# Distribution-Aware Replay for Continual MRI Segmentation











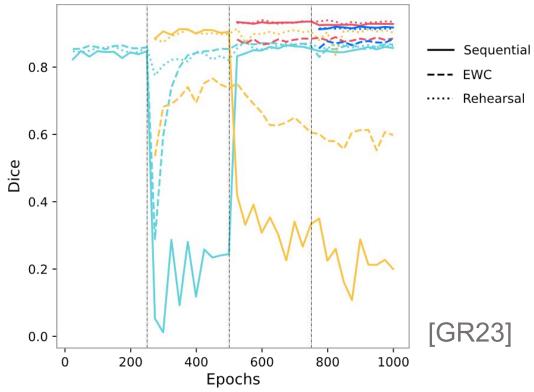


# Why Pseudo-Rehearsal?



- Regularisation / Distillation: Do not perform well enough [GL20]
- Expansion: Model size grows
- Rehearsal: Performs well, but suffers from privacy breach [GL20]

Solution: Pseudo-Rehearsal



[GL20] González, C., Lemke, N., Sakas, G., Mukhopadhyay, A.: What is wrong with continual learning in medical image segmentation? arXiv:2010.11008 (2020)
[GR23] González, C., Ranem, A., Pinto dos Santos, D., Othman, A., & Mukhopadhyay, A.: Lifelong nnU-Net: a framework for standardized medical continual learning. Scientific Reports, 13(1), 9381 (2023)

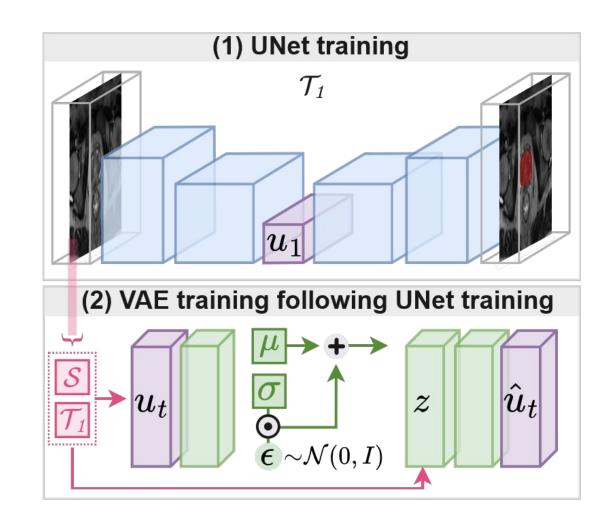
## **Second-Stage Modeling**



- Mathematically grounded [DW18, HM22]
- Additional privacy preservation
- Resource-efficient

Built-in OoD detection

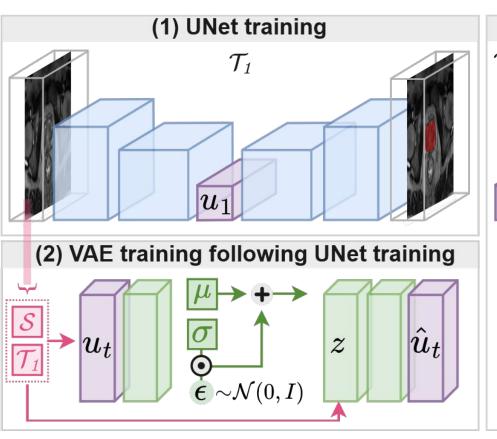
$$\log p(u) \geq \underbrace{\mathbb{E}_{z \sim q(z|u)} \left[\log p(u|z)
ight]}_{ ext{Reconstruction loss}} - \underbrace{ ext{KL} \left[q(z|u)||p(z)
ight]}_{ ext{KL divergence}}$$

