Appendix

In this appendix, we include the following details which we could not include in the main paper owing to space constraints. We will release our code publicly on acceptance, and provide all other implementation details herein.

Table of Contents

A.1 Concepts: What and Why?

In this work, we refer to *intermediate text semantics that describe a class label* as "concepts". We state this to explicitly differentiate from other uses of the term. In recent literature in the field, concepts have been interpreted as: (1) (Soft) binary labels that may not directly be grounded on human-understandable semantics and attempt to reconstruct a class label, as in (Koh et al. 2020); (2) Visual features that commonly appear in most instances of a given class, as in (Rymarczyk et al. 2023); and (3) intermediate text semantics that describe a class label, as in (Oikarinen et al. 2023; Yang et al. 2023). We follow the third characterization in this work. The first connotation has been observed to not capture intended semantics (Margeloiu et al. 2021), while the second conntation of prototypes are effective in certain settings, like instance-specific explanations. Our approach follows recent work (Oikarinen et al. 2023; Yang et al. 2023) in viewing concepts as a compelling means to learn via explanations, rather than learn via prediction. Below are a few advantages of our approach:

- *Generalizable Abstraction for Intermediate Semantics:* Text attributes provide a means to capture intermediate semantics that represents what a model is 'thinking' or 'considering important'. Unlike prototypes, which are based on specific instances or examples from training data, such text attributes can be generalized across instances. This abstraction facilitates a more human-relatable understanding of the underlying relationships that a model has learned.
- *Human-Interpretable:* Concepts, as used herein, provide a means to connect latent embeddings inside a transformer to human-interpretable text, providing a pathway to better understand a model's functioning. Prototypes, while illustrative, may not provide this degree of interpretability, especially when the prototypes are derived from complex or non-intuitive examples. Text attributes can serve to succinctly communicate what features or aspects in the data influence the model's decisions.
- *Flexibility and Adaptability:* Text attributes offer flexibility in adapting to different models and contexts. They can be easily modified, combined, or expanded upon to suit the specific needs of an experience or to improve interpretability. This adaptability is particularly beneficial in complex domains where the model's functioning needs to be thoroughly understood and communicated. With Large Language Models, they are also feasible to obtain at a class label level rather inexpensively.
- *Avoidance of Overfitting to Specific Instances:* Relying on prototypes can sometimes lead to overfitting to specific instances in the training data, which may not generalize well to new, unseen data. Text attributes, by focusing on general concepts rather than specific examples, promote a more generalizable understanding of the model's behavior.
- *Low Cost:* With Large Language Models, it is very feasible to obtain text attributes/concepts at a class label level at relatively low cost. (Note that we only need concepts at a class level, and not at a instance level.)
- *Integration with Explanation Frameworks:* While this is the not the explicit focus of our work herein, text attributes can be integrated with existing explanation frameworks, such as feature importance measures, decision trees, or rule-based explanations. Such integration can enhance the comprehension and utility of explainability tools, making them more actionable for users.
- *Other Use Cases:* Text attributes can also be used to address other use cases such as biases in AI models by highlighting sensitive or critical concepts that require scrutiny. This is more challenging with prototypes, as the selection of representative examples may inadvertently reinforce existing biases or overlook subtle but important biases in the model's decisions on one particular sample.

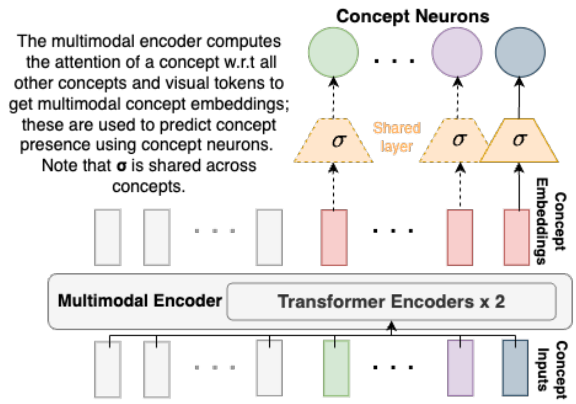

Figure A7: Concept Embeddings and Concept Neurons

A.2 Architecture and Implementation Details

Illustration of Concept Neurons. In Fig A7, we provide an illustration of concept neurons. As shown in the figure, the same layer is applied on top of all multimodal embeddings to obtain the neuron values.

Use of VLMs. In order to study if Vision-Language Model (VLM) pre-alignment is necessary for our method, we empirically study 9 different VL encoder pairs: CLIP (Radford

Dataset	Text / Vision	FLAVA	CLIP	BERT
CIFAR-100	**FLAVA**	0.625	0.625	0.627
	CLIP	0.642	0.631	0.621
	ViT	**0.712**	0.635	0.660
ImageNet-100	**FLAVA**	0.709	0.642	0.667
	CLIP	0.735	0.693	0.708
	ViT	**0.792**	0.758	0.737
CUB200	**FLAVA**	0.722	0.553	0.677
	CLIP	0.756	0.670	0.717
	ViT	**0.822**	0.780	0.807

Table A6: FAA on benchmark datasets for diff VLMs

et al. 2021) and FLAVA (Singh et al. 2022), which have pre-aligned vision-language encoders, as well as BERT (Devlin et al. 2018) and ViT (Dosovitskiy et al. 2021) models trained on unimodal data, where our model explicitly aligns the modalities.

Table A6 presents the results which indicate that using pre-aligned VL models is not optimal; our method's performance using dedicated encoders is, in fact, superior to pre-aligned models. We hypothesize this is because pre-aligned VL models are trained at a general image level, while our explicit approach allows more fine-grained association between image and text.

Vision, Language, and Multimodal Encoders ($\mathcal{F}, \mathcal{T}, \mathcal{M}$). We use the FLAVA (Singh et al. 2022) language encoder paired with the ViT (Dosovitskiy et al. 2021) image encoder. Each encoder has a latent embedding dimension of 768. Our multimodal encoder uses two stacked transformer blocks with the same latent embedding size. In case any encoder does not have the required dimension (e.g. CLIP), we add a single trainable linear layer to project the embeddings to the required dimensions. We use the *HuggingFace*[1] library to implement the transformer in case of the Full Attention version, or the *fast-transformers*[2] library to implement transformer blocks with Linear Attention. The experimental setup is implemented using *PyTorch*[3], and all experiments are run on a single RTX 3090 GPU.

