Rethinking Few Shot CLIP Benchmarks: A Critical Analysis in the Inductive Setting

Supplementary Material

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7. Ease of Benchmarking and Compute Requirements

Our main experiments can be performed on a single NVIDIA GeForce RTX 3090 GPU with 24GB of memory. Tab. 4 displays the processing time required to compute the gradients for unlearning CLIP across various datasets. Hence, the process of creating a new benchmark is quick and allows rapid setup for additional datasets. Furthermore, our benchmarking pipeline is not only very rapid to setup, but also easy to test with novel few-shot learning methods. Once a CLIP model has been unlearned, it is ready to be tested on a new benchmark; testing it with a new few-shot method is straightforward and requires only a change in the checkpoint file.

To train CLIP from scratch, we use 4 NVIDIA GeForce RTX 3090 GPUs to process the entire batch size of 1000, which is the number of classes of ImageNet.

Dataset	Number of Data Points	Processing Time (min:sec)
StanfordDogs	6144	01:00
StanfordCars	6528	01:25
Caltech101	4160	00:35
OxfordFlowers	4096	00:44
CUB	3648	00:39
UCF101	7680	01:05
FGVCAircraft	3392	00:57

Table 4. Processing times for selected datasets.

8. Mathematical Formulation of SEPRES

This section formalizes the mathematical framework underlying our proposed SEPRES method, introduced in Section 4.3 of the main paper. Our work builds upon the Self-Enhanced Prompt Tuning (SEP) method, which refines visual prompts using a Token Fusion Module (TFM). While SEP is highly effective at extracting knowledge from CLIP, as the latent learnable prompts are passed through CLIP's frozen internal layers, they are constrained by CLIP's intermediate representations, which limits the model's ability to acquire new and independent knowledge not seen during pre-training. To address this limitation, we introduce learnable residual parameters into the final textual embeddings of CLIP, inspired by TaskRes approach. This enables the model to acquire new, independent knowledge from few-shot examples rather than merely conforming to CLIP's existing representations that are constrained by its internal operations. In this section, we first provide the mathematical formulation of SEP and subsequently extend it to demonstrate the modifications leading to SEPRES.

Standard CLIP Classification

For zero-shot classification with CLIP over K classes, each class label is embedded into a textual prompt (e.g., "A photo of a $\{\text{class}\}$") and processed through CLIP's text encoder to generate a weight matrix $\mathbf{W}^{\text{clip}} \in \mathbb{R}^{K\times d}$, where d is the embedding dimension. Given a test image, it is encoded into an embedding $\mathbf{G}^{\text{clip}} \in \mathbb{R}^{d}$ by CLIP's image encoder. Classification logits are computed as:

$$\text{logits} = \mathbf{G}^{\text{clip}}(\mathbf{W}^{\text{clip}})^T, \quad \text{logits} \in \mathbb{R}^K. \tag{8}$$

SEPRES Method

Let $\mathbf{E} \in \mathbb{R}^{n_e\times D}$ denote the image embeddings, where n_e is the token length and D is the hidden dimension. We initialize a learnable global visual prompt $\mathbf{Q} \in \mathbb{R}^{n_p\times D}$, where n_p is the length of the prompt. These are concatenated as:

$$\mathbf{Z}_0 = [\mathbf{E}, \mathbf{Q}] \in \mathbb{R}^{(n_e+n_p)\times D}. \tag{9}$$

The sequence is passed through the first visual encoder layer ψ_1, resulting in:

$$\mathbf{Z}_1 = \psi_1(\mathbf{Z}_0) \in \mathbb{R}^{(n_e+n_p)\times D}. \tag{10}$$

The Token Fusion Module (TFM) refines the visual embeddings by integrating information from frozen and learned tokens. $\mathbf{Z}_1$ is split into pre-trained tokens $\mathbf{Z}_1^v$ (first n_e tokens) and prompt tokens $\mathbf{Z}_1^p$ (last n_p tokens). The TFM updates the prompt embeddings through cross-attention:

$$\tilde{\mathbf{Z}}^p = \text{TFM}(\mathbf{Z}^v, \mathbf{Z}^p) = \text{softmax}\left(\frac{\tilde{\mathbf{Z}}^v(\mathbf{Z}^p)^T}{\sqrt{D}}\right)\tilde{\mathbf{Z}}^v, \tag{11}$$

where $\tilde{\mathbf{Z}}^v$ denotes the top-n_p tokens with the highest activation scores, calculated as the mean squared values of token features.

The final visual token output for layer 1 is:

$$\tilde{\mathbf{Z}}_1 = [\mathbf{Z}_1^v, \tilde{\mathbf{Z}}_1^p], \tag{12}$$

which is passed to subsequent encoder layers:

$$\tilde{\mathbf{Z}}^{l+1} = \psi_{l+1}([\mathbf{Z}_l^v, \text{TFM}(\mathbf{Z}_l^v, \mathbf{Z}_l^p)]), \quad l \geq 1. \tag{13}$$

Similarly, enhanced textual tokens $\tilde{\mathbf{T}}_l$ are computed.

Enhanced Classifier with Residual Parameters With the enhanced prompts, an updated classifier's weight matrix $\mathbf{W}^{\text{sep}}$ and visual prompt $\mathbf{G}^{\text{sep}}$ are generated. We introduce learnable residual parameters to $\mathbf{W}^{\text{sep}}$. This approach enables the model to acquire new, independent knowledge rather than merely conforming to CLIP's existing representations that are constrained by its internal operations. The resulting classifier weight matrix is defined as:

$$\mathbf{W}^{\text{sepres}} = \mathbf{W}^{\text{sep}} + \alpha\mathbf{Y}, \tag{14}$$

where $\mathbf{Y}$ are learnable residual textual parameters of the same shape as $\mathbf{W}^{\text{sep}}$, initialized to zeros, and α is a scaling constant.

Optimization During training, the global visual/textual prompts and residual textual parameters are optimized using the following loss function:

$$L = \mathcal{L}_{\text{ce}}(\mathbf{G}^{sep}, \mathbf{W}^{\text{sepres}}) + \omega_t\mathcal{L}_{\text{kg}}(\mathbf{W}^{\text{clip}}, \mathbf{W}^{\text{sepres}}) \tag{15}$$

$$+ \omega_v\mathcal{L}_{\text{kg}}(\mathbf{G}^{sep}, \mathbf{G}^{clip}) + \mathcal{L}_{\text{ce}}(\mathbf{G}^{clip}), \tag{16}$$

where:

- $\mathcal{L}_{\text{ce}} = -\sum_{i=1}^N y_i \log(\hat{y}_i)$: Cross-entropy loss for classification.
- $\mathcal{L}_{\text{kg}} = \|A - B\|_2^2$: Knowledge-guided loss between weight matrices.
- ω_t, ω_v: Balancing coefficients.

9. SEPRES Ablations

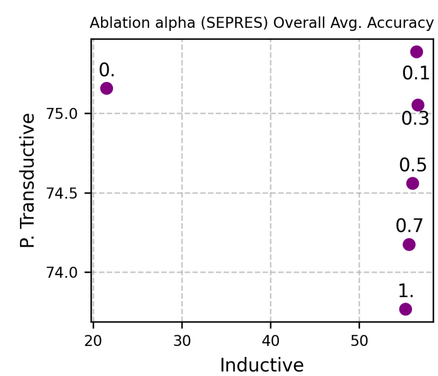

Figure 7. Ablation on α parameter of SEPRES.

9.1. Weight of Residual Features Ablation

We conduct an ablation study for the residual feature importance in SEPRES, shown in Fig. 7. Without residual features ($\alpha = 0.$) the accuracy is worse in both settings but mostly in P. Transductive, where the residual features are essential to learn new, independent knowledge to generalize in less known domains, which were removed through unlearning. Increasing α from 0.1 towards 1, the accuracy declines in the P. Transductive setting and slightly in the inductive one. We achieve the best result for $\alpha = 0.1$.

