CorrLoss: Integrating Co-Occurrence Domain Knowledge for Affect Recognition

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Abstract—Neural networks are widely adopted, yet the integration of domain knowledge is still underutilized. We propose to integrate domain knowledge about co-occurring facial movements as a constraint in the loss function to enhance the training of neural networks for affect recognition. As the co-occurrence patterns tend to be similar across datasets, applying our method can lead to a higher generalizability of models and a lower risk of overfitting. We demonstrate this by showing performance increases in cross-dataset testing for various datasets. We also show the applicability of our method for calibrating neural networks to different facial expressions.

A purely data-driven approach for training neural networks may reach its limits, for example, when there is training data of low quality or when there are constraints the model must satisfy such as natural laws or other regulations [1]. Additionally, as neural networks become more complex, the need for interpretability increases. Integration of domain knowledge can tackle all of these disadvantages by forcing the neural network to adhere to constraints, which also enhances the interpretability.

In our approach, we propose to integrate domain knowledge on co-occurring target classes directly in the loss function to enhance affect recognition models. For our experiments, we concentrate on detecting facial movements called Action Units (AUs). AUs are a psychological framework to describe distinct, objective facial muscle movements such as lowering the brow, or raising the cheek in a modular way. For more information about AUs see the description by Ekman and Friesen [2] and the survey on automatic facial AU analysis by Zhi et al. [3].

One disadvantage of affective computing and especially AU datasets are the varying properties regarding their recording conditions, i.e. in-the-lab vs. in-the-wild or acted vs. natural. Training on datasets with very specific properties leads to models which suffer from bad generalizability and therefore do not evaluate well on datasets with different properties [4] in a cross-dataset setting. Domain knowledge can tackle this disadvantage, since it is to a certain degree disentangled from the dataset properties (e.g. recording setting or subject metadata) and therefore provides general information about the task. For AUs, domain knowledge in the form of co-occurrences exist due to the fact that facial expressions such as emotions, pain or stress activate specific subgroups of AUs [5]. Furthermore, because of the anatomically predetermined dependence of movements in the face, the contraction of muscles can lead to the activation of several AUs. Since the patterns for the same facial expression are similar across subjects, we propose to use the co-occurrence information to enhance the model’s generalizability and to calibrate models on distinct facial expressions.

More specifically, we formulate the co-occurrence information as a weighted regularization term (CorrLoss) to optimize positive and negative AU correlations and combine it with binary crossentropy loss (BCE). In contrast other approaches that model the co-occurrence information in a hypothesis space (see Section I), we formulate the co-occurrence constraint as a regularization term. We find this a lightweight solution, which is furthermore flexible to steer as the domain knowledge does not need to be modeled first. For highlighting the interpretability aspect, we provide visualizations of the ground truth and learned co-occurrences that can be inspected with respect to plausibility (Fig. 1). To the best of our knowledge, we are the first to formalize a co-occurrence constraint directly in the loss function and to finetune with this knowledge on facial expressions. We are also the first to conduct a comprehensive cross-dataset evaluation for assessing the generalizability of using co-occurrence knowledge. Concisely, we answer the following research questions. Does CorrLoss improve

1) within dataset performance?
2) cross-dataset performance?
3) calibration on facial expressions?

To evaluate our approach we use several AU benchmark datasets (Section II-A): BP4D ([6], [7]), CK+ [8], [9], and GFT [10], Actor Study [11], AffWild2 ([12]–[15]), and EmotiNet (manually annotated part) [16].

Our key findings are: (1) When evaluating the within dataset performance, using our CorrLoss decreases the variance over different data folds, but does not significantly increase the mean results (Section III-C). The lower variance over several different data folds can indicate enhanced robustness. We can also observe a decreased risk of overfitting in the training. (2) When evaluating our CorrLoss in a cross-dataset setting, the mean performance increases and variance decreases for most datasets compared to our baseline. This means that CorrLoss can increase the robustness and generalizability of the model (Section III-C). This is also reflected in our state-of-the-art comparison as our model outperforms in the cross-dataset evaluation (Table VI). (3) We can see a performance gain when we calibrate our trained models with CorrLoss on
specific facial expression tasks like happiness or pain (Section III-D).

