to capture salient emotional expressions from human verbal and nonverbal communication.
- Extensive experiments and analysis demonstrate the superiority and transferability of our method on various downstream datasets in emotion understanding.

2. Related Work

Emotion Recognition from Visual Clues. Facial expression recognition [19, 38, 69] has been well studied in the field of emotion recognition, mainly because faces are not only expressive but also easy to model. Handcrafted features have been developed to describe different facial expressions [13, 43, 74]. Recently, deep learning-based approaches have begun to emerge [38]. Principal research focuses on the design of novel modules for conventional network architectures [88], distinct loss functions for facial tasks [15, 71, 85], and addressing label uncertainties [8, 80].

Recently, with the growing interest in recognizing emotion in the wild, the focus of research has gradually shifted to modeling body language [21, 45, 59] and context [29, 53, 54]. Several datasets for understanding human emotional states in unconstrained environments have been proposed [5, 60, 77]; Kosti *et al*. [29] and Yu *et al*. [45] established the first benchmark for image and video data, respectively. Follow-up work mainly focuses on context-aware emotion recognition, which usually adopts a multi-branch structure where one branch focuses on the face or body and the other focuses on capturing context [12,34,53,59]. Moreover, some approaches take into account temporal causality [54] or represent context information via graphs [96]. To the best of our knowledge, there are no pre-trained models or effective methods for leveraging unlabeled data in the domain of visual emotion recognition.

Vision-Language Pre-training. Visual-language pre-training has achieved remarkable progress recently. CLIP [62] demonstrated the feasibility of using contrastive learning [10, 56] to learn transferable and powerful visual representations from large-scale image-text pairs [72]. Many follow-up approaches have been proposed to transfer the pre-trained model to downstream tasks [22, 97, 100] or leverage the scheme for different domains [37, 57, 64, 83, 98]. A line of research endeavors to expand CLIP for general video understanding [26,35,40,44,55,82,87]. The majority of the effort focuses on fine-tuning datasets with textual annotations [27,32,39]. However, not only are these curated annotations challenging to obtain, but they also limit the model's potential in various applications. Another line of work [36, 87] extends the image-level pre-training by utilizing unlabeled narrated videos [2, 52], similar to ours. However, we aim to learn abstract *emotion representations* rather than low-level visual patterns, which are beyond the reach of current models. EmotionNet [84] and its sequel [99], which likewise seeks to learn visual emotion repre-

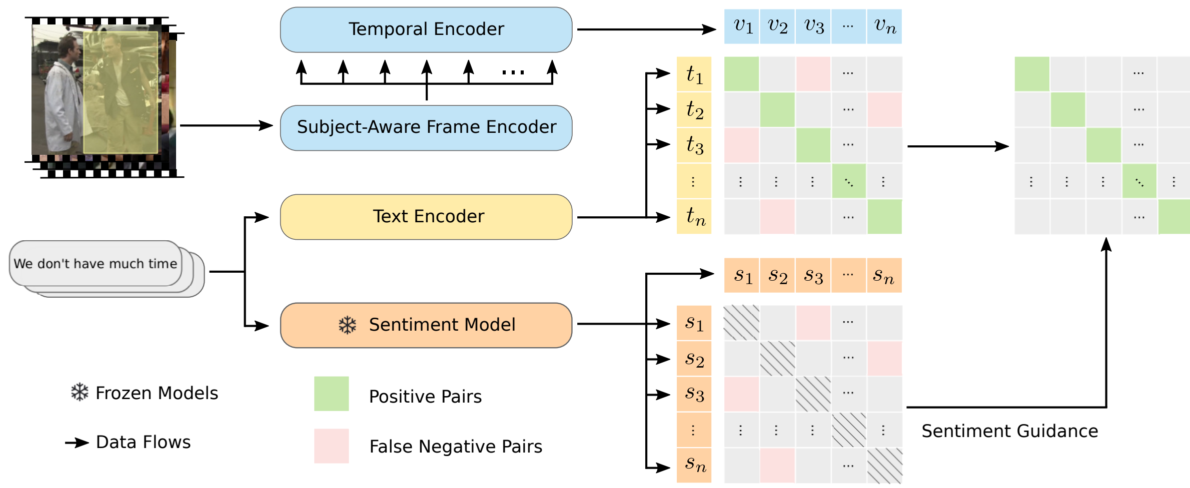

Figure 2. Illustration of **EmotionCLIP**. For *nonverbal communication*, subject and context information is modeled by a frame encoder and further aggregated into video-level representations by a temporal encoder. For *verbal communication*, textual information is encoded as text representations and sentiment scores by a text encoder and sentiment analysis model, respectively. The model learns emotion representations under sentiment guidance in a contrastive manner, by exploring the consistency of verbal and nonverbal communication.

sentations, are connected to ours. However, their primary focus is on the images' stimuli rather than the recognition of human emotional expressions in the wild.

3. Methodology

Our core idea is to learn directly from human communication how they express their emotions, by exploring the consistency between their verbal and nonverbal expressions [41]. We tackle this learning task under the vision-language contrastive learning framework [62], that is, the model is expected to learn consistent emotion representations from the verbal expressions (*e.g.*, utterance and dialogue) and nonverbal expressions (*e.g.*, facial expression, body language, and contextual environment) of the same individuals. We give a brief introduction of our data collection procedure in Sec. 3.1 before presenting the overview of EmotionCLIP in Sec. 3.2. We further discuss how the model is guided to learn emotion-relevant representations from the nonverbal perspective in Sec. 3.3, and from the verbal perspective in Sec. 3.4. Please see Appendix for details of the dataset and implementations.

3.1. Data Collection

Publicly available large-scale vision-and-language datasets do not provide desired verbal and nonverbal information because they either comprise only captions of low-level visual elements [2, 72] or instructions of actions [52]. The captions mostly contain a brief description of the scene or activity, which is insufficient to reveal the underlying emotions; the instruction videos rarely include humans in the scene or express neutral emotions, which fail to provide supervision signals for emotion understanding. To overcome such problems, we gather a large-scale video-and-text paired dataset. More specifically, the videos are TV series, while the texts are the corresponding closed captions. We collected 3,613 TV series from YouTube, which is equivalent to around a million raw video clips. We processed them using the off-the-shelf models to group the words in closed caption into complete sentences [23], tag each sentence with a sentiment score [68], and extract human bounding boxes [79].

3.2. Overview of EmotionCLIP

Fig. 2 presents an overview of our approach. We follow the wildly adopted vision-language contrastive learning paradigm [62] where two separate branches are used to encode visual inputs (*i.e.*, nonverbal expressions) and textual inputs (*i.e.*, verbal expressions), respectively.

Video Encoding. The visual branch of EmotionCLIP takes two inputs, including a sequence of RGB frames X_v and a sequence of binary masks X_m. The binary mask has the same shape as the frame and corresponds to the frame one-to-one, indicating the location of the subject within the frame. The backbone of the subject-aware frame encoder f_i is a Vision Transformer [17]. In particular, it extracts m non-overlapping image patches from the frame and projects them into 1D tokens $z_i \in \mathbb{R}^d$. The sequence of tokens passed to the following Transformer encoder [76] is $\mathbf{z} = [z_1, \cdots, z_m, z_{cls}, z_{hmn}]$, where z_{cls}, z_{hmn} are two additional learnable tokens. The mask X_m is converted to an array of indices P indicating the image patches containing the subject. The frame encoder further encodes $\mathbf{z}, P$ into a frame-level representation. All frame representa-

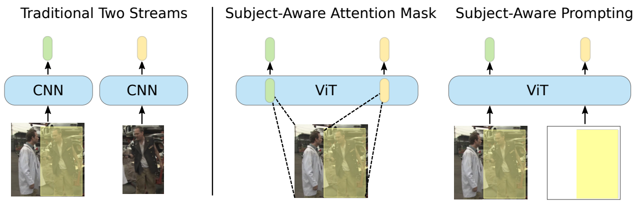

Figure 3. The traditional approaches (*left*) ignore the dependencies between context and subject, and encode a portion of the image redundantly. The proposed approaches (*right two diagrams*) efficiently model the subject and context in a synchronous way.

tions are then passed into the temporal encoder f_p to produce a video-level representation as $v = f_v(\mathbf{z}, P)$, where $f_v = f_p \circ f_i$ and $v \in \mathbb{R}^d$.