9.2. Visual Features and Components Ablation

In Tab. 5 we analyze the impact of adding the residual component on visual features (vRES). Incorporating vRES results in marginally lower accuracy while adding extra parameters to the model. The ablation study further demonstrates that both SEP and RES components are essential to the SEPRES method, as their individual removal leads to a performance drop.

Ablation	Acc. Inductive	Acc. P. Transductive
only SEP	11.511	65.271
only RES	21.492	75.157
SEPRES	**56.428**	**75.387**
SEPRES + vRES	56.17	75.021

Table 5. Ablation study on SEPRES components (SEP and RES) and on visual RES (vRES).

10. Unlearning Analysis

In this section, we provide additional unlearning analysis extending Sec. 4.1 of the main paper. Specifically, we present additional unlearning techniques evaluated in our experiments. We explored two zero-shot unlearning methods, one utilizing Lipschitz regularization (Lip) [24] and another based on adjusting textual projection weights (TextProj) [22]. Additionally, we experimented with the non-zero-shot unlearning approach, SalUN [6]. These are compared against the SSD method we utilized in our main experiments, described in Sec. 4.1 of the main paper.

Forget Ds	Unlearning Method	Avg. Forget Ds Acc. (↓)	Avg. Knowledge Lost (↓)
Dogs, Cars, Flowers	SSD (Our)	0.024	0.0283
Dogs, Cars, Flowers	SalUn [6]	0.0	0.3617
Dogs, Cars, Flowers	Lip [24]	0.1907	0.3053
Dogs, Cars, Flowers	TextProj [22]	0.043	0.0967

Table 6. Comparison of 4 unlearning methods on StanfordDogs, StanfordCars and OxfordFlowers datasets. SSD achieves the best trade-off between effective unlearning of targeted knowledge while minimizing unintended knowledge loss.

Tab. 6 shows the average unlearning performance on the StanfordDogs, StanfordCars and OxfordFlowers datasets. The SSD method demonstrates the most balanced performance, effectively unlearning the target classes while minimizing the loss of knowledge on the validation set. SalUn — a non-zero-shot approach — achieves strong unlearning for targeted classes but struggles to preserve knowledge of non-targeted ones. Among the zero-shot methods, Lip is better at retaining knowledge than SalUn of non-targeted classes but falls short in unlearning the targeted classes. The TextProj method performs unlearning comparable to SSD for the targeted classes but incurs greater knowledge loss on the validation set, highlighting its trade-off limitations relative to SSD.

11. Discussion

Unlearning is a broad concept that cannot be easily guaranteed, and there are multiple metrics available to evaluate it. SSD unlearning was evaluated using accuracy and Membership Inference Attacks (MIA) [31], which assesses whether a particular data point was part of the training dataset used to train a machine learning model. For both metrics SSD has shown good results. Even if we do not know the exact data CLIP was trained on, we can assume that it has seen similar images of the standard few-shot evaluation benchmark datasets whose training set can be used for unlearning that knowledge. As our pipeline is general, when better unlearning methods with more theoretical unlearning guarantees become available, these can be used to create more robust benchmarks using our pipeline and understand true generalization of large models. Our pipeline is general and can be applied to any model as long as there is a good unlearning method available for it.

12. UMAP Visual Features Distribution for all Subsets

In this section, we provide UMAP visual features visualizations on additional subsets that we discussed in Sec. 5.3. Fig. 8 shows these results for ”birds”, ”vehicles” and ”dogs” subsets from ImageNet. *No subset* represents CLIP trained from scratch excluding the subset, *unlearned* is CLIP trained from scratch on full data and unlearning the subset, and *full* is CLIP trained from scratch on full dataset. In the figure, we used different colours for samples from the subset that is excluded and samples belonging to other classes. Some classes from the excluded subset are highlighted. As in our main paper that described the results for ”birds”, similar observations can be drawn for the other two subsets, namely that: (1) in both *No subset* and *unlearned*, the highlighted classes from the excluded subset are more sparse and overlapping compared to *full* where samples from the excluded subset belonging to the same class are more clustered together and do not overlap with other classes (clear separation). (2) the unlearned subset in both *No subset* and *unlearned* overlap much more with other classes compared to *full*.

Figure 8. Visual features distributions across different settings with CLIP trained from scratch. Left visualisation: Excluding the subset from training. Middle visualisation: Unlearning the subset. Right visualisation: Without any unlearning. Classes to unlearn are shown in red while other classes are in light green. *No subset* and *unlearned* settings with the highlighted classes from the excluded subset are more sparse and overlapping compared to the *full* setting. The unlearned subset in both *no subset* and *unlearned* settings overlap much more with other classes compared to full setting. All indicate that *no subset* and *unlearned* settings are similar.

13. CLIP Trained from Scratch Full Results

In this section we present the full results for our oracle method discussed in Sec. 5.3 evaluated under two distinct settings - excluding a subset and unlearning a subset. Tab. 7 reports the performance of various few-shot learning methods with CLIP trained from scratch on the full ImageNet dataset, excluding the subset specified in the *Dataset* column. The results are shown for different shot counts and subsets, averaged over three random seeds. Similarly, we present results for the unlearning setting in Tab. 8.

Comparing the average performance across the two tables for different methods, we observe that the results are similar, demonstrating that excluding and unlearning the subset yield comparable outcomes. Furthermore, SEPRES achieves the best results in both scenarios, highlighting its effectiveness.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Birds	1	7.243	8.100	1.733	1.467	6.633	6.650	8.137	6.633	2.497	6.967	8.600	8.100	8.200	**10.033**
Birds	2	6.237	7.800	1.767	1.833	6.833	7.200	8.137	5.900	2.523	7.600	9.567	8.133	8.200	**12.300**
Birds	4	7.672	7.433	1.300	1.933	7.267	7.300	8.140	5.633	2.733	8.800	11.833	8.700	8.200	**15.900**
Birds	8	10.565	7.367	1.467	1.600	7.367	8.500	8.043	6.000	2.653	9.200	15.200	9.900	8.333	**20.733**
Birds	16	17.051	8.633	4.700	2.667	8.467	9.000	8.180	6.867	2.903	13.250	21.367	13.233	8.733	**28.567**
Dogs	1	3.928	5.967	1.200	1.900	5.967	4.567	6.467	6.367	2.463	5.100	5.667	5.667	**6.567**	6.400
Dogs	2	3.528	5.000	1.400	2.100	6.033	5.500	6.467	5.933	2.627	6.067	6.333	5.767	6.600	**7.167**
Dogs	4	3.983	5.467	2.100	2.033	5.900	5.333	6.467	5.233	2.533	5.867	8.067	6.233	6.633	**9.200**
Dogs	8	5.694	5.867	1.800	2.433	6.067	5.367	6.547	5.233	3.073	5.667	10.067	7.000	6.700	**12.067**
Dogs	16	7.578	6.333	2.000	4.500	6.267	6.500	6.450	5.000	3.457	5.233	11.300	7.767	7.067	**13.467**
Vehicles	1	6.389	7.733	1.967	3.400	8.367	6.067	8.467	8.233	3.237	6.700	7.867	9.067	8.467	**12.100**
Vehicles	2	7.344	7.867	1.867	3.467	7.667	6.943	8.353	7.600	2.633	8.633	9.367	9.167	8.500	**14.067**
Vehicles	4	8.389	7.233	1.967	3.800	5.067	6.067	8.400	3.967	3.600	8.667	11.267	10.867	8.567	**18.367**
Vehicles	8	11.233	7.067	2.700	5.067	4.667	8.433	8.387	6.600	3.980	10.433	13.567	12.233	9.267	**24.633**
Vehicles	16	16.144	8.433	2.767	5.633	4.467	9.467	8.467	5.800	3.613	11.433	19.300	13.633	10.533	**30.100**
Average	1	5.853	7.267	1.633	2.256	6.989	5.761	7.690	7.078	2.732	6.256	7.378	7.611	7.744	**9.511**
Average	2	5.703	6.889	1.678	2.467	6.844	6.548	7.652	6.478	2.594	7.433	8.422	7.689	7.767	**11.178**
Average	4	6.682	6.711	1.789	2.589	6.078	6.233	7.669	4.944	2.956	7.778	10.389	8.600	7.800	**14.489**
Average	8	9.164	6.767	1.989	3.033	6.033	7.433	7.659	5.944	3.236	8.433	12.944	9.711	8.100	**19.144**
Average	16	13.591	7.800	3.156	4.267	6.400	8.322	7.699	5.889	3.324	9.972	17.322	11.544	8.778	**24.044**
Average (Overall)	-	8.199	7.087	2.049	2.922	6.469	6.860	7.674	6.067	2.968	7.974	11.291	9.031	8.038	**15.673**

