Extrapolative Continuous-time Bayesian Neural Network for Fast Training-free Test-time Adaptation

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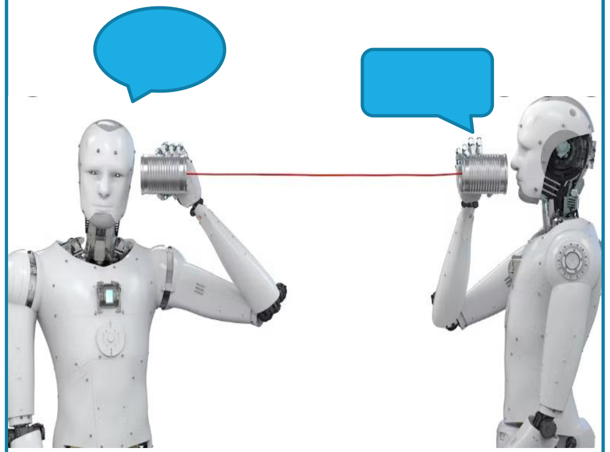
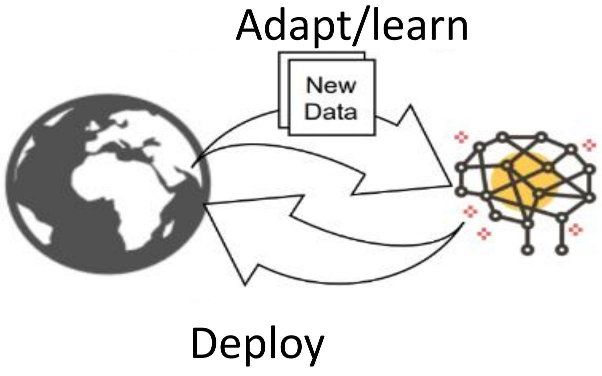
Background: mainstream artificial intelligence (AI)



Conversational AI

Generative AI



Adaptive AI

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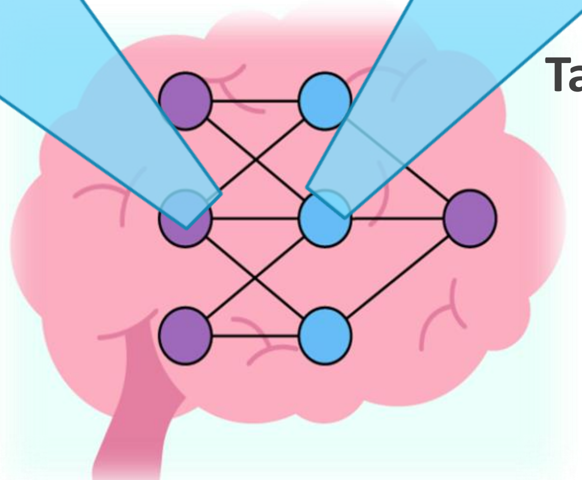
Background: brain-informed artificial intelligence (BAI)

Brain-informed component

- Modern theories and bio-solutions in Brain science

Task-specific component

- Target tasks in mainstream AI
- Conversational AI [**Huang**, et al. ICML 2020]
- Generative AI [**Huang**, et al. ICML 2021]

