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A. ResNet Full Results

Table 4. Forgetting results with ResNet visual encoder. We compare our methods with five others on three classes for four selected datasets. We bold the best results comparing only among the first four methods that are zero-shot methods for a fair comparison.

Method	Dataset	Class name	Target Class acc.		Other Classes acc.		Target Class acc.		StanfordCars		StanfordDogs		Caltech101		OxfordFlowers		Avg. Score (↓)
			BF	AF	BF	AF	Synt. train	Real valid.	BF	AF	BF	AF	BF	AF	BF	AF	
Lip	StanfordDogs	Pekinese	0.705	0.066	0.515	0.514	0.062	0.0	0.558	0.559	-	-	0.857	0.867	0.661	0.658	**0.02**
Lip	StanfordDogs	toy poodle	0.574	0.033	0.516	0.518	0.031	0.0	0.558	0.559	-	-	0.857	0.867	0.661	0.647	**0.016**
Lip	StanfordDogs	Scotch terrier	0.5	0.047	0.517	0.516	0.047	0.083	0.558	0.557	-	-	0.857	0.865	0.661	0.66	**0.019**
Lip	StanfordCars	2009 Spyker C8 Coupe	0.262	0.024	0.559	0.553	0.0	0.0	-	-	0.517	0.518	0.857	0.865	0.661	0.66	**0.021**
Lip	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.143	0.558	0.544	0.0	0.0	-	-	0.517	0.502	0.857	0.845	0.661	0.638	0.091
Lip	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.0	0.558	0.555	0.0	0.0	-	-	0.517	0.52	0.857	0.869	0.661	0.661	**0.001**
Lip	Caltech101	euphonium	0.789	0.0	0.858	0.868	0.016	0.0	0.558	0.557	0.517	0.52	-	-	0.661	0.658	**0.001**
Lip	Caltech101	minaret	0.826	0.043	0.857	0.863	0.0	0.067	0.558	0.556	0.517	0.515	-	-	0.661	0.661	**0.012**
Lip	Caltech101	platypus	0.9	0.2	0.857	0.866	0.062	0.286	0.558	0.558	0.517	0.524	-	-	0.661	0.653	0.047
Lip	OxfordFlowers	gazania	0.957	0.0	0.658	0.649	0.062	0.0	0.558	0.559	0.517	0.513	0.857	0.869	-	-	**0.004**
Lip	OxfordFlowers	tree mallow	1.0	0.0	0.658	0.643	0.047	0.0	0.558	0.557	0.517	0.51	0.857	0.869	-	-	**0.008**
Lip	OxfordFlowers	trumpet creeper	0.588	0.0	0.661	0.643	0.047	0.083	0.558	0.557	0.517	0.503	0.857	0.866	-	-	**0.011**
Emb	StanfordDogs	Pekinese	0.705	0.361	0.515	0.484	0.0	0.318	0.558	0.559	-	-	0.857	0.84	0.661	0.633	0.127
Emb	StanfordDogs	toy poodle	0.574	0.361	0.516	0.481	0.0	0.217	0.558	0.553	-	-	0.857	0.832	0.661	0.613	0.161
Emb	StanfordDogs	Scotch terrier	0.5	0.062	0.517	0.472	0.031	0.083	0.558	0.551	-	-	0.857	0.837	0.661	0.617	0.063
Emb	StanfordCars	2009 Spyker C8 Coupe	0.262	0.024	0.559	0.529	0.0	0.0	-	-	0.517	0.508	0.857	0.841	0.661	0.639	0.043
Emb	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.119	0.558	0.542	0.047	0.0	-	-	0.517	0.512	0.857	0.857	0.661	0.654	**0.069**
Emb	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.119	0.558	0.539	0.0	0.125	-	-	0.517	0.509	0.857	0.852	0.661	0.654	0.059
Emb	Caltech101	euphonium	0.789	0.263	0.858	0.833	0.0	0.385	0.558	0.548	0.517	0.506	-	-	0.661	0.616	0.093
Emb	Caltech101	minaret	0.826	0.13	0.857	0.827	0.0	0.133	0.558	0.54	0.517	0.507	-	-	0.661	0.639	0.055
Emb	Caltech101	platypus	0.9	0.0	0.857	0.829	0.047	0.0	0.558	0.549	0.517	0.49	-	-	0.661	0.597	**0.039**
Emb	OxfordFlowers	gazania	0.957	0.739	0.658	0.632	0.0	0.875	0.558	0.551	0.517	0.503	0.857	0.849	-	-	0.172
Emb	OxfordFlowers	tree mallow	1.0	0.353	0.658	0.612	0.094	0.583	0.558	0.554	0.517	0.504	0.857	0.849	-	-	0.093
Emb	OxfordFlowers	trumpet creeper	0.588	0.235	0.661	0.632	0.0	0.167	0.558	0.555	0.517	0.508	0.857	0.853	-	-	0.094
Amns	StanfordDogs	Pekinese	0.705	0.459	0.515	0.486	0.0	0.409	0.558	0.561	-	-	0.857	0.847	0.661	0.65	0.147
Amns	StanfordDogs	toy poodle	0.574	0.492	0.516	0.423	0.016	0.261	0.558	0.55	-	-	0.857	0.839	0.661	0.628	0.225
Amns	StanfordDogs	Scotch terrier	0.5	0.031	0.517	0.488	0.0	0.083	0.558	0.559	-	-	0.857	0.859	0.661	0.651	0.027
Amns	StanfordCars	2009 Spyker C8 Coupe	0.262	0.143	0.559	0.516	0.016	0.0	-	-	0.517	0.51	0.857	0.854	0.661	0.646	0.132
Amns	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.429	0.558	0.49	0.047	0.222	-	-	0.517	0.5	0.857	0.868	0.661	0.658	0.244
Amns	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.5	0.558	0.489	0.078	0.375	-	-	0.517	0.507	0.857	0.868	0.661	0.656	0.221
Amns	Caltech101	euphonium	0.789	0.316	0.858	0.856	0.016	0.385	0.558	0.557	0.517	0.519	-	-	0.661	0.655	0.082
Amns	Caltech101	platypus	0.9	0.5	0.857	0.832	0.0	0.571	0.558	0.555	0.517	0.495	-	-	0.661	0.634	0.134
Amns	Caltech101	minaret	0.826	0.174	0.857	0.813	0.031	0.267	0.558	0.546	0.517	0.493	-	-	0.661	0.591	0.087
Amns	OxfordFlowers	gazania	0.957	0.87	0.658	0.595	0.391	0.875	0.558	0.557	0.517	0.489	0.857	0.834	-	-	0.217
Amns	OxfordFlowers	tree mallow	1.0	0.0	0.658	0.598	0.094	0.0	0.558	0.511	0.517	0.476	0.857	0.843	-	-	0.054
Amns	OxfordFlowers	trumpet creeper	0.588	0.294	0.661	0.584	0.0	0.25	0.558	0.554	0.517	0.494	0.857	0.828	-	-	0.14
EMMN	StanfordDogs	Pekinese	0.705	0.0	0.515	0.073	-	-	0.558	0.102	-	-	0.857	0.574	0.661	0.129	0.562
EMMN	StanfordDogs	toy poodle	0.574	0.0	0.516	0.041	-	-	0.558	0.118	-	-	0.857	0.622	0.661	0.13	0.557
EMMN	StanfordDogs	Scotch terrier	0.5	0.0	0.517	0.046	-	-	0.558	0.1	-	-	0.857	0.284	0.661	0.061	0.661
EMMN	StanfordCars	2009 Spyker C8 Coupe	0.262	0.0	0.559	0.057	-	-	-	-	0.517	0.055	0.857	0.491	0.661	0.07	0.623
EMMN	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.0	0.558	0.049	-	-	-	-	0.517	0.042	0.857	0.435	0.661	0.068	0.644
EMMN	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.0	0.558	0.058	-	-	-	-	0.517	0.032	0.857	0.348	0.661	0.07	0.665
EMMN	Caltech101	euphonium	0.789	0.0	0.858	0.442	-	-	0.558	0.107	0.517	0.083	-	-	0.661	0.173	0.574
EMMN	Caltech101	minaret	0.826	0.0	0.857	0.34	-	-	0.558	0.106	0.517	0.093	-	-	0.661	0.119	0.611
EMMN	Caltech101	platypus	0.9	0.0	0.857	0.411	-	-	0.558	0.078	0.517	0.066	-	-	0.661	0.098	0.621
EMMN	OxfordFlowers	gazania	0.957	0.0	0.658	0.107	-	-	0.558	0.11	0.517	0.104	0.857	0.643	-	-	0.538
EMMN	OxfordFlowers	tree mallow	1.0	0.0	0.658	0.115	-	-	0.558	0.136	0.517	0.089	0.857	0.66	-	-	0.528
EMMN	OxfordFlowers	trumpet creeper	0.588	0.0	0.661	0.14	-	-	0.558	0.116	0.517	0.142	0.857	0.725	-	-	0.492
AmnsRetain	StanfordDogs	Pekinese	0.705	0.049	0.515	0.667	-	-	0.558	0.531	-	-	0.857	0.835	0.661	0.61	0.044
AmnsRetain	StanfordDogs	toy poodle	0.574	0.082	0.516	0.663	-	-	0.558	0.521	-	-	0.857	0.831	0.661	0.605	0.065
AmnsRetain	StanfordDogs	Scotch terrier	0.5	0.0	0.517	0.659	-	-	0.558	0.511	-	-	0.857	0.847	0.661	0.616	0.033
AmnsRetain	StanfordCars	2009 Spyker C8 Coupe	0.262	0.071	0.559	0.719	-	-	-	-	0.517	0.513	0.857	0.886	0.661	0.623	0.067
AmnsRetain	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.0	0.558	0.712	-	-	-	-	0.517	0.504	0.857	0.878	0.661	0.62	0.017
AmnsRetain	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.048	0.558	0.704	-	-	-	-	0.517	0.51	0.857	0.879	0.661	0.622	0.033
AmnsRetain	Caltech101	euphonium	0.789	0.0	0.858	0.926	-	-	0.558	0.537	0.517	0.506	-	-	0.661	0.624	0.022
AmnsRetain	Caltech101	minaret	0.826	0.0	0.857	0.927	-	-	0.558	0.516	0.517	0.501	-	-	0.661	0.63	0.03
AmnsRetain	Caltech101	platypus	0.9	0.0	0.857	0.923	-	-	0.558	0.526	0.517	0.508	-	-	0.661	0.654	0.017
AmnsRetain	OxfordFlowers	gazania	0.957	0.0	0.658	0.931	-	-	0.558	0.554	0.517	0.512	0.857	0.865	-	-	0.004
AmnsRetain	OxfordFlowers	tree mallow	1.0	0.0	0.658	0.931	-	-	0.558	0.552	0.517	0.503	0.857	0.872	-	-	0.008
AmnsRetain	OxfordFlowers	trumpet creeper	0.588	0.176	0.661	0.903	-	-	0.558	0.553	0.517	0.515	0.857	0.861	-	-	0.062
Salun	StanfordDogs	Pekinese	0.705	0.049	0.515	0.668	-	-	0.558	0.509	-	-	0.857	0.838	0.661	0.605	0.053
Salun	StanfordDogs	toy poodle	0.574	0.066	0.516	0.654	-	-	0.558	0.502	-	-	0.857	0.841	0.661	0.614	0.061
Salun	StanfordDogs	Scotch terrier	0.5	0.016	0.517	0.661	-	-	0.558	0.497	-	-	0.857	0.826	0.661	0.587	0.058
Salun	StanfordCars	2009 Spyker C8 Coupe	0.262	0.119	0.559	0.718	-	-	-	-	0.517	0.498	0.857	0.871	0.661	0.58	0.123
Salun	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.024	0.558	0.711	-	-	-	-	0.517	0.494	0.857	0.853	0.661	0.563	0.051
Salun	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.048	0.558	0.707	-	-	-	-	0.517	0.481	0.857	0.862	0.661	0.58	0.056
Salun	Caltech101	euphonium	0.789	0.0	0.858	0.924	-	-	0.558	0.531	0.517	0.498	-	-	0.661	0.65	0.02
Salun	Caltech101	minaret	0.826	0.0	0.857	0.925	-	-	0.558	0.522	0.517	0.508	-	-	0.661	0.638	0.023
Salun	Caltech101	platypus	0.9	0.0	0.857	0.923	-	-	0.558	0.532	0.517	0.5	-	-	0.661	0.637	0.023
Salun	OxfordFlowers	gazania	0.957	0.0	0.658	0.92	-	-	0.558	0.521	0.517	0.503	0.857	0.86	-	-	0.018
Salun	OxfordFlowers	tree mallow	1.0	0.059	0.658	0.928	-	-	0.558	0.539	0.517	0.502	0.857	0.858	-	-	0.024
Salun	OxfordFlowers	trumpet creeper	0.588	0.118	0.661	0.922	-	-	0.558	0.541	0.517	0.503	0.857	0.853	-	-	0.052
ULip	StanfordDogs	Pekinese	0.705	0.705	0.515	0.506	-	-	0.558	0.563	-	-	0.857	0.863	0.661	0.656	0.205
ULip	StanfordDogs	toy poodle	0.574	0.082	0.516	0.395	-	-	0.558	0.494	-	-	0.857	0.81	0.661	0.611	0.124
ULip	StanfordDogs	Scotch terrier	0.5	0.5	0.517	0.509	-	-	0.558	0.561	-	-	0.857	0.853	0.661	0.657	0.205
ULip	StanfordCars	2009 Spyker C8 Coupe	0.262	0.119	0.559	0.389	-	-	-	-	0.517	0.492	0.857	0.825	0.661	0.63	0.178
ULip	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.071	0.558	0.497	-	-	-	-	0.517	0.51	0.857	0.859	0.661	0.643	0.065
ULip	StanfordCars	2011 Ford Ranger SuperCab	0.524	0.19	0.558	0.486	-	-	-	-	0.517	0.504	0.857	0.86	0.661	0.644	0.109
ULip	Caltech101	euphonium	0.789	0.316	0.858	0.849	-	-	0.558	0.556	0.517	0.5	-	-	0.661	0.64	0.095
ULip	Caltech101	minaret	0.826	0.783	0.857	0.855	-	-	0.558	0.564	0.517	0.514	-	-	0.661	0.659	0.192
ULip	Caltech101	platypus	0.9	0.9	0.857	0.858	-	-	0.558	0.561	0.517	0.513	-	-	0.661	0.657	0.203
ULip	OxfordFlowers	gazania	0.957	0.957	0.658	0.64	-	-	0.558	0.559	0.517	0.51	0.857	0.856	-	-	0.208
ULip	OxfordFlowers	tree mallow	1.0	1.0	0.658	0.646	-	-	0.558	0.56	0.517	0.51	0.857	0.86	-	-	0.207
ULip	OxfordFlowers	trumpet creeper	0.588	0.118	0.661	0.483	-	-	0.558	0.528	0.517	0.445	0.857	0.82	-	-	0.141