Text Encoding. The textual branch of EmotionCLIP takes sentences X_t as inputs. The text encoder f_t is a Transformer [16] with the architecture modification described in [63], and the sentiment model f_s is a pre-trained sentiment analysis model [68] that is frozen during training. The input text is encoded by both models as $t = f_t(X_t)$ and $s = f_s(X_t)$, where $t \in \mathbb{R}^d$ is the representation of the text and $s \in \mathbb{R}^7$ is the pseudo sentiment score.

Training Objective. The training objective is to learn the correspondence between visual inputs and textual inputs by minimizing the sentiment-guided contrastive loss $\mathcal{L}$.

We discuss the details of the proposed subject-aware encoding approaches in Sec. 3.3 and the sentiment-guided contrastive learning framework in Sec. 3.4.

3.3. Subject-Aware Context Encoding

Context encoding is an important part of emotion understanding, especially in unconstrained environments, as it has been widely shown in psychology that emotional processes cannot be interpreted without context [47, 51, 65]. We intend to guide the model to focus on the interaction between the subject of interest and context. As shown in Fig. 3, the cropped character and the whole image are usually encoded by two separate networks and fused at the ends [34, 53, 59]. This approach is inflexible and inefficient since it overlooks the dependency between subject and context and encodes redundant image portions. Following this line of thought, we propose two potential subject-aware context encoding strategies, *i.e.*, subject-aware attention masking (SAAM) and subject-aware prompting (SAP). The former can be regarded as an efficient implementation of the traditional two-stream approach but avoids the problem of redundant encoding. The latter is a novel encoding strategy that enables adaptive modeling of the interaction between the context and the subject by providing necessary prompts.

Subject-Aware Attention Masking. The canonical attention module [76] in a Transformer is defined as:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right)\mathbf{V}\,. \tag{1}$$

We model the context and subject in a synchronous way by modifying the attention module to

$$\text{Attention}^*(\mathbf{Q}, \mathbf{K}, \mathbf{V}, \mathbf{U}) = \underbrace{\text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right)(\mathbf{J}-\mathbf{A})\mathbf{V}}_{\text{context}} + \underbrace{\text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right)\mathbf{A}\mathbf{U}\mathbf{V}}_{\text{subject}}\,, \tag{2}$$

where $\mathbf{J}$ is a matrix with all ones, $\mathbf{A}$ is a learnable parameters containing values in range $[0, 1]$, and $\mathbf{U}$ is a weight matrix constructed using P. Intuitively, we shift $\mathbf{A}$ amount of attention from a total of $\mathbf{J}$ amount of attention from the context to the subject. To partition the $\mathbf{A}$ amount of attention to all image patches containing subject, we compute $\mathbf{U}$ as the following:

$$\mathbf{U} = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top + \mathbf{M}}{\sqrt{d}}\right)\,. \tag{3}$$

The masking matrix $\mathbf{M}$ is defined as:

$$\mathbf{M} = \begin{bmatrix} \mathbf{M}^{(1)} & \mathbf{M}^{(2)} \\ \mathbf{M}^{(3)} & \mathbf{M}^{(4)} \end{bmatrix}\,, \tag{4}$$

where $\mathbf{M}^{(1)} = \mathbf{0}_{(m+1)\times(m+1)}$, $\mathbf{M}^{(4)} = \mathbf{0}_{1\times 1}$, $\mathbf{M}^{(2)}_{i\notin P} = \mathbf{M}^{(3)}_{i\notin P} = -\infty$, $\mathbf{M}^{(3)}_{(m+1)} = -\infty$, and all other entries are zero. Intuitively, $\mathbf{M}^{(2)}$ and $\mathbf{M}^{(3)}$ represent the attention between all image patches z_i and the human token z_{hmn} to model the subject stream; we mask out all attention between non-human patches and the human token. Moreover, we mask out attention from z_{hmn} to z_{cls}, $\mathbf{M}^{(3)}_{(m+1)}$, to ensure z_{hmn} only encodes the subject.

Subject-Aware Prompting. Prompting is a parameter-free method that restricts the output space of the model by shaping inputs. In our case, we hope to prompt the model to distinguish between the context and the subject. A recent visual prompting method, CPT [89], provides such a prompt by altering the original image, *i.e.*, imposing colored boxes on objects of interest. It shows that a Transformer is able to locate objects with the help of positional hints. However, introducing artifacts on pixel space may not be optimal as it causes large domain shifts. To address this issue, we propose to construct prompts in the latent space based on positional embeddings, considering that they are inherently designed as indicative information. Formally, let e_i be the positional embedding corresponding to the patch token z_i, and P are the indicator set of the subject location. The prompting token is designed as $z_{hmn} = \sum_{i \in P} e_i$.

We argue the sum of positional embeddings is enough to provide hints about the subject location. The previous study [78] demonstrates a Transformer treats all tokens without positional embedding uniformly but with positional embedding differently. This result shows positional embeddings play a vital role in guiding model attention.

3.4. Sentiment-Guided Contrastive Learning

We train the model to learn emotion representations from verbal and nonverbal expressions in a contrastive manner. In the traditional contrastive setting, the model is forced to repel all negative pairs except the only positive one. However, many expressions in daily communication indeed have the same semantics from an emotional perspective. Contrasting these undesirable negative pairs encourages the model to learn spurious relations. This problem comes from false negatives, *i.e.*, the affectively similar samples are treated as negatives. We address this issue by introducing a trained sentiment analysis model [68] from the NLP domain for the suppression of false negatives, thereby guiding our model to capture emotion-related concepts from verbal expressions. Specifically, we propose a sentiment-guided contrastive loss:

$$\mathrm{SNCE}(v, t, s) = -\sum_{i \in B} \left(\log \frac{\exp\left(v_i \cdot t_i / \tau\right)}{\sum\limits_{j \in B} \exp\left(v_i \cdot t_j / \tau - w_{i,j}\right)} \right), \tag{5}$$

where B is a batch. The reweighting term $w_{i,j}$ is defined as

$$w_{i,j} = \begin{cases} \beta \cdot \mathrm{KL}(s_i \| s_j)^{-1} & i \neq j \\ 0 & i = j \end{cases}, \tag{6}$$

where β is a hyper-parameter for controlling the reweighting strength. The total loss is defined as:

$$\mathcal{L} = \frac{1}{2|B|} \Big(\mathrm{SNCE}(v, t, s) + \mathrm{SNCE}(t, v, s) \Big) . \tag{7}$$

As shown in Fig. 4, the false negative sample with similar emotion to the positive sample is greatly suppressed, while other negatives are not affected. Note that when $i \neq j$ but $s_i = s_j$, we have $w_{i,j} = \infty$, which is equivalent to removing jth sample from the negative pairs; when s_i and s_j are very different, $w_{i,j}$ is negligible; we set $w_{i,i} = 0$ to not affect the true positive pair. Since s is the sentiment score, the sentiment-related differences are emphasized and weighted more during training. Therefore, the proposed contrastive loss is expected to provide cleaner supervision signals for learning emotion-related representations.

Figure 4. A sample batch where both the positive pair (*green*) and the false negative pair (*red*) exist. The green bar and gray bar represent the similarity between all text and the positive video before and after reweighting.

4. Experiments and Results

We first introduce the datasets for evaluation in Sec. 4.1 before analyzing various components of EmotionCLIP in Sec. 4.2. Then, we compare EmotionCLIP with the state-of-the-art methods on various datasets in Sec. 4.3. Please see Appendix for more experimental results.