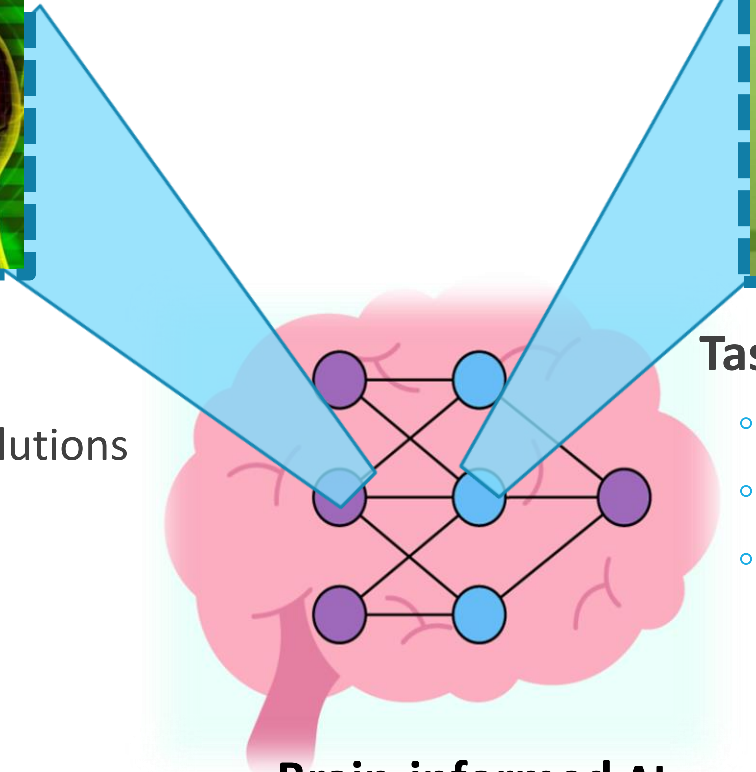


Brain-informed AI

Background: brain-informed artificial intelligence (BAI)

Brain-informed component

- Modern theories and bio-solutions in Brain science



Task-specific component

- Target tasks in mainstream AI
- Conversational AI [**Huang**, et al. ICML 2020]
- Generative AI [**Huang**, et al. ICML 2021]

Brain-informed AI

This work focus on adaptive AI. [**Huang**, et al. NeurIPS 2022]

Motivation: bio-adaptation VS artificial-adaptation

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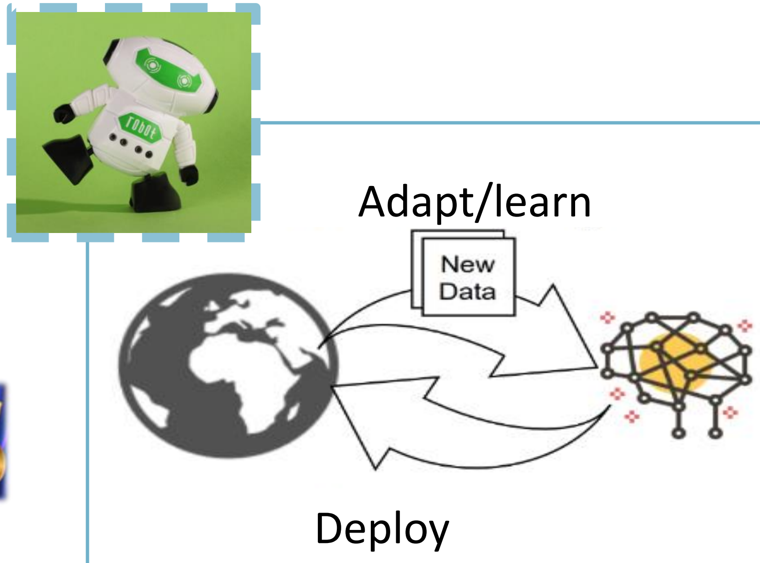
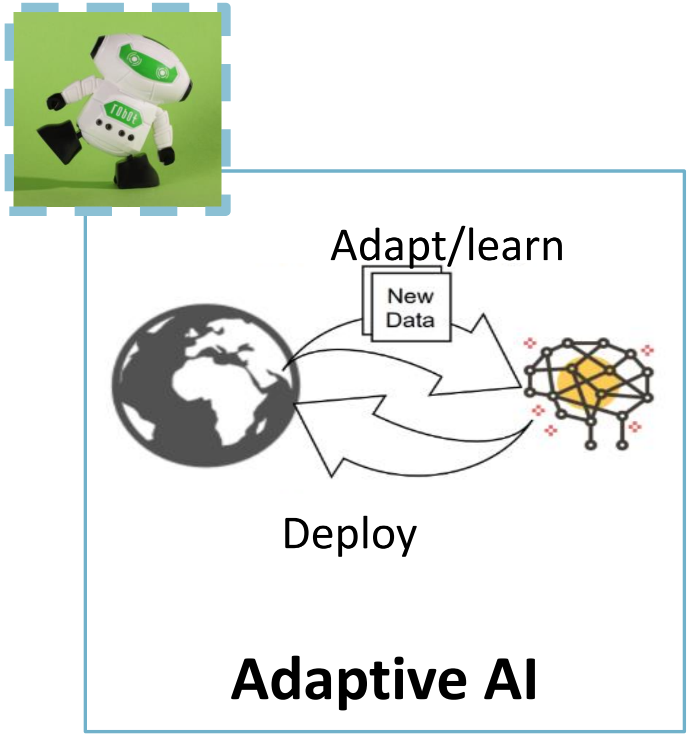
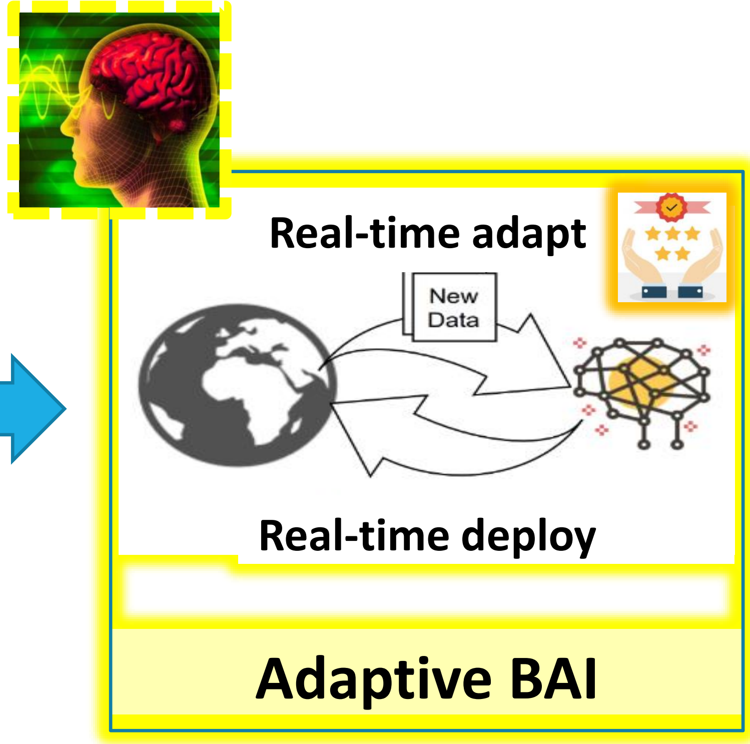


