LoRRaL: Facial Action Unit Detection Based on Local Region Relation Learning

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Abstract

End-to-end convolution representation learning has been proved to be very effective in facial action unit (AU) detection. Considering the co-occurrence and mutual exclusion between facial AUs, in this paper, we propose convolution neural networks with Local Region Relation Learning (LoRRaL), which can combine latent relationships among AUs for an end-to-end approach to facial AU occurrence detection. LoRRaL consists of 1) use bi-directional long short-term memory (BiLSTM) to dynamically and sequentially encode local AU feature maps, 2) use self-attention mechanism to dynamically compute correspondences from local facial regions and to re-aggregate AU feature maps considering AU co-occurrences and mutual exclusions, 3) use a continuous-state modern Hopfield network to encode and map local facial features to more discriminative AU feature maps, that all these networks take the facial image as input and map it to AU occurrences. Our experiments on the challenging BP4D and DISFA Benchmarks without any external data or pre-trained models results in F1-scores of 63.5% and 61.4% respectively, which shows our proposed networks can lead to performance improvement on the AU detection task.

1 Introduction

Facial action unit detection aims to detect the occurrence of facial muscle movements, named Action Units (AUs) defined by FACS, the Facial Action Coding System [6]. Each AU represents a basic facial muscle movement or expression change. AU detection has a vast range of applications. For example, the improvement of labor productivity by taking care of employees psychology and improve their motivation, or to estimate customers satisfaction and to improve their purchasing motivation (digital marketing), etc.. In these cases, a detail description of AU occurrence needs to be estimated from the facial images to complete the subsequent tasks, e.g., facial expression analysis. Thus it is a problem that must be solved in order to achieve satisfactory performance in subtle facial analysis tasks.

Traditional approaches, such as hand-crafted feature-based [12, 24] and shallow model-based [3, 2, 26, 7, 27] methods, have limited ability to capture subtle muscle movements. Recently, a large number of techniques based on deep learning are proposed for this task. Zhao et al. [30] presented deep regional feature learning and multi-label learning modules in a unified architecture for facial AU detection. Li et al. [14] proposed EAC-Net that can learn both features enhancing and region cropping functions simultaneously. Corneanu et al. [4] proposed a deep structured inference network (DSIN) for AU detection by combining learned local and global features in its initial stages and structure inference to capture AU relations by passing information between predictions in later stages. Niu et al. [16] improved the AU recognition by using facial shape information extracted from landmarks. Shao et al. [21, 20] developed an end-to-end framework for joint facial AU detection and face alignment, which can contribute to each other by sharing features and initializing the attention maps with the results of face alignment.

Although these methods are effective, there are still two difficulties in facial AU detection that have not been resolved, the first is that the facial appearance changes are subtle according to the AU occurrence,
and we don’t have any prior information of the subjects, while individuals may have different levels of expressiveness due to their own physical characteristics. The second difficulty is that co-occurrences and exclusion of different AUs may influence the overall prediction results. Considering the linkage of facial expression to multiple AUs and the anatomical characteristics of faces, that we know AUs are not independent of one another. Since facial AU detection has been mainly treated as a multi-label classification problem, which means several AUs can be active at the same time and certain AU combinations are more likely than others. As an example in Figure 1, a surprising expression activates AU1 (Inner Brow Raiser), AU2 (Outer Brow Raiser), and AU5 (Upper Lid Raiser), and an angry expression activates AU4 (Brow Lowerer), AU7, and AU9 (Nose Wrinkler). By contrast, due to structural limitations of the facial anatomy, certain action units are generally unlikely to be activated simultaneously, e.g., we cannot open our mouth and lift our cheeks at the same time, or as shown in Figure 1(c) and Figure 1(d), AU12 (Lip Corner Puller) and AU15 (Lip Corner Depressor) are difficult to appear at the same time.

(a) Co-occurrence of AU1, AU2, and AU5. (b) Co-occurrence of AU4, AU7, and AU9. (c) Sample of AU12. (d) Sample of AU15.

Figure 1: Examples of co-occurrence and mutually exclusive relations between AUs. A surprised expression may cause AU1, AU2, and AU5 to appear together. An angry expression may cause AU4, AU7, and AU9 to appear together. Generally AU12 and AU15 will not appear at the same time.