Training Hyperparameters. For Cifar100, we train the model for 10 epochs in every experience, with a starting learning rate of 0.001 and a batch size of 48. In the case of CUB, we train our model for 25 epochs in every experience and stop training after 15 epochs if the model converges. We start with a learning rate of 0.0003 and a batch size of 64. In the case of Imagenet100, we train the model for 5 epochs in every experience, with a starting learning rate of 0.001 and batch size of 48. In all three cases, we use Cosine Annealing to schedule the learning rate, decreasing it down to 0.0001.

Additional Details about Concept Bottlenecks. A Concept Bottleneck layer, introduced by (Koh et al. 2020), is a layer where each neuron corresponds to a specific concept. Models containing such bottlenecks can be trained sequentially or jointly with the classification layer. Sequential and joint settings are applicable when the model contains a bottleneck layer followed by a classification layer. In the sequential setting, the model is first trained to predict concept labels. Post-training, a classifier is trained on top of concept logits predicted for the input images. The model and classifier are optimized separately. In joint training, both concept predictions and the classifier are trained end-to-end and optimized jointly.

Attention Head Visualization We build upon known methods of attention head visualization to extract image regions that the model focuses on for a particular concept. Briefly, our algorithm consists of three steps, shown in Fig A8: (1) We

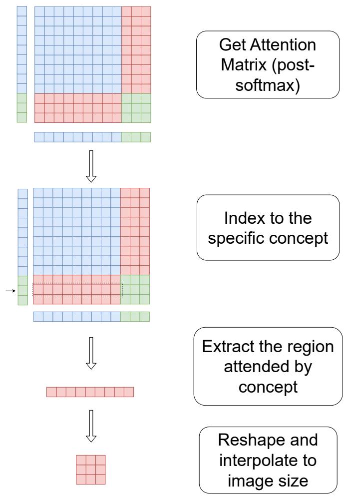

Figure A8: Our attention visualization method. We induce localization via indexing through concepts instead of through CLS tokens, as done by other methods.

extract the post-softmax attention matrix of a chosen head after an input image and concept set has been processed. (2) The row indexed by the concept to be visualized gives attention scores over all concepts and image patches. Since we are only interested in the image patches, we extract the corresponding subcolumns from the concept row to get a single vector. The size of this vector is same as the number of visual tokens. (3) Post extraction, we visualize the attended regions by reshaping the extracted vector and performing interpolation to get a heatmap of the same size as the image.

A.3 More Results and Analysis

Varying Buffer Sizes for Experience Replay: We compare our method with baseline methods for different buffer sizes of 500, 2000, and 5000 on 5 and 10 experiences. The results for a buffer size of 500 were provided in the main paper, in table 1. In table A7 and A8, we show the results for other buffer sizes using ER.

Sensitivity to λ_1 and λ_2: We evaluate these hyperparameters by performing a grid search over different values. The

[1]https://huggingface.co/
[2]https://fast-transformers.github.io/
[3]https://pytorch.org/

	CIFAR-100				CUB				ImageNet-100			
	5Exp		10Exp		5Exp		10Exp		5Exp		10Exp	
Method	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S (2020)	0.47	0.47	0.49	0.47	0.53	0.20	0.46	0.26	0.51	0.35	0.47	0.38
CBM-J (2020)	0.39	0.55	0.34	0.59	0.56	0.11	0.46	0.20	0.46	0.40	0.39	0.44
ICIAP-S (2022)	0.39	0.42	0.37	0.49	0.53	0.20	0.46	0.26	0.41	0.33	0.36	0.37
ICIAP-J (2022)	0.39	0.53	0.32	0.61	0.56	0.11	0.46	0.20	0.47	0.39	0.37	0.46
Label-Free (2023)	0.34	**0.24**	0.30	**0.19**	0.45	0.45	0.58	0.47	0.09	0.30	0.17	0.30
LaBo (2023)	0.30	0.70	0.10	0.79	0.31	0.50	0.07	0.61	0.44	0.48	0.06	0.56
MuCIL (Ours)	**0.71**	0.29	**0.67**	0.33	**0.82**	**0.06**	**0.81**	**0.07**	**0.79**	**0.09**	**0.80**	**0.08**

Table A7: Continual learning performance of different methods averaged over three random model initializations, on 5 and 10 experiences with buffer size 2000. Our method delivers consistently better performance than the baselines.

	CIFAR-100				CUB				ImageNet-100			
	5Exp		10Exp		5Exp		10Exp		5Exp		10Exp	
Method	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S (2020)	0.57	0.33	0.54	0.39	0.59	0.11	0.52	0.19	0.60	0.24	0.58	0.27
CBM-J (2020)	0.50	0.38	0.45	0.44	0.57	0.06	0.51	0.12	0.53	0.31	0.49	0.34
ICIAP-S (2022)	0.46	0.32	0.47	0.39	0.59	0.11	0.52	0.19	0.52	0.23	0.46	0.28
ICIAP-J (2022)	0.52	0.36	0.47	0.42	0.57	0.06	0.51	0.12	0.55	0.29	0.49	0.33
Label-Free (2023)	0.40	**0.21**	0.33	**0.18**	0.47	0.46	0.62	0.35	0.18	0.19	0.35	0.18
LaBo (2023)	0.31	0.65	0.10	0.77	0.31	0.46	0.08	0.59	0.43	0.46	0.06	0.54
MuCIL (Ours)	**0.74**	0.25	**0.71**	0.29	**0.83**	**0.03**	**0.82**	**0.06**	**0.81**	**0.08**	**0.80**	**0.08**

Table A8: Continual learning performance of different methods averaged over three random model initializations, on 5 and 10 experiences with buffer size 5000. Our method delivers consistently better performance than the baselines.

results show that they directly relate to the interpretability aspects of the model, as described in the main paper (shown in Table A9). We see that FAA values are within statistical error of the values of Table 1 in the main paper, implying that λ values do not significantly affect classification accuracy. We show the alignment scores ($-\mathcal{L}_G$) in Table A10 and Linear Accuracy scores in Tables A11, and see a much wider range, indicating the impact of λ values on these metrics.

More Qualitative Results. More results for attention localization similar to Figure 5 are shown in Figure A9. Here too, we see that MuCIL is able to localize specific areas in the input images that relate to certain visual concepts, as opposed to GradCAM on CBMs that produces diffused regions of interest. For interventions, we provide qualitative results in Fig A10. We see that chaning a few key attributes helps the model classify the image correctly. For example, when increasing the strengths of concepts relating to "beak", "tail and feathers", and "tree", we see that the model changes an incorrect prediction from "Hammerhead Shark" to "Jay".