4.1. Datasets and Evaluation Metrics

We evaluate the performance of EmotionCLIP on a variety of recently published challenging benchmarks, including four video datasets and an image dataset. The annotations of these datasets are mainly based on three physiological models: Ekman's basic emotion theory [18] (7 discrete categories), the fine-grained emotion model [14] (26 discrete categories), and the Valence-Arousal-Dominance emotion model [67] (3 continuous dimensions). The evaluation metrics are consistent with previous methods.

BoLD [45] is a dataset for understanding human body language in the wild, consisting of 9,827 video clips and 13,239 instances, in which each instance is annotated with 26 discrete categories and VAD dimensions.

MovieGraphs [77] is a dataset for understanding human-centric situations consisting of graph-based annotations on social events that appeared in 51 popular movies. Each graph comprises multiple types of nodes to represent actors' emotional and physical attributes, as well as their relationships and interactions. Following the preprocessing and evaluation protocol proposed in previous work [29, 54], we extract relevant emotion attributes from the graphs and group them into 26 discrete emotion categories.

MELD [60] is an extension to the EmotionLines [9], which is an emotion corpus of multi-party conversations initially proposed in the NLP domain. It offers the same dialogue examples as EmotionLines and includes audio and visual modalities along with the text. It contains around 1,400 dialogues and 13,000 utterances from the Friends tv show, where each example is annotated with 7 discrete categories.

Liris-Accede [5] is a dataset that contains videos from a set of 160 professionally made and amateur movies covering a

	mAP	AUC	R^2
EmotionCLIP (vanilla)	21.97	68.85	0.130
+ SAAM	21.53$_{-0.44}$	68.56$_{-0.29}$	0.137$_{+0.007}$
+ SAP	22.28$_{+0.31}$	69.06$_{+0.21}$	0.131$_{+0.001}$
+ SAP & SNCE	22.51$_{+0.54}$	69.30$_{+0.45}$	0.133$_{+0.003}$

Table 1. Component-wise analysis of our method on BoLD.

variety of themes. Valence and arousal scores are provided continuously (*i.e.*, every second) along movies.

Emotic [29] is an image dataset for emotion recognition in context, comprising 23,571 images of 34,320 annotated individuals in unconstrained real-world environments. Each subject is annotated with 26 discrete categories.

4.2. Ablation Study

4.2.1 Analysis of Subject-Aware Context Encoding

In this series of experiments, we start with a vanilla model and analyze it by adding various subject-aware approaches. As shown in Table 1, decent results can be achieved in downstream tasks using the vanilla EmotionCLIP. This result supports our argument that models can learn non-trivial emotion representations from human verbal and nonverbal expressions by matching them together.

The SAP achieves better results and improves over the baseline by a reasonable margin. This improvement demonstrates the design of SAP can incorporate location-specific information to guide the model in acquiring target-related content without impacting global information modeling.

Additionally, we note that the model with SAAM yields mediocre performance. As discussed earlier, SAAM can be regarded as an efficient implementation of the multi-stream strategy in the Transformer. This outcome suggests that the multi-stream strategy, commonly used in previous methods, may not be optimal. To rule out the possibility of fusion at inappropriate layers, we explore the impact of different fusion positions by applying SAAM up to a certain layer in the Transformer. It shows that the performance change does not correlate to the fusion layer change, and SAAM consistently underperforms SAP, irrespective of the fusion location. This finding implies that imposing hard masks on the model's attention may introduce unanticipated biases, while adaptively modeling context-subject interaction is more reasonable. In subsequent experiments and discussions, we use SAP as the standard implementation, unless otherwise stated.

Qualitative Analysis. SAP offers merely a positional hint, as opposed to the mandatory attention-shifting in SAAM. Since the purpose of SAP is to ensure subject-aware encoding, it is necessary to understand if the attention guidance is appropriate. We analyze SAP by plotting HMN token's attention to all patches on the image. As shown in Fig. 5, HMN tokens first focus on random locations, but gradually turn their attention to the subject (*i.e.*, the person with a bounding box) as we move to later layers, demonstrating that SAP offers sufficient guidance to the network attention.

Figure 5. Attention weights for the HMN token from layer 1-4 (*left to right*) of the frame encoder in one trained network. Each row represents one frame. The green and yellow spots are the high-attention areas.

4.2.2 Analysis of Sentiment-Guided Contrastive Learning

We first compare models trained with different β, the hyperparameter used to control the strength of reweighting in SNCE. Note that the training objective is equivalent to the vanilla infoNCE loss [56] when β is set to zero. As β increases, more negative samples within the batch are suppressed. As shown in Table 1 and Fig. 6, reweighting with appropriate strength can significantly increase the performance of the model as it guides the direction of learning by eliminating some significant false negatives. However, an excessively large β can hinder the training of the model, which is within expectation. First, the sentiment scores used in the reweighting process are weak pseudo-labels provided by a pre-trained sentiment analysis model, which is not entirely reliable and accurate. Second, previous work has clearly demonstrated that batch size has a decisive impact on self-supervised learning [10, 24, 62]. A too-large β will cause too many negative samples to be suppressed, reducing the effective batch size and thus hindering the learning process.

Qualitative Analysis. We show how the text expressing different emotions are treated by our sentiment-guided loss. Given a positive pair, the logits are the scaled similarities between texts and the positive video; the model is penalized on large logits unless it is associated with the positive text.

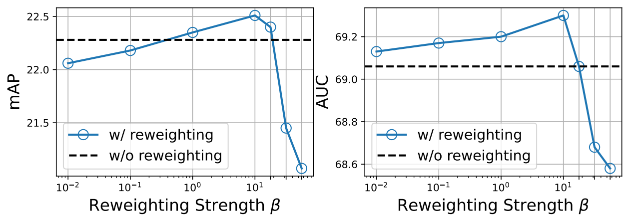

Figure 6. The effect of varying the strength of reweighting in SNCE. The larger the β, the stronger the suppression of negative samples.

Text	Logit
I'm sorry to keep you any longer than is necessary. (positive sample)	10.65
I'm sorry Tom couldn't join us.	12.6 $\rightarrow$ -697
I hate to say it guys but it's getting late.	9.81 $\rightarrow$ -97.6
I still say it was a wild idea.	13.8 $\rightarrow$ 13.6
Well, that was truly fascinating.	15.2 $\rightarrow$ 15.0

Table 2. An example batch containing both false negative and true negative samples. The logits represent the similarity between every text input and the positive video from a random epoch during training. $\rightarrow$ represents the sentiment-guided reweighting process.

As shown in Table 2, the texts in the second and third rows provide undesired contributions to the loss as they express similar emotions as the positive sample. After reweighting, false negatives (*2nd and 3rd*) are effectively eliminated while true negatives (*4th and 5th*) are negligibly affected.

4.2.3 Analysis of Model Implementation

The frame and text encoders of our model are initialized with the image-text pre-training weights from CLIP [62]. Research in neural science has demonstrated the necessity of basic visual and language understanding capabilities for learning high-level emotional semantics [58, 70]. To validate the effectiveness of using image-text pre-training for weight initialization, we evaluate variants with different implementations.

We first consider encoders with random initialization. As shown in Table 3, the model's performance drops sharply when training from scratch. This result is within expectation for two reasons. From an engineering perspective, previous works have demonstrated the necessity of using pre-training weights for large video models [1, 6] and vision-language models [35, 55]. From a cognitive point of view, it is nearly infeasible to learn abstract concepts directly without basic comprehension skills [58]; if the model cannot recognize people, it is impossible to understand body language and facial expressions properly.

We then consider frozen encoders with pre-training

Text Encoder	Frame Encoder	Temporal Encoder	mAP	AUC
✓	✓	-	22.51	69.30
-	✓	-	12.43 −45%	54.96 −21%
-	-	-	11.02 −51%	50.28 −27%
✗	✓	-	13.40 −40%	57.38 −17%
✗	✗	-	18.43 −18%	65.08 −6.0%
✓	✓	∘	21.17 −5.9%	68.74 −0.8%

Table 3. Ablation study on different model implementations. ✓means trainable, initialization with pre-training weights. ✗means frozen, initialization with pre-training weights. - means trainable, random initialization. ∘ means no parameters.

weights. This is a standard paradigm for video-language understanding that trains models with offline extracted features [36, 87]. As shown in Table 3, our model with variants using fixed encoders performs worse compared with the model using trainable encoders. This reflects the fact that affective tasks rely on visual and verbal semantics differently from low-level vision tasks, which is what CLIP and its successors overlooked [40].