To tackle the above limitations, we propose an end-to-end AU detection based on convolution neural networks with Local Region Relation Learning (LoRRaL), which can dynamically calculate the relationship between all AUs based on each input picture, and strengthen the expressive ability of AU feature maps.

The remainder of this paper is organized as follows: Section 3 describe our proposed LoRRaL and the AU detection algorithm in detail. The experimental setup and results are presented in Section 4. We conclude this paper in Section 5.

The remainder of this paper is organized as follows: First describe our proposed HOPFIELD and the AU detection algorithm in detail. The experimental setup and results are presented and discussed. Finally we give the conclusion of this paper.

2 Related work

Our LoRRaL is closely related to existing deep learning aided facial AU detection methods as well as AU modeling with relation (graph) learning methods, since we combine both AU detection models and relation (graph) learning models.

Chu et al. [3] proposed a hybrid deep learning framework that both strengths of CNNs and LSTMs to model and utilize both spatial and temporal cues. Ertugrul et al. [8] proposed a simple sigmoidal attention mechanism for weighting the local facial patches to detect specific AUs. Li et al. [13] combined the fixed knowledge graph of AU correlation into a convolution neural network to enhance AU detection. Reale et al. [18] extracted local AU features in the 3D space based on cloud input. Tu et al. [23] implemented an identity-aware architecture of multi-task network cascades where one task is to extract identity information, and the other task is to subtract that identity information and do AU detection. Fan et al. [10] presented a new learning framework that automatically learns the latent relationships of AUs via establishing semantic correspondences between feature maps.

Our proposed LoRRaL is a more flexible solution that can treat all AU feature maps as a sequence data or a graph data at the same time. We can dynamically calculate the relationship between AUs based on
the input image in real-time, and use this relationship to enhance the characterization ability of AU feature maps. In other words, our method is naturally independent of a person’s identity.

3 AU recognition with LoRRaL

The goal of AU recognition or detection is to estimate the occurrences of certain individual facial muscle movement signals from images or videos. Figure 2 illustrates the framework of our proposed approach to achieve this goal. The framework consists of six components, including patch learning, global facial representation learning, local AU representation learning, local AU relation learning, AU occurrence prediction, and facial landmark estimation.

Firstly the patch learning [30] maps a facial image to its latent feature representation with precise features of local regions. In order for a better capability of localization and classification, this patch learning uses an operation called ‘PatchConv’ [30] as shown in Figure 3(b). It consists of a 2-D convolution (Conv2D), several independent same branches of batch normalization (BatchNorm) [11], parametric ReLU (PReLU), Conv2D, and concatenation (Concatenate). Thus in this PatchConv operation, a feature map is evenly divided into several sub-feature maps, and then each sub-feature map undergoes several independent but identical convolution operations, and then concatenated back into a complete feature map.

Then inspired by DSIN [4], all global facial feature, facial landmark feature, and local AU feature representations are extracted through several layers of ‘FeatConv’, as shown in Figure 3(a) which consists of 2 Conv2Ds, BatchNorms, PReLUs, and a 2-D max-pooling (Max Pool2D). Here for the local AU features, the local region feature map corresponding to certain AUs are cropped according to the predicted facial landmark and the AU centers. The approximate center locations of all AUs are shown in the Figure 4. In order to mine and use the relationship between AUs, all local AU features will pass through an AU relation learning module, and the output is the new Local AU features, which will be concatenated with global facial feature and landmark feature. Finally motivated by [20], multi-task learning for simultaneously face alignment and AU recognition is employed for the back-end of LoRRaL.

In LoRRaL, the AU relation learning module is the main contribution and main focus of this paper, and will be elaborated in Section 3.1,3.2, and 3.3.

3.1 AU relation learning with BiLSTM

As we described in Section 1, the AUs have a mutual exclusion and co-occurrence relationship. In fact, AU also has a sequential relationship, which can be observed from two perspectives. First, since when people are facing a face image, the position of attention is always changing and moving in a certain order. On the other hand, when a person is making a certain expression, due to the physical characteristics of the facial muscles, the appearance of AU is in a specific sequence. Thus we thought that maybe we can model AU through certain time series models, such as BiLSTM.