Adaptive AI

Fail to handle non-stationary data in real-time.

Research goal: from adaptive AI to adaptive BAI





Unsupervised domain adaptation (UDA)

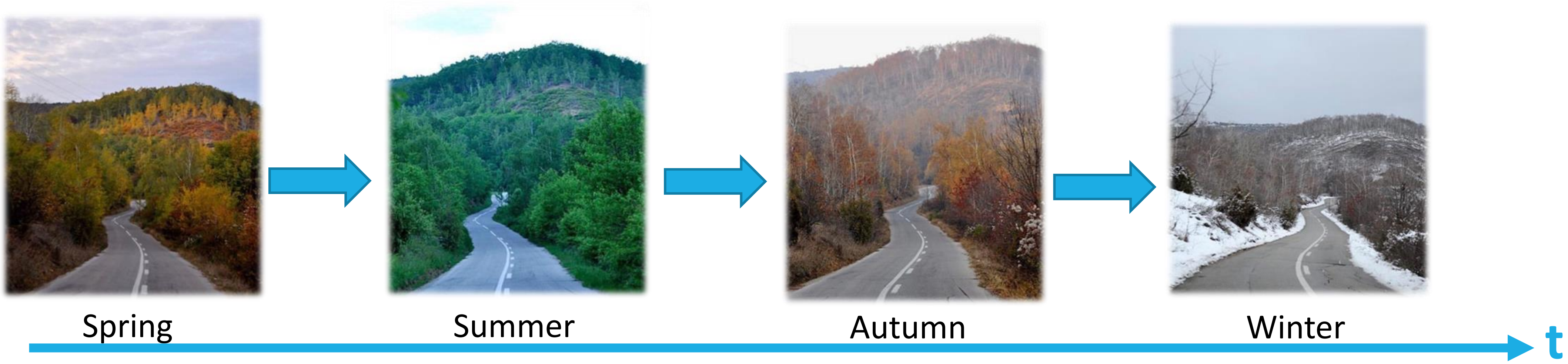
- Non-stationary (time-evolving) environment
- Labeled source domain and unlabeled target domain
- Effectively and efficiently learn from testing data
- Training-free test-time adaptation

Bio-solution: internal predictive modeling

An mechanism that supports bio-adaptation, which allows organisms to immediately and continuously adapt to non-stationary environment.