Table 7. Few-shot results with CLIP trained from scratch on full ImageNet **excluding** the subset.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Birds	1	8.147	5.867	2.133	3.567	5.900	6.900	4.907	5.800	2.623	7.633	6.400	7.300	6.200	**15.933**
Birds	2	9.729	6.933	5.300	4.367	6.533	7.367	4.907	6.100	2.420	8.600	7.933	8.433	6.400	**21.300**
Birds	4	11.989	8.267	5.567	4.067	8.133	9.033	5.017	7.267	3.357	11.267	11.800	13.200	6.567	**32.833**
Birds	8	15.932	9.367	8.167	4.967	9.600	10.633	5.093	7.933	3.480	14.067	10.533	16.633	9.633	**47.067**
Birds	16	22.983	10.667	9.467	6.400	10.567	13.300	5.713	8.533	3.267	17.200	24.967	22.267	16.300	**56.433**
Dogs	1	4.778	4.567	2.900	4.033	4.333	4.000	4.340	4.233	1.287	4.467	4.800	5.567	4.967	**7.533**
Dogs	2	5.572	4.800	4.033	4.033	4.633	4.233	4.357	4.267	0.903	5.667	5.133	6.400	5.067	**10.633**
Dogs	4	6.389	4.767	4.400	4.767	4.900	5.733	4.507	4.433	3.500	6.667	5.533	7.267	5.967	**16.233**
Dogs	8	7.922	4.867	4.700	4.733	5.367	6.400	4.497	5.133	4.413	7.067	5.967	9.067	9.500	**23.000**
Dogs	16	9.911	5.100	4.933	4.633	6.167	7.300	4.453	5.300	4.020	7.600	11.000	10.667	17.767	**27.367**
Vehicles	1	5.833	5.333	4.433	4.867	5.933	5.267	5.937	5.833	2.200	6.400	6.367	6.567	6.867	**9.967**
Vehicles	2	6.433	5.567	3.733	4.900	5.500	5.233	5.877	5.800	2.023	6.400	6.467	7.700	7.333	**13.600**
Vehicles	4	7.944	6.167	4.367	4.900	6.000	6.567	5.970	5.867	2.310	8.167	7.967	8.733	7.567	**21.467**
Vehicles	8	11.000	6.700	4.567	6.533	6.900	8.200	6.067	5.967	2.653	9.833	8.533	9.800	8.933	**34.367**
Vehicles	16	13.422	7.900	6.600	6.833	8.167	9.933	6.167	7.000	3.667	10.767	10.033	12.433	15.033	**41.600**
Average	1	6.253	5.256	3.156	4.156	5.389	5.389	5.061	5.289	2.037	6.167	5.856	6.478	6.011	**11.144**
Average	2	7.245	5.767	4.356	4.433	5.556	5.611	5.047	5.389	1.782	6.889	6.511	7.511	6.267	**15.178**
Average	4	8.774	6.400	4.778	4.578	6.344	7.111	5.164	5.856	3.056	8.700	8.433	9.733	6.700	**23.511**
Average	8	11.618	6.978	5.811	5.411	7.289	8.411	5.219	6.344	3.516	10.322	8.344	11.833	9.356	**34.811**
Average	16	15.439	7.889	7.000	5.956	8.300	10.178	5.444	6.944	3.651	11.856	15.333	15.122	16.367	**41.800**
Average (Overall)	-	9.866	6.458	5.020	4.907	6.576	7.340	5.187	5.964	2.808	8.787	8.896	10.136	8.940	**25.289**

Table 8. Few-shot results with CLIP trained from scratch on full ImageNet **unlearning** the subset.