A.4 Dataset Descriptions

Cifar100 consists of 50000 training images and 10000 validation images spanning 100 classes. Each image is a 3-channel RGB image of size 32x32 pixels. Concept annotations per class are not provided, and hence we query a Large Language Model as described by (Oikarinen et al. 2023) to get the concept set, excluding the concept filters applied post-training for reduction in the number of concepts. We get a total of 925 concepts for Cifar100. **CUB200 (CalTech-UCSD Birds 200)** is a fine-grained bird identification dataset consisting of 11000 RGB images of 200 different bird species. In this case, the concept annotations are provided by human annotators. All concepts are shared among a few classes, which means that the entire concept set is available from the first experience itself. This gives us a platform to show that our method gives state-of-the-art results even on fine-grained visual classification in a much simpler setting where existing methods still fail to perform comparably. **ImageNet100** is a subset of the Imagenet1K dataset consisting of 100 classes with 1300 training images and 50 validation images per class. The subset includes both coarse and fine-grained classes. We choose classes such that each class in a new experience adds new concepts, in addition to using concepts available from past experiences. We provide a subset of some classes and concepts per dataset in A13. To use the datasets in a continual setting, we split each dataset into 5 or 10 experiences having overlapping concept sets. Details of the number of concepts in each experience for Imagenet100 and Cifar100 for 5 experiences have been provided in Table A12. In the case of CUB, all experiences

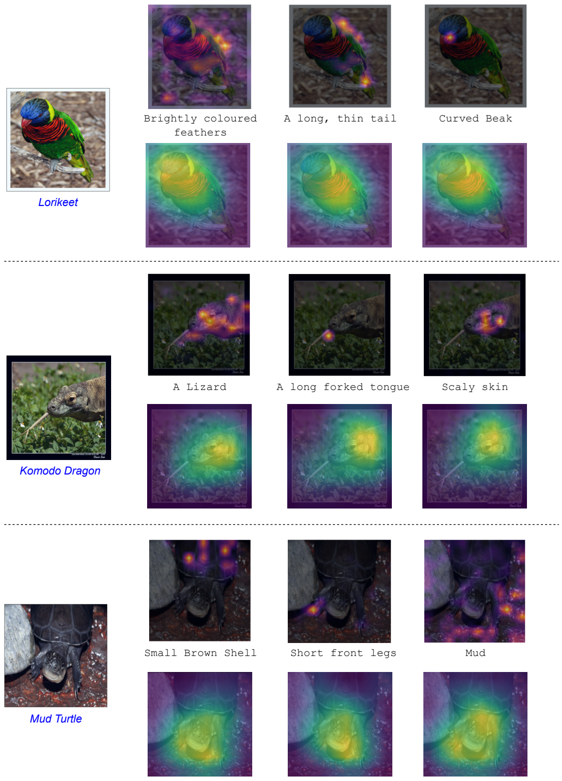

Figure A9: More localization results. Alternate rows present the localization results using MuCIL versus when localizing the same concepts using GradCAM on CBMs, showing that MuCIL can provide superior post-hoc visual explanations.

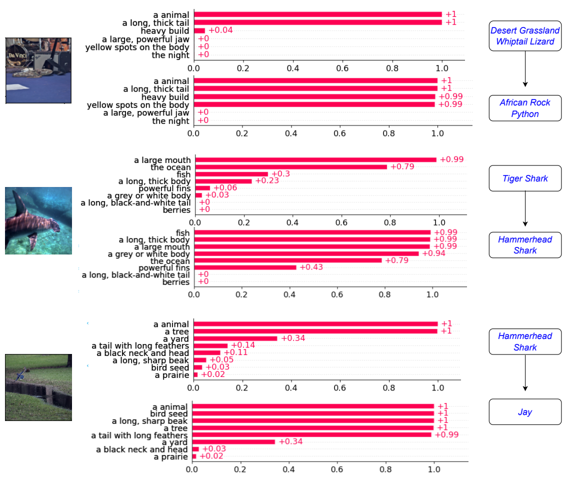

Figure A10: Qualitative results on manual interventions; as illustrated, concept strengths are adjusted to correct class predictions.

Dataset	λ_1 \ λ_2	0	0.001	1	5	10	100
CUB200	**0**	0.80	0.79	0.80	0.81	0.81	0.79
	0.001	0.81	0.81	0.80	0.81	0.81	0.79
	1	0.80	0.81	0.80	0.82	0.82	0.78
	5	0.81	0.81	0.81	0.81	0.82	0.78
	10	0.82	0.81	0.82	0.83	0.82	0.79
	100	0.81	0.80	0.81	0.81	0.81	0.80
INet100	**0**	0.80	0.79	0.78	0.79	0.80	0.79
	0.001	0.79	0.79	0.79	0.80	0.81	0.80
	1	0.79	0.78	0.79	0.80	0.81	0.79
	5	0.81	0.79	0.79	0.79	0.80	0.79
	10	0.81	0.80	0.80	0.80	0.80	0.80
	100	0.79	0.80	0.78	0.78	0.79	0.79

Table A9: FAA on ImageNet-100 and CUB datasets for different values of λ_1 and λ_2.

Dataset	λ_1 \ λ_2	0	0.001	1	5	10	100
CUB	**0**	4e-32	0.79	0.94	0.98	0.99	1.00
	0.001	8e-32	0.80	0.94	0.98	0.99	1.00
	1	1e-31	0.82	0.95	0.98	0.99	1.00
	5	1e-31	0.83	0.94	0.98	0.99	1.00
	10	1e-31	0.84	0.94	0.97	0.98	1.00
	100	1e-31	0.86	0.90	0.94	0.95	0.99
INet100	**0**	9e-33	0.38	1.00	1.00	1.00	1.00
	0.001	7e-32	0.41	1.00	1.00	1.00	1.00
	1	1e-31	0.53	1.00	1.00	1.00	1.00
	5	2e-31	0.69	0.99	1.00	1.00	1.00
	10	7e-32	0.71	0.99	1.00	1.00	1.00
	100	3e-31	0.72	0.90	0.98	0.99	1.00

Table A10: $-\mathcal{L}_G$ on ImageNet-100 and CUB datasets for different values of λ_1 and λ_2.

share the same set of 312 concepts. Thus, for CUB, we follow the continual learning setting as in (Marconato et al. 2022).