We study the effect of the temporal encoder. We consider a variant where the temporal encoder is replaced by a mean pooling layer that simply averages the features of all frames. As shown in Table 3, the performance gap is obvious compared with the baseline. This phenomenon suggests that temporal dependency plays a vital role in emotion representations.

4.3. Comparison with the State of the Art

Based on our previous ablation experiments, we choose the model with SAP and SNCE as the default implementation and compare it with the state-of-the-art. In addition, we also compare with VideoCLIP [87] and X-CLIP [55], both of which are state-of-the-art vision-language pre-training models for general video recognition purposes. To evaluate the quality of learned representations, we follow the practice in CLIP [62] and use linear-probe evaluation protocol [10, 24] for vision-language pre-training models.

BoLD. As shown in Table 4a, EmotionCLIP substantially outperforms the state-of-the-art supervised learning methods on the challenging 26-class emotion classification task and achieves comparable results on continuous emotion regression. It is worth noting that a complex multi-stream model is used in [59] to integrate the human body and context information, while we achieve better results with a single-stream structure using RGB information only. This difference reflects that the subject-aware approach we designed models the relationship between the subject and context. We also notice that other vision-language-based meth-

(a) BoLD [45]

Method	mAP ↑	AUC ↑	R^2 ↑
Supervised			
ST-GCN [94]	12.63	55.96	0.044
TSN [81]	17.02	62.70	0.095
Filntisis *et al.* [21]	16.56	62.66	0.092
Pikoulis *et al.* [59]	19.29	66.82	**0.149**
Linear-Eval			
VideoCLIP [87]	11.19	51.23	-5.11
X-CLIP [55]	13.26	56.86	-0.03
EmotionCLIP	**22.51**	**69.30**	0.133

(b) MovieGraphs [77]

Method	Val Acc ↑	Test Acc ↑
Supervised		
EmotionNet [84]	35.60	27.90
*Affect2MM [54]	39.88	30.58
Linear-Eval		
VideoCLIP [87]	29.91	23.44
X-CLIP [55]	29.06	23.58
EmotionCLIP	**41.60**	**32.35**

(c) Emotic [29]

Method	mAP ↑	AUC ↑
Supervised		
CAER-Net [34]	20.84	-
Affective Graph [96]	28.42	-
Fusion Model [29]	29.45	-
EmotiCon (GCN) [53]	32.03	-
EmotiCon (Depth) [53]	**35.48**	-
Linear-Eval		
VideoCLIP [87]	19.92	56.31
X-CLIP [55]	22.80	61.31
EmotionCLIP	32.91	**71.41**

(d) MELD [60]

Method	Acc ↑	W. F_1 ↑
Supervised		
M2FNet (Visual) [12]	45.63	32.44
*M2FNet [12]	67.85	66.71
Linear-Eval		
VideoCLIP [87]	45.19	32.06
X-CLIP [55]	38.31	32.46
EmotionCLIP	**48.28**	**34.59**

(e) Liris-Accede [5]

Method	V. MSE ↓	A. MSE ↓
Supervised		
Quan *et al.* [61]	0.115	0.171
Ko *et al.* [28]	0.102	**0.149**
*CERTH-ITI [4]	0.117	0.138
*THUHCSI [25]	0.092	0.140
*Yi *et al.* [91]	0.090	0.136
*GLA [75]	0.084	0.133
*Zhao *et al.* [95]	0.071	0.137
*Affect2MM [54]	0.068	0.128
Linear-Eval		
VideoCLIP [87]	0.142	0.151
X-CLIP [55]	0.133	0.246
EmotionCLIP	**0.096**	0.155

Abbreviation	Meaning
A. MSE	Arousal MSE
V. MSE	Valence MSE
W. F_1	Weighted F_1
Acc.	Top-1 Accuracy
↓	Lower is better
↑	Higher is better

Table 4. Comparisons to the state-of-the-art across multiple datasets. Methods marked with * use multimodal inputs, *i.e.*, audio and text. Bold numbers indicate the best results achieved using visual inputs only.

ods perform poorly on emotion recognition tasks, although they are designed for general video understanding purposes. This phenomenon is largely attributed to the lack of proper guidance; the model can only learn low-level visual patterns and fails to capture semantic and emotional information.

MovieGraphs. As shown in Table 4b, EmotionCLIP substantially outperforms the best vision-based method and even surpasses Affect2MM [54], a powerful multimodal approach that uses audio and text descriptions in addition to visual information. Instead, other vision-language pretraining models are still far from supervised methods.

MELD. EmotionCLIP performs well on MELD as shown in Table 4d; it achieves comparable results to the state-of-the-art vision-based methods. It is worth noting that this dataset is extended from an NLP dataset, so the visual data is noisier than the original text data. In fact, according to the ablation experiments in [12], it is possible to achieve an accuracy of 67.24% using only text, while adding visual modality information only improves the accuracy by about 0.5%. This result explains why our method significantly lags behind multimodal methods using text inputs.

Liris-Accede. As shown in Table 4e, EmotionCLIP achieves promising results using visual inputs only. It even competes with many multimodal approaches that are benefited from the use of audio features [93].

Emotic. As shown in Table 4c, EmotionCLIP outperforms all RGB-based supervised methods while other vision-language models perform poorly. The improvement of [53] is attributable to the use of additional depth information. This result demonstrates the capability of EmotionCLIP in learning relevant features from complex environments.

5. Conclusion

The pre-training methodology, which has brought about significant advancements in numerous CV and NLP domains, has not yet been employed in AEI research. We address this void by introducing EmotionCLIP, the first vision-language pre-training framework that circumvents the need for curated data and annotations. Our study establishes the viability of acquiring generalized emotion representations directly from human communication, thereby considerably broadening the horizons of current AEI research. The emergence of this pre-training paradigm offers an alternative solution to data scarcity, paving the way for a myriad of potential applications. We anticipate that our work will stimulate further investigation in this area and contribute to the evolution of more adaptable and efficacious approaches for affective computing.

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A. Data

A.1. Data Collection

The video-text pairs for pre-training were obtained using Python implementation of YouTube API, youtube-search-python [1]. This API provides the exact query result as the YouTube webpage. We searched for keywords such as "TV series" and "TV shows," and filtered only those with English closed captions from the resulting videos. Next, we filtered out all the "TV" videos that were less than 40 minutes long to remove some false results. We then manually removed videos appearing in downstream datasets based on YouTube id and movie title. This process resulted in 3,613 filtered videos or about 1.1 million video clips. Due to resource limitations, we only processed and stored the videos at 8 FPS. We refer to this dataset as the TV dataset.

We further processed the video frames, and the corresponding closed captions to obtain additional information. We extracted all the frames and resized the smaller edge to 256 without changing the aspect ratio. All the closed captions were processed using FullStop [2] to produce complete sentences; each word obtained a punctuation label, and we split on the termination punctuation. Furthermore, we applied a sentiment model, a DistilRoBERTa-base [2], to generate sentiment scores of seven emotion categories (*i.e.*, anger, disgust, fear, joy, sadness, surprise, and neutral) for texts. Moreover, all the frames were processed using YOLOv7 [9] to generate bounding boxes for all humans. The detailed parameter for bounding boxes generation is in Tab. 1.

Image Size	Confidence Threshold	IOU Threshold
640×640	0.25	0.45

Table 1. The important parameters for YOLOv7 to generate human bounding boxes.