I. RELATED WORK

There are different ways to include domain knowledge in deep learning models as a constraint. Borghesi et al. [17] highlight the following main approaches: feature engineering, modelling the hypothesis space e.g. with a Graph Neural Network [18], using constrained data augmentation, and adding a regularization term that includes mathematically formulated constraint knowledge. Based on these categories, we can categorize the related work with respect to our approach:

a) Regularization Term: A regularization term for enforcing domain constraints needs to be mathematically formulated in such a way that the term is differentiable and therefore suitable for updating the weights in a neural network. To the best of our knowledge we are the first to incorporate co-occurrence domain knowledge in a loss function. However, there are approaches that formulate regularization terms based on other domain knowledge. Muralidhar et al. [19] incorporate monotonicity and approximation constraints in the loss function for predicting the solubility of oxygen in water. Song et al. [20] use an additional channel correlation loss for image classification in order to constrain the relations between classes and channels. Since there are different constraints, we cannot build on their approaches.

b) Model Hypothesis Space: Most approaches using AU correlations model this information in a hypothesis space. Corneanu et al. [21] apply Structure Inference that is inspired by graphical models to exploit the correlation information and update the AU predictions accordingly. Before applying Structure Inference, they use patch learning and fuse the patches. Li et al. [22] use a Gated Graph Neural Network, which is guided by a knowledge graph containing AU correlations. Like Corneanu et al. [21], they combine it with patch learning. Cui et al. [23] use a Bayesian Network to model the correlation information as a weak supervision for backpropagation. Song et al. [24] employ different Bayesian graph structures to capture different correlations for each facial expression. In contrast to our work they do not use the correlations to finetune or evaluate on facial expressions. All these approaches demonstrate increasing performance on the same dataset, which is encouraging but in contrast to us, they do not evaluate cross-dataset to demonstrate the model’s generalizability. Furthermore, modeling the information in a hypothesis space is an extra step our approach does not need, which gives us for example the opportunity to finetune easily on new data.

c) Other: Wang et al. [25] use the correlation information between AUs and emotions as a probability for generating pseudo AU expressions in a semi-supervised approach. They evaluate their approach cross-dataset with three datasets, but do not compare with and without correlation information. Also, since it is a semi-supervised approach it is not suitable for comparison. Zhao et al. [26] propose a patch-learning approach that takes region patches of co-occurring AUs into account and thus preserve the correlation of the dataset. Shao et al. [27] reach state-of-the-art results by learning AU detection and face alignment together. We compare our results to their JAA model.

All in all, none of these approaches use the AU correlation information directly as a constraint in the loss function and we can conclude that there is a lack of cross-dataset evaluation. To the best of our knowledge we are also the first to use co-occurrence information for calibration on facial expression.

II. METHODS

A. Data Pre-Processing

Table I describes the different properties of our datasets. For training, we load the video frames or images in color and crop the faces with the OpenCV [28] DNN module for face detection, a state-of-the-art and open-source framework.
TABLE I
OVERVIEW OF DIFFERENT DATASET PROPERTIES. not spec. STANDS FOR NOT SPECIFIED, seq. FOR SEQUENCE LABELED

| Dataset          | Subjects | Frames  | Coding                  | Affect                                      | Recording Setting |
|------------------|----------|---------|-------------------------|---------------------------------------------|-------------------|
| Actor Study      | 21       | 146,663 | frame                   | posed & natural (actors reproduce AUs, emotions are triggered) | lab               |
| AffWild2         | 47       | 303,250 | frame                   | natural                                    | in-the-wild videos (varying quality) |
| BP4D             | 41       | 366,955 | frame                   | natural (subjects were stimulated)          | lab               |
| CK+              | 123      | 10,734  | seq.                    | posed videos (neutral face to peak)        | lab (mostly gray scale) |
| EmotioNet (manual)| not spec.| 24,598  | frame                   | natural                                    | in-the-wild (web images) |
| GFT              | 96       | 172,800 | frame                   | natural (social situation)                 | lab               |

Fig. 2. Visualization of the CorrLoss regularization term $c$ (see Eq. 2). $p$ stands for pearson correlation.