14. Original CLIP Full Results

14.1. Default runs unlearned CLIP.

In this section, we present full results across different methods, number of shots and datasets after unlearning CLIP. Aggregated results are discussed in Sec. 5.2 of the main paper. SEPRES consistently outperforms other methods across all datasets and shot configurations. For the *FgvcAircraft* dataset, the performance of SEP and CLIP-LoRA is comparable to SEPRES. However, these methods fall short across other datasets, demonstrating their lack of consistency. In contrast, SEPRES reliably delivers superior performance across all settings, highlighting its robustness and effectiveness.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Stanforddogs	0	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020	0.020
Stanforddogs	1	3.515	2.000	2.900	3.467	2.733	2.267	3.120	1.233	3.287	5.533	5.733	4.850	2.200	**14.767**
Stanforddogs	2	7.226	2.167	2.500	6.133	3.000	6.200	3.447	1.667	3.830	10.100	10.300	8.367	2.333	**27.367**
Stanforddogs	4	11.592	2.467	3.200	9.733	5.733	9.500	5.067	3.233	6.910	14.400	14.500	13.100	2.700	**44.300**
Stanforddogs	8	15.279	2.733	4.150	13.600	9.967	16.433	7.340	4.600	11.247	17.867	17.933	16.067	4.700	**57.333**
Stanforddogs	16	19.458	4.000	7.150	17.333	15.133	18.933	9.450	9.867	15.977	19.833	20.233	18.350	11.767	**67.933**
Stanfordcars	0	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Stanfordcars	1	3.971	1.167	1.167	3.050	1.233	1.600	1.400	1.550	1.720	4.300	5.000	3.533	1.333	**7.667**
Stanfordcars	2	8.602	1.200	1.333	5.300	2.333	4.633	1.490	1.000	3.610	7.333	9.400	6.533	1.533	**16.067**
Stanfordcars	4	17.937	1.433	2.033	8.350	2.867	7.200	0.990	1.467	3.657	12.800	18.100	10.800	1.733	**32.033**
Stanfordcars	8	29.897	1.967	2.533	11.600	6.067	16.100	3.127	2.533	7.200	25.133	27.900	15.633	2.833	**52.800**
Stanfordcars	16	39.129	3.033	3.833	15.700	11.367	26.167	5.493	4.700	9.827	34.333	35.133	20.267	6.100	**69.633**
Oxfordflowers	0	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054	0.054
Oxfordflowers	1	20.395	6.133	7.100	23.633	6.400	7.833	7.103	5.833	7.130	31.300	31.067	24.167	5.767	**62.000**
Oxfordflowers	2	34.768	6.367	7.900	33.967	10.900	34.800	6.713	6.000	7.010	39.900	43.467	38.867	5.800	**80.600**
Oxfordflowers	4	42.360	6.800	10.400	40.567	19.367	41.867	8.607	13.233	12.083	45.200	47.000	45.533	6.133	**90.300**
Oxfordflowers	8	47.449	7.600	22.800	45.200	37.367	46.767	9.460	23.233	23.967	48.467	48.933	47.833	7.367	**95.067**
Oxfordflowers	16	50.020	10.867	32.500	48.033	45.667	49.433	12.910	41.933	38.760	50.000	49.967	49.000	15.900	**97.567**
Caltech101	0	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080	0.080
Caltech101	1	12.319	8.000	7.767	10.367	10.567	13.533	9.073	7.033	8.707	13.833	14.767	13.000	13.867	**71.567**
Caltech101	2	13.550	8.067	8.467	12.767	9.733	12.733	8.600	8.967	9.873	16.500	16.400	15.967	14.800	**83.833**
Caltech101	4	16.619	8.133	9.533	15.133	13.867	13.767	11.020	11.833	13.930	17.500	17.367	16.933	22.067	**89.700**
Caltech101	8	17.904	8.267	11.100	16.833	15.800	17.367	13.660	12.700	14.253	17.700	17.900	17.600	33.800	**93.067**
Caltech101	16	18.039	8.533	12.767	17.300	15.800	18.033	16.770	16.267	15.120	18.167	18.200	17.767	59.833	**94.767**
Fgvcaircraft	0	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
Fgvcaircraft	1	3.530	1.100	1.267	4.133	1.467	2.933	2.120	1.467	2.230	5.400	6.167	4.867	1.000	**8.833**
Fgvcaircraft	2	9.671	1.000	1.767	6.467	2.400	4.367	1.840	1.800	2.990	9.000	12.967	9.067	0.967	**13.533**
Fgvcaircraft	4	17.902	1.333	2.067	11.700	2.567	9.433	4.400	1.967	5.400	16.767	21.633	15.600	1.167	**23.600**
Fgvcaircraft	8	31.613	2.367	3.800	15.133	6.300	16.700	5.600	3.600	8.650	27.500	32.967	21.700	1.700	**34.300**
Fgvcaircraft	16	46.115	3.633	4.533	20.167	9.900	31.800	10.400	6.067	13.760	41.667	46.033	28.733	3.333	**47.967**
Ucf101	0	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052	0.052
Ucf101	1	8.195	5.400	4.733	6.800	7.467	7.333	7.727	3.533	8.203	9.867	10.367	8.300	6.833	**37.933**
Ucf101	2	11.296	5.500	7.400	11.200	9.167	8.267	8.083	6.400	8.450	12.767	13.533	10.833	7.400	**54.233**
Ucf101	4	13.490	6.000	8.067	13.333	10.800	13.233	10.213	8.700	11.437	14.667	15.300	13.900	9.733	**65.633**
Ucf101	8	15.764	6.933	8.633	14.533	12.233	15.200	11.373	9.567	13.457	15.700	16.533	15.467	13.600	**75.200**
Ucf101	16	17.076	7.967	9.367	16.167	14.733	16.533	13.817	12.433	14.513	16.967	17.667	16.867	28.367	**80.833**
Cub	0	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015
Cub	1	3.625	2.233	2.333	5.067	2.367	3.000	1.533	1.733	2.603	8.133	7.900	5.967	1.600	**25.867**
Cub	2	7.721	2.167	2.767	8.000	3.450	8.350	2.003	1.833	5.887	12.767	13.867	11.500	1.867	**44.667**
Cub	4	13.376	2.167	4.633	11.133	4.250	13.600	2.563	3.367	9.117	16.967	19.733	16.600	2.567	**61.567**
Cub	8	19.537	2.533	5.733	16.533	10.100	17.900	4.123	4.467	11.817	21.567	23.333	21.467	5.900	**73.033**
Cub	16	23.063	3.900	8.300	19.233	12.400	20.900	7.430	10.700	14.513	23.600	24.933	23.667	21.067	**79.400**
Average	0	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035	0.035
Average	1	7.936	3.719	3.895	8.074	4.605	5.500	4.582	3.198	4.840	11.195	11.571	9.240	4.657	**32.662**
Average	2	13.262	3.781	4.590	11.976	5.855	11.336	4.597	3.952	5.950	15.481	17.133	14.448	4.957	**45.757**
Average	4	19.040	4.048	5.705	15.707	8.493	15.514	6.123	6.257	8.933	19.757	21.948	18.924	6.586	**58.162**
Average	8	25.349	4.629	8.393	19.062	13.976	20.924	7.812	8.671	12.941	24.848	26.500	22.252	9.986	**68.686**
Average	16	30.414	5.990	11.207	21.990	17.857	25.971	10.896	14.567	17.496	29.224	30.310	24.950	20.910	**76.871**
Overall Average (excl. zs)	-	19.200	4.433	6.758	15.362	10.157	15.849	6.802	7.329	10.032	20.101	21.492	17.963	9.419	**56.428**

Table 9. Few-shot performance results for unlearned CLIP with *minimum* level of knowledge lost evaluated across multiple datasets, methods, and shot counts. For shot counts greater than zero, the top-performing results are indicated in **bold**. Average results are shown at the end of the table. The table also includes averages for each shot count, with a final overall average calculated by excluding the zero-shot results.

14.2. Aggressive Unlearning with 25% knowledge lost.

In this section, we present full results across different methods, number of shots and datasets after unlearning CLIP losing 25% of its general knowledge. Aggregated results are presented and discussed in Sec. 5.4 of the main paper. Even under this knowledge reduction, SEPRES consistently outperforms all other methods across datasets and shot configurations.

