SALIENCY-DRIVEN EXPERIENCE REPLAY FOR CONTINUAL LEARNING

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Problem Background

Machine Learning models struggles with **Continual Learning** (CL) – the ability to learn new information without forgetting previously acquired knowledge.

Traditional models face **Catastrophic Forgetting** (CF) when exposed to non-stationary data streams, leading to a decrease in accuracy on previously learned tasks.

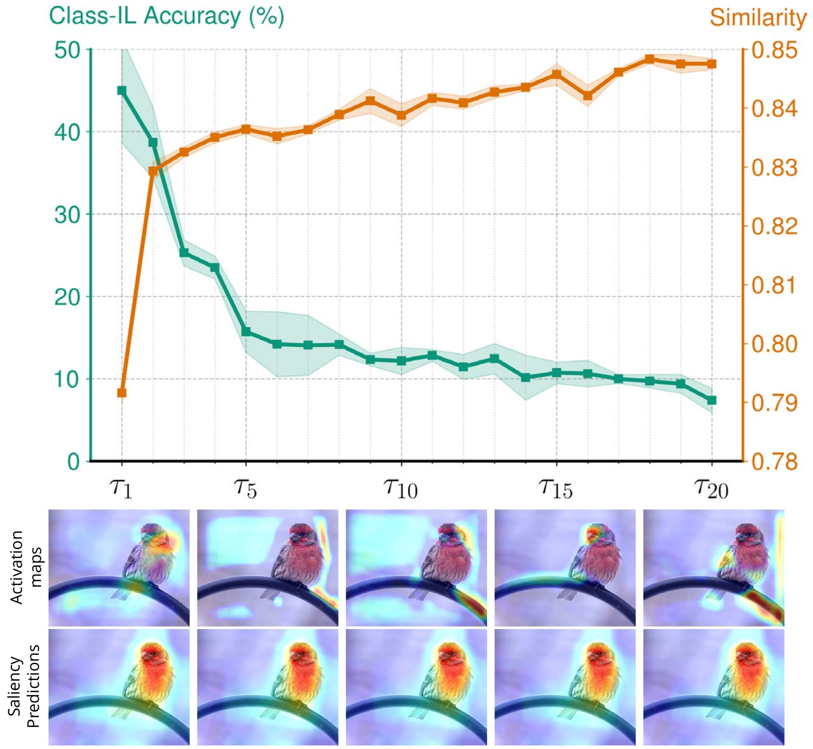
Our goal is to find a biologically inspired method to make CL more effective, reducing CF and making models more stable over time.

Human-Learning insight

- ➢In humans, the Visual System prioritizes salient information of the visual scene (e.g., movements, contrast, …)

- ➢**Selective Attention** retains an ancestral saliency bias, highlighting a stable, inherited visual processing trait that resists forgetting over time [1].

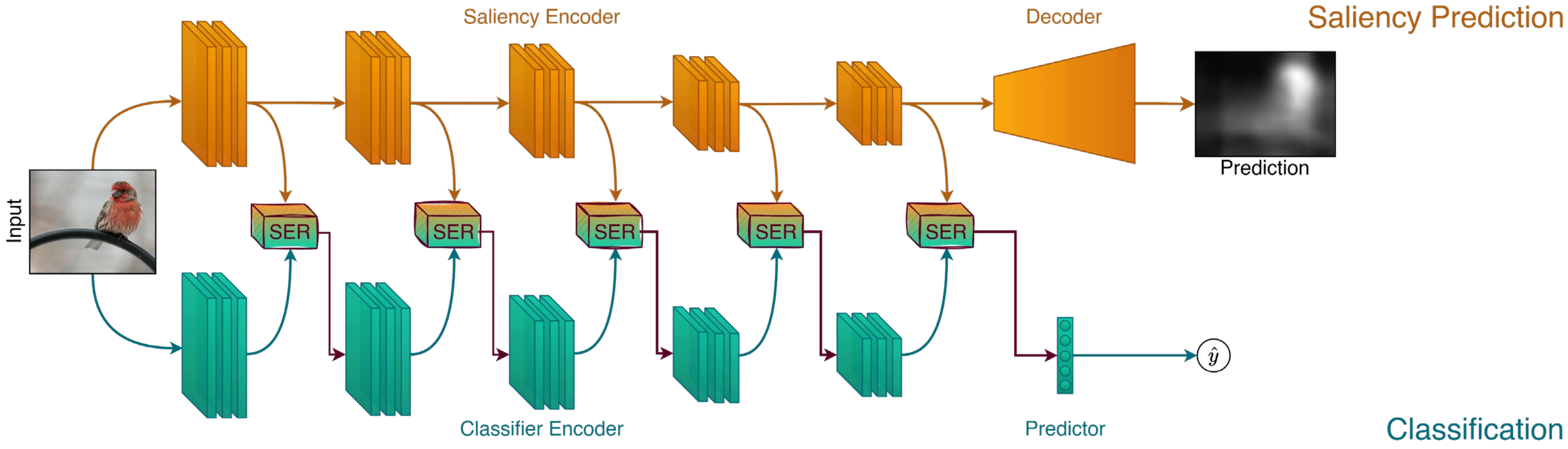
- ➢Visual features from a Saliency Predictor are **highly robust** to CF.