B. Additional Ablations

B.1. Full Results Synthetic Sampels CuPL Templates

Tab. 7 contains more granular results of forgetting on synthetic samples generated with randomly selected CuPL templates.

B.2. Full Results Evaluation with Different Template

Tab. 8 contains more granular results of forgetting evaluation with different templates.

B.3. Full Results Forgetting of ULip with Synthetic Samples

Tab. 11 contains more granular results of forgetting with ULip with synthetic samples.

B.4. Varying All the Parameters

When all parameters are allowed to vary without selective forgetting, CLIP tends to overforget. These findings are shown in Tab.5 for *AllParamsVary* ablation type and granular results in Tab. 10. Therefore, greater control over the varying parameters is necessary in CLIP to achieve forgetting. This differs from the approach used with vision models in [7], where all parameters were allowed to vary. This discrepancy can be attributed to the size of the CLIP model, which contains a vast amount of information unlike the smaller models trained on limited data in [7], as well as the structural differences that necessitate more controlled updates.

B.5. Forgetting Using One Iteration

In [7] authors used a single epoch for forgetting. In Tab. 5 in *OneIter* ablation type we can clearly see that this is often not enough to forget as the model most of the time still maintains a very high accuracy on the class to forget. Thus, multiple iterations are required to achieve a desirable level of forgetting. Tab. 9 contains more granular results.

B.6. Perturbation to Text Embedding

We analyze how adding noise to the text embeddings, which are in continuous space, rather than using image input changes the forgetting results. Comparing the results in Tab. 6 for *TextEmbPeturb* ablation type and *Original* we see that perturbing textual embedding makes forgetting slightly worse, which is likely due to the fact that perturbing textual embeddings is less meaningful compared to image pixels or discrete text tokens.

Table 5. Different ablations. *Original*: results with our method (Lip) from Tab.1. *AllParamsVary*: forgetting on synthetic data allowing all parameters to vary. *OneIter*: forgetting on synthetic data with a single epoch. *NoTextLoss*: ULip forgetting on synthetic data. *CuPLGen*: synthetic samples generated with CuPL templates. *EvalTemplChange*: evaluation with different templates.

Ablation Type	**Method**	**Avg. Target Class acc.**		**Avg. Other Classes acc.**		**Avg. StanfordCars**		**Avg. StanfordDogs**		**Avg. Caltech101**		**Avg. OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
Original	Lip	0.669	0.046	0.648	0.644	0.558	0.557	0.517	0.514	0.857	0.865	0.661	0.655	**0.018**
AllParamsVary	Lip	0.669	0.0	0.648	0.033	0.558	0.015	0.517	0.014	0.857	0.091	0.661	0.011	0.954
OneIter	Lip	0.655	0.173	0.629	0.631	0.558	0.561	0.517	0.522	0.857	0.869	0.661	0.662	0.053
NoTextLoss	ULip	0.669	0.606	0.648	0.641	0.558	0.557	0.517	0.511	0.857	0.854	0.661	0.651	0.189
CuPLGen	Lip	0.669	0.038	0.648	0.609	0.558	0.535	0.517	0.494	0.857	0.838	0.661	0.625	0.055
EvalTemplChange	Lip	0.522	0.133	0.544	0.538	0.492	0.494	0.412	0.414	0.81	0.801	0.518	0.519	0.068

Table 6. Ablations on perturbation to text embedding.

Ablation Type	**Dataset**	**Avg. Target Class acc.**		**Avg. Other Classes acc.**		**Avg. StanfordCars**		**Avg. StanfordDogs**		**Avg. Caltech101**		**Avg. OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
Original	StanfordCars	0.397	0.056	0.558	0.551	-	-	0.517	0.513	0.857	0.86	0.661	0.653	**0.034**
Original	StanfordDogs	0.593	0.048	0.516	0.516	0.558	0.558	-	-	0.857	0.866	0.661	0.655	**0.018**
Original	Caltech101	0.839	0.081	0.857	0.865	0.558	0.557	0.517	0.52	-	-	0.661	0.657	**0.021**
Original	OxfordFlowers	0.848	0.0	0.659	0.645	0.558	0.557	0.517	0.51	0.857	0.868	-	-	**0.008**
TextEmbPeturb	StanfordCars	0.397	0.056	0.558	0.55	-	-	0.517	0.513	0.857	0.859	0.661	0.652	0.035
TextEmbPeturb	StanfordDogs	0.593	0.267	0.516	0.509	0.558	0.557	-	-	0.857	0.864	0.661	0.648	0.097
TextEmbPeturb	Caltech101	0.839	0.114	0.857	0.866	0.558	0.558	0.517	0.515	-	-	0.661	0.652	0.031
TextEmbPeturb	OxfordFlowers	0.848	0.02	0.659	0.631	0.558	0.553	0.517	0.503	0.857	0.867	-	-	0.02

Table 7. We perform forgetting on synthetic samples generated with randomly selected CuPL templates.