Key features:

① Capture the statistics and dynamics of surrounding environment



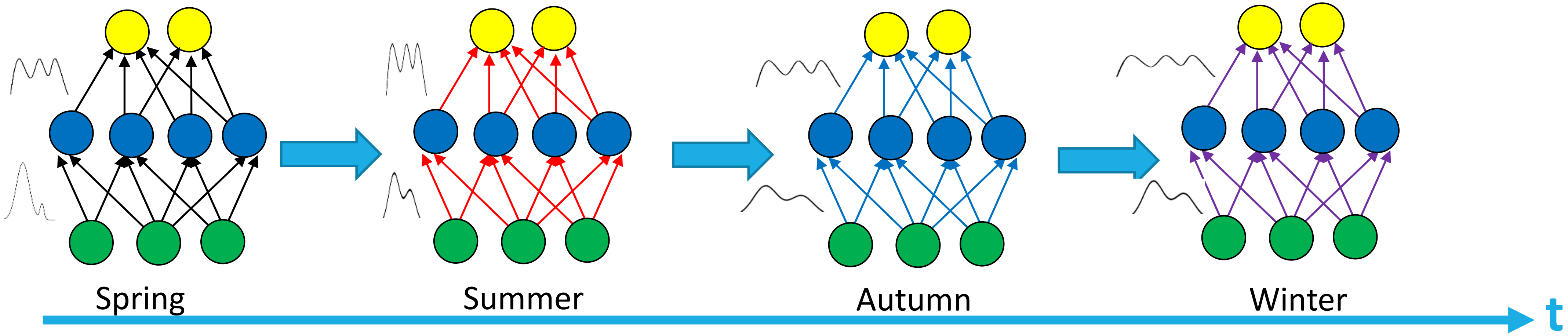
Artur Luczak and Yoshimasa Kubo. Predictive Neuronal Adaptation as a Basis for Consciousness. Frontiers in Systems Neuroscience, 15, 2022.

Bio-solution: internal predictive modeling

An mechanism that supports bio-adaptation, which allows organisms to immediately and continuously adapt to non-stationary environment.

Key features:

② Continually update an internal model based on "the learned dynamics"



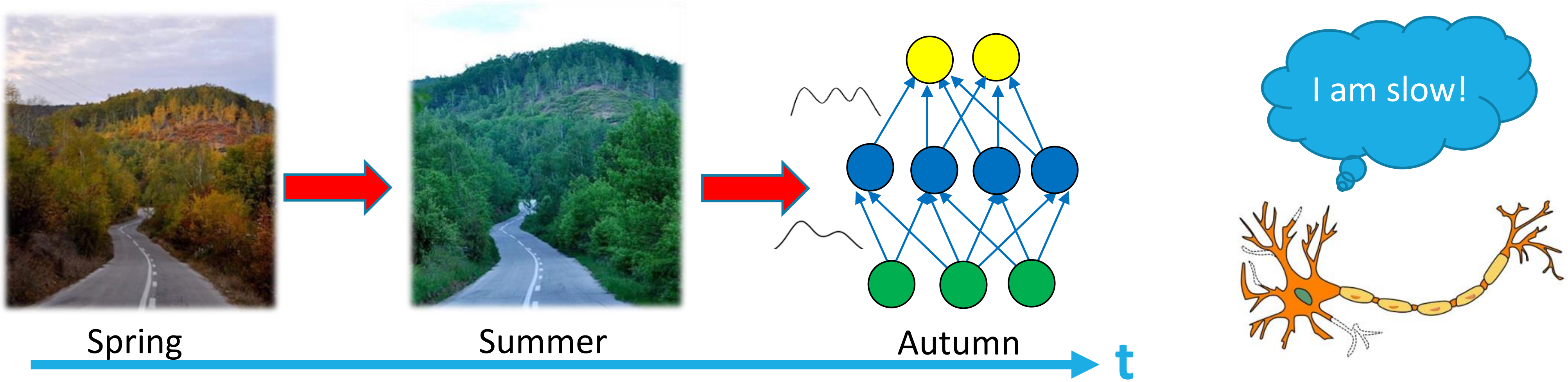
Ezgi Kayhan, et al. Ninemonth-old infants update their predictive models of a changing environment. Developmental cognitive neuroscience, 38:100680, 2019.

