Abstract—Human affect recognition is a well-established research area with numerous applications, e.g. in psychological care, but existing methods assume that all emotions-of-interest are given a priori as annotated training examples. However, the rising granularity and refinements of the human emotional spectrum through novel psychological theories and the increased consideration of emotions in context brings considerable pressure to data collection and labeling work. In this paper, we conceptualize one-shot recognition of emotions in context—a new problem aimed at recognizing human affect states in finer particle level from a single support sample. To address this challenging task, we follow the deep metric learning paradigm and introduce a multi-modal emotion embedding approach which minimizes the distance of the same-emotion embeddings by leveraging complementary information of human appearance and the semantic scene context obtained through a semantic segmentation network. All streams of our context-aware model are optimized jointly using weighted triplet loss and weighted cross entropy loss. We conduct thorough experiments on both, categorical and numerical emotion recognition tasks of the Emotic dataset adapted to our one-shot recognition problem, revealing that categorizing human affect from a single example is a hard task. Still, all variants of our model clearly outperform the random baseline, while leveraging the semantic scene context consistently improves the learnt representations, setting state-of-the-art results in one-shot emotion recognition. To foster research of more universal representations of human affect states, we will make our benchmark and models publicly available to the community under https://github.com/KPeng9510/Affect-DML.

I. INTRODUCTION

Can one recognize human emotional state given a single visual example? Human affect, also referred as human emotion, has always been a great concern of psychology research, as it is directly linked to the mental- and physical health [31]. Assessment of human emotion allows doctors to diagnose conditions such as Parkinson [3], Huntington [15], Depression [1] and Alzheimer [40] early on. Positive emotions have capability to make human lives better and lead to better health and more productive work [38].

Deep learning has lead to great success in many human observation tasks [6], [20], [21], [29], and also strongly influenced the field of visual emotion recognition [42], [24], [33], [17], [18]. However, deep Convolutional Neural Networks (CNNs) are known to be data-hungry and fairly limited in their ability to adapt to new situations. Like in many other computer vision fields, the vast majority of human affect recognition research assumes that a high amount of labelled examples is available during training for all flavours of emotions we want to recognize [42], [24], [33], [17]. This is problematic for two reasons. First, human affect is a complex topic and the categorization schemes constantly evolve and become increasingly refined following the progress of psychological theories [34], [12]. For example Cowen et al. [7] identified 27 types of human affect, where the emotions can be generalizations, specializations or combinations of each other. Second, the increasing interest in emotions-in-context [17] leads to the set of possible situations being much more diverse and dynamic, eventually changing over time, as we cannot capture and annotate all possible types of environments influencing the emotion. Bringing the idea of categorizing new flavors of emotions without excessive data labelling to the scope of researchers’ attention is therefore the main motivation of our work.

In this work, we propose to incorporate generalization to previously unseen human affects in finer particle level through a single visual example in the evaluation of emotion
recognize recognition models and introduce the one-shot recognition of emotions in context task (see problem formulation in Figure 1). Given a label-rich dataset of known categories, we aim to train a model which learns discriminative emotion embeddings that are well-adaptable for classification of novel label-scarce categories. To meet the challenge of learning generalizable affect embeddings, we follow the deep metric learning [22] paradigm, augmenting the existing emotion classification models [18] trained on Emotic dataset [17] with additional triplet loss [4], which minimizes the distance of the same-emotion embeddings. Furthermore, we introduce a new architecture for one-shot emotion classification, which leverages the semantic scene context obtained from a semantic segmentation framework. We believe that our Sem2Vec context embeddings carry highly discriminative information specifically for emotions in context, as it allows to effectively interpret the surroundings in the case of scarce training data, which is empirically validated through our experiments.