[1] J. New et al. “Category-specific attention for animals reflects ancestral priorities, not expertise”. National Academy of Sciences, 2007.

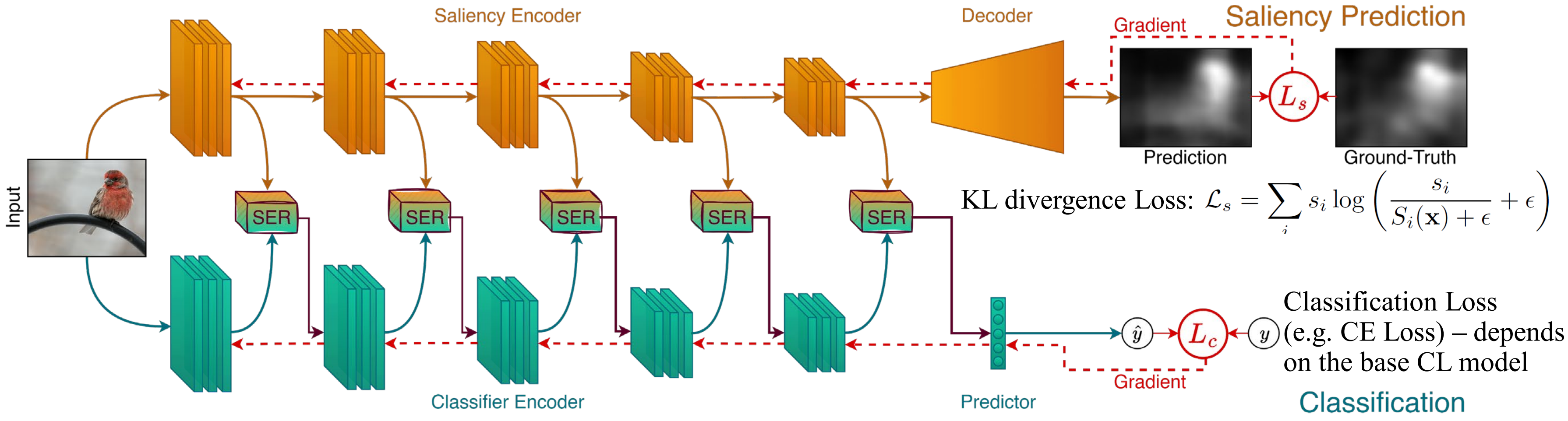
SER: Saliency-based Experience Replay

- A dual-branch architecture, with a Saliency Predictor **S** and a Continual Classifier **C**.
- **S** modulates the feature learning of **C** by emphasizing “salient” features at intermediate representations.