As shown in Figure 5, the input of BiLSTM is the sequence of AU feature maps obtained by the previous AU feature extraction. For example, for BP4D, we will use the natural encoding order as the input here, that is, AU1, AU2, ..., AU23, and AU24. The reason for using bi-directional LSTM is to consider that the AUs in the front and in the back among the sequence will affect each other. Mutually exclusive AUs will reduce the probability of each other’s appearance, and AUs that can co-occur will mutually strengthen the features of each other. In this way, after processing of BiLSTM, each new AU feature will be combined with the feature expression of other AUs, thereby enhancing its own discriminative ability.

3.2 AU relation learning with self-attention encoding

BiLSTM is a time series model, but the AU feature maps are not just a sequence structure, are more like a graph structure [10, 28, 13]. If the AU feature maps are treated as the nodes of the graph, the edge of the graph can be the probability that two AUs appear together or distance of the two AU feature maps. If the probability of occurrence 2 AUs is high, then the value of the edge is also higher. Otherwise, when if the probability of AU co-occurrence is very low, for example, the value of the edge between AU12 and AU15 should be 0 or very small. In this section we use Transformer or self-attention [25] to model both the graph and sequence structure of AUs simultaneously.
Figure 2: The architecture of LoRRal consists of 1) patch learning (refer Figure 3(b) for PatchConv), 2) global facial representation learning (refer Fig. 3(a) for FeatConv), 3) AU representation learning (refer Fig. 5, 6, and 7), 4) AU relation learning, 5) local AU occurrence prediction, and 6) facial landmark estimation. First, the patch learning module is used to convert input facial signal into its corresponding representation. Then, the global facial feature, local AU features, and facial landmark features are extracted based on this representation. Before concatenating these three features, the AU features are recombined through the interaction between AUs to maximize the characterization ability. The AU occurrences and facial landmarks are predicted based on the concatenated representations.
Figure 3: The structure of FeatConv and PatchConv in the pipeline of LoRRal. PatchConv works as follows. First, the input feature map passes through a plain convolutional layer, and then the obtained feature map is divided into several sub-feature maps, each passing through an independent convolution layer with the same structure, and finally, the processed output sub-feature maps will be concatenated together as the output of PatchConv.

As shown in Figure 3, the AU feature map first passes through the preprocessing module. In the preprocessing module, there are fully connected linear unit (Linear), layer normalization (LayerNorm) [1], dropout (Dropout) [22], and a position encoding module. Here the position encoding is as follows:

\[
pe(pos, 2i) = \sin(pos/10000^{2i/d}) \quad (3.1)
\]
\[
pe(pos, 2i + 1) = \cos(pos/10000^{2i/d}) \quad (3.2)
\]

where \(pos\) is the position of the AU feature in the input AU graph and \(i\) is the dimension in the Linear transformed AU features, and \(d\) is the output dimension of Linear module in the preprocessing module. This \(pe\) vector is added with the Linear transformed AU features. After the preprocessing module, we get the input AU feature maps for the self-attention encoding module.

Several identical self-attention encoding layers can be used in our framework. In each self-attention encoding layer, the input consists of queries and keys of dimension \(d_k\), and values of dimension \(d_v\). Here queries, keys, and values are the different avatars of the same AU feature map, although through different Linear transformations. Then we compute the attention function on a set of queries simultaneously, packed together into a matrix \(Q\). The keys and values are also packed together into matrices \(K\) and \(V\). We compute the matrix of outputs as:

\[
\text{Self-Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V. \quad (3.3)
\]

Indeed \(\frac{QK^T}{\sqrt{d_k}}\) describes the distances between all AU node pairs in the graph. Thus Self-Attention\((Q, K, V)\) is indeed the weighted sum of AU features according to the relations computed by \(\frac{QK^T}{\sqrt{d_k}}\), thus result in new AU representations. That means co-occurrence AU will enhance each other and mutual exclusive AU will reduce the probability of each other.
Figure 4: The centers of AUs.