Contributions and Summary. Given the dynamic nature of environments influencing human affect and the continuous refinement of the emotion taxonomies through new findings of psychological research, we argue that reducing the burden of data collection for incoming categories of finer human-affect categories is an important and under-researched problem. This paper makes a step towards generalizable emotion recognition models which are able to adapt to novel categories with a single visual example and has two major contributions. (1) First, we formalize the under-researched task of one-shot recognition of emotions in context (see Figure 1), extending the conventional setup [17] with novel label-scarce types of affect present at test time. To this intent, we augment the original Emotic dataset [17] with single-example emotions present during evaluation, defining the benchmark protocols for one-shot categorization of human affect as both, categorical- and numerical (i.e. emotion assessment on a continuous scale) problems. (2) To achieve more generalizable representations of human affect, we follow the deep metric learning paradigm and introduce an approach for context-aware one-shot human affect recognition. We build on the off-the-shelf approach for conventional emotion classification [18], augmenting it with a semantic scene context branch, which obtains semantic embeddings (Sem2Vec) of the surroundings through a semantic segmentation framework [45] and is optimized jointly with the core network using triplet loss and cross entropy loss. Thereby, Sem2Vec mitigates the problem of data scarcity through discriminative environment representation achieved through knowledge transfer from a segmentation model, outperforming the native affect classification architecture by > 8% in our one-shot context. To encourage future research of more universal emotion representations and release the pressure brought by extensive labelling of new examples, we will make our benchmark available to the public.

II. RELATED WORK

A. Human affect recognition

Most of the classical affect recognition methods focus on facial expressions [5], [11], [39] and sometimes leverage additional cues, such as body pose [25], [26], [35] or eye gaze [49]. The recently emerged Emotic dataset [17] enabled large-scale studies of recognizing emotions in context, considering diverse surrounding scenes influencing human affect and resulting in multiple neural architectures developed for this task [2], [23], [30], [18]. Mittal et al. [23] leveraged three interpretations, i.e., multi-modal, attention-driven and depth-based context for dynamic emotion recognition. Ruan et al. [30] designed an architecture that makes use of both global image context and local details of the target person for multi-label emotion recognition. Antoniadis et al. [2]
proposed to exploit emotional dependencies by using a graph convolutional network. Differently from these works, we propose a semantic-aware one-shot human affect recognition method which handles the challenges of novel classes emerging in unconstrained conditions, while leveraging context encoding based on semantic segmentation maps.

B. One-shot recognition

One-shot learning has been a hot research topic over the last years. Existing methods mainly pursue the paradigms including data augmentation, transfer learning, deep embedding learning, and meta learning. Data augmentation based methods [10] enrich the training data to produce more diverse examples or hallucinate examples of novel classes. Transfer learning based methods [19], [48] aim to reuse knowledge in learned tasks. Deep embedding learning methods [16], [44] are built to design low-dimension embedding spaces to yield more discriminative feature representations. Meta learning models [32], [48] attempt to harvest knowledge among multiple tasks. There are additional few-shot learning methods [13], [22], [28], [36] for various tasks like face- and action recognition, driver observation, and semantic segmentation. The work most similar to ours is presumably the one of Cruz et al. [8] (2014) who proposed a Haar-like-features-based framework for one-shot classification of facial expressions. However, the setting of [8] is very restrictive compared to modern datasets [17] and puts the environment aside while focusing on frontal facial images only. Furthermore, Wang et al. [46] addressed on few-shot sentiment analysis on social media, while Zhan et al. [50] considered zero shot emotion categorization, which, however, is very different from the one-shot task as it is centered around finding good textual embeddings for the unknown emotions, while one-shot learning assumes a single visual example present at test-time. In this work, we conceptualize a novel task of one-shot emotion recognition in context, which has been largely overlooked in previous research.

III. ONE-SHOT RECOGNITION OF HUMAN AFFECT

A. Problem Formulation & One-Shot Emotic Benchmark

We tackle the problem of one-shot recognition of emotions in context from image data, which aims to assign the correct human affect class given a single support set sample for the unseen categories. First, we provide a formal definition of the problem, with an overview illustrated in Figure 1. Conceptually, one-shot human affect recognition aims to transfer a priori knowledge acquired from a label-rich dataset of known categories to categorize human affect in finer-grain level given a single support set sample.