Method	**Dataset**	**Avg. Target Class acc.**		**Avg. Other Classes acc.**		**Avg. StanfordCars**		**Avg. StanfordDogs**		**Avg. Caltech101**		**Avg. OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
Lip	StanfordCars	0.397	0.032	0.558	0.525	-	-	0.517	0.494	0.857	0.844	0.661	0.635	0.047
Lip	StanfordDogs	0.593	0.066	0.516	0.478	0.558	0.532	-	-	0.857	0.838	0.661	0.604	0.068
Lip	Caltech101	0.839	0.014	0.857	0.859	0.558	0.548	0.517	0.508	-	-	0.661	0.637	0.017
Lip	OxfordFlowers	0.848	0.039	0.659	0.575	0.558	0.525	0.517	0.48	0.857	0.831	-	-	0.067

Table 8. We aggregate across three different evaluation templates to assess sensitivity of models after forgetting to the change in evaluation template.

Method	Dataset	Avg. Target Class acc.		Avg. Other Classes acc.		Avg. StanfordCars		Avg. StanfordDogs		Avg. Caltech101		Avg. OxfordFlowers		Avg. Score (↓)
		BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	
Lip	StanfordCars	0.272	0.048	0.493	0.494	-	-	0.412	0.413	0.81	0.802	0.518	0.512	0.041
Lip	StanfordDogs	0.306	0.103	0.416	0.397	0.492	0.491	-	-	0.81	0.795	0.518	0.504	0.087
Lip	Caltech101	0.897	0.211	0.809	0.809	0.492	0.499	0.412	0.422	-	-	0.518	0.547	0.047
Lip	OxfordFlowers	0.698	0.187	0.518	0.51	0.492	0.493	0.412	0.41	0.81	0.805	-	-	0.06

Table 9. Forgetting with Lipschitz loss and synthetic data using a single epoch.

Method	Dataset	Avg. Target Class acc.		Avg. Other Classes acc.		Avg. StanfordCars		Avg. StanfordDogs		Avg. Caltech101		Avg. OxfordFlowers		Avg. Score (↓)
		BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	
Lip	StanfordCars	0.397	0.008	0.558	0.556	-	-	0.517	0.524	0.857	0.87	0.661	0.665	0.005
Lip	StanfordDogs	0.593	0.201	0.516	0.527	0.558	0.56	-	-	0.857	0.87	0.661	0.66	0.068
Lip	Caltech101	0.845	0.405	0.857	0.866	0.558	0.56	0.517	0.521	-	-	0.661	0.662	0.084
Lip	OxfordFlowers	0.848	0.189	0.659	0.653	0.558	0.562	0.517	0.519	0.857	0.867	-	-	0.046

Table 10. Forgetting with Lipschitz loss and synthetic data when varying all the parameters.

Method	Dataset	Avg. Target Class acc.		Avg. Other Classes acc.		Avg. StanfordCars		Avg. StanfordDogs		Avg. Caltech101		Avg. OxfordFlowers		Avg. Score (↓)
		BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	
Lip	StanfordCars	0.397	0.0	0.558	0.032	-	-	0.517	0.018	0.857	0.114	0.661	0.008	0.753
Lip	StanfordDogs	0.593	0.0	0.516	0.009	0.558	0.013	-	-	0.857	0.074	0.661	0.011	0.771
Lip	Caltech101	0.839	0.0	0.857	0.073	0.558	0.014	0.517	0.012	-	-	0.661	0.013	0.769
Lip	OxfordFlowers	0.848	0.0	0.659	0.019	0.558	0.017	0.517	0.013	0.857	0.086	-	-	0.763

Table 11. Forgetting with ULip loss and synthetic data.

Method	Dataset	Avg. Target Class acc.		Avg. Other Classes acc.		Avg. StanfordCars		Avg. StanfordDogs		Avg. Caltech101		Avg. OxfordFlowers		Avg. Score (↓)
		BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	
ULip	StanfordCars	0.397	0.222	0.558	0.545	-	-	0.517	0.504	0.857	0.849	0.661	0.648	0.128
ULip	StanfordDogs	0.593	0.534	0.516	0.512	0.558	0.558	-	-	0.857	0.856	0.661	0.651	0.185
ULip	Caltech101	0.839	0.859	0.857	0.855	0.558	0.557	0.517	0.515	-	-	0.661	0.655	0.208
ULip	OxfordFlowers	0.848	0.809	0.659	0.654	0.558	0.556	0.517	0.513	0.857	0.857	-	-	0.194

C. Lip Unlearning Real vs Synthetic

Table 12. Forgetting results with **synthetic** data using Lipschitz loss. We show the forgetting results on three classes for four different datasets.

Dataset	**Class name**	**Target Class acc.**		**Other Classes acc.**		**Target Class acc.**		**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**Synt. train**	**Real valid.**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
StanfordDogs	Pekinese	0.705	0.066	0.515	0.514	0.062	0.0	0.558	0.559	-	-	0.857	0.867	0.661	0.658	0.02
StanfordDogs	toy poodle	0.574	0.033	0.516	0.518	0.031	0.0	0.558	0.559	-	-	0.857	0.867	0.661	0.647	0.016
StanfordDogs	Scotch terrier	0.5	0.047	0.517	0.516	0.047	0.083	0.558	0.557	-	-	0.857	0.865	0.661	0.66	0.019
StanfordCars	2009 Spyker C8 Coupe	0.262	0.024	0.559	0.553	0.0	0.0	-	-	0.517	0.518	0.857	0.865	0.661	0.66	0.021
StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.143	0.558	0.544	0.0	0.0	-	-	0.517	0.502	0.857	0.845	0.661	0.638	0.091
StanfordCars	2011 Ford Ranger SuperCab	0.524	0.0	0.558	0.555	0.0	0.0	-	-	0.517	0.52	0.857	0.869	0.661	0.661	0.001
Caltech101	euphonium	0.789	0.0	0.858	0.868	0.016	0.0	0.558	0.557	0.517	0.52	-	-	0.661	0.658	0.001
Caltech101	minaret	0.826	0.043	0.857	0.863	0.0	0.067	0.558	0.556	0.517	0.515	-	-	0.661	0.661	0.012
Caltech101	platypus	0.9	0.2	0.857	0.866	0.062	0.286	0.558	0.558	0.517	0.524	-	-	0.661	0.653	0.047
OxfordFlowers	gazania	0.957	0.0	0.658	0.649	0.062	0.0	0.558	0.559	0.517	0.513	0.857	0.869	-	-	0.004
OxfordFlowers	tree mallow	1.0	0.0	0.658	0.643	0.047	0.0	0.558	0.557	0.517	0.51	0.857	0.869	-	-	0.011
OxfordFlowers	trumpet creeper	0.588	0.0	0.661	0.643	0.047	0.083	0.558	0.557	0.517	0.503	0.857	0.866	-	-	0.011

Table 13. Forgetting results with **real** data using Lipschitz loss. We show the forgetting results on three classes for four different datasets.

Dataset	**Class name**	**Target Class acc.**		**Other Classes acc.**		**Target Class acc.**	**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**Real valid.**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
StanfordDogs	Pekinese	0.705	0.066	0.515	0.514	0.045	0.558	0.563	-	-	0.857	0.873	0.661	0.654	0.021
StanfordDogs	toy poodle	0.574	0.033	0.516	0.506	0.022	0.558	0.565	-	-	0.857	0.871	0.661	0.646	0.02
StanfordDogs	Scotch terrier	0.5	0.016	0.517	0.509	0.043	0.558	0.562	-	-	0.857	0.862	0.661	0.654	0.011
StanfordCars	2009 Spyker C8 Coupe	0.262	0.024	0.559	0.517	0.059	-	-	0.517	0.509	0.857	0.849	0.661	0.642	0.044
StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.405	0.024	0.558	0.557	0.0	-	-	0.517	0.52	0.857	0.866	0.661	0.655	0.014
StanfordCars	2011 Ford Ranger SuperCab	0.524	0.048	0.558	0.561	0.029	-	-	0.517	0.521	0.857	0.87	0.661	0.658	0.019
Caltech101	euphonium	0.789	0.0	0.858	0.853	0.0	0.558	0.549	0.517	0.495	-	-	0.661	0.625	0.023
Caltech101	minaret	0.826	0.043	0.857	0.865	0.026	0.558	0.563	0.517	0.51	-	-	0.661	0.657	0.014
Caltech101	platypus	0.9	0.5	0.857	0.866	0.235	0.558	0.559	0.517	0.517	-	-	0.661	0.652	0.114
OxfordFlowers	gazania	0.957	0.0	0.658	0.65	0.026	0.558	0.561	0.517	0.515	0.857	0.866	-	-	0.003
OxfordFlowers	tree mallow	1.0	0.353	0.658	0.652	0.0	0.558	0.56	0.517	0.512	0.857	0.861	-	-	0.074
OxfordFlowers	trumpet creeper	0.588	0.059	0.661	0.658	0.069	0.558	0.56	0.517	0.515	0.857	0.864	-	-	0.022

D. Forgetting on Multiple Classes and Error Analysis

We assess forgetting on multiple classes in Tab. 16. *Other Classes acc.* represents the performance on the remaining classes before forgetting (BF) and after forgetting (AF) respectively on the dataset specified in *Dataset*. We observe that after forgetting multiple classes, the accuracy on remaining classes and other datasets remains relatively high on StanfordDog and Caltech101 while reducing slightly more on other two datasets. This is due to the 1.5% loss in accuracy on other classes when unlearning *2010 Dodge Ram Pickup 3500 Crew Cab* and 2% when unlearning *trumpet creeper* alone as shown in Tab. 4 for LIP unlearning, leading to more forgetting subsequently on other classes when forgetting multiple classes. This does not happen on StanfordDogs and Caltech101 datasets where the reduction in performance after forgetting on not targeted classes is low. Indeed, replacing *2010 Dodge Ram Pickup 3500 Crew Cab* with *2012 Rolls-Royce Ghost Sedan* that has a smaller reduction in performance on other classes after forgetting as shown in Tab.15, forgetting on multiple classes also improves. These are shown on the last row in Tab.15. In general, it is normal to expect that as the number of classes to forget increases, the accuracy on other classes will gradually decrease, as demonstrated in our experiments, albeit at a relatively slow rate.

Notably, on the *OxfordFlowers* dataset, the accuracy decrease is more pronounced compared to other datasets when forgetting was applied, indicating higher sensitivity. This observation held true for single class forgetting as well. Therefore, we examined how close in terms of their position in the sorted list of logits scores the correct prediction of the original model and incorrect prediction of the forget model were before and after forgetting. If their proximity in terms of position and logits scores was significant, it would suggest that the model was already uncertain about those predictions. Consequently, a minor, targeted forgetting may have resulted in a subtle change in logits scores, swapping the predictions.