Figure 5: AU relation learning with BiLSTM. The feature maps corresponding to all AUs are input into BiLSTM as a sequence, and the output is the AU feature maps after recombination and transformation. The reason for using LSTM in two directions is to hope that all AUs before and after can influence and interact with each other.
Figure 6: AU relation learning with self-attention encoding. The encoding is composed of two parts. The first is to perform the preprocessing of a linear transformation on the old AU feature maps, and in this process the coded position information of the AU feature maps are added. The second is the self-attention encoding layers, which self-attention can be described as mapping a query and a set of key-value pairs to an output, where the query, key, value, and output are all vectors. The output is calculated as a weighted sum of values, where the weight assigned to each value is calculated by using the corresponding key query compatibility function.
3.3 AU relation learning with continuous Hopfield layer

Recently Ramsauer et al. [17] proposed a modern Hopfield network with continuous states. They first generalized the original Hopfield network into a new Hopfield network with continuous states (this network has a natural graph structure), and then proposed a simple and effective training method for this new Hopfield network. The basic principle of the training method is to obtain attention by constantly providing queries to the network, and this mechanism is basically the same as the Transformer’s mechanism. Through this discovery, they have improved the existing Transformer. Here we also try to use this new model to learn the relationship between AUs and strengthen the characterization ability of AU feature maps.

As shown in Figure 7, it can be seen that the difference of modern Hopfield network from Transformer is that the update formula of Equation 3.3 can be applied iteratively to the initial state of each Hopfield layer header. After the last update, the new state will be projected to the resulting pattern. Therefore, the Hopfield layer allows multiple update steps forward without changing the number of parameters. You can specify the number of update steps per Hopfield header. In addition, a threshold can be set for the number of updates based on the size of each Hopfield header.

3.4 Losses

In this paper, we use three kinds of losses, namely the cross-entropy loss of AU occurrence based on the concatenated feature maps, the cross-entropy loss of AU occurrence based on the local AU feature maps,
and the Euclidean loss of landmark prediction accuracy based on the landmark feature maps.

### 3.5 Two-step training

During the experiment, we found that the two-step training method works better. That is, firstly we train the pipeline in Figure 2 without local AU relation learning module to get the best patch learning, global facial representation learning, and local AU representation learning modules. Then the local AU relation learning module added back to result in the LoRRaL, and the parameters the best patch learning, global facial representation learning, and local AU representation learning modules are fixed, only train local AU relation learning, AU occurrence prediction, and facial landmark estimation modules. The training algorithm we use is SGD, with a momentum of 0.9 and a weight decay of 0.0005. We train LoRRaL with an initial learning rate of 0.01 for up to 30 epochs, where the learning rate is multiplied by a coefficient of 0.3 for every 2 epochs.

### 4 Experiments

#### 4.1 Dataset and evaluation metrics

Our LoRRaL is evaluated on two widely used challenge datasets for AU detection, i.e. BP4D [28] and DISFA [15], in which both AU and landmark labels are provided.

BP4D contains 41 subjects, including 23 women and 18 men. Each involves 8 sessions. There are 328 videos including about 140,000 frames with AU labels. 49 landmarks are provided for each frame. Similar to the setting of Zhao et al. [30], Li et al. [14], and Shao et al. [20], 12 AUs (1, 2, 4, 6, 7, 10, 12, 14, 15, 17, 23, and 24) are evaluated using subject exclusive 3-fold cross-validation, where two folds are used for training and the remaining one is used for testing.

DISFA contains 27 video recordings from 12 women and 15 men, each has 4,845 frames. Every frame is labeled with AU intensity ranging from 0 to 5, and 66 landmarks are provided. According to the setting of Zhao et al. [30], Li et al. [14], and Shao et al. [20], AU intensity equal to or greater than 2 are considered as occurrence. Others are treated as non-occurrence. Eight AUs (1, 2, 4, 6, 9, 12, 25, and 26) were evaluated.

What we want to emphasize here is that in our experiments, we did not use any additional data or pre-trained models, including our results on DISFA. That is to say, we only use BP4D and DISFA’s own data for training and test. When experimenting with DISFA, we did not use the pre-trained model on BP4D.

Follow the previous method Zhao et al. [30], Li et al. [14], and Shao et al. [20], F1-score (%) are reported for comparison.

#### 4.2 Results and Discussions

In this experiment, LoRRaL is compared with several classical and state-of-the-art approaches, such as LSVM [9], JPML [29], DRML [30], CPM [27], EAC-Net [14], DSIN [4], CMS [19], LP-Net [16], ARL [21], and JAA [20].

Table 1 and 2 lists the results obtained by our methods and almost all the results in the past four years. Compared with these baselines, LoRRaL obtained an absolute advantage, once again surpassing the performance of state-of-the-art. LoRRaL is 1.1% and 2.7% higher than the previous state-of-the-art method, respectively on BP4D and DISFA datasets.