Formally, let $C_{novel}$ denote the unseen classes and $C_{base}$ indicate the seen classes. One-shot recognition is the task of classifying examples in a set of unseen classes $C_{novel}$ given one single sample per unseen class in the support set, and a large amount of training data for the seen classes $C_{base}$. Formally, we start with a training set $D = \{(d_s, y_s)\}_{s=1}^{N_s}$, $y_s \in C_{base}$. Then a support set $R = \{\{x_i\}_{i=1}^{N_{novel}}\}$, where $C_{base} \cap C_{novel} = \emptyset$, and a query set $Q = \{q_i\}_{i=1}^{M}$ are supplied and the goal is to assign a class $y \in C_{novel}$ to each $q_i \in Q$. Note that the query set is also the testing set.

### Categorical benchmark

In order to provide a benchmark for one-shot recognition of emotions in context, we reformulate the 26 categories covered by the well-established Emotic dataset [17] developed for conventional human affect classification to our one-shot recognition task. To achieve this, we split the dataset category-wise in the seen classes $C_{base}$, and unseen classes $C_{novel}$, following Table I. As our support set $R$ we select the first sample of the corresponding unseen category generated through random order, while the remaining categories constitute the query set $Q$ also noted as test set. Due to the trend of making human affect taxonomies more and more fine-grained, our seen classes $C_{base}$ comprise coarser types of human affects, which are anger, sadness, joy, love, fear and surprise constructed by the emotional categories provided by Emotic dataset [17]. The fine-to-coarse cluster relationship of these human affect categories follows the human affect tree structure proposed by Shaver et al. [37]. The test set $C_{novel}$ therefore represents more fine-grained human affects. To honor the one-shot learning premise, we reassure disjoint training and testing categories, i.e. $C_{base} \cap C_{novel} = \emptyset$ also taking into account generalizations to make sure there is no overlapping. We consider two kinds of train-test split for the categorical one-shot human affect recognition task, denoted as CAT-6:4 and CAT-6:6, with the detailed overview provided in Table I.

#### Reformulated numerical benchmark

We further refor-
mulate numerical human affect regression task into one-shot recognition task to further verify the efficiency of our approach on the unnamed human affect categories defined by different level of the three main components, which are valence, arousal and dominance in Emotic dataset [17] based on the work from Posner et al. [27], considering the discrete level annotation from 1 to 10 as in [17] as category labels for each component, with the splits denoted as LEV-7:3 and LEV-6:4 for different seen-unseen proportions.

Dealing with multi-label annotations. Since Emotic [17] is a multi-label dataset, we leverage a multiple-to-single label mapping approach to realize unique label encoding for each sample, demonstrated in detail in following. Assuming $N$ classes in total for both training and testing, let $e$ denote a $N$-dimensional zero vector. If emotional labels for one sample are contained by list $W$, then the desired label $y$ for this sample can be encoded as

$$ e[\text{Label2index}(l_i)] = 1, \text{ for } l_i \text{ in } W, $$

$$ y = \text{argmax}(e), $$

where Label2index maps a label from Emotic dataset [17] into one-shot encoded label according to Table 1 considering the column index for categorical human affects, and for numerical human affect one-shot recognition, $[1, 3, 5, 6, 8, 9, 10]$ is selected as training set for LEV-7:3 train-test split and $[1, 3, 5, 6, 8, 9]$ is selected as training set for LEV-6:4 train-test split while the rest classes are set as testing set for each. The Label2Index is identity mapping for numerical human affect one-shot recognition benchmark. The final label for each sample is generated through an Argmax operation according to the encoded vector $e$.