When comparing the results to those in Tab. 9, SEPRES maintains robust performance, with the average accuracy dropping from 56.4% to 48.8% — a reduction of only 8%. In contrast, the performance of other methods declines by approximately half, highlighting their vulnerability to general knowledge loss. This underscores SEPRES's resilience and effectiveness, even in scenarios with significant reductions in CLIP's knowledge.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Stanforddogs	0	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
Stanforddogs	1	1.228	0.700	0.967	1.733	1.133	1.267	0.993	0.967	1.330	1.733	1.967	1.633	2.600	**9.633**
Stanforddogs	2	2.067	0.667	1.367	2.167	1.567	1.567	0.783	1.100	1.363	2.767	3.100	2.500	3.033	**17.367**
Stanforddogs	4	2.715	0.667	1.167	2.700	1.333	1.867	0.997	1.200	2.003	3.200	3.833	3.267	6.300	**31.367**
Stanforddogs	8	4.343	0.700	1.667	3.767	1.767	2.700	1.637	1.833	3.203	4.300	4.867	4.100	11.433	**47.567**
Stanforddogs	16	5.134	0.833	1.967	4.633	3.200	4.900	3.347	2.300	4.520	4.933	5.567	4.867	18.600	**60.300**
Stanfordcars	0	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
Stanfordcars	1	2.139	0.867	0.733	2.067	1.367	1.467	1.117	0.667	1.320	2.400	2.467	1.900	0.600	**6.100**
Stanfordcars	2	4.659	0.900	1.067	3.800	1.233	1.767	1.497	0.733	3.133	4.733	5.900	3.433	0.600	**12.700**
Stanfordcars	4	10.592	1.067	1.100	5.967	1.867	4.500	1.843	1.433	5.020	8.033	11.500	6.533	0.700	**24.767**
Stanfordcars	8	20.661	1.400	1.933	8.333	3.400	8.767	2.720	2.000	7.687	15.900	17.600	10.000	1.200	**43.433**
Stanfordcars	16	30.552	1.867	2.567	10.867	6.067	17.833	2.753	3.300	9.543	24.467	25.033	13.300	6.267	**61.467**
Oxfordflowers	0	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038
Oxfordflowers	1	10.137	3.400	4.133	11.067	3.767	2.400	4.305	3.033	5.280	14.567	15.667	11.400	4.400	**48.300**
Oxfordflowers	2	17.107	3.400	5.533	16.400	5.600	13.767	4.385	2.300	5.753	19.367	22.900	18.667	4.433	**67.500**
Oxfordflowers	4	23.603	3.833	9.600	21.033	8.933	21.733	5.990	6.533	7.457	24.967	26.267	23.200	5.233	**81.500**
Oxfordflowers	8	28.177	4.333	11.000	25.367	15.733	26.567	9.243	12.600	11.017	27.767	28.500	25.967	7.533	**90.533**
Oxfordflowers	16	31.222	6.133	13.967	27.267	23.133	28.600	12.993	18.067	17.730	29.433	29.533	27.567	16.367	**95.367**
Caltech101	0	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077	0.077
Caltech101	1	9.790	7.233	5.433	7.733	6.800	9.667	8.277	6.233	8.303	10.400	10.533	8.633	25.933	**60.133**
Caltech101	2	10.453	7.000	7.100	8.733	5.133	8.767	8.113	7.833	9.307	10.400	11.367	9.633	29.300	**77.800**
Caltech101	4	11.778	6.400	6.833	10.600	8.533	11.733	8.317	9.700	10.413	11.400	12.333	11.033	41.567	**86.967**
Caltech101	8	12.508	6.133	9.300	11.367	11.100	12.100	10.153	10.433	11.387	11.800	12.533	11.467	51.600	**91.933**
Caltech101	16	12.603	6.500	9.900	12.267	10.767	12.433	9.857	11.533	12.130	12.400	12.767	12.233	67.400	**94.400**
Fgvcaircraft	0	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Fgvcaircraft	1	3.070	1.067	1.700	3.400	1.767	2.833	1.730	1.933	2.350	5.367	5.767	4.267	1.100	**8.033**
Fgvcaircraft	2	7.651	1.133	2.167	5.833	2.367	3.800	1.370	1.567	2.110	7.867	11.467	7.400	1.133	**11.967**
Fgvcaircraft	4	15.972	1.300	2.300	10.067	3.000	6.600	2.810	2.133	6.040	15.133	20.100	12.767	1.400	**20.267**
Fgvcaircraft	8	28.393	1.633	4.067	13.800	4.800	16.067	3.390	3.567	10.860	25.400	30.933	18.133	1.767	**30.967**
Fgvcaircraft	16	44.304	2.467	4.833	18.400	8.933	26.433	5.450	5.433	15.720	38.733	43.667	25.267	3.200	**44.667**
Ucf101	0	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Ucf101	1	1.727	1.033	1.200	2.000	1.800	1.167	1.893	1.300	1.667	3.533	3.633	2.467	7.667	**28.833**
Ucf101	2	3.216	1.000	1.267	3.367	2.167	2.567	1.913	1.200	1.743	4.533	5.033	3.267	9.833	**45.633**
Ucf101	4	4.661	1.100	2.000	4.167	3.000	3.633	1.973	1.833	3.487	5.133	5.467	4.500	14.700	**58.267**
Ucf101	8	6.353	1.133	2.200	4.567	3.533	5.000	2.820	1.500	5.030	5.800	6.333	5.800	22.533	**69.967**
Ucf101	16	6.705	1.333	3.500	5.833	5.267	6.367	3.500	2.867	5.673	6.667	6.733	6.300	36.900	**76.233**
Cub	0	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
Cub	1	1.688	1.400	1.100	1.233	0.800	1.400	1.400	1.167	1.340	1.867	1.633	1.900	1.900	**12.400**
Cub	2	2.066	1.467	1.333	1.800	1.300	2.450	1.597	1.300	2.110	2.650	2.533	2.633	2.267	**25.300**
Cub	4	2.949	1.400	1.333	2.267	1.400	3.150	1.850	1.833	2.607	2.700	4.033	2.967	3.900	**42.150**
Cub	8	4.124	1.400	1.867	3.200	2.267	3.500	1.953	1.967	3.243	3.500	4.967	3.733	9.533	**57.650**
Cub	16	5.905	1.800	2.200	3.700	3.133	4.950	2.100	2.500	3.983	5.350	5.900	4.933	18.667	**68.750**
Average	0	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022	0.022
Average	1	4.254	2.243	2.181	4.176	2.490	2.886	2.816	2.186	3.084	5.695	5.952	4.600	6.314	**24.776**
Average	2	6.746	2.224	2.833	6.014	2.767	4.955	2.808	2.290	3.646	7.474	8.900	6.790	7.229	**36.895**
Average	4	10.324	2.252	3.476	8.114	4.010	7.602	3.397	3.524	5.290	10.081	11.933	9.181	10.543	**49.326**
Average	8	14.937	2.390	4.576	10.057	6.086	10.671	4.560	4.843	7.490	13.495	15.105	11.314	15.086	**61.721**
Average	16	19.489	2.990	5.562	11.852	8.643	14.502	5.714	6.571	9.900	17.426	18.457	13.495	23.914	**71.598**
Overall Average (excl. zs)	-	11.150	2.420	3.726	8.043	4.799	8.123	3.859	3.883	5.882	10.834	12.070	9.076	12.617	**48.863**

Table 10. Few-shot performance results for unlearned CLIP with *25%* of knowledge lost evaluated across multiple datasets, methods, and shot counts. For shot counts greater than zero, the top-performing results are indicated in **bold**. Average results are shown at the end of the table. The table also includes averages for each shot count, with a final overall average calculated by excluding the zero-shot results.