#### 4.3 Ablation study

For the ablation study, Table 3 and 4 shows that LoRRaL pipelines perform better than the pipeline in Figure 2 without relation learning modules in F1-scores. That means the local AU relation learning modules are effective in boosting the performance. The effect of local AU relation learning is to increase the F1-score of the pipeline in Figure 2 without relation learning modules by 0.9% and 2.1% on BP4D and DISFA respectively.
Table 1: F1-score(%) in a comparative study of different state-of-the-art detection methods on the BP4D dataset. LoRRaL(SA), LoRRaL(H), LoRRaL(B) stands for LoRRaL with self-attention, Hopfield, and BiLSTM respectively.

| AU   | 1     | 2     | 4     | 6     | 9     | 12    | 14    | 15    | 17    | 23    | 24    | Avg  |
|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| LSVM | 23.2  | 22.8  | 23.1  | 27.2  | 47.1  | 63.7  | 64.3  | 18.4  | 33.0  | 19.4  | 20.7  | 35.3 |
| JMLP | 32.6  | 25.6  | 37.4  | 42.3  | 50.5  | 72.2  | 74.1  | 65.7  | 38.1  | 40.0  | 30.4  | 42.3  | 45.9 |
| DRML | 36.4  | 41.8  | 43.0  | 55.0  | 67.0  | 66.3  | 65.8  | 54.1  | 33.2  | 48.0  | 31.7  | 30.0  | 48.3 |
| CPM  | 43.4  | 40.7  | 43.3  | 59.2  | 61.3  | 62.1  | 68.5  | 52.5  | 36.7  | 54.3  | 39.5  | 37.8  | 50.0 |
| EAC-Net | 39.0 | 35.2  | 48.6  | 76.1  | 23.2  | 81.9  | 86.2  | 58.8  | 37.5  | 59.1  | 35.9  | 35.8  | 55.9 |
| DSIN | 51.7  | 40.4  | 50.0  | 76.1  | 73.5  | 79.9  | 85.4  | 62.7  | 37.2  | 69.2  | 38.8  | 41.6  | 58.9 |
| CMS  | 49.1  | 44.1  | 50.3  | 79.2  | 74.7  | 80.9  | 88.3  | 63.9  | 44.4  | 60.3  | 41.4  | 51.2  | 60.6 |
| LP-Net | 43.4 | 38.0  | 54.2  | 77.1  | 76.7  | 83.8  | 87.2  | 63.3  | 45.3  | 60.5  | 48.1  | 54.2  | 61.0 |
| ARL  | 45.8  | 39.8  | 55.1  | 75.7  | 77.2  | 82.3  | 86.6  | 68.7  | 47.6  | 62.1  | 47.4  | 55.4  | 61.1 |
| JAA  | 53.8  | 47.8  | 58.2  | 78.5  | 75.8  | 82.7  | 88.2  | 63.7  | 43.3  | 61.8  | 45.6  | 49.9  | 62.4 |

| AU    | 51.1  | 51.7  | 59.0  | 78.0  | 73.4  | 84.9  | 89.9  | 64.5  | 50.8  | 61.9  | 47.2  | 48.8  | 63.4 |
| LoRRaL(SA) | 53.1  | 52.9  | 59.8  | 79.0  | 73.2  | 88.0  | 90.6  | 61.3  | 46.2  | 63.4  | 48.1  | 46.9  | 63.5 |
| LoRRaL(H) | 52.1  | 53.8  | 60.7  | 76.3  | 73.3  | 87.1  | 90.1  | 64.0  | 45.1  | 63.3  | 48.5  | 45.6  | 63.3 |

Table 2: F1-score(%) in a comparative study of different state-of-the-art detection methods on the DISFA dataset. LoRRaL(SA), LoRRaL(H), LoRRaL(B) stands for LoRRaL with self-attention, Hopfield, and BiLSTM respectively. For a fair comparison, we did not list some results of using BP4D pre-training, e.g. JAA [20].