B. Deep Metric Learning Architecture

To address one-shot recognition of emotions-in-context task, we follow the deep metric learning paradigm [22] (main workflow illustrated in Figure 2). Our model takes an image $I$ as input together with the location of the person-of-interest (as in [17]) which we use to obtain the body crop image $I_{body}$. This information is passed through the networks $f_{body}, f_{img}, f_{emb}$ to produce the features $f_{body}(I_{body}), f_{img}(I_{img}), f_{emb}(I_{emb})$ capturing target person, full image and its semantic context respectively. Those features are fused and embedded through network $f_{emb}$. The network is optimized to learn highly separable human affect representations with deep metric learning (DML). During inference, the finer unseen classes are classified based on the sample in support set closest to them in the embedding space. We now describe key components of our architecture in detail.

C. Feature encoders

All three feature encoders $f_{body}, f_{img}, f_{emb}$ are off-the-shelf networks with the exception of $f_{emb}$ where we enhance an existing architecture to build a compact segmentation feature vector. ResNet [14] classification model is leveraged to form $f_{body}$ and $f_{img}$ individually while discarding softmax layer, and separately the crop of person $I_{body}$ and full image $I_{img}$ are utilized as input for two individual feature extraction branches. Finally, the final semantic embedded feature can be demonstrated as $f_{emb} = M_g \circ Sem2Vec$, where $Sem2Vec$ consists of an off-the-shelf segmentation network together with a layer providing the set of predicted semantic classes in a one-hot-encoded form and $M_g$ denotes fully-connected layers. To elaborate on Sem2Vec, assume that $Sem$ is the segmentation network and $Sem(I)$ denotes the semantic segmentation result of image $I$. If $Set \cap Sem(I)$ is the set of all distinct classes appearing on at least one pixel, and $X = Sem2Vec(I)$, then

$$ X[i] = \begin{cases} 
1, & \text{if } i \in Set \cap Sem(I) \\
0, & \text{otherwise}
\end{cases} $$

The length of $X$ is fixed as the number of pre-defined total classes of semantic segmentation network. The features of the three branches are embedded to the vector $f_{emb}(I_{img}, I_{body}, I_{sem}) = G_0 \circ F(f_{body}(I_{body}), f_{img}(I_{img}), f_{emb}(I_{sem})), \text{ where } F$ is concatenation operation and $G_0$ denotes a fully-connected layer, mapping the concatenated feature into desired-dimensional representation.

D. Deep Metric learning

Our training procedure builds on the deep metric learning pipeline of [22]. On the sampling phase, a batch of samples $B = \{(x_a, y_a)\}_{a=1}^{N_b}$ is picked and embedded via $f_{emb}$ to $B_{emb} = \{(z_a, y_a)\}_{a=1}^{N_b}$. The batch size is denoted as $N_b$. Right after, the Multi-Similarity Miner [47] is used to select the most informative positive and negative pairs of embeddings. Namely, if $\{(z_{a_i}, z_{p_i})\}_{i=1}^{N_p}$ and $\{(z_{a_i}, z_{n_i})\}_{i=1}^{N_n}$ are all possible positive and negative pairs of $B_{emb}$ and $S$ is cosine similarity, where $N_p$ denotes negative sample number and $N_p$ denotes positive sample number. Then the filter processing is defined as

$$ S(z_{a_i}, z_{p_i}) > \max_{y \neq z_{a_i}} S(z_{a_i}, y) + \epsilon $$

$$ S(z_{a_i}, z_{n_i}) < \min_{y \neq z_{a_i}} S(z_{a_i}, y) - \epsilon $$

Thus we keep only the positive pairs containing relatively smaller (relative to $\epsilon$) similarity than the most similar negative pair of the anchor and the negative pairs containing a slightly higher similarity than the least similar positive pair of the anchor.