A.5 Limitations, Future Directions and Broader Impact

The primary dependency of our framework is the need for an LLM to provide the concepts at a class level. We however believe that this has become very feasible in recent times, especially since we only need this at a class level. As shown in Section 4 of the main paper, replay currently plays a very important role in preserving concept-class relationships. It would be interesting to see if exemplar-free continual learning approaches (without replay) can still preserve these relationships, even though they don't have access to labeled concept-class pairs from past experiences. From an interpretability viewpoint, developing an improved intervention mechanism that can be used on our model - even in between experiences, without an explicit linear layer would be an in-

Dataset	λ_1 \ λ_2	**0**	**0.001**	**1**	**5**	**10**	**100**
CUB	**0**	0.01	0.01	0.01	0.01	0.01	0.01
	0.001	0.01	0.02	0.02	0.01	0.02	0.01
	1	0.75	0.75	0.75	0.79	0.80	0.80
	5	0.77	0.76	0.77	0.80	0.79	0.79
	10	0.78	0.78	0.79	0.79	0.79	0.80
	100	0.78	0.77	0.79	0.79	0.80	0.80
INet100	**0**	0.01	0.01	0.01	0.01	0.01	0.01
	0.001	0.03	0.01	0.12	0.13	0.04	0.03
	1	0.76	0.80	0.78	0.78	0.78	0.78
	5	0.80	0.79	0.80	0.80	0.77	0.78
	10	0.79	0.81	0.80	0.81	0.80	0.79
	100	0.79	0.76	0.79	0.77	0.77	0.77

Table A11: LA on ImageNet-100 and CUB datasets for different values of λ_1 and λ_2.

Exp	CIFAR-100	ImageNet-100
E1	257 (257)	214 (214)
E2	460 (527)	359 (416)
E3	638 (794)	457 (594)
E4	798 (1046)	545 (762)
E5	925 (1309)	641 (945)

Table A12: Number of concepts per class over 5 experiences, excluding duplicates across experiences (Exp) (inclusive numbers in parentheses)

teresting direction of future work.

In this work, we introduced a unique mechanism that enables scaling up the number of concepts and classes without increasing the number of parameters. This method can thus be easily adapted to learn new prototypes continually as well. The multimodal concept embeddings provided by our method can also be extended beyond continual learning applications to incorporate other experiences such as concept-based novel class discovery and concept-based open-world classification. Furthermore, due to the flexibility of our multimodal concept encoder, we can extend our work to process other input modalities such as audio. In such an application, a natural choice of concept anchors could be phoneme representations. Lastly, to the best of our knowledge, our framework does not pose explicit ethical concerns.

A.6 Per-Experience Performance Results

In continuation to the results in Section 4 of the main paper, we herein report the performance of **MuCIL** and baseline methods across 5 and 10 experiences using ER, providing the values of Average Accuracies and Forgetting at every experience. These numbers are reported for different exemplar buffer sizes: 500, 2000, and 5000. The best-performing method is highlighted across each table.

Dataset	Class	Concepts
CIFAR100	Bicycle	a tire, object, a helmet, a handlebar, a bicycle seat, pedals attached to the frame, mode of transportation, two wheels of equal size, a seat affixed to the frame, a chain
	Chair	furniture, a person, object, legs to support the seat, an office, a computer, a desk, four legs, a backrest, armrests on either side
	Kangaroo	a grassland, short front legs, an animal, a safari, mammal, a long, powerful tail, brown or gray fur, marsupial, long, powerful hind legs, Australia
Imagenet100	Chickadee	trees, grayish upperparts, vertebrate, a short beak, white cheeks, chordate, gray wings and back, an animal, leaves, a small, round shape
	American Bullfrog	an animal, a stream, a large size, a log, a webbed foot, a marsh, a lily pad, long, powerful hind legs, a large body, a swamp, a carnivorous diet, a lake, a woods, large, webbed hind feet, a large mouth, a river, a pond, spots or blotches on the skin, a green or brown body
	Komodo Dragon	a large size, a keeper, scales, a tree, a dish, scaly skin, a rock, long, sharp claws, a long, thick tail, a long, forked tongue, an animal, reptile, a fence, vertebrate, a water dish, a zoo, a heat lamp, a large, bulky body, a cage, a lizard
CUB	Black-footed Albatross	back pattern: solid, under tail color: rufous, wing shape: long-wings, belly color: red, wing color: red, upperparts color: brown, breast pattern: multi-colored, upperparts color: rufous, bill shape: cone, tail shape: notched tail, back color: blue
	American Crow	back pattern: solid, wing shape: long-wings, upperparts color: brown, bill shape: cone, tail shape: notched tail, back color: blue, under tail color: grey, wing shape: tapered-wings, belly color: iridescent, wing color: iridescent
	Lazuli Bunting	back pattern: solid, under tail color: rufous, throat color: pink, wing shape: long-wings, wing color: red, upper tail color: pink, upperparts color: brown, breast pattern: multi-colored, bill shape: cone, tail shape: notched tail

Table A13: Sample classes and a subset of their corresponding concepts for the three datasets

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S	0.9177	N/A	0.6997	0.7691	0.4949	0.7669	0.3956	0.6652	0.3005	0.5459
CBM-J	0.8497	N/A	0.5641	0.8105	0.3876	0.7696	0.3004	0.7269	0.2293	0.6513
ICIAP-S	0.8745	N/A	0.5598	0.7842	0.3831	0.6763	0.2738	0.5945	0.2132	0.4345
ICIAP-J	0.8449	N/A	0.5719	0.7785	0.3971	0.7691	0.2981	0.7192	0.2450	0.6304
LabelFree	0.1847	N/A	0.2033	0.6675	0.1985	0.3915	0.2030	**0.2443**	0.2172	**0.0675**
LaBo	0.9065	N/A	0.6999	0.9401	0.5679	0.7381	0.4558	0.7648	0.3004	0.6016
MuCIL	**0.9545**	N/A	**0.8069**	**0.3795**	**0.7391**	**0.3545**	**0.7078**	0.3795	**0.6657**	0.2789