14.3. Aggressive Unlearning with 50% knowledge lost.

In this section, we present full results across different methods, number of shots and datasets after unlearning CLIP losing 50% of its general knowledge. Aggregated results are presented and discussed in Sec. 5.4 of the main paper. Even under this knowledge reduction, SEPRES consistently outperforms all other methods across datasets and shot configurations.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Stanforddogs	0	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
Stanforddogs	1	1.338	0.933	1.167	1.100	0.933	1.267	1.137	0.833	1.013	1.467	1.600	1.267	2.733	**7.300**
Stanforddogs	2	1.607	1.000	1.067	1.733	1.133	1.433	1.207	0.933	1.310	2.600	2.533	2.000	3.133	**13.033**
Stanforddogs	4	2.627	1.067	1.400	2.500	1.233	1.733	1.350	1.100	1.767	2.733	3.767	2.833	5.167	**25.633**
Stanforddogs	8	3.659	1.067	1.567	3.467	1.600	2.933	2.140	1.533	2.817	3.600	4.733	3.733	8.433	**39.333**
Stanforddogs	16	4.589	1.200	2.133	4.000	2.233	4.333	2.773	1.567	4.003	4.367	5.100	4.300	14.167	**53.150**
Stanfordcars	0	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
Stanfordcars	1	1.393	0.567	0.700	1.533	0.800	1.633	0.720	0.500	1.400	1.533	2.200	1.533	0.600	**4.600**
Stanfordcars	2	2.682	0.600	0.867	2.300	1.400	1.667	0.880	1.033	2.430	2.800	2.500	2.050	0.733	**7.600**
Stanfordcars	4	5.609	0.667	1.133	3.767	1.300	1.967	1.070	1.200	3.860	4.500	6.700	2.900	0.933	**15.400**
Stanfordcars	8	12.063	0.967	1.367	5.067	2.000	5.267	1.397	1.033	5.180	9.400	9.950	5.150	2.333	**27.800**
Stanfordcars	16	23.065	1.433	1.800	7.333	3.167	9.967	1.713	2.567	7.637	14.700	10.750	7.400	6.300	**44.900**
Oxfordflowers	0	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.018
Oxfordflowers	1	10.908	2.667	3.300	9.200	2.700	5.433	2.760	1.767	5.075	12.667	15.533	11.200	3.700	**41.367**
Oxfordflowers	2	17.228	2.833	3.667	14.000	2.967	12.367	3.140	1.700	6.925	19.067	21.433	16.767	4.600	**60.467**
Oxfordflowers	4	23.021	2.867	6.800	18.867	4.567	20.033	4.870	4.133	10.980	23.700	25.067	21.767	6.300	**75.733**
Oxfordflowers	8	27.000	3.033	8.100	23.067	13.333	24.733	6.520	9.167	15.955	26.567	27.400	24.467	9.367	**87.300**
Oxfordflowers	16	30.072	4.633	10.400	24.933	19.633	28.500	11.287	16.333	22.330	28.633	28.833	26.333	16.633	**93.300**
Caltech101	0	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046	0.046
Caltech101	1	5.882	4.733	7.333	7.700	6.667	8.733	5.680	6.833	8.540	9.767	8.600	7.000	9.800	**48.550**
Caltech101	2	8.749	4.900	5.867	9.800	7.000	9.700	6.800	5.967	8.773	10.100	10.633	7.733	11.100	**68.900**
Caltech101	4	10.196	5.033	6.767	10.300	8.500	10.533	6.547	7.133	6.670	10.567	11.200	7.500	16.467	**79.950**
Caltech101	8	12.157	5.033	7.000	11.300	8.533	11.767	6.720	10.333	9.047	11.767	12.000	8.633	28.233	**88.800**
Caltech101	16	12.306	5.133	7.167	11.250	11.900	11.767	8.963	11.000	10.360	12.200	12.567	9.667	51.300	**92.200**
Fgvcaircraft	0	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011	0.011
Fgvcaircraft	1	2.840	0.833	1.467	3.300	1.700	2.600	1.060	1.333	3.560	5.067	5.667	3.267	1.100	**6.667**
Fgvcaircraft	2	6.961	0.900	1.733	5.367	2.167	4.733	1.380	1.867	3.890	7.367	10.167	5.533	1.067	**10.900**
Fgvcaircraft	4	14.721	1.100	2.000	9.400	3.300	8.367	1.440	1.833	7.730	12.633	18.900	9.833	1.000	**19.067**
Fgvcaircraft	8	26.663	1.633	3.233	12.700	4.500	14.533	1.720	3.200	11.590	24.533	30.567	14.800	1.300	**30.733**
Fgvcaircraft	16	**43.684**	2.500	4.333	16.033	6.967	28.267	4.220	6.100	15.190	36.533	41.400	20.733	3.400	43.333
Ucf101	0	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
Ucf101	1	1.692	1.567	1.300	1.367	1.400	1.267	0.943	1.300	1.490	2.500	2.533	1.450	3.667	**19.467**
Ucf101	2	2.749	1.367	1.300	2.700	1.100	2.200	1.567	1.067	1.460	3.600	4.500	2.250	4.467	**33.333**
Ucf101	4	3.551	1.200	1.100	2.500	1.967	2.967	1.490	1.400	2.793	4.667	4.500	2.567	7.467	**46.233**
Ucf101	8	5.049	1.067	2.100	4.733	2.500	4.633	1.720	1.133	4.097	5.467	5.733	3.633	13.967	**58.467**
Ucf101	16	5.763	1.500	2.500	5.067	4.067	5.333	2.803	1.867	5.040	5.833	6.367	5.367	23.967	**67.867**
Cub	0	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
Cub	1	1.104	1.067	0.800	1.067	1.300	1.367	1.013	0.900	1.277	1.333	1.150	1.000	1.800	**9.367**
Cub	2	1.417	1.100	1.100	1.433	1.200	1.533	0.990	1.100	1.573	1.933	1.800	1.350	2.500	**19.433**
Cub	4	2.179	1.100	1.300	1.900	1.333	2.167	0.940	1.133	2.030	2.367	3.400	1.650	3.200	**34.900**
Cub	8	3.732	1.100	1.467	2.567	1.350	3.100	1.120	1.300	2.410	2.700	4.400	2.050	7.750	**52.067**
Cub	16	5.321	1.133	1.567	3.133	1.900	4.133	1.313	1.900	2.920	3.333	5.533	2.600	14.200	**63.200**
Average	0	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016	0.016
Average	1	3.594	1.767	2.295	3.610	2.214	3.186	1.902	1.924	3.194	4.905	5.326	3.817	3.343	**19.617**
Average	2	5.913	1.814	2.229	5.333	2.424	4.805	2.280	1.952	3.766	6.781	7.652	5.383	3.943	**30.524**
Average	4	8.844	1.862	2.929	7.033	3.171	6.824	2.530	2.562	5.119	8.738	10.505	7.007	5.790	**42.417**
Average	8	12.903	1.986	3.548	8.986	4.831	9.567	3.048	3.957	7.299	12.005	13.540	8.924	10.198	**54.929**
Average	16	17.828	2.505	4.271	10.250	7.124	13.186	4.725	5.905	9.640	15.086	15.793	10.914	18.567	**65.421**
Overall Average (excl. zs)	-	9.816	1.987	3.054	7.042	3.953	7.513	2.897	3.260	5.803	9.503	10.563	7.209	8.368	**42.581**

Table 11. Few-shot performance results for unlearned CLIP with *50%* level of knowledge lost evaluated across multiple datasets, methods, and shot counts. For shot counts greater than zero, the top-performing results are indicated in **bold**. Average results are shown at the end of the table. The table also includes averages for each shot count, with a final overall average calculated by excluding the zero-shot results.