We resize images to $224x224$ pixels and normalize by zero-centering each color channel with respect to the ImageNet dataset used for pretraining.

AU datasets are often imbalanced, because AUs are not equally represented in facial expressions. Because AU detection is a multi-label problem, we apply a multi-label balancing optimizer [29] that operates on unique label sets. We use the following values: weighting parameter $\lambda = 0.000001$, iterations=4000, and maximum occurrence of one image $n_i=6$. We use slight augmentations as recommended in [29].

B. Pearson Correlation Coefficient

Because co-occurrence patterns between AUs vary greatly with dataset setting and task, we do not utilize literature AU correlation information, but take a dataset-based approach. For calculating the strength of co-occurrences between AUs in the datasets, we employ the pearson correlation coefficient. Eq. 1 shows the pearson correlation formula between two AU classes $a$ and $b$, where $N$ is the batch size. The pearson correlation computes the ratio of the covariance of two variables, normalized by the product of their standard deviations. In the case of binary variables the pearson correlation returns the Phi coefficient, also known as Matthews correlation coefficient.

$$p(a, b) = \frac{\sum_{i=1}^{N} (a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_{i=1}^{N} (a_i - \bar{a})^2} \sqrt{\sum_{i=1}^{N} (b_i - \bar{b})^2}}$$

The correlation coefficient ranges from $-1$ (strong negative correlation) to $1$ (strong positive correlation) with $0$ indicating that no relationship exists. Two classes are medium correlated when the value is in the range $[0.3, 0.49]$. For our experiments, we select the following AUs, as they are the intersection of annotated AUs of our training datasets BP4D, GFT, and CK+: 1,2,4,6,7,10,12,14,15,17,23, and 24. Based on these AUs, we select for each of our training datasets the AUs that have at least a correlation strength of 0.4 with one other AU. Figure 5, 6, and 7 in the appendix show the ground truth correlation matrices of the datasets.

C. Loss Function

For training our models, we apply for each batch the combined loss from the CorrLoss and BCE. The CorrLoss (Fig. 2) enforces a reduction of the distance between the ground truth and predicted co-occurrence matrix during training. Eq. 2 shows our CorrLoss $c$ for two AUs $a$ and $b$. The variables $p(a, b)_y$ and $p(a, b)_{\hat{y}}$ note the pearson correlation for ground truth $y$ and predicted labels $\hat{y}$ respectively. Furthermore, we add 1 to make correlation values positive for computational reasons. In the denominator, the variable $U$ is the number of AU classes. The denominator scales the result by the number of correlations.

$$c(a, b) = \frac{\left| p(a, b)_y + 1 - p(a, b)_{\hat{y}} + 1 \right|}{0.5(U^2 - U)}$$

For reasons of simplicity it is omitted in Eq. 2, but when computing the CorrLoss for more than two AUs, the difference matrix is summed up. Also omitted is that we add a small error term $\epsilon$ to $y$ and $\hat{y}$ for numerical stability. Furthermore, to ignore double values in the matrix we apply a boolean matrix mask of the same size with values of 1 only above the diagonal. This mask would also offer the possibility to select specific correlations. Regarding differentiability, CorrLoss is not differentiable when $p(a, b)_y - p(a, b)_{\hat{y}} = 0$ because of the absolute value. But this is an unlikely event to occur for our experiments, since our averaged training loss is above 0 for every epoch.

Eq. 3 is the calculation of the BCE $e$, which we use since AU detection is a multi-class multi-label problem. $U$ is the number of AU classes.

$$e = -\frac{1}{U} \sum_{i=1}^{U} (y_i \log \hat{y}_i + (1 - y_i) \log (1 - \hat{y}_i))$$

Eq. 4 is our final loss function $l$ combining the CorrLoss $c$ and BCE $e$. Dividing $c$ by two squishes the CorrLoss into the range $[0,1]$ due to shifting the value range before. Variable $\rho$ weighs the CorrLoss and the BCE against each other. Setting $\rho$ to 1
ignores the BCE and setting it to 0 ignores the CorrLoss. We chose this design in order to be able to evaluate the influence of both terms in a grid search (Fig. 3).