Table A14: Per Experience Results for CIFAR100 with 500 Exemplars and 5 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S	0.9177	N/A	0.7971	0.5826	0.6590	0.4797	0.5660	0.4385	0.4698	0.3782
CBM-J	0.8497	N/A	0.6761	0.5985	0.5351	0.5682	0.4581	0.5508	0.3855	0.4638
ICIAP-S	0.8688	N/A	0.6879	0.5690	0.5639	0.4120	0.4632	0.3977	0.3937	0.3157
ICIAP-J	0.8229	N/A	0.6762	0.6082	0.5468	0.5687	0.4742	0.4938	0.3854	0.4391
LabelFree	0.3013	N/A	0.3121	0.5504	0.3133	**0.2628**	0.3238	**0.1246**	0.3398	**0.0314**
LaBo	0.9076	N/A	0.7123	0.7908	0.5888	0.6485	0.4612	0.7004	0.3048	0.5600
MuCIL	**0.9559**	N/A	**0.8470**	**0.3097**	**0.7860**	0.3017	**0.7452**	0.3011	**0.7120**	0.2372

Table A15: Per Experience Results for CIFAR100 with 2000 Exemplars and 5 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S	0.9177	N/A	0.8471	0.4077	0.7245	0.3661	0.6307	0.3142	0.5724	0.2279
CBM-J	0.8497	N/A	0.7398	0.4353	0.6217	0.4080	0.5683	0.3507	0.4969	0.3383
ICIAP-S	0.8745	N/A	0.7489	0.4348	0.6247	0.3259	0.5373	0.2537	0.4587	0.2688
ICIAP-J	0.8450	N/A	0.7323	0.3976	0.6384	0.3547	0.5571	0.3425	0.5160	0.3544
LabelFree	0.3815	N/A	0.3713	0.4710	0.3905	**0.2472**	0.3975	**0.0988**	0.4027	**0.0330**
LaBo	0.9085	N/A	0.7151	0.7663	0.5969	0.6315	0.4674	0.6927	0.3095	0.5258
MuCIL	**0.9560**	N/A	**0.8849**	**0.2614**	**0.8177**	**0.2665**	**0.7805**	0.2644	**0.7425**	0.1963

Table A16: Per Experience Results for CIFAR100 with 5000 Exemplars and 5 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-Seq	0.7121	N/A	0.5967	0.5383	0.5033	0.4463	0.4038	0.4517	0.3494	0.3854
CBM-J	0.6845	N/A	0.5569	0.4656	0.4765	0.3463	0.4068	0.3358	0.3753	0.2992
ICIAP-S	0.7121	N/A	0.5967	0.5383	0.5033	0.4463	0.4038	0.4517	0.3494	0.3854
ICIAP-J	0.6845	N/A	0.5569	0.4656	0.4765	0.3463	0.4068	0.3358	0.3753	0.2992
LabelFree	0.0557	N/A	0.1049	0.6942	0.0751	0.2910	0.0529	0.2858	0.3121	0.2497
LaBo	0.6435	N/A	0.5869	0.5532	0.5606	0.5030	0.3942	0.6065	0.2869	0.6107
MuCIL	**0.8655**	N/A	**0.8246**	**0.1539**	**0.8245**	**0.0722**	**0.7782**	**0.1086**	**0.7832**	**0.1151**

Table A17: Per Experience Results for Per Experience Results for CUB (Caltech-UCSD Birds-200-2011) with 500 Exemplars and 5 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-Seq	0.7121	N/A	0.6667	0.2654	0.6041	0.1675	0.5450	0.2033	0.5332	0.1796
CBM-J	0.6845	N/A	0.6218	0.1452	0.5759	0.0850	0.5473	0.1008	0.5566	0.0917
ICIAP-S	0.7121	N/A	0.6667	0.2654	0.6041	0.1675	0.5450	0.2033	0.5332	0.1796
ICIAP-J	0.6845	N/A	0.6218	0.1452	0.5759	0.0850	0.5473	0.1008	0.5566	0.0917
LabelFree	0.1807	N/A	0.2104	0.5700	0.0875	0.3257	0.0000	0.4436	0.4508	0.4434
LaBo	0.6449	N/A	0.6021	0.4912	0.574	0.4365	0.4204	0.5336	0.3062	0.5205
MuCIL	**0.8591**	N/A	**0.8356**	**0.0787**	**0.8458**	**0.0297**	**0.8195**	**0.0680**	**0.8215**	**0.0551**

Table A18: Per Experience Results for Per Experience Results for CUB (Caltech-UCSD Birds-200-2011) with 2000 Exemplars and 5 Experiences

Model	Experience 1		Experience 2		Experience 3		Experience 4		Experience 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-Seq	0.7121	N/A	0.6667	0.1806	0.6147	0.0937	0.5792	0.0808	0.5915	0.0721
CBM-J	0.6845	N/A	0.6218	0.1178	0.5832	0.0255	0.5558	0.0500	0.5716	0.0575
ICIAP-S	0.7121	N/A	0.6667	0.1806	0.6147	0.0937	0.5792	0.0808	0.5915	0.0721
ICIAP-J	0.6845	N/A	0.6218	0.1178	0.5832	0.0255	0.5558	0.0500	0.5716	0.0575
LabelFree	0.4211	N/A	0.0000	0.3211	0.0000	0.5338	0.0000	0.5276	0.4664	0.4569
LaBo	0.6460	N/A	0.6322	0.4594	0.5382	0.3897	0.4472	0.4897	0.3121	0.4896
MuCIL	**0.8432**	N/A	**0.8414**	**0.0472**	**0.8446**	**0.0158**	**0.8229**	**0.0322**	**0.8333**	**0.0274**

Table A19: Per Experience Results for Per Experience Results for CUB (Caltech-UCSD Birds-200-2011) with 5000 Exemplars and 5 Experiences

Model	Experience 1		Experience 2		Experience 3		Experience 4		Experience 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S	0.9246	N/A	0.6547	0.7484	0.5028	0.6569	0.3380	0.5867	0.2904	0.4655
CBM-J	0.8605	N/A	0.5548	0.6657	0.4313	0.5960	0.3277	0.5865	0.3040	0.4990
ICIAP-S	0.8827	N/A	0.5855	0.7702	0.4136	0.5246	0.2968	0.4704	0.2199	0.4399
ICIAP-J	0.8536	N/A	0.5781	0.7099	0.4089	0.5413	0.2968	0.5615	0.3100	0.4788
LabelFree	0.0813	N/A	0.0593	0.8393	0.1107	0.3600	0.0667	**0.0360**	0.0716	**0.0000**
LaBo	0.5721	N/A	0.3547	0.5466	0.4116	0.4543	0.3891	0.4543	0.4071	0.6453
MuCIL	**0.9403**	N/A	**0.8563**	**0.1017**	**0.8119**	**0.1098**	**0.7368**	0.1193	**0.7975**	0.0261

Table A20: Per Experience Results for ImageNet100 with 500 Exemplars and 5 Experiences