The positive and negative pairs sharing the same anchor are combined to create triplets $\{(z_{a_i}, z_{p_i}, z_{n_i})\}_{i=1}^{N_t}$ which are used in computing the triplet loss with margin $\lambda$, with $N_t$ denotes triplet number:

$$ \mathcal{L}_{triplet} = \sum_{i=1}^{N_t} \|z_{a_i} - z_{n_i}\| - \|z_{a_i} - z_{p_i}\| + \lambda $$

Aside from being used to compute $\mathcal{L}_{triplet}$, the embeddings $B_{emb}$ are passed through a fully-connected layer and generate a classification loss $\mathcal{L}_{class}$ (cross entropy). The total loss is then a weighted sum of the aforementioned two losses:

$$ \mathcal{L}_{total} = \alpha \mathcal{L}_{triplet} + \beta \mathcal{L}_{class} $$
E. Inference

Deep metric learning pushes the embedder to learn class-divisible representations in the embedding space. This makes it possible to reduce the one-shot recognition problem to a nearest neighbour search in the embedding space, aiming at reducing the distance inside class and increase the distance between different classes.

Let \( R = \{ x_i \}_{i=1}^{|C|} \), where \( C = C_{\text{novel}} \) is the set of novel classes, be the support set of the one-shot recognition and \( x = (I_{\text{body}}, I_{\text{Image}}, I_{\text{sem}}) \) is a single example to classify. Also assume \( R_{\text{emb}} = \{ z_i \}_{i=1}^{|C|} \) and \( z \) are the embedded vectors of those examples via \( f_{\text{emb}} \). We make the assumption that for each class \( i \), the probability of a sample belonging to that class is given by an isotropical distribution centered around \( z_i \). We also assume that the density of the distribution is strictly decreasing on the distance from \( z_i \), thus the density is defined as \( p(z|y_i) = f(||z - z_i||) \). A concrete candidate for \( f \) could be for example the density of a multidimensional isotropical normal distribution centered around \( z_i \). We further assume that the support classes are independent from each other and they occur with equal frequencies. Then by Bayes rule we have:

\[
P(y_i|z) = \frac{p(z|y_i)P(y_i)}{\sum_{j\in C} p(z|y_j)P(y_j)}
\]

\[
= \frac{p(z|y_i)1^{|C|}}{\sum_{j\in C} p(z|y_j)1^{|C|}} \gamma f(||z - z_i||).
\]

where \( \gamma \) is constant for different classes and a fixed value of \( z \). But then, the predicted class of \( x \) reduces to

\[
y_{\text{pred}} = \arg \max_{y_i \in C} f(||z - z_i||),
\]

which is equivalent to selecting the nearest neighbour of \( z \) in the embedding space. Note that though the above assumptions are quite restricting, they are in some sense the best one can hope for given the very limited information one-shot learning provides us with, illustrating the ability of deep metric learning to create a good embedding space for both seen and unseen classes which decides how well our proposed approach can separate the unseen classes.

**Segmentation-driven context encoding.** In order to extract semantic related attributes-based features from full image,
Sem2Vec approach is proposed in our work to leverage underlying semantic cues to enhance the recognition of human affect. First, as aforementioned segmentation image is generated through well-trained HRNet [45] model based on ADE20K [52] dataset with \( N_{\text{sem}} \) semantic segmentation classes given the full image as input (we use 150 segmentation categories in our experiments). After the generation binary encoded vector as aforementioned to describe which kind of object occurred in the full image and provide semantic cues for human affect recognition illustrated as \( X = \text{Sem2Vec}(x) \), the final representation \( f_{\text{sem}} \) harvesting semantic cues is extracted based on the vector representation of the semantic information:

\[
 f_{\text{sem}} = M_3(\text{Sem2Vec}(x)), \tag{11}
\]

where \( M_3 \) denotes fully-connected layers with ReLU and normalization.

IV. EXPERIMENTS

We conduct extensive experiments on the One-Shot-Emotic benchmark. First, we describe the implementation details of our proposed approach in Section IV-A. Then, we present our quantitative results on both categorical and numerical one-shot human affect recognition in Section IV-B and Section IV-C accordingly. Finally, Section IV-D conducts an ablation of the model architecture choices and provides qualitative examples of the predictions.

