

abbreviations	Method	Link	Citation	Published	Components	Experiment Dataset	Experiment Results	Use case	Challenges/limitation
iCaRL	Incremental Classifier and Representation Learning	https://arxiv.org/abs/1611.07725	2856	2017	<ul style="list-style-type: none">• Nearest-mean classifier: Classifies based on the mean representation of stored examples.• Herdng selection: Selects representative samples to store in memory.• Representation learning: Updates the model to accommodate new classes.	CIFAR-100, ImageNet-100 0.	<ul style="list-style-type: none">• CIFAR-100: 57.2%• ImageNet-100: 54.0%	model needs to incrementally learn new classes	The memory buffer size limits the number of stored examples, potentially reducing performance as the number of classes increases.
Mnemonics	Mnemonics Training: Multi-Class Incremental Learning without Forgetting	https://arxiv.org/abs/2002.10211	278	2020	<ul style="list-style-type: none">• Learnable memories: Adapts memory samples to improve representation.• Memory optimization: Optimizes the stored samples for better recall.• Incremental replay: Uses optimized samples for replay during learning.	CIFAR-100, ImageNet-100 0.	<ul style="list-style-type: none">• CIFAR-100: 64.1%• ImageNet-100: 63.3%	When adaptive memory representation is needed. (Chatbot learn from new interactions while retaining knowledge of past interactions to provide consistent support.)	Complexity in optimizing memory samples.
GDumb	Greedy Sampler and Dumb Learner	https://arxiv.org/pdf/2009.13765	439	2020	<ul style="list-style-type: none">• Greedy Sampler: select a subset of the data from the memory buffer that maximizes the learning utility.• Dumb Learner: optimize the learning process by focusing on the most valuable data samples, especially in resource-constrained environments.	MNIST, CIFAR-10	varied	<ul style="list-style-type: none">• Best use when simplicity and computational efficiency are prioritized over sophisticated memory strategies.	Suboptimal performance in complex scenarios.
GSS	Gradient-based Sample Selection	https://arxiv.org/abs/1903.08671	609	2019	<ul style="list-style-type: none">• Gradient-based selection: Chooses samples based on their gradient impact.• Memory efficiency: Optimizes memory usage by selecting impactful samples.• Incremental updates: Updates model incrementally based on selected samples.	CIFAR-10, CIFAR-100.	<ul style="list-style-type: none">• CIFAR-10: 85.3%• CIFAR-100: 58.1%	When it's essential to maximize learning from a fixed memory buffer	Computational overhead from calculating gradients for selection.
DER++	Dark Experience Replay++		556	2020	<ul style="list-style-type: none">• Experience replay: Uses past experiences for learning.• Regularization techniques: Adds constraints to improve learning stability.• Incremental learning: Continuously learns new tasks without forgetting old ones.	CIFAR-10, ImageNet-10, Mnist-360	Pic-1	<ul style="list-style-type: none">• When the learning process requires stability and robustness over long periods.	<ul style="list-style-type: none">• Increased complexity from additional regularization -> not practical to training data-stream• Performance limits to Buffersize
TPCIL	Task-Proportional Continual Incremental Learning	https://www.ecva.net/papers/eccv_2020/papers_ECCV/papers/123640256.pdf	133	2020	<ul style="list-style-type: none">• Elastic Hebbian Graph (EHG): Constructs a dynamic graph to model feature space relationships, ensuring the preservation of topological properties.• Topology-Preserving Loss (TPL): Penalizes alterations in the EHG's neighborhood structure to maintain the feature space topology and reduce forgetting.• Incremental Learning Mechanism: Continuously updates the model with new class information while preserving knowledge of previously learned classes.• Feature Space Regularization: Stabilizes feature representations across incremental learning phases to prevent significant drifts.• Knowledge Distillation: Transfers knowledge from earlier model states to the updated model, helping retain information about old classes.	CIFAR-100, ImageNet-100 0, ImageNet-100 .	<ul style="list-style-type: none">• CIFAR-100: 65.34%/5 Sessions• ImageNet-100: 63.58%/10 Sessions• ImageNet-100: 64.89%/5 Sessions• ImageNet-100: 62.88%/10 Sessions• ImageNet-100: 74.81%/10 Sessions• ImageNet-100: 76.27%/5 Sessions• ImageNet-100: 74.81%/10 Sessions	<ul style="list-style-type: none">• Where topological relationships within the feature space are required to be preserved.• Be able to handle large and evolving datasets, making it suitable for complex, real-world applications where continuous learning is essential.	<ul style="list-style-type: none">• Sensible to hyperparameters lamda and number of exemplar in a class.• Computation expensive/ Storing representations for preserving the topology might be a problem in Scalability aspect.• Efficiently updating the model and the EHG during incremental learning phases without significantly increasing training time remains a challenge.
RMM	Reinforced memory management	https://arxiv.org/pdf/2301.05792	58	2023	<ul style="list-style-type: none">• Dynamic Memory Allocation: dynamically allocates memory resources based on the importance and recency of data using Reinforcement learning	CIFAR-100, ImageNet-100 0, ImageNet-100	Pic-2	<ul style="list-style-type: none">• When both memory efficiency and learning stability are critical in a dynamically changing environment.	<ul style="list-style-type: none">• More computation -> additional time cost.• RMM is built based on series of technical assumptions, not directly apply to all real-world scenario• Data privacy
HAL	Hindsight Anchor Learning	https://arxiv.org/abs/2002.08165	180	2021	<ul style="list-style-type: none">• Anchor Points: HAL selects critical points (anchors) from past data to guide future learning.• Hindsight Learning: The model revisits and reinforces learning of anchor points from previous tasks during new task training	P-Mnist, R-Mnist, S-CIFAR, S-ImageNet-10	Pic-3	<ul style="list-style-type: none">• When specific past knowledge must be retained to guide future learning in a consistent manner. (Personalized AI to guide Studying)	<ul style="list-style-type: none">• Revisiting / Reinforcing past data -> more computational load.• Determining effective anchors can be challenging.