Model	Experience 1		Experience 2		Experience 3		Experience 4		Experience 5	
	FAA	AF	FAA	AF	FAA	AF	FAA	AF	FAA	AF
CBM-S	0.9246	N/A	0.7753	0.4383	0.6216	0.3980	0.5255	0.2962	0.5079	0.2490
CBM-J	0.8605	N/A	0.6417	0.4446	0.5584	0.3825	0.4373	0.4399	0.4588	0.3169
ICIAP-S	0.8827	N/A	0.6732	0.4611	0.5536	0.3379	0.4364	0.3109	0.4095	0.2071
ICIAP-J	0.8536	N/A	0.6751	0.4415	0.5691	0.3875	0.4385	0.4308	0.4676	0.3151
LabelFree	0.1500	N/A	0.1133	0.7700	0.1307	0.2083	0.1333	0.2270	0.0944	**0.0010**
LaBo	0.5746	N/A	0.3757	0.5310	0.4402	0.3963	0.429	0.3744	0.4353	0.6064
MuCIL	**0.9347**	N/A	**0.8606**	**0.1116**	**0.8106**	**0.1141**	**0.7526**	**0.1362**	**0.7924**	0.0161

Table A21: Per Experience Results for ImageNet100 with 2000 Exemplars and 5 Experiences

Model	Experience 1		Experience 2		Experience 3		Experience 4		Experience 5	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.9246	N/A	0.8032	0.3329	0.6950	0.2766	0.6029	0.2077	0.5936	0.1516
CBM-J	0.8605	N/A	0.7212	0.3337	0.6210	0.3331	0.5222	0.3427	0.5289	0.2175
ICIAP-S	0.8827	N/A	0.7213	0.3024	0.6039	0.2423	0.5346	0.1498	0.5193	0.2147
ICIAP-J	0.8536	N/A	0.7074	0.2933	0.6225	0.3129	0.5168	0.3256	0.5465	0.2127
LabelFree	0.2987	N/A	0.2633	0.6233	0.3213	**0.0507**	0.2853	**0.1000**	0.1782	**0.0000**
LaBo	0.5736	N/A	0.3723	0.5037	0.4344	0.3746	0.4362	0.3574	0.4305	0.5926
MuCIL	**0.9354**	N/A	**0.8652**	**0.0831**	**0.8153**	0.1036	**0.7626**	0.1046	**0.8057**	0.0265

Table A22: Per Experience Results for ImageNet100 with 5000 Exemplars and 5 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5		Exp 6		Exp 7		Exp 8		Exp 9		Exp 10	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.95	N/A	0.80	0.75	0.71	0.74	0.63	0.69	0.50	0.83	0.46	0.72	0.41	0.71	0.36	0.64	0.33	0.70	0.28	0.66
CBM-J	0.91	N/A	0.65	0.85	0.50	0.85	0.43	0.80	0.32	0.86	0.29	0.82	0.26	0.75	0.23	0.80	0.20	0.77	0.15	0.77
ICIAP-S	0.92	N/A	0.69	0.76	0.60	0.77	0.51	0.70	0.39	0.79	0.34	0.68	0.30	0.63	0.26	0.60	0.22	0.66	0.20	0.65
ICIAP-J	0.91	N/A	0.64	0.85	0.50	0.84	0.40	0.82	0.32	0.85	0.28	0.82	0.24	0.85	0.19	0.80	0.19	0.82	0.13	0.75
LabelFree	0.16	N/A	0.18	0.76	0.15	**0.39**	0.18	0.34	0.16	**0.18**	0.16	**0.21**	0.19	**0.11**	0.16	**0.05**	0.17	**0.07**	0.19	**0.06**
LaBo	0.94	N/A	0.18	0.94	0.38	0.53	0.32	0.65	0.25	0.74	0.13	0.86	0.13	0.83	0.12	0.81	0.11	0.86	0.10	0.97
MuCIL	**0.98**	N/A	**0.88**	**0.39**	**0.81**	0.44	**0.77**	**0.35**	**0.72**	0.39	**0.71**	0.46	**0.70**	0.35	**0.65**	0.37	**0.70**	0.41	**0.63**	0.25

Table A23: Per Experience Results for CIFAR100 with 500 Exemplars and 10 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5		Exp 6		Exp 7		Exp 8		Exp 9		Exp 10	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.95	N/A	0.89	0.52	0.81	0.53	0.76	0.42	0.70	0.60	0.65	0.50	0.60	0.41	0.55	0.46	0.54	0.49	0.49	0.32
CBM-J	0.91	N/A	0.76	0.62	0.68	0.58	0.60	0.55	0.53	0.60	0.48	0.65	0.44	0.56	0.41	0.57	0.39	0.61	0.34	0.53
ICIAP-S	0.92	N/A	0.75	0.65	0.72	0.44	0.66	0.44	0.61	0.55	0.55	0.53	0.52	0.48	0.44	0.46	0.43	0.46	0.37	0.42
ICIAP-J	0.91	N/A	0.78	0.64	0.68	0.60	0.60	0.62	0.52	0.65	0.48	0.60	0.44	0.62	0.39	0.61	0.40	0.60	0.32	0.59
LabelFree	0.29	N/A	0.29	0.63	0.26	**0.30**	0.30	**0.29**	0.29	**0.18**	0.28	**0.15**	0.29	**0.08**	0.27	**0.05**	0.29	**0.04**	0.29	**0.01**
LaBo	0.93	N/A	0.20	0.93	0.38	0.47	0.33	0.63	0.26	0.74	0.14	0.84	0.13	0.83	0.12	0.85	0.10	0.89	0.10	0.94
MuCIL	**0.98**	N/A	**0.91**	**0.32**	**0.85**	**0.38**	**0.81**	0.30	**0.77**	0.34	**0.77**	0.44	**0.74**	0.30	**0.72**	0.34	**0.73**	0.30	**0.67**	0.25

Table A24: Per Experience Results for CIFAR100 with 2000 Exemplars and 10 Experiences