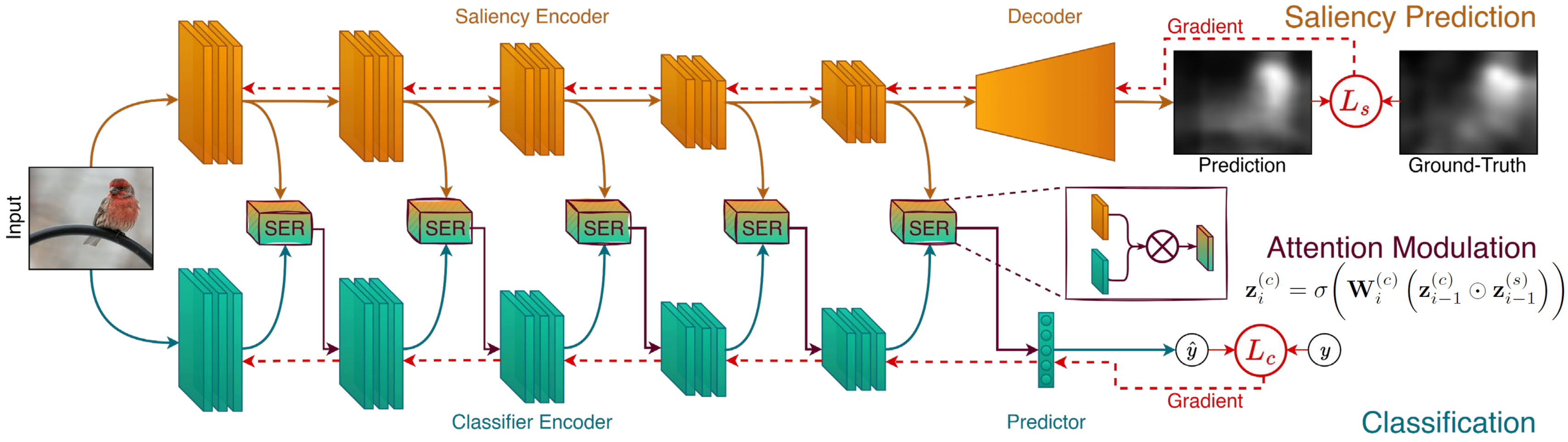
SER: Saliency-based Experience Replay

➢ **S** and **C** observe the same data stream, but they are trained with different objective functions.



SER: Saliency-based Experience Replay

- **S** and **C** observe the same data stream, but they are trained with different objective functions.
- Saliency modulation is performed through a Hadamard product between corresponding features.



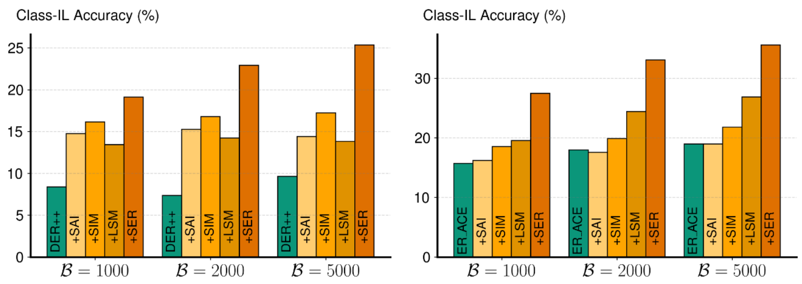
Performance Comparison

Table 1: **Class-Incremental accuracy of SOTA rehearsal-based methods** with and without SER.

Model	**Split Mini-ImageNet**			**Split FG-ImageNet**		
Joint	14.79±1.17			9.06±1.07		
Fine-tune	3.43±0.35			2.43±0.81		
Buffer size	**1000**	**2000**	**5000**	**1000**	**2000**	**5000**
DER++	14.95±3.11	12.82±4.97	14.58±2.55	8.08±1.54	8.27±1.72	9.20±0.86
↪**SER**	**19.13**±1.62	**22.92**±2.25	**25.35**±2.56	**11.71**±2.36	**12.97**±1.62	**13.73**±1.95
ER-ACE	20.86±3.69	24.93±3.20	26.31±5.22	14.28±0.96	16.45±1.24	18.21±3.45
↪**SER**	**27.48**±2.83	**33.09**±1.28	**35.58**±1.79	**20.03**±3.13	**23.80**±2.11	**28.68**±0.50
CoPE	21.58±1.60	23.58±4.39	24.77±3.56	16.45±1.38	16.81±0.83	17.77±2.02
↪**SER**	**26.66**±2.22	**33.35**±4.67	**45.04**±2.44	**18.17**±2.79	**27.14**±1.62	**34.34**±3.51
	Dual-branch methods					
TwF	23.78±1.67	29.05±2.02	–	15.32±2.59	18.72±1.75	–
↪**SER**	**28.36**±3.72	**35.55**±0.61	–	**20.04**±1.63	**22.54**±2.20	–
DualNet	20.57±0.91	27.41±1.79	32.08±1.55	15.62±1.54	21.04±1.08	22.07±2.08
↪**SER**	**28.58**±1.40	**33.76**±1.21	**36.44**±0.77	**19.48**±0.59	**22.53**±1.56	**24.83**±2.01