14.4. Aggressive Unlearning with 90% knowledge lost.

In this section, we present full results across different methods, number of shots and datasets after unlearning CLIP losing 90% of its general knowledge. This is almost equivalent of performing few-shot on an almost not trained CLIP model. Aggregated results are presented and discussed in Sec. 5.4 of the main paper. SEPRES still outperforms all other methods across most datasets and shot configurations, demonstrating SEPRES general applicability.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Stanforddogs	0	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
Stanforddogs	1	0.880	0.900	0.767	0.800	0.767	0.800	0.850	0.700	0.773	0.733	0.767	0.700	1.967	**2.200**
Stanforddogs	2	0.868	0.900	0.833	0.800	0.833	0.867	0.813	0.833	0.827	0.867	0.933	0.800	2.467	**2.633**
Stanforddogs	4	1.076	0.900	0.767	0.767	0.700	0.867	0.820	0.767	0.733	0.733	0.900	0.767	2.800	**3.467**
Stanforddogs	8	1.160	0.967	0.867	0.800	0.800	0.867	0.853	0.933	0.750	0.833	1.233	0.867	3.200	**5.267**
Stanforddogs	16	1.639	0.967	0.933	0.800	0.933	1.033	0.807	0.967	0.913	0.900	1.167	0.933	4.000	**9.067**
Stanfordcars	0	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
Stanfordcars	1	1.003	0.633	0.600	0.900	0.600	0.767	0.680	0.667	0.803	0.833	1.000	0.700	1.233	**2.267**
Stanfordcars	2	1.356	0.600	0.767	1.267	0.867	0.733	0.820	0.767	1.187	1.067	1.300	0.900	1.233	**3.200**
Stanfordcars	4	2.114	0.600	0.733	1.700	0.867	1.267	0.860	0.867	1.650	1.200	1.433	1.067	1.267	**4.867**
Stanfordcars	8	4.469	0.600	1.033	2.267	0.967	1.833	0.817	0.833	2.220	1.833	0.700	1.367	2.000	**7.867**
Stanfordcars	16	8.258	0.700	1.200	3.000	0.967	3.200	1.100	1.100	2.897	2.967	1.200	2.000	3.233	**13.650**
Oxfordflowers	0	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007	0.007
Oxfordflowers	1	6.171	0.700	0.967	3.367	1.433	2.600	0.703	1.567	2.573	4.633	4.967	2.600	3.333	**16.833**
Oxfordflowers	2	11.003	0.900	1.833	6.433	1.567	4.333	0.663	1.967	2.830	7.633	10.800	3.933	4.200	**26.733**
Oxfordflowers	4	15.970	1.233	1.767	10.967	2.267	8.633	1.513	2.367	8.283	11.767	17.067	7.933	7.700	**38.433**
Oxfordflowers	8	20.016	1.733	2.367	13.600	3.600	13.400	0.863	2.300	12.627	16.833	20.667	11.433	13.800	**52.000**
Oxfordflowers	16	23.549	2.267	3.033	16.000	5.100	18.167	2.857	3.267	15.767	20.633	23.867	14.767	25.200	**68.233**
Caltech101	0	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Caltech101	1	0.933	0.500	1.700	1.167	1.433	1.233	0.823	0.600	0.977	0.900	0.900	0.933	1.767	**2.433**
Caltech101	2	1.149	0.500	1.533	1.100	1.133	1.567	0.863	1.067	1.203	1.600	1.433	1.433	2.533	**3.133**
Caltech101	4	1.596	0.500	1.233	1.100	1.067	1.033	0.957	1.000	1.107	1.300	1.200	1.000	2.767	**6.200**
Caltech101	8	2.150	0.533	1.167	0.900	0.600	0.867	0.823	0.700	1.203	1.567	1.600	1.133	3.767	**9.967**
Caltech101	16	2.637	0.567	1.200	1.167	0.800	1.267	1.070	1.233	1.393	1.600	2.167	1.567	5.133	**10.700**
Fgvcaircraft	0	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012
Fgvcaircraft	1	1.720	1.267	1.133	1.133	1.033	1.533	1.140	1.233	1.040	1.467	1.433	1.333	**1.933**	1.800
Fgvcaircraft	2	1.580	1.267	1.067	1.100	1.233	1.700	1.040	1.367	1.310	1.567	1.733	1.200	**2.533**	2.367
Fgvcaircraft	4	2.120	1.300	1.600	1.167	1.633	1.833	1.560	1.333	1.050	1.900	1.767	1.267	2.967	**3.300**
Fgvcaircraft	8	3.150	1.300	1.700	1.200	1.833	1.867	1.710	1.633	1.030	1.900	2.033	1.433	2.900	**4.000**
Fgvcaircraft	16	3.650	1.267	1.800	1.700	1.800	1.867	1.610	1.833	1.050	1.800	2.300	1.867	3.533	**4.933**
Ucf101	0	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012	0.012
Ucf101	1	1.322	1.200	1.033	1.333	1.367	1.300	1.350	1.033	1.120	1.367	1.567	1.167	1.600	**6.000**
Ucf101	2	1.419	1.200	0.800	1.300	1.133	1.067	1.337	0.967	1.307	1.633	1.500	1.433	2.067	**10.067**
Ucf101	4	1.357	1.167	0.967	1.500	1.433	1.233	1.480	1.000	1.727	1.333	1.500	1.367	3.100	**13.033**
Ucf101	8	1.956	1.100	1.100	1.400	1.067	1.800	1.797	1.167	1.613	1.833	1.967	1.533	3.800	**17.367**
Ucf101	16	2.696	1.233	1.333	1.900	1.533	1.667	1.667	1.667	2.097	1.533	2.200	1.800	7.433	**22.800**
Cub	0	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
Cub	1	0.399	0.500	0.650	0.500	0.533	0.500	0.490	0.500	0.533	0.533	0.500	0.700	**1.233**	0.900
Cub	2	0.556	0.500	0.600	0.533	0.467	0.433	0.503	0.600	0.490	0.633	0.633	0.533	**1.333**	1.133
Cub	4	0.541	0.500	0.900	0.467	0.567	0.333	0.533	0.467	0.490	0.633	0.567	0.500	1.300	**1.500**
Cub	8	0.712	0.500	0.800	0.500	0.400	0.433	0.510	0.433	0.500	0.600	0.533	0.467	1.533	**1.700**
Cub	16	1.061	0.500	0.700	0.533	0.467	0.367	0.483	0.400	0.537	0.600	0.567	0.567	**2.133**	1.967
Average	0	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
Average	1	1.775	0.814	0.979	1.314	1.024	1.248	0.862	0.900	1.117	1.495	1.590	1.162	1.867	**4.633**
Average	2	2.561	0.838	1.062	1.790	1.033	1.529	0.863	1.081	1.308	2.143	2.619	1.462	2.338	**7.038**
Average	4	3.539	0.886	1.138	2.524	1.219	2.171	1.103	1.114	2.149	2.695	3.490	1.986	3.129	**10.114**
Average	8	4.802	0.962	1.290	2.952	1.324	3.010	1.053	1.143	2.849	3.629	4.105	2.605	4.429	**14.024**
Average	16	6.213	1.071	1.457	3.586	1.657	3.938	1.370	1.495	3.522	4.290	4.781	3.357	7.238	**18.764**
Overall Average (excl. zs)	-	3.778	0.914	1.185	2.433	1.251	2.379	1.050	1.147	2.189	2.850	3.317	2.114	3.800	**10.915**

Table 12. Few-shot performance results for unlearned CLIP with *90%* level of knowledge lost evaluated across multiple datasets, methods, and shot counts. For shot counts greater than zero, the top-performing results are indicated in **bold**. Average results are shown at the end of the table. The table also includes averages for each shot count, with a final overall average calculated by excluding the zero-shot results.

14.5. Default Runs Without Unlearning

In this section, we present full results across different methods, number of shots and datasets on standard CLIP without unlearning. Aggregated results are presented and discussed in Sec. 5.2 of the main paper. SEPRES remains competitive also in a normal setting, showing overall best average performance.