A.2. Data Exploration

We first explore the textural data in the TV dataset. We notice that many texts are not helpful for emotion understanding; they do not provide desired emotional signals. As shown in Tab. 2, the neutral score is the probability that the trained sentiment model predicts that the text is neutral.; we can see that the text expresses stronger emotion when the neutral score is low; the emotion signal is most apparent in the last three rows. This observation aligns with our intuition that instructional or descriptive language, such as those in [5] and [1], are not usually emotional and support our motivation for collecting the TV dataset. Based on the above observation, we believe that the model may be misled if too many samples with high neutral scores were used. Therefore, we must limit the number of samples with a high chance of neutrality to better direct the model's attention toward other more valuable emotional expressions. Moreover, the distribution of the neutral scores for the TV dataset is in Fig. 1; it forms a bimodal distribution where more data are closer to the left (non-neutral). Clearly, the left peak represents the desirable emotional samples, and the right peak represents the instructional or descriptive samples that can be discarded. To confirm our intuitions and to find a good threshold for filtering useless examples, we tested multiple neutral score thresholds on the TV dataset. As shown in Fig. 2, the model's performance on downstream tasks increases when more neutral examples are eliminated, supporting our conjecture that too many neutral samples are not helpful for emotion understanding. Furthermore, the performance peaks at around 0.05 and drops dramatically as too few samples were left when using a small threshold. Based on this observation, we keep only the samples with a neutral score of less than 0.05. This filtering process results in about 250k samples which is still much larger than the current emotion understanding datasets. Finally, we evaluate how the filtering process changed the probability distribution of other emotion labels. The comparison of the distribution before and after filtering for the other six emotion categories is in Fig. 3; the distribution of the original TV dataset is highly skewed where the majority of samples had probabilities close to zero for each of the six emotions. Following filtering, the skewness is reduced and the proportion of samples containing relevant information signals is enhanced. The filtered TV dataset is expected to provide better supervision for EmotionCLIP.

Some examples from the filtered TV dataset are shown in Fig. 4. It can be clearly felt that most of the examples showed strong emotional expression from both verbal and nonverbal cues. The word cloud in Fig. 5 is constructed based on the filtered TV dataset. We can see that some words related to emotional expression appear frequently in the dataset, such as *'sorry', 'happy', 'afraid', 'fear', 'angry', 'worried', 'love', etc*. In general, there are a large number of verbal communications with rich emotional expressions, which can hardly be covered by basic emotions.

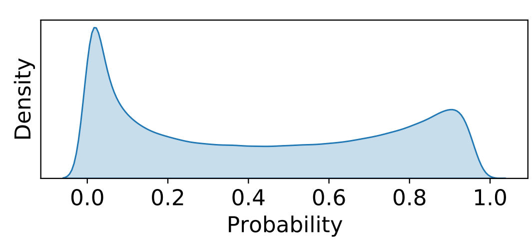


Figure 1. The distribution of the neutral scores on the TV dataset.

[1] https://github.com/alexmercerind/youtube-search-python
[2] https://huggingface.co/j-hartmann/emotion-english-distilroberta-base

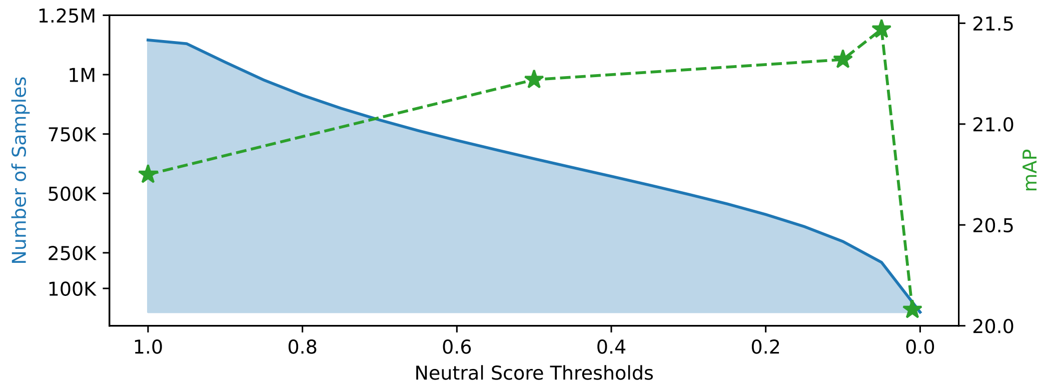


Figure 2. Effect of filtering with neutral scores on sample size and model performance.

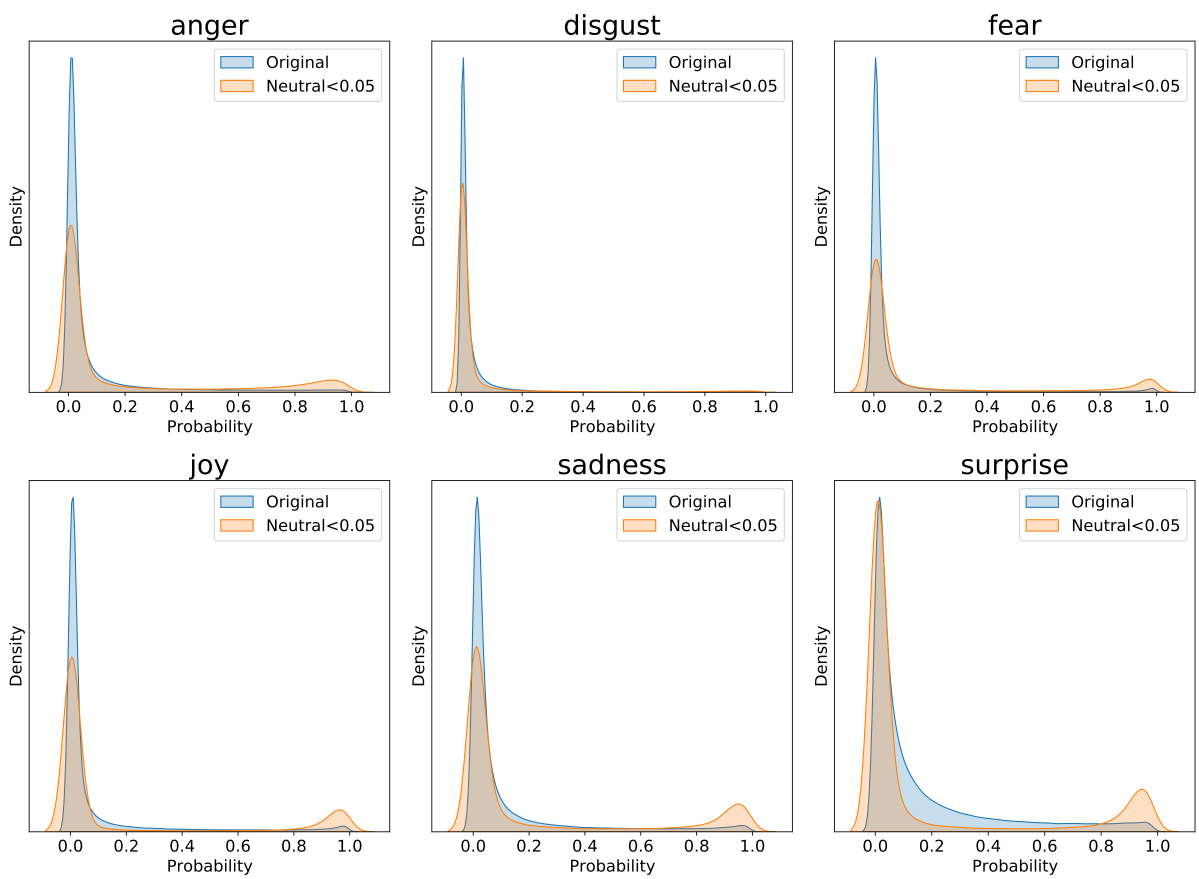


Figure 3. The effect of filtering out text with a neutral score greater than 0.05 on the distribution of the predicted probability of other emotion categories.

(a) Yes. Poor Georgie. He was dropped after he broke his hip.

(b) Fantastic rock and roll. Thank you.

(c) What happened to Danny? Why'd you let him die? I tried to help him.

(d) Our pleasure, Mr. Kyle. Our pleasure.

(e) She was suspicious of everything I did.

(f) Oh, why won't you? It's none of your business.