\[ l = \frac{1}{N} \sum_{i=1}^{N} e_i + \rho \frac{c}{2} \]  

(4)

D. Evaluation Metric

We use the macro F1-score (Eq. 5) as our result metric because it compensates for both imbalanced classes and an imbalanced ratio of occurring and non-occurring AUs. Furthermore, applying this metric is widespread in the AU research field. Variable \( tp \) stands for true positives, \( fp \) refers to false positives, and \( fn \) to false negatives.

\[ F1_{macro} = \frac{1}{U} \sum_{i=1}^{U} \frac{tp_i}{tp_i + \frac{1}{2}(fp_i + fn_i)} \]  

(5)

Our correlation metric \( |p(a, b)_u + 1| - |p(a, b)_f + 1| \) shows how much the correlation matrix of the predicted values differs from the ground truth correlation matrix, where lower is better. We use it to measure the effect of our CorrLoss.

E. Model and Training

In order to facilitate comparability of our approach, we use a VGG16 [30] neural network architecture, which is pretrained on ImageNet [31]. Pretrained VGG16 Networks achieve good results for AU detection: Niinuma et al. [32] evaluate different settings for AU detection learning such as pre-training and find out that generic pre-training using the ImageNet dataset yields better results than pretraining on face-specific datasets. We employ a 5-fold cross-validation with subject-dependent splits, which keeps subjects from leaking between training and validation data. For training we freeze the weights up to layer block5_conv3. After the convolutional layers, we apply one fully connected layer with 256 neurons and a ReLu [33] activation function. A dropout layer [34] is placed between the fully connected layer and the output layer. A sigmoid activation function is used in the output layer. We save the best model when the validation loss is the lowest. For deterministic and reproducible training, we set seeds and use the deterministic implementation of TensorFlow when training on GPUs. We use the Adam optimizer with a learning rate of 0.0001 for all experiments. Gradient clipping with a clipvalue of 1 proved to be beneficial. We train with a batch size of 64 for all experiments.

III. RESULTS

A. Gridsearch

We use a gridsearch on all training datasets to determine the best correlation weight \( \rho \) in each case for computing the CorrLoss. Figure 3 shows the performance of the different \( \rho \) We can see a difference between the frame labeled datasets BP4D and GFT and the sequence labeled dataset CK+. While BP4D with and without AU10 and GFT show a decreasing performance with a rising \( \rho \), CK+ shows a high performance until a \( \rho \) value of 0.95. The CK+ dataset has more noisy frames since in each sequence the expression builds up from a neutral face to a maximum expression, but the whole sequence is labeled with the same AUs. Thus, it is possible that the CorrLoss can serve as a denoising measure.

We can see a lower but more consistent performance of the BP4D dataset over the different \( \rho \) when training without AU10 (BP4D w/o AU10). The optimal \( \rho \) is also higher (0.3 to 0.45) when leaving the AU10 out, which is an indicator that our algorithm works better. The reason is that in BP4D only selected parts of sequences are labeled. It is therefore prone to an unusual imbalance: For some AUs, the number of occurrences is higher than the number of non-occurrences. AU10 occurs most often and therefore the neural network learns to predict the occurrence of AU10 above average. To not have this dataset bias impede our approach, we decide to train without AU10. We also conclude that the algorithm is sensitive to class occurrence distribution in the training set. In general, our proposed loss function has a high performance for different \( \rho \) and is therefore quite stable. For our training we choose the best \( \rho \) per dataset.

Figure 4 shows the training and validation loss for the gridsearch. We can see that the overfitting decreases as \( \rho \) increases. Thus, the CorrLoss likely serves as a regularization.
B. Within Dataset Evaluation

Table II gives an overview of our within dataset performance of the 5-fold cross-validation, which answers our first research question. The results show no clear tendency for better mean performance using the CorrLoss. However, the variance of the 5-fold cross-validation decreases in most experiments using $\rho>0$. Since each fold contains different subjects, a smaller variance can mean a more stable and robust learning of AUs despite different appearances.