| AU   | 1     | 2     | 4     | 6     | 9     | 12    | 25    | 26    | Avg  |
|------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| LSVM | 10.8  | 10.0  | 21.8  | 15.7  | 11.5  | 70.4  | 12.0  | 22.1  | 21.8 |
| APL  | 11.4  | 12.0  | 31.2  | 12.4  | 10.1  | 65.9  | 21.4  | 26.9  | 23.8 |
| DRML | 17.3  | 17.7  | 37.4  | 29.0  | 10.7  | 37.7  | 38.5  | 20.1  | 26.7 |
| EAC-Net | 41.5 | 26.4  | 66.4  | 50.7  | 80.5  | 89.3  | 88.9  | 15.6  | 48.5 |
| DSIN | 42.4  | 39.0  | 68.4  | 28.6  | 46.8  | 70.8  | 90.4  | 42.2  | 53.6 |
| CMS  | 40.2  | 44.3  | 53.2  | 57.1  | 50.3  | 73.5  | 81.1  | 59.7  | 57.4 |
| LP-Net | 29.9 | 24.7  | 72.7  | 46.8  | 49.6  | 72.9  | 93.8  | 65.0  | 56.9 |
| ARL  | 43.9  | 42.1  | 63.6  | 41.8  | 40.0  | 76.2  | 95.2  | 66.8  | 58.7 |

| AU    | 60.1  | 59.2  | 71.3  | 26.5  | 55.3  | 71.5  | 93.8  | 53.1  | 61.4 |
| LoRRaL(SA) | 61.0  | 57.2  | 70.6  | 32.4  | 51.4  | 70.7  | 90.7  | 51.1  | 60.6 |
| LoRRaL(H) | 59.3  | 59.0  | 69.5  | 35.4  | 46.2  | 72.2  | 94.1  | 48.3  | 60.5 |

5 Conclusion

In this paper, we investigated the effectiveness of local AU feature map relation modeling for AU detection. We propose LoRRaL do to AU recognition. Benefits from the strength of BiLSTM, self-attention encoding, and continuous Hopfield encoding, the best performance of LoRRaL achieves the new state-of-the-art of 63.5% F1-score on the public BP4D data corpus.

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Table 3: F1-score(%) in a ablation study of LoRRaL on the BP4D dataset. LoRRaL(SA), LoRRaL(H), LoRRaL(B) stands for LoRRaL with self-attention, Hopfield, and BiLSTM respectively.

| AU | 1  | 2  | 4  | 6  | 7  | 10 | 12 | 14 | 15 | 17 | 23 | 24 | Avg |
|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|
| w/o LoRRaL | 50.6 | 50.8 | 56.5 | 79.9 | 74.7 | 88.2 | 90.3 | 68.5 | 40.2 | 63.5 | 43.7 | 44.2 | 62.6 |
| LoRRaL(SA) | 51.1 | 51.7 | 59.0 | 78.0 | 73.4 | 84.9 | 89.9 | 64.5 | 50.8 | 61.9 | 47.2 | 48.8 | 63.4 |
| LoRRaL(H) | 53.1 | 52.9 | 59.8 | 79.0 | 73.2 | 88.0 | 90.6 | 61.3 | 46.2 | 63.4 | 48.1 | 46.9 | 63.5 |
| LoRRaL(B) | 52.1 | 53.8 | 60.7 | 76.3 | 73.3 | 87.1 | 90.1 | 64.0 | 45.1 | 63.3 | 48.5 | 45.6 | 63.3 |

Table 4: F1-score(%) in a ablation study of LoRRaL on the DISFA dataset. LoRRaL(SA), LoRRaL(H), LoRRaL(B) stands for LoRRaL with self-attention, Hopfield, and BiLSTM respectively.

| AU | 1  | 2  | 4  | 6  | 9  | 12 | 25 | 26 | Avg |
|----|----|----|----|----|----|----|----|----|-----|
| w/o LoRRaL | 58.1 | 52.2 | 70.8 | 20.6 | 47.9 | 70.4 | 91.4 | 62.8 | 59.3 |
| LoRRaL(SA) | 60.1 | 59.2 | 71.3 | 26.5 | 55.3 | 71.5 | 93.8 | 53.1 | 61.4 |
| LoRRaL(H) | 61.0 | 57.2 | 70.6 | 32.4 | 51.4 | 70.7 | 90.7 | 51.1 | 60.6 |
| LoRRaL(B) | 59.3 | 59.0 | 69.5 | 35.4 | 46.2 | 72.2 | 94.1 | 48.3 | 60.5 |

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