(g) No, I'm sorry.

(h) I know you saying that Miss. Bowden was deliberately seeking to endanger the life of the mother and child.

(i) I ought to punch you right in the nose.

(j) I find this rather embarrassing Mr. Barris. I don't see why.

(k) Okay. I can't keep running after you and cleaning up your mess.

(l) Worst case scenario a man can actively invite the demons in.

(m) I just think he'd be better off out of the ranch.

(n) After all I was persuaded. I can't let people down.

(o) Mrs. Matsen, I know this has been a terrible shock.

(p) Yeah. Happy in Jordan Hill's.

(q) Why did you do it? I must be punished.

(r) Be my pleasure, and I've enjoyed the evening.

(s) Oh, I felt so frightened. I was shaking.

(t) Oh, I'm ever so sorry.

(u) Oh, that's wonderful. I'll tell you they had a bunch of them.

(v) What do you want from me? Apologies? I don't apologize.

(w) I'm not gonna let those cattle die because of some fool notion in your head.

(x) Rhoda be thrilled to see you when she gets home.

Figure 4. Examples from TV Dataset.

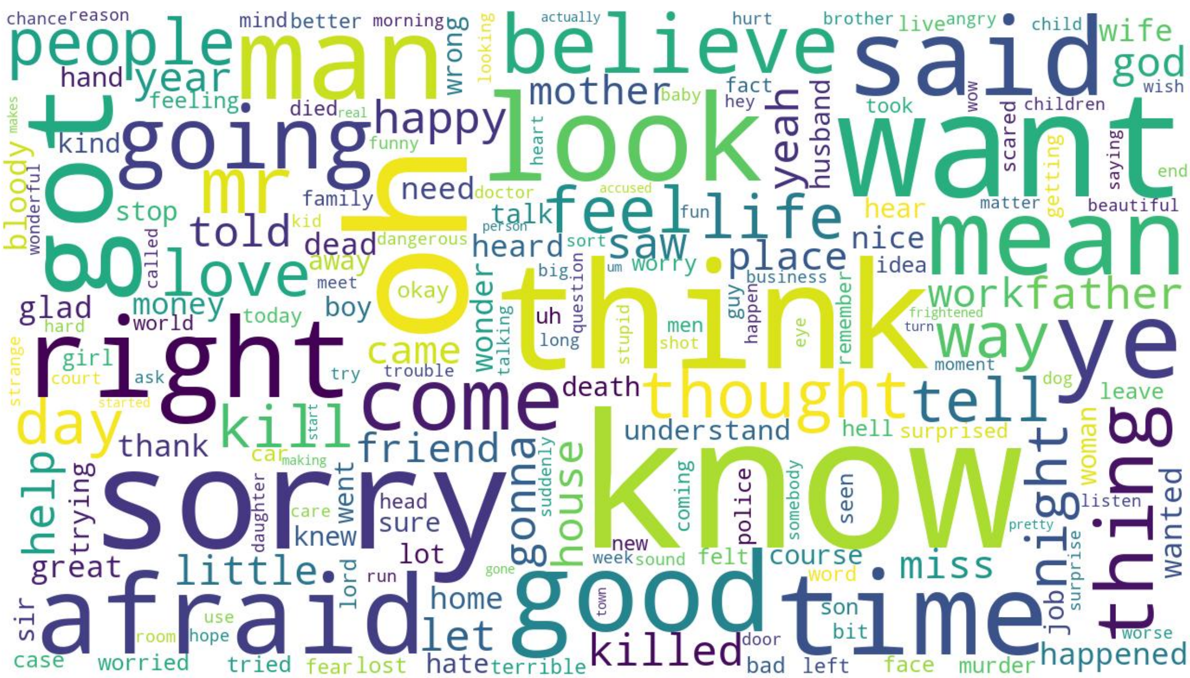


Figure 5. A word cloud generated from the collected TV dataset.

Text	Neutral Score
Only then it will become picture perfect	0.931
I do know they once owned the painting	0.924
Valerie had to wait a few months for hers and his mother	0.834
Tell him that we will meet at 6.	0.828
can you tell us what you know about that	0.734
They have also received a bill	0.717
So many of them did not clear	0.543
he’s the only collector	0.519
he was on his way to Pennsylvania the night	0.452
Do you want me to do it and bring a glass	0.351
I haven’t taken my vows and I probably never will	0.300
some of his new patients like three-year-old Harriet are definitely unusual	0.253
yes in your statement you said you saw the defendant running from the heat	0.234
I don’t want to lose the money any more than you do	0.185
any one of them might be guilty	0.164
I couldn’t have done it myself I didn’t even think of it	0.031
it’s a whole new world for me	0.027
I know our dream house yes David our dream house	0.009

Table 2. Example texts, and their corresponding neutral score predicted by the sentiment model.

B. Implementation Details

B.1. Model Details

EmotionCLIP adopts CLIP (ViT/B-32) [8] as part of the frame encoder and text encoder. Specifically, the frame encoder is a ViT ($L = 12, N_h = 12, d = 768, p = 32$), the text encoder is a Transformer ($L = 12, N_h = 8, d = 512$), and the temporal encoder is another Transformer ($L = 6, N_h = 8, d = 512$), where L is the number of layers, N_h is the number of attention heads, d is the embedding dimension, and p is the patch size. The sentiment model a fine-tuned checkpoint of DistilRoBERTa-base [3], which is frozen during training. Following the practice of CLIP, both the text encoder and sentiment model operate on a lower-cased byte pair encoding (BPE) representation of the text with a 49,152 vocab size. The max length of the text sequence is capped at 76 and bracketed with [SOS] and [EOS] tokens. The specific implementation of subject-aware context encoding in the frame encoder is as follows:

Subject-Aware Attention Masking. Follow the equation

$$\text{Attention}^*(\mathbf{Q}, \mathbf{K}, \mathbf{V}, \mathbf{U}) = \underbrace{\text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right)(\mathbf{J} - \mathbf{A})\mathbf{V}}_{\text{context}} + \underbrace{\text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d}}\right)\mathbf{A}\mathbf{U}\mathbf{V}}_{\text{subject}}, \tag{1}$$

defined in the main document, we make a few implementation choices to speed up the computation. First, we use $\mathbf{V}^{(l)}$ for the context encoding and $\mathbf{V}^{(l-1)}$ for the subject encoding, where l denotes the layer. Since each token at layer l is a weighted average of the token at layer $l - 1$, the model is able to extract similar information to $\mathbf{V}^{(l)}$ by reweighting $\mathbf{V}^{(l-1)}$. Next, we set A to the attention from each token to the current layer HMN token. This modification ensures all entries in A are in $[0, 1]$ and values are automatically learned by the model. The above two modifications allow us to reuse the original multi-head attention layer by setting the attention mask to $\mathbf{M}$ as defined in the main document.

Subject-Aware Prompting. As described in the main document, we set HMN as $z_{hmn} = \sum_{i \in P} e_i$. Note that the indices in P represent the presence or absence of the subject in the non-overlapping image patches. This information is obtained from bounding boxes which may not align with the non-overlapping image patches. To address this issue, we add the indices of all tokens that have overlap $o_i > 0$ with the bounding boxes to P and compute $z_{hmn} = \sum_{i \in P} o_i e_i$

[3]https://huggingface.co/j-hartmann/emotion-english-distilroberta-base

B.2. Training Details

The frame encoder and text encoder are initialized using the pre-trained weights provided by OpenCLIP [4]. We use the AdamW optimizer to train the model, where $\beta_1 = 0.98, \beta_2 = 0.9, \epsilon = 1e{-}10, \lambda = 0.1$. The base learning rate of the parameters in the frame encoder and text encoder is set to 5e-5 for gains and biases, and 1e-8 for the remaining parameters. The learning rate of the parameters in the temporal encoder is set to 1e-6. The decoupled weight decay regularization is applied to all weights that are not gains or biases. Models are trained for 25 epochs with a batch size of 128. The learning rate is linearly warmed up for 2500 steps and decayed to 1e-10 following a cosine schedule for the rest of the training. For each video, we randomly sample 8 frames in each iteration to form an input sequence. The input frames have a spatial resolution of 224x224 and are obtained by random cropping. The sequence of the subject mask is obtained with the same operation as the corresponding frame.