Model	Exp 1		Exp 2		Exp 3		Exp 4		Exp 5		Exp 6		Exp 7		Exp 8		Exp 9		Exp 10	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.95	N/A	0.91	0.42	0.87	0.39	0.82	0.29	0.78	0.49	0.73	0.45	0.66	0.39	0.60	0.34	0.62	0.38	0.54	0.34
CBM-J	0.91	N/A	0.82	0.48	0.75	0.41	0.68	0.39	0.60	0.51	0.60	0.44	0.55	0.46	0.51	0.46	0.50	0.46	0.45	0.36
ICIAP-S	0.92	N/A	0.81	0.45	0.76	0.31	0.72	0.32	0.66	0.50	0.61	0.35	0.59	0.37	0.55	0.35	0.53	0.44	0.47	0.36
ICIAP-J	0.91	N/A	0.84	0.46	0.76	0.37	0.69	0.38	0.64	0.46	0.59	0.43	0.57	0.44	0.51	0.40	0.50	0.41	0.47	0.42
LabelFree	0.32	N/A	0.33	0.59	0.30	**0.29**	0.34	**0.26**	0.33	**0.17**	0.33	**0.12**	0.34	**0.07**	0.32	**0.07**	0.32	**0.04**	0.33	**0.03**
LaBo	0.92	N/A	0.24	0.92	0.40	0.41	0.36	0.60	0.29	0.72	0.18	0.81	0.13	0.81	0.13	0.82	0.11	0.87	0.10	0.93
MuCIL	**0.98**	N/A	**0.95**	**0.24**	**0.90**	**0.31**	**0.85**	0.28	**0.81**	0.31	**0.80**	0.39	**0.78**	0.25	**0.76**	0.30	**0.75**	0.29	**0.71**	0.19

Table A25: Per Experience Results for CIFAR100 with 5000 Exemplars and 10 Experiences

Model	**Exp 1**		**Exp 2**		**Exp 3**		**Exp 4**		**Exp 5**		**Exp 6**		**Exp 7**		**Exp 8**		**Exp 9**		**Exp 10**	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.70	N/A	0.67	0.50	0.58	0.56	0.50	0.61	0.46	0.52	0.41	0.64	0.31	0.57	0.27	0.44	0.25	0.52	0.22	0.50
CBM-J	0.83	N/A	0.64	0.63	0.52	0.51	0.48	0.55	0.45	0.42	0.36	0.62	0.33	0.49	0.25	0.47	0.27	0.46	0.22	0.38
ICIAP-S	0.70	N/A	0.67	0.50	0.58	0.56	0.50	0.61	0.46	0.52	0.41	0.64	0.31	0.57	0.27	0.44	0.25	0.52	0.22	0.50
ICIAP-J	0.83	N/A	0.64	0.63	0.52	0.51	0.48	0.55	0.45	0.42	0.36	0.62	0.33	0.49	0.25	0.47	0.27	0.46	0.22	0.38
LabelFree	0.06	N/A	0.04	0.80	0.08	0.48	0.07	0.49	0.05	0.43	0.04	0.56	0.06	0.44	0.05	0.39	0.05	0.38	0.42	0.35
LaBo	0.43	N/A	0.18	0.43	0.34	0.58	0.30	0.42	0.25	0.57	0.16	0.76	0.12	0.79	0.11	0.80	0.08	0.90	0.07	0.77
MuCIL	**0.93**	N/A	**0.84**	**0.13**	**0.84**	**0.22**	**0.81**	**0.13**	**0.81**	**0.09**	**0.79**	**0.10**	**0.78**	**0.16**	**0.76**	**0.11**	**0.75**	**0.14**	**0.76**	**0.15**

Table A26: Per Experience Results for CUB (Caltech-UCSD Birds-200-2011) with 500 Exemplars and 10 Experiences

Model	**Exp 1**		**Exp 2**		**Exp 3**		**Exp 4**		**Exp 5**		**Exp 6**		**Exp 7**		**Exp 8**		**Exp 9**		**Exp 10**	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.70	N/A	0.68	0.22	0.63	0.36	0.58	0.26	0.58	0.17	0.55	0.26	0.48	0.24	0.46	0.25	0.45	0.28	0.46	0.28
CBM-J	0.83	N/A	0.63	0.27	0.58	0.20	0.56	0.19	0.57	0.21	0.53	0.14	0.49	0.23	0.45	0.23	0.47	0.16	0.46	0.14
ICIAP-S	0.70	N/A	0.68	0.22	0.63	0.36	0.58	0.26	0.58	0.17	0.55	0.26	0.48	0.24	0.46	0.25	0.45	0.28	0.46	0.28
ICIAP-J	0.83	N/A	0.63	0.27	0.58	0.20	0.56	0.19	0.57	0.21	0.53	0.14	0.49	0.23	0.45	0.23	0.47	0.16	0.46	0.14
LabelFree	0.36	N/A	0.19	0.51	0.27	0.28	0.00	0.35	0.00	0.54	0.00	0.68	0.00	0.49	0.00	0.47	0.00	0.50	0.58	0.43
LaBo	0.44	0.00	0.20	0.44	0.36	0.48	0.31	0.34	0.27	0.52	0.20	0.71	0.13	0.71	0.13	0.75	0.09	0.84	0.07	0.72
MuCIL	**0.94**	N/A	**0.86**	**0.12**	**0.84**	**0.10**	**0.83**	**0.07**	**0.83**	**0.06**	**0.82**	**0.06**	**0.82**	**0.08**	**0.80**	**0.04**	**0.81**	**0.05**	**0.81**	**0.06**

Table A27: Per Experience Results for CUB (Caltech-UCSD Birds-200-2011) with 2000 Exemplars and 10 Experiences

Model	**Exp 1**		**Exp 2**		**Exp 3**		**Exp 4**		**Exp 5**		**Exp 6**		**Exp 7**		**Exp 8**		**Exp 9**		**Exp 10**	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-Seq	0.70	N/A	0.68	0.18	0.63	0.27	0.58	0.22	0.59	0.15	0.56	0.15	0.51	0.18	0.49	0.13	0.49	0.16	0.52	0.25
CBM-J	0.83	N/A	0.63	0.21	0.58	0.16	0.56	0.16	0.58	0.05	0.55	0.10	0.52	0.12	0.50	0.06	0.51	0.11	0.51	0.10
ICIAP-S	0.70	N/A	0.68	0.18	0.63	0.27	0.58	0.22	0.59	0.15	0.56	0.15	0.51	0.18	0.49	0.13	0.49	0.16	0.52	0.25
ICIAP-J	0.83	N/A	0.63	0.21	0.58	0.16	0.56	0.16	0.58	0.05	0.55	0.10	0.52	0.12	0.50	0.06	0.51	0.11	0.51	0.10
LabelFree	0.60	N/A	0.15	0.27	0.17	0.33	0.25	0.43	0.24	0.29	0.11	0.42	0.16	0.42	0.11	0.31	0.07	0.38	0.62	0.29
LaBo	0.44	N/A	0.23	0.43	0.39	0.54	0.33	0.29	0.29	0.47	0.21	0.73	0.16	0.66	0.13	0.77	0.09	0.8	0.08	0.64
MuCIL	**0.94**	N/A	**0.86**	**0.07**	**0.87**	**0.07**	**0.84**	**0.07**	**0.85**	**0.03**	**0.83**	**0.06**	**0.84**	**0.08**	**0.82**	**0.06**	**0.81**	**0.07**	**0.82**	**0.05**