We conducted this analysis on the model after forgetting the selected classes. Looking at Tab. 16, following the forgetting of three classes from *Caltech101* datasets, there were 106 incorrect predictions after forgetting compared to the model's performance before forgetting on the *OxfordFlowers* dataset. Among these, we found that in 88 instances (83.02%), the correct class in an ordered set of logits predicted by CLIP shifted by one place. This means that instead of the correct class having the highest score, it ranked second-highest after forgetting. At the same time, to be included in those 88 instances the new highest incorrect prediction of the forget model must have been the second highest class in the original model's logits.

To explain this procedure with an example, consider a given image of a *Poodle* for which the original model predicted the classes in the following way: *Poodle, Labrador, Spaniel* ordered by logits assumed to be *15, 14.9, 12*. Here, *Poodle* was the correct prediction with the highest score, as we only examined cases where the original model was correct and assessed how that changed after forgetting. After the forgetting process, the new model predicts: *Labrador, Poodle, Spaniel* with sorted scores *15.1, 14.9, 11.8*. In this case, the correct prediction (*Poodle*) moved from the highest to second highest score, i.e., one step away from its original position, and the difference in scores is 0.02 (corresponding to *One-Step Avg. LogitScore* in Tab. 14). Also, the new incorrect prediction with the highest score, *Labrador*, was the second highest prediction in the original model logits, thus this example would be included in calculating the *One-Step %*.

Similarly, looking at shifts of up to two places, where the correct class ranked either second or third highest, we found that 99 cases (93.4%) moved away by a maximum of two places from the correct prediction.

For *StanfordDogs*, there were 120 incorrect labels. In 100 cases (83.33%), the correct class moved away by one place, and in 112 cases (93.33%), it shifted by a maximum of two places.

For *StanfordCars*, we took the model after forgetting on classes shown on the last row of Tab. 6. There were 124 incorrect labels. In 104 cases (83.87%), the correct class moved away by one place, and in 116 cases (93.54%), it shifted by a maximum of two places.

These results are summarized in Table 14. The Δ *One-Step Avg. LogitScore* represents the standardized average change in logits scores between the model's new incorrect and correct predictions. Similarly, for Δ *Two-Step Avg. LogitScore*, considering a shift of two places.

This analysis indicates that the greater than expected drop in accuracy on the *OxfordFlowers* dataset is attributed to the model's original uncertainty about those cases. Thus, despite our demonstrated ability to precisely target the parameters for forgetting the target class, the model's initial uncertainty contributes to the relatively more pronounced decrease in accuracy.

Table 14. Sensitivity Analysis on OxfordFlowers dataset.

Model	One-Step %	Δ One-Step Avg. LogitScore	Two-Step %	Δ Two-Step Avg. LogitScore
StanfordDogs	83.02	0.014	93.4	0.014
StanfordCars	83.87	0.015	93.54	0.016
Caltech101	83.33	0.015	93.33	0.017

Table 15. Forgetting other examples using Lipschitz loss.

Forgetting Data	Dataset	Class name	Target Class acc.		Other Classes acc.		Target Class acc.		StanfordCars		StanfordDogs		Caltech101		OxfordFlowers		Avg. Score (↓)
			BF	AF	BF	AF	Synt. train	Real valid.	BF	AF	BF	AF	BF	AF	BF	AF	
Generated	StanfordCars	2012 Chevrolet Avalanche Crew Cab	0.622	0.044	0.557	0.494	0.281	0.0	-	-	0.517	0.501	0.857	0.87	0.661	0.633	0.05
Generated	StanfordCars	2012 Rolls-Royce Ghost Sedan	0.526	0.07	0.557	0.557	0.078	0.15	-	-	0.520	0.527	0.857	0.862	0.66	0.658	0.04
Generated	StanfordCars	2009 Spyker C8 Coupe, 2012 Rolls-Royce Ghost Sedan, 2011 Ford Ranger SuperCab	0.397	0.12	0.558	0.535	-	-	-	-	0.517	0.501	0.857	0.862	0.661	0.631	0.08

Table 16. Forgetting multiple classes with generated data using Lipschitz loss.

Dataset	Classes	Avg. Target Classes acc.		Other Classes acc.		StanfordCars		StanfordDogs		Caltech101		OxfordFlowers		Avg. Score (↓)
		BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	
StanfordDogs	Pekinese,toy poodle,Scotch terrier	0.593	0.09	0.517	0.507	0.558	0.547	-	-	0.857	0.865	0.661	0.633	0.046
StanfordCars	2009 Spyker C8 Coupe, 2010 Dodge Ram Pickup 3500 Crew Cab, 2011 Ford Ranger SuperCab	0.397	0.2	0.558	0.519	-	-	0.517	0.482	0.857	0.84	0.661	0.607	0.16
Caltech101	euphonium,minaret,platypus	0.839	0.125	0.857	0.869	0.558	0.549	0.517	0.515	-	-	0.661	0.633	0.042
OxfordFlowers	gazania,tree mallow,trumpet creeper	0.848	0.0	0.661	0.609	0.558	0.552	0.517	0.498	0.857	0.863	-	-	0.023

E. Synthetic Images Visualization

In Fig. 4 we can see an example of a synthetic image for a class from four different datasets we tested on. These synthetic samples do not have a clear appearance of the sample class but are enough for unlearning the class.

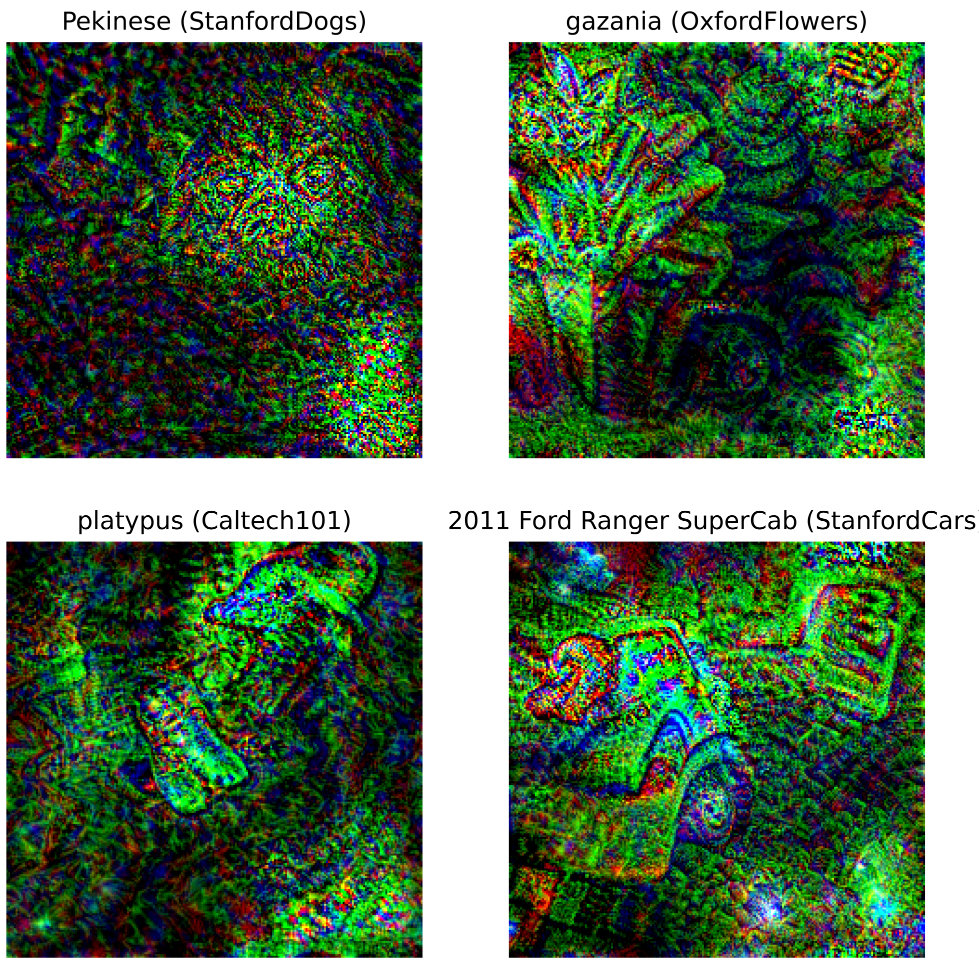

Figure 4. Synthetic images examples.

F. ViT Results

Results for CLIP with ViT-B/16 visual encoder are included in Tab. 20. In general we observe that forgetting with ViT compared to ResNet architecture is harder and the class accuracy after forgetting, even if decreases, it often does not go to zero. This difference may be attributed to the fact that ViT learns more fine-grained representations of the input images compared to ResNet thanks to its self-attention mechanism. As a result, specific classes could be encoded in a more intricate manner within ViT's learned representations, making them harder to unlearn without affecting other aspects of the model's knowledge. When it comes to other methods for comparison the conclusions are similar to the ones highlighted for ResNet. Aggregated results are shown in Tab. 17

Table 17. Aggregated forgetting results with ViT-B/16 visual encoder. We compare our method (Lip) to five other methods averaging across three classes for four selected datasets. We aim to minimize the *Avg. Target Class acc. AF* while maintaining *Avg. Other Classes acc. AF* and other datasets at a similar level to that before forgetting (BF). We bold the best results comparing only among the first four methods that are zero-shot methods for a fair comparison.

