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Learning Fast, Learning Slow: A General Continual Learning Method based on Complementary Learning System



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Problem Statement: Catastrophic Forgetting

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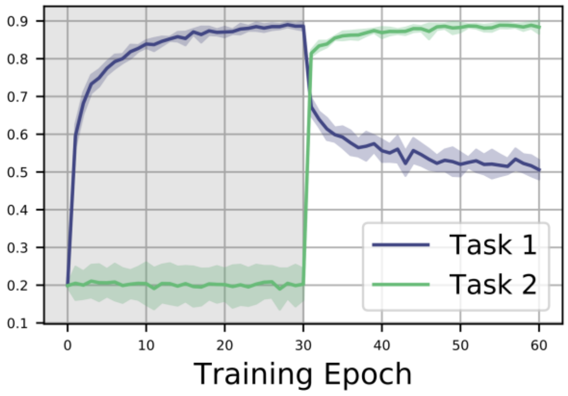
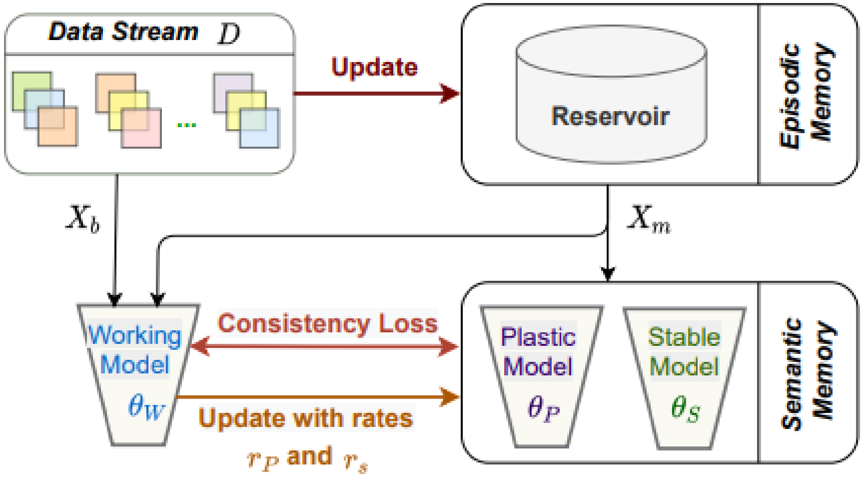
- The major challenge towards enabling **Continual learning** in deep neural networks is that the acquisition of incrementally available information from non-stationary data distributions leads to **catastrophic forgetting** whereby the performance of the model on previously learned tasks drops drastically.

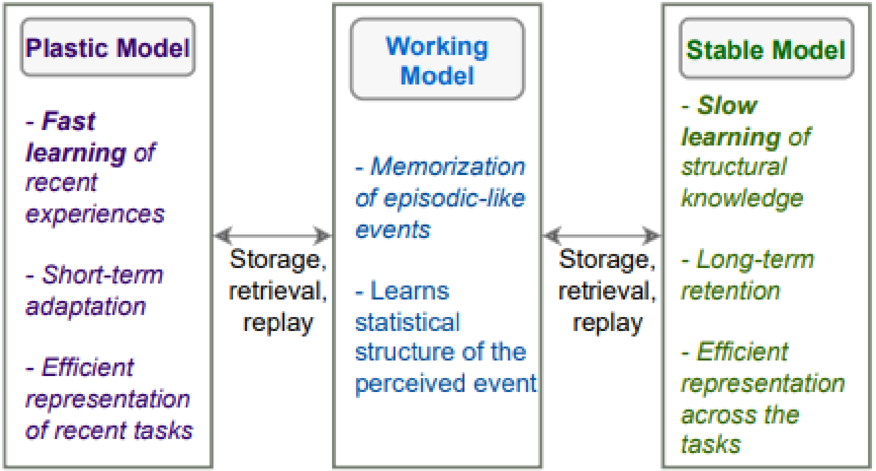
- Learning agent must be able to consolidate new information with the previously acquired information. This requires an effective balance between the **stability** and **plasticity** of the model.



Ramasesh, et. al. "Anatomy of Catastrophic Forgetting: Hidden Representations and Task Semantics." *ICLR* 2020.