DER++ : P. Buzzega et al. “Dark Experience for General Continual Learning”. NeurIPS 2020.
Er-ACE: L. Caccia et al. “New Insights on Reducing Abrupt Representation Change in Online Continual Learning”. ICLRW 2022.
CoPE: M. De Lange and T. Tuytelaars. Continual prototype evolution: Learning online from nonstationary data streams”. ICCV 2021.
TwF: M. Boschini et al. ”Transfer without forgetting”. ECCV 2022.
DualNet: Q. Pham et al. “Dualnet: Continual learning, fast and slow”. NeurIPS 2021.

Assessing saliency integration strategies



	Split Mini-ImageNet		Split FG-ImageNet	
SER Scheme	**DER++**	**ER-ACE**	**DER++**	**ER-ACE**
1 1 1 0 0	12.97±2.62	23.72±0.77	6.54±0.67	18.08±0.96
1 1 1 1 0	17.46±1.02	26.44±2.33	8.77±1.45	16.55±2.55
1 1 1 1 1	**22.92**±2.25	**33.09**±1.28	**12.97**±1.62	**23.80**±2.11

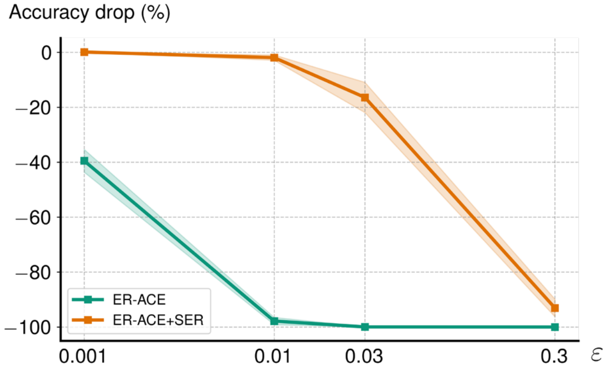
Alternative saliency integration methods evaluated:

- SAI: Saliency as additional input
- SIM: Saliency-based input modulation
- LSM: Learning saliency-based modulation

Selective-driven modulation applied across the entire network flow yields the best results, aligning with neurophysiological insights [2, 3]

[2] S. Treue and J. C. nez Trujillo. "Feature-based attention influences motion processing gain in macaque visual cortex". Nature, Jun 1999.
[3] J. C. Martinez-Trujillo and S. Treue. Feature-based attention increases the selectivity of population responses in primate visual cortex". Curr Biol, May 2004

Effects of saliency features on Model robustness



Method	Class-IL	Task-IL
ER-ACE	50.07±3.88	86.77±1.63
ER-ACE$^{\mathcal{SF}}$	28.46±3.46	74.40±4.37
$\hookrightarrow$**SER**	**44.08**±3.67	**83.04**±3.06

- In case of adversarial input space perturbations (PGD attack [4]), SER significantly improves model stability by reducing performance degradation through saliency-based feature regularization.
- Testing on an ad-hoc benchmark, SER recovers almost all the performance lost due to spurious features, making the model more stable and adaptable across tasks.

[3] A Madryet al. "Towards deep learning models resistant to adversarial attacks." ICLR 2018.

Conclusions

SER, a biologically-plausible approach based on replicating human visual saliency to enhance classification models in CL.

By incorporating saliency-driven modulation, SER improves state-of-the-art CL methods, reducing forgetting.

The saliency-based modulation significantly enhance robustness to adversarial attacks

SER highlights the potential of integrating neurophysiological principles to advance CL in AI systems.

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Paper and code are available here:

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