B.3. Evaluation Details

We follow the linear-probe evaluation protocol in CLIP. Specifically, we uniformly sample 8 frames from each video to form an input sequence and extract video features using the pre-trained EmotionCLIP. For classification tasks, we train a logistic regression classifier using scikit-learn's implementation with sag solver. The maximum iteration is set to 2,000, and the regularization strength is determined by a random search on the validation sets. For the datasets that contain a validation split in addition to a test split, we use the provided validation set to perform the hyperparameter search, and for the datasets that do not provide a validation split or have not published labels for the test data, we split the training dataset to perform the hyperparameter search. For the regression tasks, we train a linear regression model using scikit-learn's Ridge implementation with default hyperparameters, followed by a Savgolet filter.

For the other two vision-language baseline models, we used the official implementations with pre-trained weights and ran them with their default settings. Specifically, for VideoCLIP [10], we use the pre-trained model provided in Fairseq [5]; for X-CLIP [7], we use the zero-shot X-CLIP-B/16 model trained on Kinetics-600 [6]. For other supervised learning methods, we use the scores reported in their papers.

[4]https://github.com/mlfoundations/open_clip
[5]https://github.com/facebookresearch/fairseq
[6]https://github.com/microsoft/VideoX/tree/master/X-CLIP

C. Detailed Results

C.1. Qualitative Results

Subject-Aware Prompting. We present additional qualitative results for SAP. As shown in Fig. 6, the attention of HMN changes according to the positional hint for the subject, which shows SAP is subject-aware. Moreover, Fig. 7 shows the exact same set of frames as Fig. 6 but the attention comes from CLS token; it is clear that the attention for CLS token tend to focus on the entire scene and does not change regardless of the positional hint. This result shows SAP behaves similarly to two stream approaches where CLS models the context and HMN models the subject but is less affected by the artifacts introduced in traditional manual subject cropping. Fig. 8 shows some examples where SAP fails to guide the attention. The majority of the failure cases are direct results of applying cropping during testing; some subjects are either entirely off the frame or partially off the frame. Moreover, there are cases where the bounding boxes are incorrect. Additionally, some subjects are too small compared to most of the subjects in the training dataset, leading to a large domain shift.

Sentiment-Guided Contrastive Learning. In this section, we demonstrate how the sentiment model guides the loss. Note that we use the inverse of the KL divergence between text from the positive sample and the negative samples to reweight the negative samples; the suppression strength is inversely proportional to the KL divergence. Tab. 4 shows some examples from the collected TV dataset; the text expressing similar emotion has a smaller KL divergence whereas the text expressing different emotion have a larger KL divergence. Since we treat the negative samples that express similar emotions to the positive samples as false negative samples, it is clear the proposed reweighting method suppresses the false negative samples.

C.2. Quantitative Results

We reported detailed emotion classification performance on BoLD and Emotic in Tab. 5. Both datasets have fine-grained emotion annotations on 26 categories. We observed an intriguing phenomenon that EmotionCLIP performs quite differently on some emotion categories compared with prior approaches based on supervised learning. As shown in Tab. 3, EmotionCLIP with linear classifier achieves comparable mAP with two other supervised learning methods using RGB inputs on Emotic. However, we notice that EmotionCLIP performs significantly better than supervised learning methods in some categories (*e.g.*, *sadness, suffering*). The performance in the remaining categories is also different from that of supervised learning methods. This result shows that emotional representations learned from communication are different from those learned through annotations, which further demonstrates the complementarity of EmotionCLIP as a pre-training method to conventional supervised learning methods.

Categories	Kosti *et al.* [3]	Emoticon [6]	EmotionCLIP
Affection	27.85	36.78	**45.81**
Anger	9.49	14.92	**26.67**
Annoyance	14.06	18.45	**21.94**
Anticipation	58.64	**68.12**	58.07
Aversion	7.48	**16.48**	10.55
Confidence	**78.35**	59.23	76.94
Disapproval	14.97	**21.21**	19.23
Disconnection	21.32	25.17	**29.44**
Disquietment	16.89	16.41	**21.82**
Doubt/Confusion	29.63	**33.15**	22.70
Embarrassment	3.18	**11.25**	2.86
Engagement	87.53	**90.45**	87.79
Esteem	17.73	**22.23**	18.58
Excitement	77.16	**82.21**	71.05
Fatigue	9.70	19.15	**20.21**
Fear	**14.14**	11.32	12.08
Happiness	58.26	68.21	**78.44**
Pain	8.94	12.54	**16.73**
Peace	21.56	**35.14**	29.67
Pleasure	45.46	**61.34**	50.23
Sadness	19.66	26.15	**43.01**
Sensitivity	9.28	9.21	**9.53**
Suffering	18.84	22.81	**43.96**
Surprise	**18.81**	14.21	10.70
Sympathy	14.71	**24.63**	17.23
Yearning	8.34	**12.23**	10.29
mAP	27.38	32.03	**32.91**

Table 3. Per-category performance (AP) on Emotic.

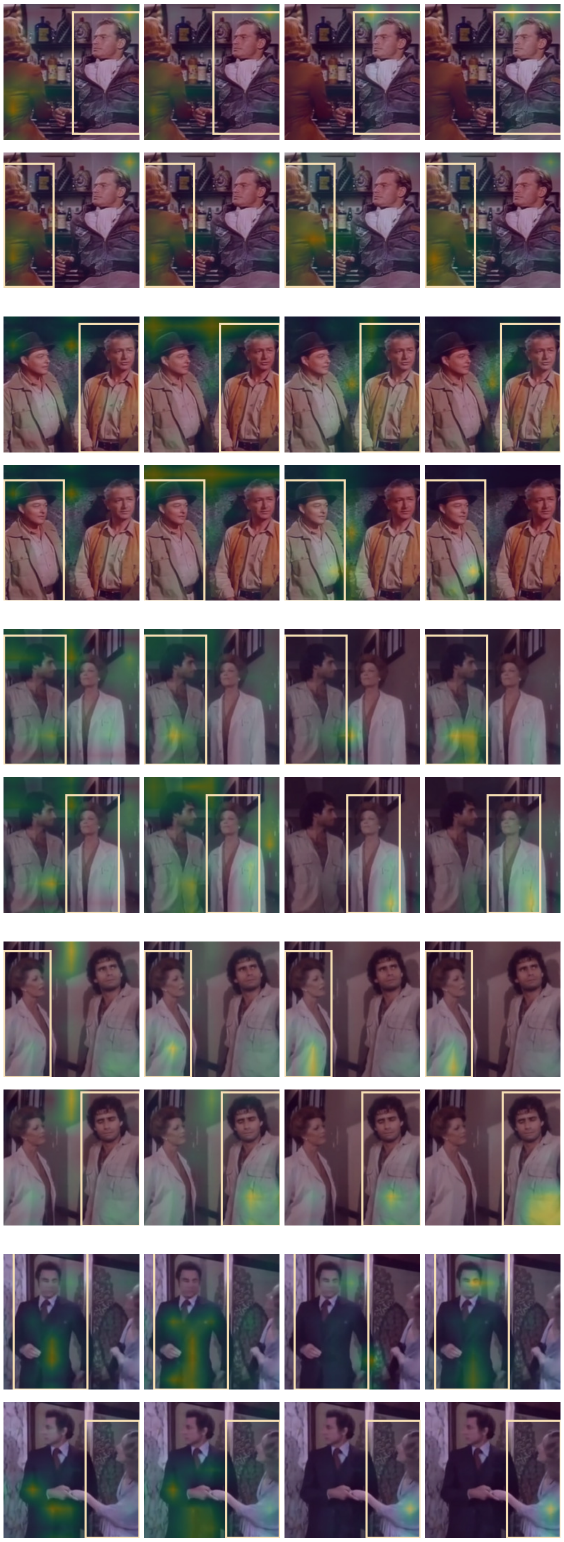


Figure 6. The attention weights for HMN token at layer 1 - 4 (left to right) for each frame. Note that changing the bounding box location causes the attention weights to change accordingly.