Method	Dataset	Forgetting Type	Avg. Target Class acc.		Avg. Other Classes acc.		Avg. StanfordCars		Avg. StanfordDogs		Avg. Caltech101		Avg. OxfordFlowers		Avg. Score (↓)
			BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	BF	AF	
Lip	StanfordCars	ZS	0.595	0.159	0.656	0.642	-	-	0.591	0.584	0.933	0.932	0.708	0.707	**0.06**
Emb	StanfordCars	ZS	0.595	0.0	0.656	0.557	-	-	0.591	0.508	0.933	0.921	0.708	0.69	0.066
Amns	StanfordCars	ZS	0.595	0.143	0.656	0.18	-	-	0.591	0.398	0.933	0.876	0.708	0.51	0.327
EMMN	StanfordCars	ZS	0.595	0.159	0.656	0.182	-	-	0.591	0.119	0.933	0.589	0.708	0.137	0.592
ULip	StanfordCars	semi ZS	0.595	0.032	0.656	0.419	-	-	0.591	0.59	0.933	0.93	0.708	0.711	0.084
AmnsRetain	StanfordCars	not ZS	0.595	0.0	0.656	0.744	-	-	0.591	0.476	0.933	0.887	0.708	0.554	0.092
Salun	StanfordCars	not ZS	0.595	0.087	0.656	0.711	-	-	0.591	0.495	0.933	0.863	0.708	0.58	0.113
Lip	StanfordDogs	ZS	0.673	0.142	0.591	0.592	0.655	0.647	-	-	0.933	0.935	0.708	0.709	**0.045**
Emb	StanfordDogs	ZS	0.673	0.071	0.591	0.518	0.655	0.632	-	-	0.933	0.93	0.708	0.699	0.056
Amns	StanfordDogs	ZS	0.673	0.219	0.591	0.358	0.655	0.59	-	-	0.933	0.901	0.708	0.572	0.209
EMMN	StanfordDogs	ZS	0.673	0.042	0.591	0.365	0.655	0.284	-	-	0.933	0.826	0.708	0.438	0.301
ULip	StanfordDogs	semi ZS	0.673	0.588	0.591	0.536	0.655	0.649	-	-	0.933	0.93	0.708	0.702	0.197
AmnsRetain	StanfordDogs	not ZS	0.673	0.021	0.591	0.698	0.655	0.472	-	-	0.933	0.841	0.708	0.495	0.142
Salun	StanfordDogs	not ZS	0.673	0.043	0.591	0.662	0.655	0.508	-	-	0.933	0.835	0.708	0.609	0.107
Lip	Caltech101	ZS	0.971	0.576	0.933	0.935	0.655	0.652	0.591	0.594	-	-	0.708	0.709	**0.12**
Emb	Caltech101	ZS	0.971	0.598	0.933	0.91	0.655	0.609	0.591	0.517	-	-	0.708	0.656	0.182
Amns	Caltech101	ZS	0.971	0.846	0.933	0.848	0.655	0.517	0.591	0.445	-	-	0.708	0.533	0.334
EMMN	Caltech101	ZS	0.971	0.284	0.933	0.813	0.655	0.352	0.591	0.302	-	-	0.708	0.473	0.341
ULip	Caltech101	semi ZS	0.971	0.812	0.933	0.916	0.655	0.65	0.591	0.584	-	-	0.708	0.702	0.177
AmnsRetain	Caltech101	not ZS	0.971	0.0	0.933	0.946	0.655	0.506	0.591	0.474	-	-	0.708	0.544	0.132
Salun	Caltech101	not ZS	0.971	0.0	0.933	0.926	0.655	0.525	0.591	0.506	-	-	0.708	0.642	0.088
Lip	OxfordFlowers	ZS	0.784	0.078	0.707	0.702	0.655	0.645	0.591	0.588	0.933	0.933	-	-	**0.026**
Emb	OxfordFlowers	ZS	0.784	0.0	0.707	0.617	0.655	0.543	0.591	0.522	0.933	0.906	-	-	0.089
Amns	OxfordFlowers	ZS	0.784	0.834	0.707	0.527	0.655	0.602	0.591	0.526	0.933	0.913	-	-	0.307
EMMN	OxfordFlowers	ZS	0.784	0.02	0.707	0.433	0.655	0.317	0.591	0.304	0.933	0.83	-	-	0.305
ULip	OxfordFlowers	semi ZS	0.784	0.02	0.707	0.529	0.655	0.64	0.591	0.554	0.933	0.913	-	-	0.077
AmnsRetain	OxfordFlowers	not ZS	0.784	0.0	0.707	0.945	0.655	0.56	0.591	0.531	0.933	0.914	-	-	0.054
Salun	OxfordFlowers	not ZS	0.784	0.059	0.707	0.923	0.655	0.537	0.591	0.503	0.933	0.857	-	-	0.097

Table 18. Forgetting with real data using Lipschitz loss ViT-B/16 visual encoder.

Dataset	**Class name**	**Target Class acc.**		**Other Classes acc.**		**Target Class acc.**	**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**		**Avg. Score** (↓)
		BF	**AF**	**BF**	**AF**	**Real valid.**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
StanfordDogs	Pekinese	0.787	0.016	0.59	0.607	0.0	0.655	0.657	-	-	0.933	0.932	0.708	0.709	0.004
StanfordDogs	toy poodle	0.607	0.131	0.591	0.581	0.022	0.655	0.64	-	-	0.933	0.94	0.708	0.715	0.051
StanfordDogs	Scotch terrier	0.625	0.047	0.591	0.56	0.085	0.655	0.64	-	-	0.933	0.937	0.708	0.709	0.03
StanfordCars	2009 Spyker C8 Coupe	0.429	0.238	0.656	0.652	0.176	-	-	0.591	0.591	0.933	0.933	0.708	0.708	0.112
StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.143	0.656	0.637	0.088	-	-	0.591	0.598	0.933	0.938	0.708	0.713	0.058
StanfordCars	2011 Ford Ranger SuperCab	0.81	0.81	0.654	0.654	0.794	-	-	0.591	0.593	0.933	0.933	0.708	0.71	0.224
Caltech101	euphonium	1.0	0.0	0.933	0.935	0.031	0.655	0.656	0.591	0.596	-	-	0.708	0.707	0.0
Caltech101	minaret	0.913	0.739	0.933	0.928	0.711	0.655	0.644	0.591	0.593	-	-	0.708	0.719	0.167
Caltech101	platypus	1.0	0.9	0.933	0.934	0.647	0.655	0.656	0.591	0.599	-	-	0.708	0.714	0.18
OxfordFlowers	gazania	1.0	0.087	0.705	0.711	0.077	0.655	0.653	0.591	0.601	0.933	0.934	-	-	0.018
OxfordFlowers	tree mallow	0.765	0.294	0.707	0.7	0.172	0.655	0.652	0.591	0.601	0.933	0.941	-	-	0.08
OxfordFlowers	trumpet creeper	0.588	0.118	0.709	0.713	0.241	0.655	0.648	0.591	0.602	0.933	0.939	-	-	0.042

Table 19. Forgetting on multiple classes using Lipschitz loss ViT-B/16 visual encoder.

Dataset	**Classes**	**Avg. Target Classes acc.**		**Other Classes acc.**		**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**		**Avg. Score** (↓)
		BF	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
StanfordDogs	Pekinese,toy poodle,Scotch terrier	0.672	0.251	0.589	0.584	0.655	0.644	-	-	0.933	0.939	0.708	0.713	0.08
StanfordCars	2009 Spyker C8 Coupe, 2010 Dodge Ram Pickup 3500 Crew Cab, 2011 Ford Ranger SuperCab	0.595	0.3	0.656	0.625	-	-	0.591	0.576	0.933	0.928	0.708	0.699	0.119
Caltech101	euphonium,minaret,platypus	0.971	0.498	0.932	0.929	0.655	0.634	0.591	0.589	-	-	0.708	0.709	0.11
OxfordFlowers	trumpet creeper,gazania,tree mallow	0.807	0.31	0.705	0.68	0.655	0.613	0.591	0.551	0.933	0.929	-	-	0.111

Table 20. Forgetting results with ViT-B/16 visual encoder. We compare our methods with five others on three classes for four selected datasets. We bold the best results comparing only among the first four methods that are zero-shot methods for a fair comparison.