LwF	Learning without Forgetting	https://arxiv.org/abs/1606.09282	3350	2017					
GEM	Gradient Episodic Memory	https://arxiv.org/abs/1706.08840	2094	2017					
A-GEM	Averaged GEM	https://arxiv.org/abs/1812.00420	1125	2019					
BIC	Bias correction	https://arxiv.org/abs/1905.13260	954	2019					
EEIL	End-to-End Incremental Learning	https://arxiv.org/abs/1807.09536	947	2018					
PODNet	Pooled Output Distillation Network	https://arxiv.org/abs/2004.13513	471	2020					
LUCIR	Learning a Unified Classifier Incrementally via Rebalancing	https://openaccess.thecvf.com/content_CVPR_2019/papers/Hou_Learning_a_Unified_Classifier_Incrementally_via_Rebalancing_CVPR_2019_paper.pdf	457	2019					
ILOD	Incremental Learning of Object Detectors without Catastrophic Forgetting	https://arxiv.org/abs/1708.06977	437	2017					
WA	Weight Aligning	https://arxiv.org/abs/1911.07053	317	2019					
DER	Dynamically Expandable Representation	https://arxiv.org/abs/2103.16788	305	2021					
DMC	Class-incremental Learning via Deep Model Consolidation	https://arxiv.org/abs/1903.07864	275	2019					
PASS	Prototype Augmentation and Self-Supervision	https://openaccess.thecvf.com/content/CVPR2021/papers/Zhu_Prototype_Augmentation_and_Self-Supervision_for_Incremental_Learning_CVPR_2021_paper.pdf	215	2021					
CoZL	Contrastive Continual Learning	https://arxiv.org/abs/2106.14413	204	2021					
CN-DPM	Continual Neural Dirichlet Process Mixture	https://arxiv.org/abs/2001.00689	178	2020					
AANets	Adaptive Aggregation Networks	https://arxiv.org/abs/2010.05063	158	2021					
ASER	Adversarial Shapley value Experience Replay	https://arxiv.org/abs/2009.00093	142	2020					
DDE	Distillation of data effect	https://arxiv.org/abs/2103.01737	140	2021					
TPCIL	Topology-Preserving Class-Incremental Learning	https://www.ecva.net/papers/eccv_2020/papers_ECCV/papers/123640256.pdf	133	2020					
SCR	Supervised Contrastive Replay	https://arxiv.org/abs/2103.13885	128	2021					
SS-IL	Separated Softmax for Incremental Learning	https://arxiv.org/abs/2003.13947	124	2020					
FOSTER	Feature Boosting and Compression	https://arxiv.org/abs/2204.04662	122	2022					
CBRS	class-balancing reservoir sampling	https://proceedings.mlr.press/v119/chrysakis20a.html	115	2020					
AFC	Adaptive Feature Consolidation	https://arxiv.org/abs/2204.00895	114	2022					
ILOS	Incremental Learning In Online Scenario	https://arxiv.org/abs/2003.13191	114	2020					
ER-ACE	ER with asymmetric cross-entropy	https://arxiv.org/abs/2104.05025	114	2021					
GeoDL	GeoDL	https://arxiv.org/pdf/2104.08572	82	2021					
CLS-ER	Complementary Learning System with experience replay	https://arxiv.org/abs/2201.12604	77	2022					
IOD-ML	Incremental Object Detection via Meta-Learning	https://arxiv.org/abs/2003.08798	73	2020					
OCM	Online Continual Learning through Mutual Information Maximization	https://proceedings.mlr.press/v162/guo22a.html	70	2022					
X-DER	eXtended DER	https://arxiv.org/abs/2201.00766	69	2022					
Scall	Classifier Weights Scaling	https://arxiv.org/abs/2001.05755	64	2020					
PoLRs	Population Learning Rate Search	https://arxiv.org/abs/2108.09020	62	2021					
MRDC	Memory Replay with Data Compression for Continual Learning	https://arxiv.org/abs/2202.06592	55	2022					
CTN	Contextual Transformation Networks	https://openreview.net/pdf?id=ox_uX-807CH	47	2020					
PCL	Per-class Continual Learning	https://www.math.pku.edu.cn/teachers/ywma/homepage/papers/aaa2021_2.pdf	46	2021					
SP-CL	Class-Incremental Learning with Strong Pre-trained Models	https://arxiv.org/abs/2204.03634	45	2022					
DVC	Online Class-Incremental Continual Learning via Dual View Consistency	https://openaccess.thecvf.com/content/CVPR2022/papers/Guo_No_1_Just_Selection_but_Exploration_Online_Class-Incremental_Continual_Learning_via_CVPR_2022_paper.pdf	45	2022					
Coil	Co-Transport for Class-Incremental Learning	https://arxiv.org/abs/2107.12654	44	2021					
CwD	Class-wise Decorrelation Approach	https://arxiv.org/pdf/2112.04731	40	2024					
InfoRS	Information-theoretic Online Memory Selection	https://arxiv.org/pdf/2204.04763	38	2022					
ELI	Energy-based Latent Aligner for Incremental Learning	https://arxiv.org/abs/2203.14952	33	2022					
InstAParam	Instance-Aware Parameterization	https://dl.acm.org/doi/pdf/10.5555/3495724.3497180	29	2020					
RAR	Repeated Augmented	https://arxiv.org/abs/2209.13917	27	2022					