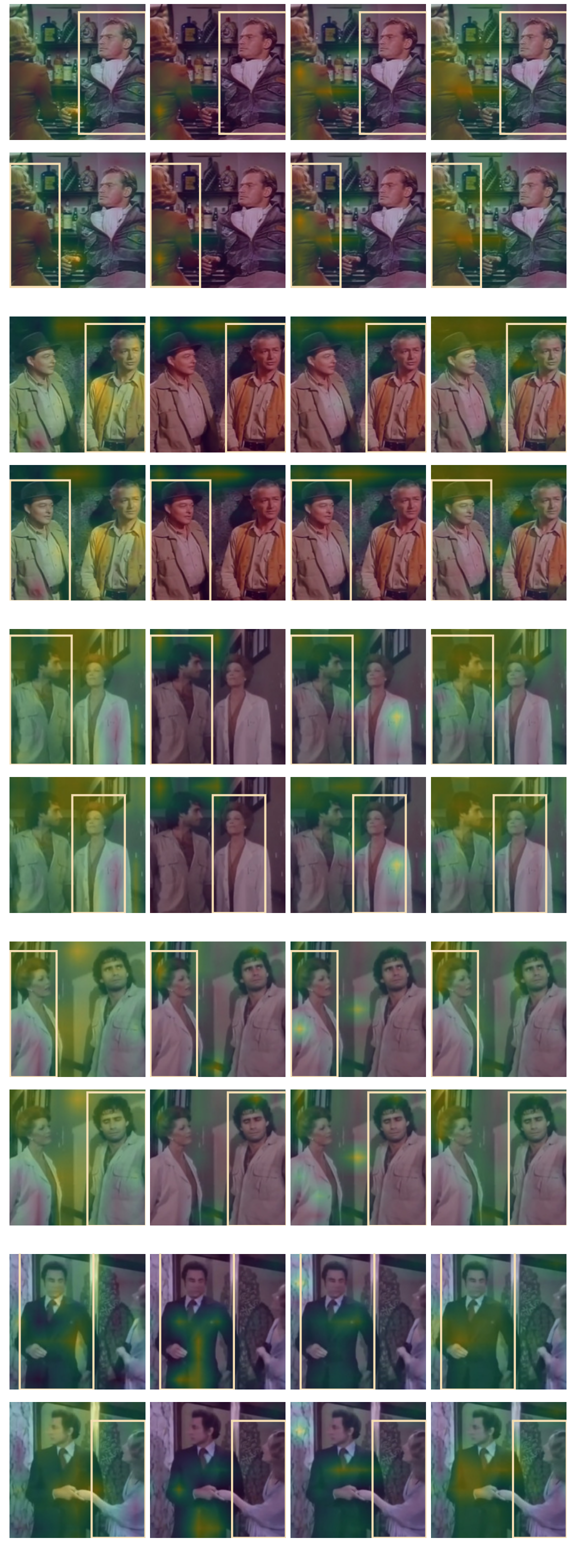
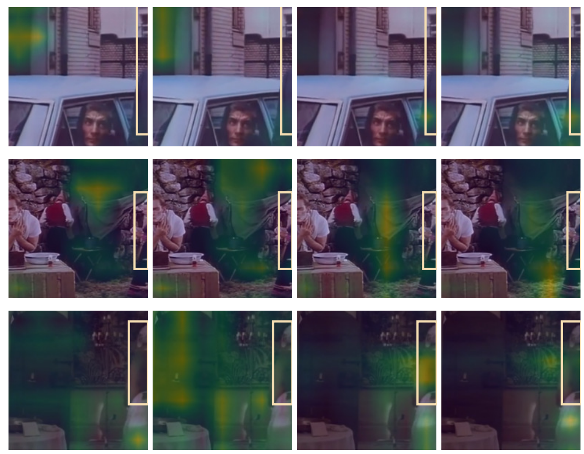


Figure 7. The attention weights for CLS token at layer 1 - 4 (left to right) for each frame. Note that changing the bounding box location does not change the attention weight.

(a) The bounding boxes are absent.



(b) The subjects are partially off the frame.

(c) The subjects bounding boxes are incorrect.

(d) The subjects are too small.

Figure 8. The different failure cases for the attention weights of HMN token at layer 1 - 4 (left to right) for each frame in BoLD dataset.

Source	Target	KL Divergence
it would baffle the police	I don't think that you could understand	9.8e-4
he'll be glad to hear	it's a very nice church	5.2e-4
you seem awfully anxious to make it look like suicide	you're scared of them	9.8e-4
I had a great childhood	I just can't wait to get back into some action	9.7e-4
I wonder if you would look at your passport and find a visa for perco for me	I just I was wondering if he was here	9.4e-4
a man is dead	I have lost my son	5.0e-4
i guess i must be the luckiest man around these parts	I'm very glad	4.8e-4
oh my goodness I didn't know I had such a devoted fans	oh my god Jimbo look who's here	4.7e-4
oh really oh yes yes yes miss Travers I'm surprised	I can't say I'm surprised though	4.3e-4
I'm sorry to keep you any longer than is necessary	I'm sorry to have to keep requesting you like this	3.6e-4
she were my nurse and after that sickness come the greatest happiness of my life	I never thought I'd ever be cold again	5.01
i have consulted with them	she doesn't think she'll ever see him again	5.04
I'm sorry to keep you any longer than is necessary	I don't think this is something you can come out of	5.48
it would baffle the police	i promised i wouldn't harm him	5.88
well that was truly fascinating	I'm afraid of you	5.92
alright I'm sorry about yesterday	you'll be surprised	6.00
she let me down	I'm Tarsus glad to meet you	6.03
i've got to get my crew out of here	i think for nancy the thrill of the chase was half of the fun	6.29
i should have known he'd be all right	the army turned me down	7.44
I like the way you laugh	he would never let you down deliberately	7.25

Table 4. Examples of false negative targets (with low KL divergence) and true negative targets (with high KL divergence). The KL divergence is calculated using sentiment scores. The proposed sentiment-guided contrastive learning method will down-weight the target if the KL divergence between the source and target is relatively low, thereby eliminating emotional false negatives.

Categories	BoLD [4] AP	BoLD [4] AUC	Emotic [3] AP	Emotic [3] AUC
Affection	42.06	84.53	45.81	79.47
Anger	15.24	71.93	26.67	76.76
Annoyance	18.78	61.56	21.94	74.04
Anticipation	32.23	60.45	58.07	61.94
Aversion	9.08	63.45	10.55	72.09
Confidence	40.33	66.63	76.94	76.51
Disapproval	14.12	57.62	19.23	79.77
Disconnection	11.08	56.86	29.44	71.33
Disquietment	23.75	68.04	21.82	63.73
Doubt/Confusion	22.82	63.28	22.70	60.82
Embarrassment	2.29	70.70	2.86	56.76
Engagement	44.54	64.34	87.79	70.34
Esteem	20.66	63.67	18.58	57.24
Excitement	28.04	73.08	71.05	73.57
Fatigue	13.17	71.04	20.21	68.88
Fear	19.41	71.74	12.08	73.06
Happiness	48.59	80.53	78.44	78.60
Pain	14.58	77.17	16.73	84.11
Peace	28.09	65.09	29.67	70.58
Pleasure	37.87	76.60	50.23	69.87
Sadness	25.85	82.49	43.01	85.05
Sensitivity	14.81	72.48	9.53	74.28
Suffering	26.61	80.15	43.96	88.04
Surprise	11.91	63.62	10.70	59.26
Sympathy	12.60	67.02	17.23	68.59
Yearning	6.66	67.65	10.29	61.88
Average	22.51	69.30	32.91	71.41

Table 5. Emotion classification performance on BoLD and Emotic. AP: average precision. AUC: ROC-AUC.

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