CLS-ER: Complementary Learning System based Experience Replay





CLS-ER: Dual Memories

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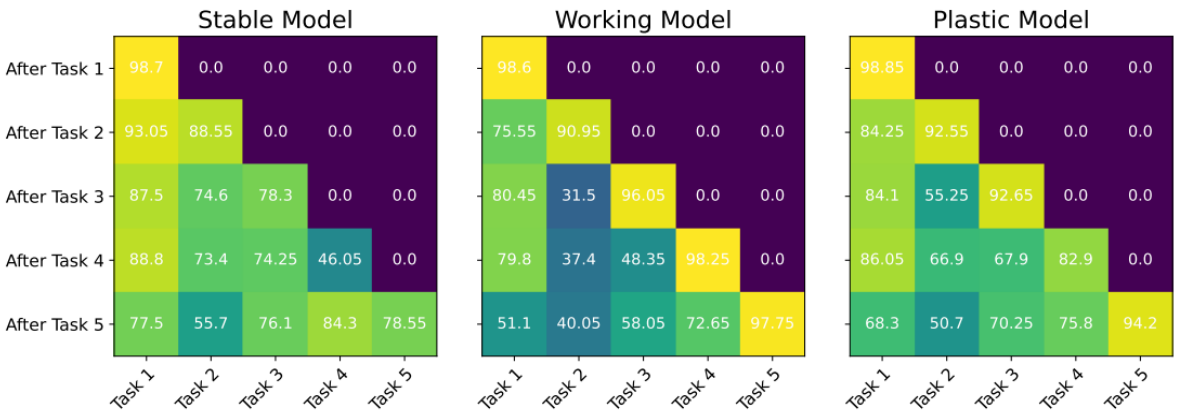
Semantic Memories:

- The acquired knowledge of the learned tasks is encoded in the weights of DNNs
- CLS-ER builds long-term (stable model) and short-term (plastic model) semantic memories by maintaining two exponentially weighted averaged models over the working model's weights.

$$\theta_i = \alpha_i \theta_i + (1 - \alpha_i)\theta_W ,$$

$$i \in \{P, S\}$$



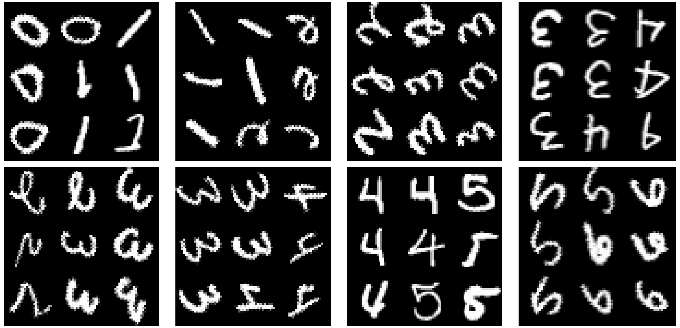
Episodic Memory:

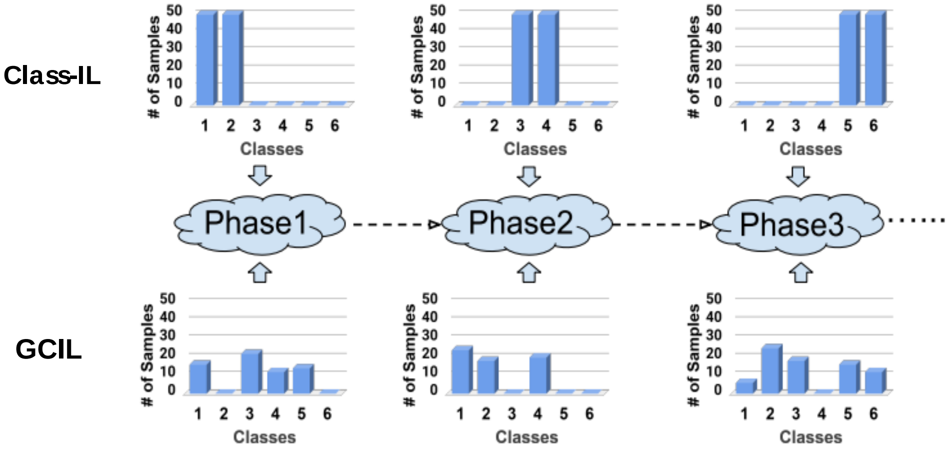
To maintain a fixed episodic memory buffer, we employ reservoir sampling which aims to match the distribution of incoming stream by assigning equal probability to each sample in the stream for being represented in the buffer.