Method	Dataset	Class name	Target Class acc.		Other Classes acc.		Target Class acc.		StanfordCars		StanfordDogs		Caltech101		OxfordFlowers		Avg. Score (↓)
			BF	AF	BF	AF	Synt. train	Real valid.	BF	AF	BF	AF	BF	AF	BF	AF	
Lip	StanfordDogs	Pekinese	0.787	0.377	0.59	0.601	0.094	0.273	0.655	0.656	-	-	0.933	0.934	0.708	0.708	0.096
Lip	StanfordDogs	toy poodle	0.607	0.033	0.591	0.593	0.0	0.0	0.655	0.639	-	-	0.933	0.932	0.708	0.707	**0.016**
Lip	StanfordDogs	Scotch terrier	0.625	0.016	0.591	0.582	0.219	0.0	0.655	0.647	-	-	0.933	0.938	0.708	0.713	**0.011**
Lip	StanfordCars	2009 Spyker C8 Coupe	0.429	0.262	0.656	0.639	0.484	0.222	-	-	0.591	0.581	0.933	0.93	0.708	0.7	**0.134**
Lip	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.048	0.656	0.634	0.062	0.0	-	-	0.591	0.58	0.933	0.933	0.708	0.708	0.028
Lip	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.167	0.654	0.653	0.984	0.125	-	-	0.591	0.59	0.933	0.933	0.708	0.713	**0.042**
Lip	Caltech101	euphonium	1.0	0.158	0.933	0.935	0.0	0.154	0.655	0.653	0.591	0.597	-	-	0.708	0.706	**0.033**
Lip	Caltech101	minaret	0.913	0.87	0.933	0.932	0.031	1.0	0.655	0.649	0.591	0.59	-	-	0.708	0.709	**0.187**
Lip	Caltech101	platypus	1.0	0.7	0.933	0.936	0.031	0.857	0.655	0.653	0.591	0.595	-	-	0.708	0.711	**0.141**
Lip	OxfordFlowers	gazania	1.0	0.0	0.705	0.7	0.297	0.0	0.655	0.642	0.591	0.587	0.933	0.935	-	-	0.007
Lip	OxfordFlowers	tree mallow	0.765	0.176	0.707	0.699	0.172	0.0	0.655	0.65	0.591	0.596	0.933	0.933	-	-	**0.05**
Lip	OxfordFlowers	trumpet creeper	0.588	0.059	0.709	0.705	0.781	0.0	0.655	0.644	0.591	0.581	0.933	0.932	-	-	**0.028**
Emb	StanfordDogs	Pekinese	0.787	0.213	0.59	0.601	0.031	0.227	0.655	0.656	-	-	0.933	0.934	0.708	0.708	**0.054**
Emb	StanfordDogs	toy poodle	0.607	0.0	0.591	0.472	0.0	0.0	0.655	0.621	-	-	0.933	0.931	0.708	0.696	0.054
Emb	StanfordDogs	Scotch terrier	0.625	0.0	0.591	0.481	0.141	0.0	0.655	0.617	-	-	0.933	0.926	0.708	0.695	0.054
Emb	StanfordCars	2009 Spyker C8 Coupe	0.429	0.0	0.656	0.479	0.016	0.0	-	-	0.591	0.392	0.933	0.908	0.708	0.659	0.14
Emb	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.0	0.656	0.626	0.078	0.0	-	-	0.591	0.59	0.933	0.934	0.708	0.713	**0.01**
Emb	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.0	0.654	0.565	0.203	0.0	-	-	0.591	0.542	0.933	0.92	0.708	0.699	0.049
Emb	Caltech101	euphonium	1.0	0.368	0.933	0.935	0.0	0.385	0.655	0.652	0.591	0.594	-	-	0.708	0.709	0.075
Emb	Caltech101	minaret	0.913	0.826	0.933	0.933	0.016	0.867	0.655	0.635	0.591	0.583	-	-	0.708	0.711	0.19
Emb	Caltech101	platypus	1.0	0.6	0.933	0.861	0.0	0.429	0.655	0.539	0.591	0.376	-	-	0.708	0.547	0.289
Emb	OxfordFlowers	gazania	1.0	0.0	0.705	0.705	0.141	0.0	0.655	0.645	0.591	0.593	0.933	0.933	-	-	**0.003**
Emb	OxfordFlowers	tree mallow	0.765	0.0	0.707	0.577	0.172	0.0	0.655	0.58	0.591	0.501	0.933	0.903	-	-	0.097
Emb	OxfordFlowers	trumpet creeper	0.588	0.0	0.709	0.569	0.0	0.0	0.655	0.406	0.591	0.472	0.933	0.88	-	-	0.167
Amns	StanfordDogs	Pekinese	0.787	0.623	0.59	0.366	0.031	0.545	0.655	0.581	-	-	0.933	0.896	0.708	0.609	0.293
Amns	StanfordDogs	toy poodle	0.607	0.033	0.591	0.234	0.0	0.0	0.655	0.57	-	-	0.933	0.899	0.708	0.482	0.229
Amns	StanfordDogs	Scotch terrier	0.625	0.0	0.591	0.473	0.062	0.042	0.655	0.618	-	-	0.933	0.908	0.708	0.626	0.08
Amns	StanfordCars	2009 Spyker C8 Coupe	0.429	0.0	0.656	0.058	0.0	0.0	-	-	0.591	0.242	0.933	0.808	0.708	0.361	0.425
Amns	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.214	0.656	0.166	0.0	0.0	-	-	0.591	0.436	0.933	0.904	0.708	0.572	0.325
Amns	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.214	0.654	0.315	0.094	0.25	-	-	0.591	0.516	0.933	0.916	0.708	0.596	0.217
Amns	Caltech101	euphonium	1.0	1.0	0.933	0.901	0.406	0.923	0.655	0.648	0.591	0.57	-	-	0.708	0.639	0.236
Amns	Caltech101	minaret	0.913	0.739	0.933	0.774	0.094	0.6	0.655	0.336	0.591	0.257	-	-	0.708	0.366	0.503
Amns	Caltech101	platypus	1.0	0.8	0.933	0.868	0.078	0.714	0.655	0.566	0.591	0.507	-	-	0.708	0.594	0.262
Amns	OxfordFlowers	gazania	1.0	0.913	0.705	0.518	0.062	0.875	0.655	0.586	0.591	0.514	0.933	0.908	-	-	0.288
Amns	OxfordFlowers	tree mallow	0.765	0.824	0.707	0.484	0.094	0.75	0.655	0.593	0.591	0.513	0.933	0.91	-	-	0.329
Amns	OxfordFlowers	trumpet creeper	0.588	0.765	0.709	0.578	0.094	0.75	0.655	0.627	0.591	0.55	0.933	0.92	-	-	0.322
EMMN	StanfordDogs	Pekinese	0.787	0.0	0.59	0.376	-	-	0.655	0.278	-	-	0.933	0.828	0.708	0.432	0.288
EMMN	StanfordDogs	toy poodle	0.607	0.0	0.591	0.373	-	-	0.655	0.308	-	-	0.933	0.836	0.708	0.446	0.275
EMMN	StanfordDogs	Scotch terrier	0.625	0.125	0.591	0.347	-	-	0.655	0.265	-	-	0.933	0.813	0.708	0.436	0.344
EMMN	StanfordCars	2009 Spyker C8 Coupe	0.429	0.0	0.656	0.188	-	-	-	-	0.591	0.116	0.933	0.614	0.708	0.148	0.53
EMMN	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.476	0.656	0.184	-	-	-	-	0.591	0.13	0.933	0.56	0.708	0.126	0.718
EMMN	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.0	0.654	0.175	-	-	-	-	0.591	0.111	0.933	0.594	0.708	0.136	0.543
EMMN	Caltech101	euphonium	1.0	0.105	0.933	0.783	-	-	0.655	0.352	0.591	0.297	-	-	0.708	0.45	0.318
EMMN	Caltech101	minaret	0.913	0.348	0.933	0.817	-	-	0.655	0.36	0.591	0.315	-	-	0.708	0.485	0.347
EMMN	Caltech101	platypus	1.0	0.4	0.933	0.838	-	-	0.655	0.345	0.591	0.294	-	-	0.708	0.484	0.359
EMMN	OxfordFlowers	gazania	1.0	0.0	0.705	0.44	-	-	0.655	0.308	0.591	0.312	0.933	0.832	-	-	0.297
EMMN	OxfordFlowers	tree mallow	0.765	0.0	0.707	0.445	-	-	0.655	0.33	0.591	0.288	0.933	0.829	-	-	0.298
EMMN	OxfordFlowers	trumpet creeper	0.588	0.059	0.709	0.413	-	-	0.655	0.312	0.591	0.31	0.933	0.828	-	-	0.326
AmnsRetain	StanfordDogs	Pekinese	0.787	0.0	0.59	0.706	-	-	0.655	0.473	-	-	0.933	0.829	0.708	0.49	0.139
AmnsRetain	StanfordDogs	toy poodle	0.607	0.0	0.591	0.709	-	-	0.655	0.475	-	-	0.933	0.847	0.708	0.507	0.13
AmnsRetain	StanfordDogs	Scotch terrier	0.625	0.062	0.591	0.679	-	-	0.655	0.468	-	-	0.933	0.848	0.708	0.488	0.158
AmnsRetain	StanfordCars	2009 Spyker C8 Coupe	0.429	0.0	0.656	0.768	-	-	-	-	0.591	0.475	0.933	0.88	0.708	0.573	0.089
AmnsRetain	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.0	0.656	0.742	-	-	-	-	0.591	0.494	0.933	0.89	0.708	0.549	0.087
AmnsRetain	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.0	0.654	0.721	-	-	-	-	0.591	0.46	0.933	0.891	0.708	0.539	0.101
AmnsRetain	Caltech101	euphonium	1.0	0.0	0.933	0.945	-	-	0.655	0.493	0.591	0.46	-	-	0.708	0.556	0.137
AmnsRetain	Caltech101	minaret	0.913	0.0	0.933	0.938	-	-	0.655	0.494	0.591	0.468	-	-	0.708	0.532	0.14
AmnsRetain	Caltech101	platypus	1.0	0.0	0.933	0.956	-	-	0.655	0.53	0.591	0.493	-	-	0.708	0.543	0.118
AmnsRetain	OxfordFlowers	gazania	1.0	0.0	0.705	0.944	-	-	0.655	0.563	0.591	0.522	0.933	0.916	-	-	0.055
AmnsRetain	OxfordFlowers	tree mallow	0.765	0.0	0.707	0.934	-	-	0.655	0.558	0.591	0.528	0.933	0.913	-	-	0.055
AmnsRetain	OxfordFlowers	trumpet creeper	0.588	0.0	0.709	0.956	-	-	0.655	0.558	0.591	0.542	0.933	0.913	-	-	0.051
Salun	StanfordDogs	Pekinese	0.787	0.049	0.59	0.669	-	-	0.655	0.521	-	-	0.933	0.842	0.708	0.605	0.102
Salun	StanfordDogs	toy poodle	0.607	0.066	0.591	0.654	-	-	0.655	0.508	-	-	0.933	0.838	0.708	0.627	0.11
Salun	StanfordDogs	Scotch terrier	0.625	0.016	0.591	0.663	-	-	0.655	0.495	-	-	0.933	0.824	0.708	0.594	0.109
Salun	StanfordCars	2009 Spyker C8 Coupe	0.429	0.167	0.656	0.718	-	-	-	-	0.591	0.5	0.933	0.869	0.708	0.583	0.157
Salun	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.048	0.656	0.709	-	-	-	-	0.591	0.497	0.933	0.855	0.708	0.563	0.107
Salun	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.048	0.654	0.707	-	-	-	-	0.591	0.488	0.933	0.865	0.708	0.592	0.094
Salun	Caltech101	euphonium	1.0	0.0	0.933	0.928	-	-	0.655	0.531	0.591	0.504	-	-	0.708	0.654	0.084
Salun	Caltech101	minaret	0.913	0.0	0.933	0.927	-	-	0.655	0.517	0.591	0.509	-	-	0.708	0.639	0.091
Salun	Caltech101	platypus	1.0	0.0	0.933	0.923	-	-	0.655	0.528	0.591	0.506	-	-	0.708	0.633	0.091
Salun	OxfordFlowers	gazania	1.0	0.0	0.705	0.922	-	-	0.655	0.525	0.591	0.506	0.933	0.86	-	-	0.084
Salun	OxfordFlowers	tree mallow	0.765	0.059	0.707	0.929	-	-	0.655	0.542	0.591	0.498	0.933	0.858	-	-	0.098
Salun	OxfordFlowers	trumpet creeper	0.588	0.118	0.709	0.919	-	-	0.655	0.542	0.591	0.506	0.933	0.854	-	-	0.12
ULip	StanfordDogs	Pekinese	0.787	0.836	0.59	0.569	-	-	0.655	0.651	-	-	0.933	0.933	0.708	0.709	0.221
ULip	StanfordDogs	toy poodle	0.607	0.098	0.591	0.508	-	-	0.655	0.646	-	-	0.933	0.927	0.708	0.694	0.069
ULip	StanfordDogs	Scotch terrier	0.625	0.828	0.591	0.531	-	-	0.655	0.649	-	-	0.933	0.931	0.708	0.704	0.289
ULip	StanfordCars	2009 Spyker C8 Coupe	0.429	0.048	0.656	0.494	-	-	-	-	0.591	0.591	0.933	0.932	0.708	0.716	0.072
ULip	StanfordCars	2010 Dodge Ram Pickup 3500 Crew Cab	0.548	0.0	0.656	0.515	-	-	-	-	0.591	0.598	0.933	0.931	0.708	0.713	0.043
ULip	StanfordCars	2011 Ford Ranger SuperCab	0.81	0.048	0.654	0.247	-	-	-	-	0.591	0.581	0.933	0.927	0.708	0.704	0.142
ULip	Caltech101	euphonium	1.0	1.0	0.933	0.919	-	-	0.655	0.645	0.591	0.59	-	-	0.708	0.705	0.207
ULip	Caltech101	minaret	0.913	0.435	0.933	0.923	-	-	0.655	0.655	0.591	0.59	-	-	0.708	0.707	0.098
ULip	Caltech101	platypus	1.0	1.0	0.933	0.907	-	-	0.655	0.65	0.591	0.571	-	-	0.708	0.694	0.218
ULip	OxfordFlowers	gazania	1.0	0.0	0.705	0.404	-	-	0.655	0.626	0.591	0.539	0.933	0.898	-	-	0.12
ULip	OxfordFlowers	tree mallow	0.765	0.34	0.707	0.672	-	-	0.655	0.653	0.591	0.572	0.933	0.925	-	-	0.06
ULip	OxfordFlowers	trumpet creeper	0.588	0.059	0.709	0.51	-	-	0.655	0.641	0.591	0.552	0.933	0.915	-	-	0.097