A. Implementation Details

We use ResNet [14] pre-trained on ImageNet [9] as our body pose encoding network \( f_{\text{body}} \) and image representation encoding network \( f_{\text{img}} \). Tables II and III provide results using the ResNet18 version of the backbone, while Table IV compares ResNet18 and ResNet50 to analyze the impact of the model capacity. The input preprocessing for body pose encoding network covers cropping the person bounding boxes through annotations provided by [18] and rescaling the cropped image to \( 256 \times 256 \). For our emotion recognition architecture, we remove the last softmax layer and append a single fully-connected layer to both human body and full image networks in order to project the output logits into a fixed 512-dimensional feature space. The aforementioned \( M_3 \) with channel setting \([256, 512]\) leveraging a Rectified Linear Unit (ReLU) as activation function followed by a batch normalization layer between fully-connected layers with batch size 32. RMSprop [41] is used as optimizer with learning rate \( 3.5 \times 10^{-4} \) for categorical human affect experiments described in Section IV-B. For the numerical human affect recognition experiments described in Section IV-C, the learning rate is also set to \( 3.5 \times 10^{-4} \) for the LEV-7:3 train-test split and to \( 3.5 \times 10^{-3} \) for the LEV-6:4 (the learning rate was chosen using grid search to optimize the validation set performance). The weight decay factor \( \gamma \) is universally set to 0.1 with a step size of 4 epochs. Our approach is trained directly with the triplet loss and cross entropy loss with weight setting 0.5 for \( \alpha \) and 0.5 for \( \beta \) to balance representation learning and classification. Further details are listed in the supplementary.

B. One-shot Categorical Recognition Results

Table III compares the original approach of Kosti et al. [18] developed for standard emotion recognition with different variants of our enhancement with DML training and our proposed segmentation-aware model. Different split types are marked as CAT-6:6 and CAT-6:4 (see Section III-A for details). We also consider the impact of the individual branches, i.e., the image- (I-DML) and the body branch (B-DML) as well as their combination with each other (IB-DML) and with the semantic segmentation branch (Sem-B-DML and Sem-IB-DML). In the following, we also refer to our full model Sem-IB-DML as Affect-DML.

Our quantitative evaluation highlights the advantage of leveraging the semantic segmentation-driven embedding \( f_{\text{sem}} \) both with and without the body-focused network. Exchanging the body network \( f_{\text{body}} \) from IB-DML with our semantic network Sem-I-DML provides a remarkable performance gain of 11.14% on CAT-6:6 and about 5.29% points on CAT-6:4. Combining the representations of all three networks (Sem-IB-DML) further increases the performance by 1.60% on CAT-6:6 and 2.78% on CAT-6:4. Our method also outperforms the original method of Kosti et al. [18] by a significant margin.

C. One-shot Numerical Recognition Results

Table III lists the one-shot evaluation results of our numerical human affect recognition benchmark on the two train-test splits indicated by LEV-7:3 and LEV-6:4 (see Section III-A). Since leveraging the body representation branch and the image feature extraction network outperforms Kosti et al. [18] extended with DML (IB-DML\(^\dagger\)) in most metrics. Once again, combining the full image representation branch with our semantic embedding branch \( f_{\text{sem}} \) from SEM-I-DML instead of a body feature extraction network from IB-DML improved the performance by 2.16% for average accuracy on the three numerical human affect dimensions valence, arousal and dominance (split LEV-7:3). Note, that we still evaluate the numerical emotion with categorical accuracy (assigning the predictions to ten partitions of the
TABLE III
EXPERIMENTAL RESULTS ON ONE-SHOT EMOTIC DATASET FOR NUMERICAL HUMAN AFFECT.

| Name          | Setting Image | Setting Body | Setting Semantic | LEV-7:3 split Acc | Val. Arousal | Dom. | Avg Acc | LEV-6:4 split Acc | Valence | Arousal | Dominance | Avg Acc |
|---------------|---------------|---------------|------------------|-------------------|--------------|------|--------|-------------------|---------|--------|------------|--------|
| Random        | ×              | ×             | ×                | 12.23             | 6.90         | 11.26| 10.79  | 7.62              | 11.73   | 13.28  | 10.88      |
| Kosti et al. [18]† | ✓             | ✓             | ×                | 36.03             | 45.01        | 45.02 | 42.02  | 28.68             | 33.65   | 37.24  | 34.78      |