Table A28: Per Experience Results for CUB (Caltech-UCSD Birds-200-2011) with 5000 Exemplars and 10 Experiences

Model	**Exp 1**		**Exp 2**		**Exp 3**		**Exp 4**		**Exp 5**		**Exp 6**		**Exp 7**		**Exp 8**		**Exp 9**		**Exp 10**	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.88	N/A	0.85	0.69	0.69	0.86	0.58	0.64	0.46	0.57	0.40	0.61	0.29	0.73	0.29	0.54	0.26	0.54	0.21	0.71
CBM-J	0.83	N/A	0.76	0.78	0.57	0.85	0.40	0.67	0.35	0.59	0.28	0.64	0.18	0.70	0.21	0.57	0.20	0.57	0.17	0.70
ICIAP-S	0.89	N/A	0.59	0.75	0.55	0.54	0.44	0.53	0.35	0.47	0.29	0.57	0.22	0.55	0.20	0.48	0.17	0.46	0.14	0.65
ICIAP-J	0.81	N/A	0.69	0.78	0.51	0.75	0.39	0.67	0.36	0.59	0.29	0.65	0.20	0.73	0.21	0.54	0.18	0.58	0.18	0.73
LabelFree	0.07	N/A	0.07	0.85	0.09	0.29	0.04	0.72	0.10	0.18	0.05	**0.07**	0.10	**0.14**	0.09	**0.02**	0.04	0.03	0.11	0.07
LaBo	0.56	N/A	0.04	0.55	0.08	0.50	0.38	0.56	0.21	0.52	0.15	0.54	0.13	0.68	0.07	0.62	0.10	0.7	0.05	0.80
MuCIL	**0.90**	N/A	**0.93**	**0.08**	**0.89**	**0.12**	**0.84**	**0.13**	**0.79**	**0.13**	**0.79**	0.08	**0.70**	**0.16**	**0.76**	0.08	**0.77**	**0.02**	**0.79**	**0.04**

Table A29: Per Experience Results for ImageNet100 with 500 Exemplars and 10 Experiences

Model	**Exp 1**		**Exp 2**		**Exp 3**		**Exp 4**		**Exp 5**		**Exp 6**		**Exp 7**		**Exp 8**		**Exp 9**		**Exp 10**	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.88	N/A	0.90	0.41	0.80	0.48	0.71	0.41	0.64	0.39	0.59	0.39	0.49	0.46	0.48	0.32	0.49	0.24	0.47	0.33
CBM-J	0.83	N/A	0.81	0.51	0.69	0.50	0.59	0.43	0.54	0.36	0.46	0.45	0.40	0.57	0.40	0.38	0.37	0.31	0.39	0.42
ICIAP-S	0.89	N/A	0.81	0.49	0.71	0.42	0.62	0.38	0.57	0.33	0.48	0.38	0.42	0.42	0.39	0.27	0.39	0.24	0.36	0.37
ICIAP-J	0.81	N/A	0.78	0.50	0.67	0.58	0.57	0.48	0.51	0.40	0.47	0.43	0.40	0.58	0.39	0.42	0.36	0.35	0.37	0.41
LabelFree	0.14	N/A	0.17	0.76	0.11	0.42	0.13	0.57	0.10	0.29	0.17	0.27	0.24	0.24	0.22	0.11	0.25	0.08	0.17	**0.00**
LaBo	0.55	N/A	0.04	0.55	0.07	0.44	0.35	0.54	0.19	0.48	0.15	0.48	0.13	0.60	0.07	0.58	0.11	0.65	0.06	0.76
MuCIL	**0.90**	N/A	**0.93**	**0.07**	**0.89**	**0.09**	**0.84**	**0.11**	**0.80**	**0.09**	**0.80**	**0.07**	**0.74**	**0.16**	**0.77**	**0.07**	**0.79**	**0.01**	**0.80**	0.04

Table A30: Per Experience Results for ImageNet100 with 2000 Exemplars and 10 Experiences

Model	**Exp 1**		**Exp 2**		**Exp 3**		**Exp 4**		**Exp 5**		**Exp 6**		**Exp 7**		**Exp 8**		**Exp 9**		**Exp 10**	
	FAA	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**	**FAA**	**AF**
CBM-S	0.88	N/A	0.90	0.29	0.85	0.37	0.78	0.31	0.73	0.26	0.69	0.25	0.61	0.31	0.61	0.22	0.61	0.18	0.58	0.22
CBM-J	0.83	N/A	0.84	0.35	0.77	0.34	0.69	0.37	0.61	0.32	0.57	0.39	0.47	0.42	0.51	0.33	0.49	0.21	0.49	0.33
ICIAP-S	0.89	N/A	0.83	0.33	0.77	0.35	0.66	0.29	0.64	0.15	0.60	0.25	0.51	0.34	0.52	0.20	0.50	0.21	0.46	0.37
ICIAP-J	0.81	N/A	0.83	0.38	0.75	0.35	0.68	0.32	0.60	0.31	0.55	0.31	0.48	0.44	0.50	0.26	0.49	0.23	0.49	0.35
LabelFree	0.18	N/A	0.25	0.73	0.27	0.25	0.30	**0.08**	0.38	0.14	0.34	0.18	0.37	**0.11**	0.41	0.07	0.36	**0.00**	0.35	0.02
LaBo	0.55	N/A	0.05	0.55	0.07	0.42	0.38	0.50	0.20	0.45	0.15	0.46	0.13	0.60	0.08	0.54	0.11	0.62	0.06	0.74
MuCIL	**0.90**	N/A	**0.93**	**0.07**	**0.89**	**0.12**	**0.84**	0.11	**0.80**	**0.09**	**0.79**	**0.09**	**0.74**	0.16	**0.78**	**0.05**	**0.79**	0.03	**0.80**	**0.02**

Table A31: Per Experience Results for ImageNet100 with 5000 Exemplars and 10 Experiences