G. Unlearning Identities

In line with our motivation of the right to be forgotten, we assess whether our unlearning method is able to forget faces. For this experiment we choose PinsFaces [1] dataset that contains 105 celebrity faces. As we can see in Tabs. 21 and 22 our method is also valid to unlearn faces.

Table 21. Unlearning Faces Full Results with RN50.

Dataset	**Class name**	**Target Class acc.**		**Other Classes acc.**		**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
PinsFaces	Gal Gadot	0.707	0.03	0.822	0.8	0.558	0.55	0.517	0.503	0.857	0.863	0.661	0.642	0.029
PinsFaces	Henry Cavil	0.866	0.062	0.82	0.781	0.558	0.545	0.517	0.492	0.857	0.857	0.661	0.623	0.049
PinsFaces	Amanda Crew	0.828	0.069	0.821	0.815	0.558	0.557	0.517	0.511	0.857	0.861	0.661	0.649	0.024

Table 22. Unlearning Faces Full Results with ViT-B/16.

Dataset	**Class name**	**Target Class acc.**		**Other Classes acc.**		**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**		**Avg. Score (↓)**
		BF	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	
PinsFaces	Gal Gadot	0.879	0.091	0.908	0.908	0.655	0.65	0.591	0.589	0.933	0.932	0.708	0.708	0.023
PinsFaces	Henry Cavil	0.959	0.216	0.907	0.903	0.655	0.646	0.591	0.585	0.933	0.932	0.708	0.695	0.055
PinsFaces	Amanda Crew	1.0	0.0	0.907	0.91	0.655	0.656	0.591	0.594	0.933	0.933	0.708	0.71	0.0

H. Forgetting Algorithm

Algorithm 1 CLIP forgetting

Require: CLIP image and text encoders: f_θ, f_ϕ
Require: Textual class to forget: x_{text}, Learning rate: α,
Require: Initial number of visual and textual layers to update: $InitV_{up}, InitT_{up}$
Require: Increase steps sigma: s, visual layers: v, textual layers: t
Require: Number of perturbations: N, Initial Gaussian perturbation: σ
Require: Accuracy stopping threshold: $GoalAcc$, Total increase steps: I
Require: Optimizer: $optim(\theta, \phi, lr = \alpha)$

```
▷ Function that generates synthetic training samples by gradient ascent as in Eq. 5
X ← SyntheticImagesGen(x_text)
for n in range(I) do
    for x_img in X do
        ℓ = 0
        for i in range(N) do
            Sample ε ~ N(0, σ^2)
            x'_img = x_img + ε
            k = (||f_θ(x_img) − f_θ(x'_img)||_2 + ||f_φ(x_text) − f_θ(x'_img)||_2) / ||ε||_2
            ℓ = ℓ + k
        end for
        ℓ = ℓ/N
        ▷ Update InitV_up and InitT_up most important layers in visual and textual branch respectively
        θ, φ ← SelectiveUpdate(optim{Δ_{θ,φ} ℓ}, InitV_up, InitT_up)
        Acc ← EvalAcc(X)                    ▷ Accuracy on synthetic training samples
        if Acc < GoalAcc then
            return θ, φ
        else
            ▷ Increase parameters to reduce more aggressively the accuracy on synthetic samples
            InitV_up ← InitV_up + v
            InitT_up ← InitT_up + t
            σ ← σ + s
        end if
    end for
end for
return θ, φ
```

I. Verification of Forgetting Success and Data Generation Threshold

Data Generation Threshold We observe that generating samples classified as the target class alone is not sufficient for effective forgetting. To achieve successful forgetting, the generated samples must exhibit a high probability of belonging to the forget class, otherwise the forgetting process might fail. Empirically, we find that selecting a threshold around 0.7 works well for ResNet50 visual encoder and around 0.9 for ViT-B/16 visual encoder, but sometimes more tuning of the threshold is required.

Verification of Forgetting Success The accuracy achieved on synthetic forget data should serve as a measure of how effectively the model has forgotten a class. We find that for this indicator to be consistent the probability of the predicted class on synthetic samples need to be close to the probability of the real samples, otherwise there might be some discrepancy. For example, in Tab. 23 in the 1st row *2009 Bentley Arnage Sedan* class maintains a high accuracy on *Synth. train* data despite *Target Class acc. AF* dropping to 5%. Conversely, in the 2nd row we observe that for *revolver* class the accuracy on *Synt. train* subset is low, yet forgetting was not successful as indicated by the true validation accuracy *Target Class acc. AF Real valid.*. It turns out that for *revolver* class the probability of the generated samples is too low while for *2009 Bentley Arnage Sedan* is too high. In most cases, we adopted a threshold of 0.7 in the standard setting. Thus, by generating synthetic samples with class predicted probability closer to that of real samples we reduce the discrepancy as demonstrated in the last two rows of Tab.23. Note that generating higher probability synthetic samples compared to probability of real samples would still generally suffice to forget the class but not to verify the forgetting success. A simple alternative is to rely on a small real validation subset of the class to forget or if available, stored past probabilities of the class prediction. This verification can be conducted by a user if they are unwilling to share their data with the company.

Table 23. Forgetting verification discrepancy examples.

Discrepancy	**Dataset**	**Class name**	**Target Class acc.**		**Other Classes acc.**		**Target Class acc.**		**StanfordCars**		**StanfordDogs**		**Caltech101**		**OxfordFlowers**	
			BF	**AF**	**BF**	**AF**	**Synt. train**	**Real valid.**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**	**BF**	**AF**
Discrepancy	Caltech101	revolver	0.96	0.92	0.856	0.862	0.016	0.875	0.558	0.552	0.517	0.507	-	-	0.661	0.632
Discrepancy	StanfordCars	2009 Bentley Arnage Sedan	0.692	0.051	0.557	0.538	0.922	0.0	-	-	0.517	0.527	0.857	0.875	0.661	0.644
No Discrepancy	Caltech101	revolver	0.96	0.16	0.856	0.855	0.016	0.0	0.558	0.524	0.517	0.48	-	-	0.661	0.604
No Discrepancy	StanfordCars	2009 Bentley Arnage Sedan	0.692	0.026	0.557	0.543	0.031	0.0	-	-	0.517	0.511	0.857	0.852	0.661	0.655

J. Additional Tasks

In the main paper, among the additional tasks we tested the image-image retrieval on the model after forgetting. We surprisingly found that even after forgetting the model is still able to retrieve images of the class it has forgotten starting from an input image. We speculated that in image retrieval, the model can still identify similar features and shapes of objects without actually recognizing or knowing the specific class they belong to. To confirm our hypothesis we conduct image-image retrieval on the **original** CLIP model on classes it predicts with **zero classification accuracy**. The results that confirm our hypothesis are shown in Tab. 24.

Table 24. Image retrieval from image input results on classes with zero classification accuracy.