General Incremental Learning

General-IL involves training the method on a long sequence of tasks where the boundaries between the tasks are not distinct and the tasks themselves are not disjoint and the method does not make sure of task boundaries during training or testing.

MNIST-360





Our focus is on GIL as it is closer to the challenges a CL agent faces in the real-world

Buzzega, et al. "Dark experience for general continual learning: a strong, simple baseline." NeurIPS (2020).
Mi, et al. "Generalized class incremental learning." ICCVW 2020.

Results: General-IL

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MNIST-360

JOINT	SGD	Buffer	ER	MER	GSS	DER++	CLS-ER
82.98±3.24	19.09±0.69	200	49.27±2.25	48.58±1.07	43.92±2.43	54.16±3.02	**66.37±0.83**
		500	65.04±1.53	62.21±1.36	54.45±3.14	69.62±1.59	**75.70±0.41**
		1000	75.18±1.50	70.91±0.76	63.84±2.09	76.03±1.61	**79.54±0.34**

GCIL-CIFAR-100

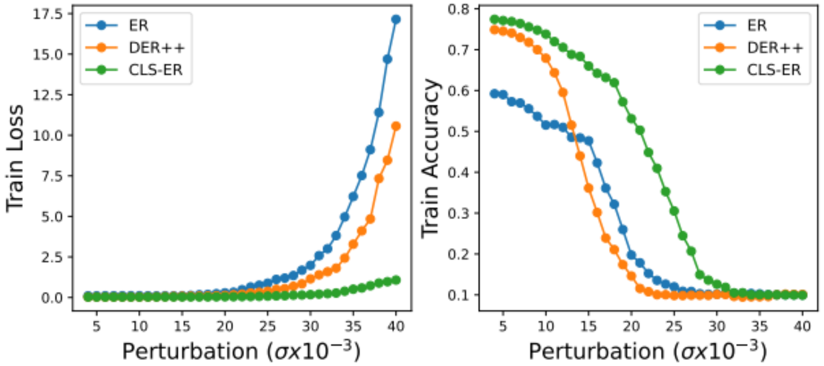
Distribution	**Uniform**			**Longtail**		
SGD	18.05±5.01			15.02±6.07		
JOINT	60.19±1.21			54.72±7.60		
Buffer	200	500	1000	200	500	1000
ER	24.20±3.12	27.65±2.42	32.89±2.47	21.56±3.70	24.79±4.18	32.25±3.00
DER++	28.79±3.57	33.14±3.13	40.51±2.62	25.27±4.24	32.59±2.83	36.97±3.78
CLS-ER	**33.15±2.83**	**37.01±1.67**	**41.09±1.58**	**29.57±3.87**	**33.26±3.66**	**39.21±3.46**