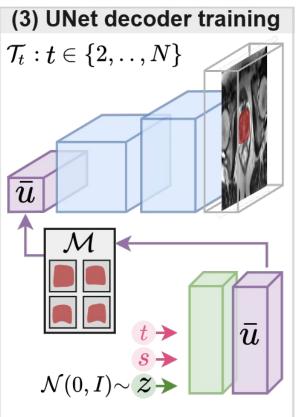


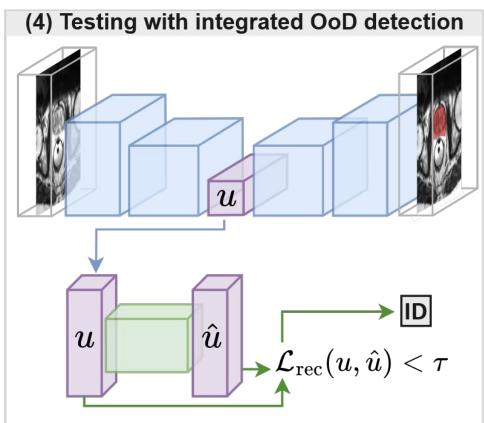
[DW18] Dai, B., Wipf, D.: Diagnosing and enhancing vae models. International Conference on Learning Representations (2018) [HM22] Hong, Y., Mundt, M., Park, S., Uh, Y., Byun, H.: Return of the normal distribution: Flexible deep continual learning with variational auto-encoders. Neural Networks 154, 397–412 (2022)

### Distribution-Aware Replay via ccVAE







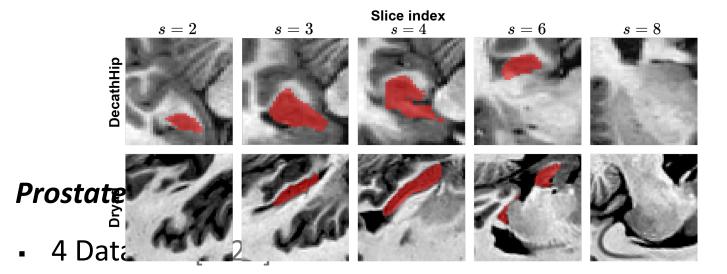


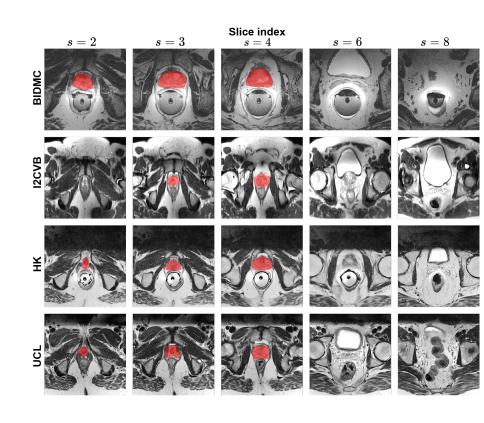
### **Experimental Setup**



#### Hippocampus:

- 2 Datasets [AR22, KB15]
- 50 to 260 samples
- Median res.: [48, 64, 64]





[AR22] Michela Antonelli, Annika Reinke, Spyridon Bakas, Keyvan Farahani, Annette Kopp-Schneider, Bennett A Landman, Geert Litjens, Bjoern Menze, Olaf Ronneberger, Ronald M Summers, et al. The medical segmentation depathles. In the communications (3(1):4128, 2022 [KB15] Jessie Kulaga-Yoskovitz, Bons C Bermarot, Seok-Jun Hong, Tommaso Mansi, Kevin E Liang, Andre JW Van Der Kouwe, Jonathan Smallwood, Andrea Bernasconi, and Neda Bernasconi. Multi-contrast submillimetric 3

tesla hippocampal subfield segmentation protocol and dataset. Scientific data, 2(1):1-9, 2015

[LY20] Quande Liu, Qi Dou, Lequan Yu, and Pheng Ann Heng. Ms-net: multi-site network for improving prostate segmentation with heterogeneous mri data. IEEE transactions on medical imaging, 39(9):2713–2724, 2020 Oct 10th, 2021 edian res.: [20, 384, 384]

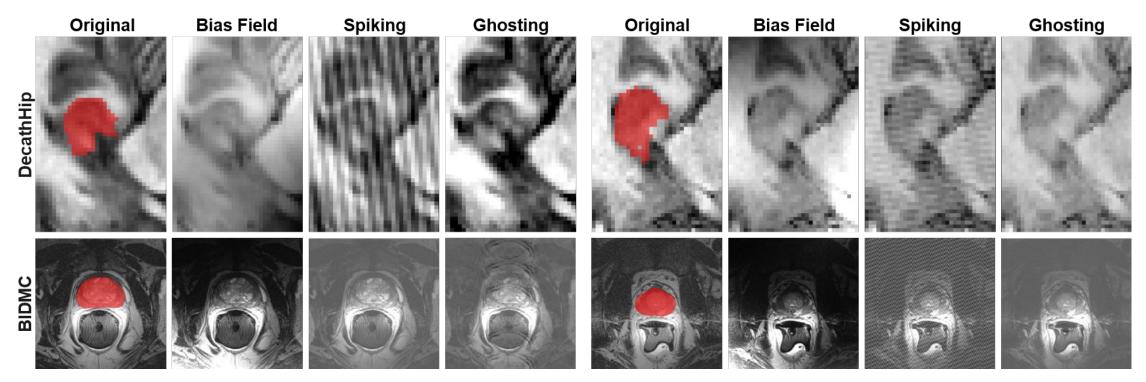
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### **Experimental Setup**