C. Cross-Dataset Evaluation

For our second research question we evaluate the cross-dataset performance (Table III). The higher mean result is in bold, if it is higher including variance, than the lower mean result. As earlier mentioned, each of our datasets display different properties regarding their recording conditions (Table I). Because of this, the results for cross-dataset cross-domain evaluation are generally much lower than for within dataset evaluation, which, however, is more realistic with regard to practical application [4]. Our cross-dataset results show that for the majority of test datasets the mean performance is better and the variance is lower when applying the CorrLoss. By using the CorrLoss as constraint we may therefore set the focus on information less susceptible to noise in the training process. This is not apparent in the within dataset evaluation, because the validation dataset has the same noise pattern as the training dataset. However, it is in the cross-dataset evaluation. Thus, the cross-dataset results show the positive impact of the CorrLoss, highlighting the generalizing effect of our method to include correlation domain knowledge.

Looking at the bold mean results dataset-wise, the benefit of the CorrLoss is the highest for models trained on CK+. As CK+ is our smallest training dataset regarding number of frames and furthermore sequence labeled, this shows how domain knowledge can be beneficial, especially for small and noisy datasets. Furthermore, CK+ contains the most persons (123) of all datasets, which emphasizes that the CorrLoss helps in generalizing across subjects. The highest mean performance for the testing datasets is reached by models trained on the GFT dataset while using the balancing optimizer. This dataset contains the second most subjects (96), which emphasizes the generalization ability across subjects. Furthermore, GFT contains only one task, which might be beneficial. As we already noticed in the gridsearch, BP4D is the most challenging training dataset. It includes a variety of different tasks and contains only 41 subjects. Conclusively, variance needs to be considered when evaluating subject-dependent splits as each fold contains different subjects. As the variance is in most cases lower with the CorrLoss, it probably even out the differences between subjects. We observe that balancing [29] the multi-label training data is beneficial for the performance in most cases. Although the performance in the cross-dataset evaluation is dataset-dependent, our results support the hypothesis that applying CorrLoss can have a positive effect on the generalizability and robustness of the models.

D. Calibration on Different Facial Expressions

Facial expressions have individual co-occurrence patterns, where only a subset of AUs are involved. For our third research question we therefore explore the calibration of a trained model on facial expressions using our CorrLoss. We take the BP4D dataset, because it includes 8 different facial expression tasks for each person. We train 8 models, each without one task, where the model does not learn the target task, e.g. happiness. As a next step, we calibrate each model trained in this way on their target expression by finetuning it for 10 epochs on half of the frames. We use a subject-dependent split. For evaluating how good the model performs on the target expression after only finetuning, we test on the second unseen half of the task. Table IV shows the testing results in macro F1-score on the left side and in correlation metric on the right side. We can see an overall performance increase when applying the CorrLoss with $\rho=0.45$. The correlation metric shows that the neural network trained only with BCE learns the co-occurrences automatically to a certain degree, but the model trained additionally with CorrLoss captures the ground truth co-occurrences better. As we recall, Figure 1 shows for the testing part of the task happiness visually that the learned correlations in a model trained with BCE and CorrLoss is closer to the ground truth correlations than when trained with only BCE. Quantitatively, Table IV shows for this testing part a better correlation metric value of 6.6 when CorrLoss is used in contrast to 8.8 when only BCE is used.

E. Comparison

Table V shows a within dataset comparison of our model with several past and recent state-of-the-art approaches: JPML[26], DSIN[21], SPERL[22], AUD-EA[23], JAA [27], and HMP-PS[24]. Our model is trained with a 5-fold cross-validation using the balancing algorithm [29] and $\rho=0.45$. As the other approaches we apply a subject-dependent splitting.