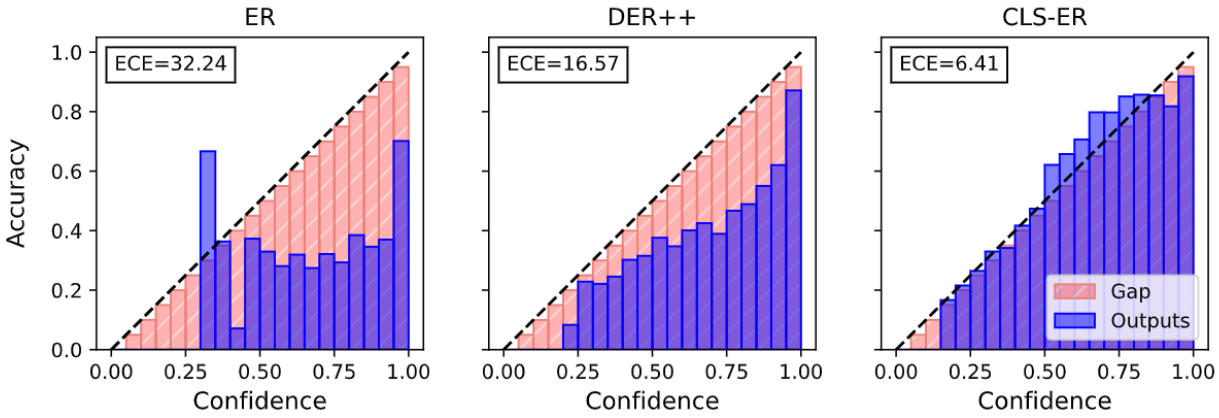
Results: Class-IL and Domain-IL

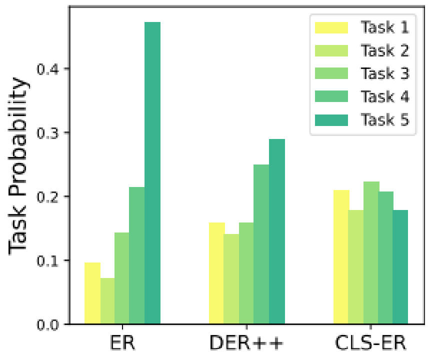
Buffer	Method	Class-IL			Domain-IL	
		S-MNIST	S-CIFAR-10	S-Tiny-ImageNet	R-MNIST	P-MNIST
–	JOINT	95.57±0.24	92.20±0.15	59.99±0.19	95.76±0.04	94.33±0.17
	SGD	19.60±0.04	19.62±0.05	7.92±0.26	67.66±8.53	40.70±2.33
200	ER	80.43±1.89	44.79±1.86	8.49±0.16	85.01±1.90	72.37±0.87
	GEM	80.11±1.54	25.54±0.76	-	80.80±1.15	66.93±1.25
	iCaRL	70.51±0.53	49.02±3.20	7.53±0.79	-	-
	FDR	79.43±3.26	30.91±2.74	8.70±0.19	85.22±3.35	74.77±0.83
	GSS	38.92±2.49	39.07±5.59	-	79.50±0.41	63.72±0.70
	DER++	85.61±1.40	64.88±1.17	10.96±1.17	90.43±1.87	83.58±0.59
	CLS-ER	**89.54±0.21**	**66.19±0.75**	**21.95±0.26**	**92.26±0.18**	**84.63±0.40**
500	ER	86.12±1.89	57.74±0.27	9.99±0.29	88.91±1.44	80.60±0.86
	GEM	85.99±1.35	26.20±1.26	-	81.15±1.98	76.88±0.52
	iCaRL	70.10±1.08	47.55±3.95	9.38±1.53	-	-
	FDR	85.87±4.04	28.71±3.23	10.54±0.21	89.67±1.63	83.18±0.53
	GSS	49.76±4.73	49.73±4.78	-	81.58±0.58	76.00±0.87
	DER++	91.00±1.49	72.70±1.36	19.38±1.41	92.77±1.05	88.21±0.39
	CLS-ER	**92.05±0.32**	**75.22±0.71**	**29.61±0.54**	**94.06±0.07**	**88.30±0.14**
5120	ER	93.40±1.29	19.70±0.07	28.97±0.41	94.19±0.44	89.90±0.13
	GEM	95.11±0.87	67.27±4.27	-	85.24±0.59	87.42±0.95
	iCaRL	70.60±1.03	55.07±1.55	14.08±1.92	-	-
	FDR	87.47±3.15	19.70±0.07	28.97±0.41	94.19±0.44	90.87±0.16
	GSS	89.39±0.75	67.27±4.27	-	85.24±0.59	82.22±1.14
	DER++	95.30±1.20	85.24±0.49	39.02±0.97	**94.65±0.33**	**92.26±0.17**
	CLS-ER	**95.73±0.11**	**86.78±0.17**	**45.92±0.30**	94.25±0.06	92.03±0.05

Model Characteristics

- Convergence to flatter minima
- Better model calibration
- More uniform task probabilities







Conclusion

- We proposed a novel dual memory experience replay method based on the complementary learning systems theory in the brain and showed the potential of incorporating the interplay of multiple memory systems in CLS theory for enabling effective CL in DNNs.

- The empirical results show the effectiveness of our approach on benchmark datasets as well as more challenging general incremental learning scenarios and achieved the new state-of-the-art in the vast majority of the continual learning settings.

- We further showed that CLS-ER converges to flatter minima, mitigates the bias towards recent tasks, and provides a well-calibrated high-performance model.

Our strong empirical results motivate further study into mimicking the complementary learning system in the brain more faithfully to enable optimal continual learning in DNNs.

Thank you!

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