#### **OoD** detection:

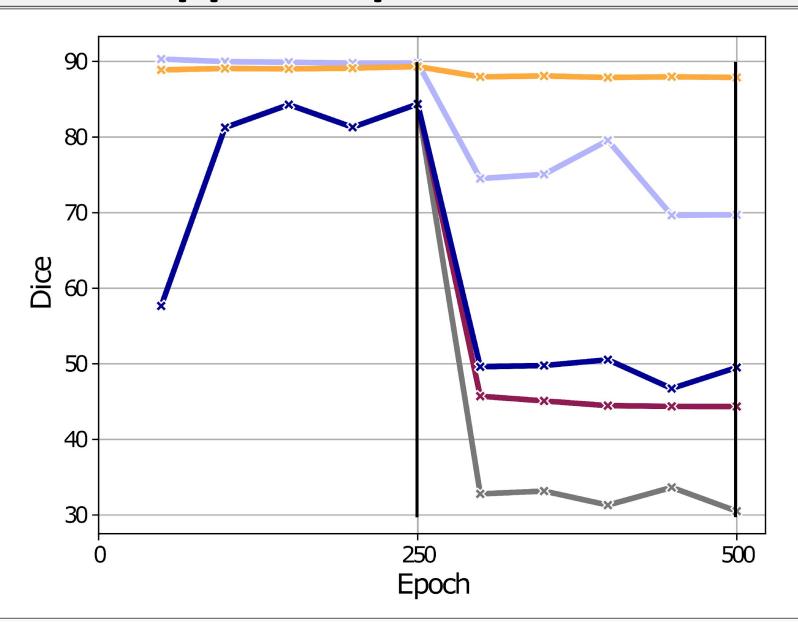
- One additional dataset per anatomy [WD17, LY20]
- Artificial data augmentations



[LY20] Quande Liu, Qi Dou, Lequan Yu, and Pheng Ann Heng. Ms-net: multi-site network for improving prostate segmentation with heterogeneous mri data. IEEE transactions on medical imaging, 39(9):2713–2724, 2020 [WD17] Laura EM Wisse, Ana M Daugherty, Rosanna K Olsen, David Berron, Valerie A Carr, Craig EL Stark, Robert SC Amaral, Katrin Amunts, Jean C Augustinack, Andrew R Bender, et al. A harmonized segmentation protocol for hippocampal and parahippocampal subregions: Why do we need one and what are the key goals? Hippocampus, 27(1):3–11, 2017.