Dataset	Shots	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
Stanforddogs	0	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117	59.117
Stanforddogs	1	63.732	60.200	32.400	59.433	63.633	62.333	62.800	**63.833**	61.275	63.333	61.600	59.533	61.033	61.933
Stanforddogs	2	65.335	60.833	63.467	63.100	64.767	65.167	63.837	64.500	64.215	**66.833**	64.900	62.867	61.400	65.200
Stanforddogs	4	67.818	61.567	65.200	66.233	67.500	69.700	65.830	67.700	67.350	**70.733**	69.067	66.900	62.667	69.267
Stanforddogs	8	72.101	62.700	66.533	70.067	70.400	73.333	67.880	69.567	68.860	**74.033**	72.800	70.433	63.733	72.550
Stanforddogs	16	75.924	65.200	68.367	74.300	72.633	76.200	69.627	72.833	73.010	**77.333**	76.867	74.367	65.367	77.067
Stanfordcars	0	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514	65.514
Stanfordcars	1	**70.360**	66.500	66.667	67.567	64.500	68.550	67.250	66.800	68.260	69.767	68.133	68.567	67.467	69.567
Stanfordcars	2	73.863	66.900	67.633	70.333	66.167	72.100	68.450	68.500	70.730	72.933	73.533	72.800	69.067	**74.200**
Stanfordcars	4	77.109	67.433	69.133	74.500	67.300	75.000	68.863	70.100	73.490	77.200	78.133	74.950	69.767	**78.300**
Stanfordcars	8	82.146	68.600	70.800	78.800	70.400	78.800	70.697	71.433	77.225	81.067	**83.167**	80.100	72.000	83.100
Stanfordcars	16	86.150	70.600	71.967	82.033	73.550	82.367	73.327	74.067	78.030	84.267	86.233	83.400	75.867	**86.267**
Oxfordflowers	0	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767	70.767
Oxfordflowers	1	84.179	71.233	71.233	80.200	74.933	83.333	79.453	76.033	80.010	85.667	87.600	85.033	73.267	**87.667**
Oxfordflowers	2	89.809	71.733	51.967	88.100	78.167	89.900	79.847	79.233	81.973	91.133	91.967	90.467	73.800	**92.100**
Oxfordflowers	4	93.707	73.133	80.567	91.700	85.033	93.233	87.063	85.633	90.527	94.000	**94.067**	93.200	75.333	94.033
Oxfordflowers	8	**96.590**	75.867	83.767	94.467	91.033	95.533	87.793	90.433	92.950	95.900	96.300	95.733	77.033	96.200
Oxfordflowers	16	**97.970**	83.967	86.933	96.800	94.267	97.133	92.083	94.100	94.563	97.767	97.433	97.067	82.067	97.467
Caltech101	0	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306	93.306
Caltech101	1	94.009	93.533	94.450	92.367	**94.867**	92.900	94.240	93.233	93.413	92.933	93.367	94.033	92.833	93.500
Caltech101	2	94.821	93.667	94.350	93.800	**94.900**	93.833	94.590	94.500	94.807	94.833	94.500	94.667	93.067	94.600
Caltech101	4	95.213	94.000	95.100	94.367	95.267	95.000	94.633	94.867	94.807	95.400	**95.533**	95.233	93.533	95.500
Caltech101	8	95.754	94.467	95.067	95.267	95.867	95.800	94.943	95.167	95.417	95.767	**96.200**	95.600	94.033	**96.200**
Caltech101	16	95.997	94.600	95.267	95.533	96.033	96.133	94.970	95.400	95.600	96.233	96.400	95.700	94.700	**96.467**
Fgvcaircraft	0	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752	24.752
Fgvcaircraft	1	30.033	26.533	13.600	21.867	22.400	21.567	28.060	26.967	27.440	28.367	30.133	28.833	26.667	**31.733**
Fgvcaircraft	2	31.513	27.300	22.967	25.867	28.800	28.400	28.320	28.733	30.520	31.800	31.967	30.500	26.667	**33.100**
Fgvcaircraft	4	37.544	28.067	19.367	32.367	29.900	36.567	32.530	26.200	33.820	38.100	37.733	35.300	28.133	**38.333**
Fgvcaircraft	8	44.894	28.700	25.067	38.067	33.200	40.167	33.740	33.067	37.210	42.800	**45.067**	40.100	29.633	44.633
Fgvcaircraft	16	**56.706**	30.600	28.700	42.433	35.967	46.567	34.610	35.500	39.790	50.000	51.833	44.133	32.600	52.067
Ucf101	0	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460	67.460
Ucf101	1	**76.227**	68.200	72.433	70.467	71.833	73.567	73.990	71.667	73.313	73.900	75.133	74.200	66.600	75.267
Ucf101	2	78.624	69.267	73.433	73.533	75.467	75.900	74.913	73.367	75.007	77.867	78.600	77.400	67.233	**78.900**
Ucf101	4	80.360	71.600	74.567	77.067	78.633	79.767	77.400	76.500	77.733	81.067	81.033	80.033	69.200	**81.167**
Ucf101	8	83.725	73.500	77.367	80.267	81.100	82.933	78.977	79.167	79.733	84.267	**84.567**	83.667	71.467	84.267
Ucf101	16	86.245	76.267	77.933	82.800	83.233	85.533	80.457	81.333	82.160	86.367	**87.167**	85.367	74.667	87.000
Cub	0	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009	55.009
Cub	1	**59.729**	56.167	57.350	55.867	58.550	58.533	57.023	58.667	58.195	58.967	58.933	58.700	50.833	59.533
Cub	2	64.152	56.900	58.150	60.033	59.400	62.933	58.640	60.300	60.120	63.800	64.067	64.133	52.100	**64.600**
Cub	4	69.217	57.833	60.000	65.467	61.300	67.533	60.307	61.500	63.427	68.633	**70.733**	68.800	53.100	70.700
Cub	8	74.402	59.433	60.450	71.167	64.750	71.900	61.957	63.267	66.847	73.500	75.800	74.500	56.500	**76.000**
Cub	16	78.625	61.700	62.250	75.333	67.600	76.467	62.963	66.867	71.755	78.100	79.933	77.600	61.067	**80.067**
Average	0	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275	62.275
Average	1	68.324	63.195	58.305	63.967	64.388	65.826	66.117	65.314	65.987	67.562	67.843	66.986	62.671	**68.457**
Average	2	71.160	63.800	61.710	67.824	66.810	69.748	66.942	67.019	68.196	71.314	71.362	70.405	63.333	**71.814**
Average	4	74.424	64.805	66.276	71.671	69.276	73.829	69.518	68.929	71.593	75.019	75.186	73.488	64.533	**75.329**
Average	8	78.516	66.181	68.436	75.443	72.393	76.924	70.855	71.729	74.035	78.190	**79.129**	77.162	66.343	78.993
Average	16	**82.517**	68.990	70.202	78.462	74.755	80.057	72.577	74.300	76.415	81.438	82.267	79.662	69.476	82.343
Overall Average (excl. zs)	-	74.988	65.394	64.986	71.473	69.524	73.277	69.202	69.458	71.245	74.705	75.157	73.540	65.271	**75.387**

Table 13. Few-shot performance results *without* unlearning evaluated across multiple datasets, methods, and shot counts. For shot counts greater than zero, the top-performing results are indicated in **bold**. Average results are shown at the end of the table. The table also includes averages for each shot count, with a final overall average calculated by excluding the zero-shot results.

14.6. Aggressive Unlearning - Aggregated Results

In Tab. 14 we show the loss in accuracy relative to the default case (from Tab. 9) as we unlearn more knowledge from CLIP. When knowledge lost is 25% SEPRES method loses less accuracy relative to its default performance compared to other methods. Similarly, when knowledge lost is 50% SEPRES is still the best. For 90% of lost knowledge all methods perform badly in few-shot setting. Note that we ignored TaskRes from calculating the minimum because it's default accuracy was lower compared to when a certain percentage of original knowledge was lost.

Shots	**Knowledge Lost (%)**	CLIPLora	CLIPAdapter	CoCoOp	CoOp	CoPrompt	IVLP	KgCoOp	MaPLe	ProGrad	PromptSRC	SEP	TCP	TaskRes	SEPRES
1	25	46.393	39.693	44.010	48.275	45.915	47.532	38.538	31.646	36.275	49.128	48.560	50.219	-35.583	**24.143**
2	25	49.136	41.184	38.278	49.781	52.745	56.291	38.905	42.048	38.727	51.723	48.054	52.999	-45.821	**19.367**
4	25	45.775	44.353	39.065	48.340	52.789	50.998	44.517	43.683	40.789	48.976	45.628	51.485	-60.087	**15.192**
8	25	41.075	48.354	45.475	47.240	56.457	48.999	41.634	44.152	42.128	45.688	43.001	49.155	-51.073	**10.139**
16	25	35.920	50.079	50.372	46.102	51.600	44.160	47.555	54.887	43.415	40.370	39.104	45.911	-14.370	**6.861**
1	50	54.714	52.497	41.076	55.293	51.913	42.078	58.495	39.836	**34.017**	56.189	53.971	58.696	28.221	39.940
2	50	55.410	52.015	51.452	55.467	58.601	57.614	50.388	50.602	36.707	56.198	55.336	62.739	20.461	**33.292**
4	50	53.552	54.000	48.664	55.222	62.658	56.016	58.687	59.056	42.703	55.772	52.137	62.972	12.075	**27.071**
8	50	49.098	57.099	57.730	52.860	65.434	54.279	60.981	54.366	43.598	51.686	48.904	59.897	-2.122	**20.029**
16	50	41.382	58.188	61.887	53.389	60.107	49.230	56.637	59.464	44.901	48.379	47.895	56.255	11.205	**14.895**
1	90	77.628	78.105	74.878	83.722	77.766	77.316	81.181	**71.854**	76.919	86.644	86.255	87.426	59.918	85.814
2	90	80.686	77.834	76.867	85.050	82.351	86.515	81.229	**72.651**	78.023	86.158	84.714	89.881	52.834	84.619
4	90	81.412	78.118	80.050	83.932	85.646	86.004	81.980	82.192	**75.949**	86.358	84.096	89.507	52.495	82.610
8	90	81.057	79.218	84.624	84.512	90.528	85.617	86.516	86.820	**77.985**	85.397	84.510	88.294	55.651	79.583
16	90	79.572	82.114	86.998	83.694	90.720	84.837	87.422	89.735	79.870	85.319	84.226	86.545	65.384	**75.590**

Table 14. Accuracy lost relative to the default case as a certain level of knowledge from CLIP is lost. SEPRES loses less accuracy relative to its default performance compared to other methods in most cases.