Baseline methods

| I-DML         | ✓              | ✓             | ×                | 46.92             | 46.89        | 55.61| 49.79  | 30.65             | 38.31   | 63.36  | 44.10      |
| B-DML         | ✓              | ×             | ×                | 35.89             | 41.95        | 54.99| 44.28  | 37.05             | 36.91   | 53.62  | 42.53      |
| IB-DML        | ✓              | ✓             | ×                | 50.75             | 46.03        | 59.16| 51.98  | 48.96             | 38.20   | 58.69  | 48.62      |
| IB-DML ( [18] with DML).† | ✓             | ✓             | ✓                | 49.00             | 43.53        | 56.23| 49.59  | 37.35             | 35.13   | 55.99  | 46.15      |

Semantic segmentation-enhanced architectures (ours)

| Semi-I-DML (ours) | ✓ | ✓ | × | 50.75 | 46.03 | 59.16 | 51.98 | 48.96 | 38.20 | 58.69 | 48.62 |
| Semi-IB-DML (ours) | ✓ | ✓ | ✓ | 52.36 | 47.19 | 64.52 | 54.89 | 58.92 | 41.37 | 62.56 | 54.28 |

IB-DML (IB-DML).†, referenced by [b]. In most examples, Affect-DML provides better predictions, a result which is consistent with the quantitative evaluation in Table II where Sem-I-DML (Affect-DML) outperforms IB-DML by 8.07% for CAT-6:4.

V. CONCLUSION

In this paper, we proposed Affect-DML – a framework for recognizing human emotions in context given a single visual example. Such one-shot recognition of human affect is a challenging but important task, because although the range of facial expressions remains the same, psychological categorization schemes and contexts-of-interest which influence the emotions continuously change. We formalize the one-shot categorization problem by augmenting the Emotic dataset and allowing only a set of coarse emotions be present during training, while during inference the model recognizes more fine-grained emotions from a single image example. Our framework differs from the existing emotion categorization

D. Architecture Analysis and Qualitative Results

In Table IV, we analyze the influence of the backbone architecture size on the recognition results (ResNet18 vs. ResNet50 [14]). The ResNet50 architectures indicates better results on some tasks like CAT-6:4, the recognition of valence and arousal on LEV-7:3 and the recognition of arousal on LEV-6:4 while the ResNet18 architecture performs better on the other tasks. When taking a closer look, the performance gains of ResNet50 are significant, while in cases where the smaller architecture shows advantages, the ResNet18 architecture only has slight performance gain of 0.4% on average over where it outperforms ResNet50.

In Figure 4 we provide a 2-dimensional t-SNE [43] analysis of the latent space embedding learnt by our best model Affect-DML. Each embedding has been colored according to its categories in testing set. There is a clear separation of the individual clusters (the color represents the ground truth emotion category). Note, that the visualization only covers categories not present during the classifier training. This indicates, that representation learned through combination of two loss functions provides representations which are highly discriminative and generalize well to novel classes, as the visualized states have not been seen during training.

Finally, we provide multiple qualitative prediction results in Figure 3. Our Affect-DML model is referenced by [a] and compared with IB-DML† (Kosti et al. [18] extended with DML), referenced by [b]. In most examples, Affect-DML provides better predictions, a result which is consistent with the quantitative evaluation in Table II where Sem-I-DML (Affect-DML) outperforms IB-DML by 8.07% for CAT-6:4.
methods in two ways. First, we optimize our model using deep metric learning, leveraging a combination of cross entropy- and triplet loss. Second, we propose to leverage an encoding of the maps produced by a semantic segmentation network, which we refer to as Sem2Vec. We believe, that semantic segmentation information is vital for generalizable models of emotions in context, which is consistently confirmed in our extensive experiments.

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