# Results: Hippocampus

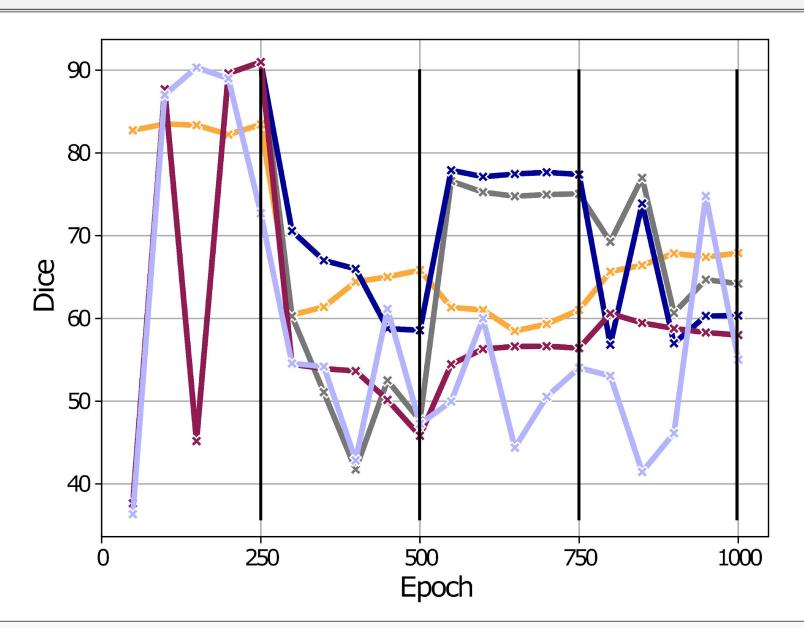


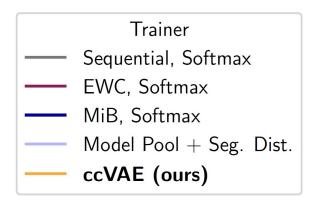




### **Results: Prostate**







### **Data Shift and Image Artifacts**



ccVAE demonstrates superior stable performance

Training stage/		$p \mid Drye$				I2CVI		HK		UCI	-
Method	Dice ↑ E	$\downarrow \mid \text{Dice } \uparrow$	$\mathbf{E}\downarrow$	Dice ↑	$\mathbf{E}\downarrow$						
	$ 63.4\pm39 51$	I				1					
EWC [KP17], SM [HG17]	$ 63.4\pm39 51$	$1.1   32.6 \pm 38$	49.6	$50.5 \pm 40$	39.8	$37.3 \pm 32$	34.2	$46.2 \pm 27$	30.2	$48.2 \pm 26$	25.3
MiB [CM20], SM [HG17]	$ 63.4\pm39 51$	$1.1 26.5\pm31$	45.3	$50.5 \pm 40$	39.8	$44.3 \pm 30$	20.6	$70.7{\pm}16$	21.8	$ 48.5\pm33 $	31.8
MPool [GR22], SD [LS23]	82.4±24 48	$3.3   47.8 \pm 40$	42.4	$47.2 \pm 42$	37.2	$37.6 \pm 34$	43.4	$46.4 \pm 34$	37.2	$ 41.4\pm 36 $	34.4
ccVAE (ours)	89.3±3 7	$.8 \mid 83.2 \pm 14$	4.7	$75.6 \pm 11$	14.8	$ 56.7\pm17 $	21.5	$49.4 \pm 21$	27.8	$58.8 \pm 15$	32.3

[CM20] Cermelli, F., Mancini, M., Bulo, S.R., Ricci, E., Caputo, B.: Modeling the back-ground for incremental learning in semantic segmentation. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (2020)

<sup>[</sup>GR22] González, C., Ranem, A., Othman, A., Mukhopadhyay, A.: Task-agnostic continual hippocampus segmentation for smooth population shifts. MICCAI Workshop on Domain Adaptation and Representation Transfer pp. 108–118 (2022)

<sup>[</sup>HG17] Hendrycks, D., Gimpel, K.: A baseline for detecting misclassified and out-of-distribution examples in neural networks. International Conference on Learning Representations (2017)

<sup>[</sup>KP17] Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A.A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A., et al.: Overcoming catastrophic forgetting in neural networks. Proceedings of the National Academy of Sciences 114(13), 3521–3526 (2017)

<sup>[</sup>LS23] Lennartz, J., Schultz, T.: Segmentation distortion: Quantifying segmentation uncertainty under domain shift via the effects of anomalous activations. International Conference on Medical Image Computing and Computer-Assisted Intervention pp. 316–325 (2023)

### **Ablation Study**



Both conditioning and OoD detection using reconstruction contribute to performance