### Table II

| Dataset | not balanced | balanced |
|---------|--------------|----------|
|         | $\rho=0$     | $\rho>0$ |
| CK+ ($\rho=0.8$) | 0.583 ± 0.027 | 0.604 ± 0.026 | 0.592 ± 0.030 | 0.596 ± 0.022 |
| BP4D ($\rho=0.3$) | 0.615 ± 0.029 | 0.625 ± 0.026 | 0.636 ± 0.033 | 0.629 ± 0.025 |
| BP4D ($\rho=0.45$) | 0.587 ± 0.017 | 0.601 ± 0.014 | 0.603 ± 0.038 | 0.586 ± 0.039 |
| GFT ($\rho=0.6$) | 0.593 ± 0.020 | 0.594 ± 0.015 | 0.616 ± 0.017 | 0.613 ± 0.019 |
TABLE III
CROSS-DATASET EVALUATION. RESULTS ARE IN MACRO F1-SCORE. HIGHER MEAN IS BOLD AND LOWER VARIANCE IS UNDERLINED.

| Train Dataset | Test Dataset | not balanced | balanced |
|---------------|--------------|--------------|----------|
|               | ρ=0 | ρ>0 | ρ=0 | ρ>0 |
| CK+: ρ=0.8    |     |     |     |     |
| (AU01, AU02, AU04, AU06, AU07, AU12, AU15, AU17, AU23, AU24) | Actor Study | 0.157 ± 0.009 | 0.183 ± 0.005 | 0.179 ± 0.015 | 0.197 ± 0.010 |
|               |     |     |     |     |
| GFT: ρ=0.6    |     |     |     |     |
| (AU01, AU02, AU06, AU07, AU10, AU12, AU17, AU23, AU24) | Actor Study | 0.289 ± 0.013 | 0.301 ± 0.011 | 0.304 ± 0.006 | 0.309 ± 0.009 |
|               |     |     |     |     |
| BP4D: ρ=0.45  |     |     |     |     |
| (w/o AU10) (AU01, AU02, AU06, AU07, AU12, AU17, AU24) | Actor Study | 0.328 ± 0.017 | 0.342 ± 0.013 | 0.316 ± 0.013 | 0.308 ± 0.009 |

TABLE IV
CALIBRATION ON DIFFERENT FACIAL TASKS. BEST RESULTS ARE BOLD.

| Tasks                  | macro F1-score | Corr. Metric |
|------------------------|----------------|--------------|
|                         | ρ=0 | ρ=0.45 | ρ=0 | ρ=0.45 |
| 1 - Happiness or Amusement | 0.61 | 0.62 | 8.8 | 6.6 |
| 2 - Sadness             | 0.63 | 0.70 | 7.8 | 6.4 |
| 3 - Surprise or Startle | 0.55 | 0.55 | 11.8 | 9.0 |
| 4 - Embarrassment       | 0.64 | 0.61 | 14.0 | 8.4 |
| 5 - Fear or Nervous     | 0.61 | 0.64 | 15.2 | 9.2 |
| 6 - Physical Pain       | 0.62 | 0.68 | 8.8 | 7.6 |
| 7 - Anger or Upset      | 0.49 | 0.57 | 9.8 | 8.4 |
| 8 - Disgust             | 0.70 | 0.68 | 6.4 | 6.4 |

We compare the results for our 7 selected AUs. Table V shows that our model reaches competitive performance on the BP4D dataset despite that in comparison with other approaches our focus of optimization is not on increasing performance on the same dataset but on other unseen datasets. Table VI shows a cross-dataset comparison from models trained on BP4D and evaluated cross-dataset on GFT. While JJA [27] reaches great results on the within dataset evaluation, we significantly outperform in the cross-dataset evaluation, which means that our model has a greater generalization ability.

IV. CONCLUSION & FUTURE WORK

We propose CorrLoss, a regularization term that formalizes domain knowledge about co-occurring facial movements as a constraint for training neural networks. We observe that applying CorrLoss improves the generalizability and robustness of neural networks when evaluated in a cross-dataset setting compared to our baseline. A comparison with state-of-the-art approaches confirms a higher performance in the cross-dataset evaluation and competitive but slightly lower performance in the within dataset evaluation. CorrLoss also proves to be effective against overfitting. Moreover, we show that CorrLoss can be applied to calibrate models on specific co-occurrences of different facial expressions.

Our CorrLoss could be used whenever predicted classes relate to different domain knowledge about co-occurring facial movements. It can be applied to various tasks such as facial expression recognition, emotion classification, or even non-facial tasks like speech recognition.

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