Model Type	Class	Classification Accuracy	Precision@1	Precision@5	Precision@10
CLIP original	Appenzeller (StanfordDogs)	0	1.0	0.4	0.2
CLIP original	Pembroke (StanfordDogs)	0	1.0	0.6	0.4
CLIP original	Cardigan (StanfordDogs)	0	0.0	0.2	0.2
CLIP original	2010 Chevrolet HHR SS (StanfordCars)	0	1.0	0.4	0.4
CLIP original	2009 HUMMER H2 SUT Crew Cab (StanfordCars)	0	1.0	0.6	0.7
CLIP original	english marigold (OxfordFlowers)	0	1.0	0.8	0.6
CLIP original	colt's foot (OxfordFlowers)	0	1.0	0.8	0.7
CLIP original	cape flower (OxfordFlowers)	0	1.0	1.0	1.0

J.1. Full results

Table 25. Image retrieval from text input results showing precision@k for k of 1, 5 and 10 using ViT-B/16 model

Model Type	Class	Precision@1	Precision@5	Precision@10
CLIP original	Scotch terrier	0.0	0.0	0.1
CLIP original	toy poodle	1.0	0.8	0.7
CLIP original	Pekinese	1.0	0.4	0.5
CLIP original	2009 Spyker C8 Coupe	1.0	0.8	0.8
CLIP original	2010 Dodge Ram Pickup 3500 Crew Cab	1.0	0.6	0.5
CLIP original	2011 Ford Ranger SuperCab	1.0	0.8	0.5
CLIP original	euphonium	1.0	1.0	1.0
CLIP original	minaret	1.0	1.0	1.0
CLIP original	platypus	1.0	1.0	0.9
CLIP original	gazania	1.0	1.0	1.0
CLIP original	tree mallow	0.0	0.4	0.4
CLIP original	trumpet creeper	1.0	0.8	0.6
CLIP original Mean	-	0.833	0.717	0.667
CLIP forget	Scotch terrier	0.0	0.4	0.4
CLIP forget	toy poodle	0.0	0.0	0.1
CLIP forget	Pekinese	0.0	0.0	0.2
CLIP forget	2009 Spyker C8 Coupe	1.0	0.8	0.8
CLIP forget	2010 Dodge Ram Pickup 3500 Crew Cab	0.0	0.0	0.1
CLIP forget	2011 Ford Ranger SuperCab	1.0	0.6	0.4
CLIP forget	euphonium	1.0	1.0	0.6
CLIP forget	minaret	1.0	1.0	0.9
CLIP forget	platypus	1.0	1.0	0.5
CLIP forget	gazania	1.0	0.2	0.4
CLIP forget	tree mallow	0.0	0.0	0.2
CLIP forget	trumpet creeper	0.0	0.2	0.2
CLIP forget Mean	-	**0.5**	**0.433**	**0.4**

Table 26. Image retrieval from image input results showing precision@k for k of 1, 5 and 10 using ViT-B/16 model

Model Type	Class	Precision@1	Precision@5	Precision@10
CLIP original	Scotch terrier	0.0	0.2	0.3
CLIP original	toy poodle	1.0	0.4	0.5
CLIP original	Pekinese	0.0	0.0	0.0
CLIP original	2009 Spyker C8 Coupe	1.0	0.4	0.3
CLIP original	2010 Dodge Ram Pickup 3500 Crew Cab	0.0	0.0	0.1
CLIP original	2011 Ford Ranger SuperCab	0.0	0.2	0.4
CLIP original	euphonium	1.0	0.8	0.9
CLIP original	minaret	1.0	1.0	1.0
CLIP original	platypus	1.0	0.6	0.5
CLIP original	gazania	1.0	1.0	0.7
CLIP original	tree mallow	1.0	1.0	0.6
CLIP original	trumpet creeper	1.0	1.0	0.7
CLIP original Mean	-	**0.667**	**0.55**	0.5
CLIP forget	Scotch terrier	0.0	0.2	0.3
CLIP forget	toy poodle	1.0	0.4	0.5
CLIP forget	Pekinese	0.0	0.0	0.0
CLIP forget	2009 Spyker C8 Coupe	1.0	0.4	0.2
CLIP forget	2010 Dodge Ram Pickup 3500 Crew Cab	0.0	0.0	0.1
CLIP forget	2011 Ford Ranger SuperCab	0.0	0.4	0.3
CLIP forget	euphonium	1.0	0.8	0.9
CLIP forget	minaret	1.0	1.0	0.9
CLIP forget	platypus	1.0	0.6	0.5
CLIP forget	gazania	1.0	1.0	0.7
CLIP forget	tree mallow	1.0	1.0	0.7
CLIP forget	trumpet creeper	1.0	1.0	0.7
CLIP forget Mean	-	**0.667**	0.567	**0.483**

Table 27. Image retrieval from text input results showing precision@k for k of 1, 5 and 10 using RN50 model

Model Type	Class	Precision@1	Precision@5	Precision@10
CLIP original	Scotch terrier	1.0	0.2	0.2
CLIP original	toy poodle	1.0	0.6	0.5
CLIP original	Pekinese	1.0	0.8	0.6
CLIP original	2009 Spyker C8 Coupe	1.0	0.6	0.5
CLIP original	2010 Dodge Ram Pickup 3500 Crew Cab	1.0	0.2	0.2
CLIP original	2011 Ford Ranger SuperCab	0.0	0.2	0.2
CLIP original	euphonium	1.0	1.0	1.0
CLIP original	minaret	1.0	1.0	1.0
CLIP original	platypus	1.0	1.0	0.6
CLIP original	gazania	1.0	1.0	1.0
CLIP original	tree mallow	0.0	0.8	0.7
CLIP original	trumpet creeper	1.0	0.8	0.5
CLIP original Mean	-	0.833	0.683	0.583
CLIP forget	Scotch terrier	0.0	0.0	0.0
CLIP forget	toy poodle	1.0	0.2	0.1
CLIP forget	Pekinese	0.0	0.0	0.0
CLIP forget	2009 Spyker C8 Coupe	0.0	0.8	0.5
CLIP forget	2010 Dodge Ram Pickup 3500 Crew Cab	0.0	0.2	0.3
CLIP forget	2011 Ford Ranger SuperCab	0.0	0.0	0.0
CLIP forget	euphonium	0.0	0.8	0.8
CLIP forget	minaret	0.0	0.4	0.2
CLIP forget	platypus	0.0	0.2	0.2
CLIP forget	gazania	0.0	0.0	0.0
CLIP forget	tree mallow	0.0	0.2	0.2
CLIP forget	trumpet creeper	0.0	0.0	0.0
CLIP forget Mean	-	**0.08**	**0.23**	**0.191**

Table 28. Image retrieval from image input results showing precision@k for k of 1, 5 and 10 using RN50 model

Model Type	Class	Precision@1	Precision@5	Precision@10
CLIP original	Scotch terrier	0.0	0.0	0.0
CLIP original	toy poodle	0.0	0.0	0.1
CLIP original	Pekinese	0.0	0.0	0.0
CLIP original	2009 Spyker C8 Coupe	1.0	0.4	0.3
CLIP original	2010 Dodge Ram Pickup 3500 Crew Cab	0.0	0.0	0.0
CLIP original	2011 Ford Ranger SuperCab	0.0	0.2	0.3
CLIP original	euphonium	0.0	0.4	0.2
CLIP original	minaret	1.0	0.8	0.6
CLIP original	platypus	0.0	0.2	0.2
CLIP original	gazania	1.0	0.8	0.6
CLIP original	tree mallow	1.0	0.8	0.8
CLIP original	trumpet creeper	1.0	0.8	0.7
CLIP original Mean	-	0.417	**0.367**	**0.317**
CLIP forget	Scotch terrier	0.0	0.0	0.0
CLIP forget	toy poodle	0.0	0.0	0.1
CLIP forget	Pekinese	0.0	0.0	0.0
CLIP forget	2009 Spyker C8 Coupe	1.0	0.4	0.3
CLIP forget	2010 Dodge Ram Pickup 3500 Crew Cab	0.0	0.0	0.1
CLIP forget	2011 Ford Ranger SuperCab	0.0	0.2	0.3
CLIP forget	euphonium	0.0	0.4	0.2
CLIP forget	minaret	0.0	0.8	0.6
CLIP forget	platypus	0.0	0.2	0.2
CLIP forget	gazania	1.0	0.8	0.6
CLIP forget	tree mallow	1.0	0.8	0.8
CLIP forget	trumpet creeper	1.0	0.8	0.7
CLIP forget Mean	-	**0.333**	**0.367**	0.325

K. Additional Figures and Implementation Details

Implementation Details For CLIP with ResNet50 visual encoder, we observed that allowing all parameters in the vision encoder to be chosen for update during the forgetting process results in poor performance on other classes. Therefore, we restrict parameter updates to the attention layers in the RN50 vision encoder while all parameters in the text encoder are eligible for the update selection. For the ViT model all the parameters are allowed to vary. Fig. 5 illustrates the top 25 most frequently updated layers of the RN50 model. We generate 64 synthetic samples and stop the forgetting process when their accuracy goes below 0.1.
We use Adam optimizer with learning rate of 5e-05, weight decay of 0.2 and betas parameters of 0.9 and 0.98. We set the number of perturbed samples N to 25. Initial σ is 0.1 increasing to 2. Initially, layers we allow to vary are 5 for both visual and textual encoders and increasing to 8 and 20 respectively if we need more forgetting according to the remaining synthetic samples accuracy. All the experiments are run on a single NVIDIA GeForce RTX 3090 with 24GB of memory.

Additional Figures In the vision encoder, the weights of the values, queries, and output projections are updated most frequently, whereas in the text encoder the MLP output projection weights are updated most often.

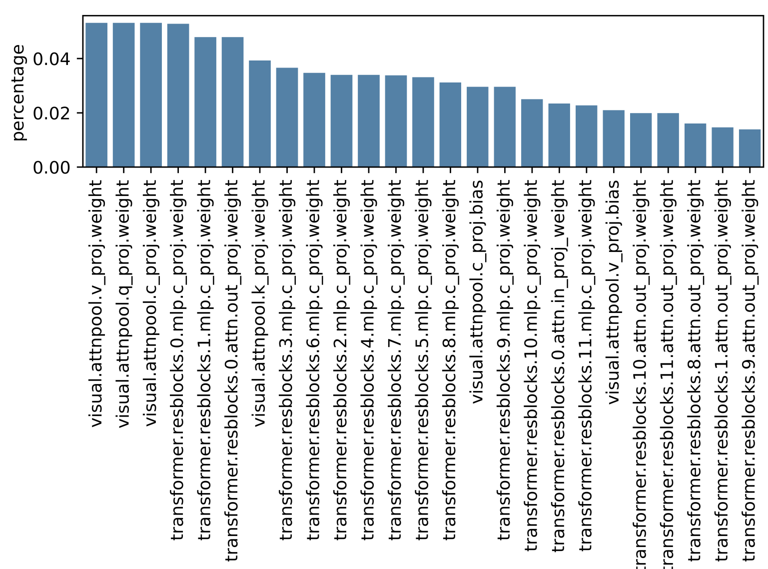

Figure 5. **Selected layers for forgetting.** The figure shows the top 25 most frequent updated layers during forgetting process across selected classes and datasets.