Training stage/	1	p   Dryad	11	1	HK	UCL
Method	$  \text{Dice} \uparrow \mathbf{E}  $	$\downarrow \mid \text{Dice} \uparrow \mathbf{E} \downarrow$	$\parallel$ Dice $\uparrow$ $\mathbf{E} \downarrow$	$\mid$ Dice $\uparrow$ $\mathbf{E} \downarrow$	Dice $\uparrow$ <b>E</b> $\downarrow$	$\mid$ Dice $\uparrow$ <b>E</b> $\downarrow$
MPool [GR22], SD [LS23]	89.8±3 33	$.4 69.7\pm35\ 20.1$	72.3±34 30.3	$ 48.6\pm34\ 35.1 $	$55.1 \pm 31 \ 31.8$	$ 55.9\pm34\ 30.2 $
ccVAE, Mah. $[GG22]$	$89.0\pm3 \ 13$	$.2 61.2\pm33 24.4$	$  39.1\pm30  29.0 $	$ 60.5\pm13 34.7$	$60.4 \pm 18 \ 34.2$	$67.9 \pm 10\ 22.6$
cVAE, Rec.	$89.3\pm3$ 3.	$8 \mid 87.6 \pm 4 \mid 16.8$	$83.4\pm2$ 24.4	$64.7 \pm 9 \ 19.4$	$65.4 \pm 12 \ 17.3$	$65.4 \pm 10$ 28.6
ccVAE	89.4±3 4.	$7 \mid 87.9 \pm 5 \mid 14.5$	$83.4\pm2$ 25.5	$66.2 \pm 9 \ 27.2$	$60.0\pm19\ 35.5$	$67.9 \pm 10   37.8$

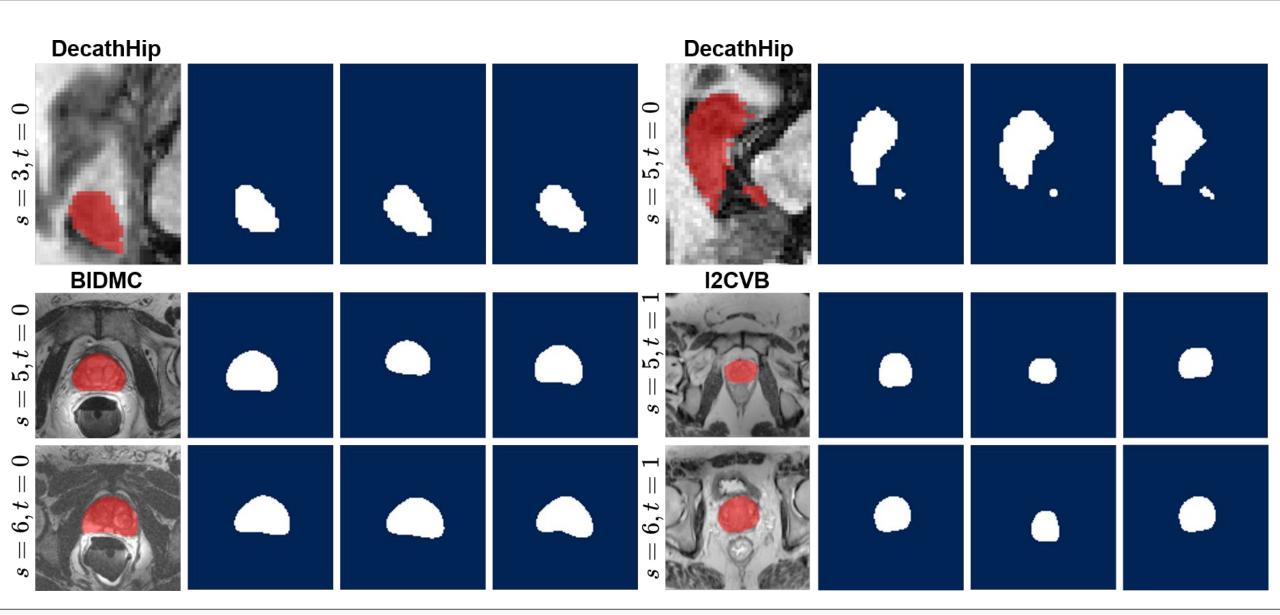
<sup>[</sup>GG22] González, C., Gotkowski, K., Fuchs, M., Bucher, A., Dadras, A., Fischbach, R., Kaltenborn, I.J., Mukhopadhyay, A.: Distance-based detection of out-of-distribution silent failures for covid-19 lung lesion segmentation. Medical image analysis 82, 102596 (2022)

<sup>[</sup>GR22] González, C., Ranem, A., Othman, A., Mukhopadhyay, A.: Task-agnostic continual hippocampus segmentation for smooth population shifts. MICCAI Workshop on Domain Adaptation and Representation Transfer pp. 108–118 (2022)

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### **Generated Features**





### Conclusion



- No modification of segmentation model
- ccVAE models data distributions
- Pseudo-rehearsal tackles catastrophic forgetting
- Distribution-awareness detects OoD subjects















**Martin Mundt**