Bio-solution: internal predictive modeling

An mechanism that supports bio-adaptation, which allows organisms to immediately and continuously adapt to non-stationary environment.

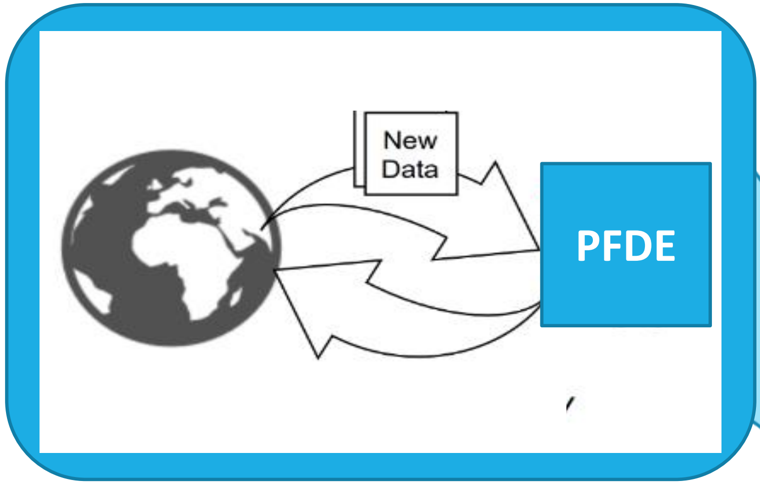
Key features:

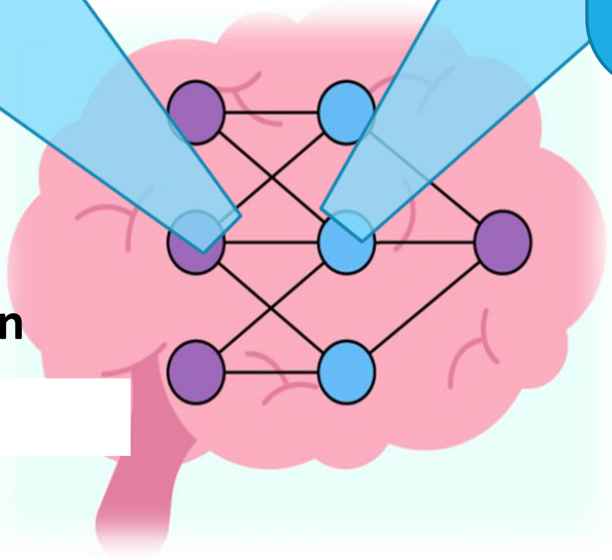
③ Effectively learn from history data to generate the “future model”, reducing latency and overcoming neural transmission delays.

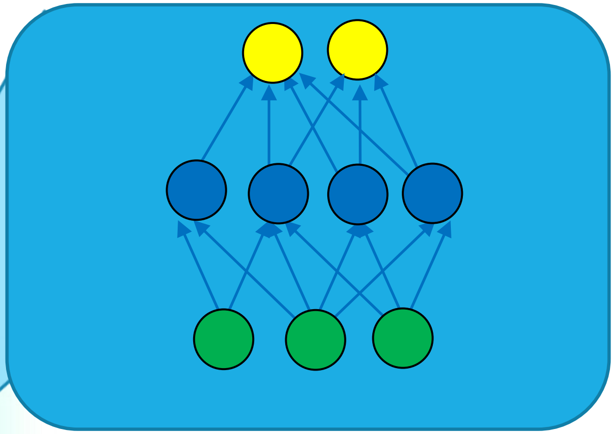


Hinze Hogendoorn. Perception in real-time: predicting the present, reconstructing the past. Trends in Cognitive Sciences, 26(2):128–141, 2022

Overview: connecting internal predictive modeling with adaptive AI







Brain-informed component

Particle filter differential equation (PFDE)

- Internal predictive modeling as a stochastic dynamical system

Task-specific component

Adaptive AI

- Unsupervised domain adaptation (UDA) models for streaming data

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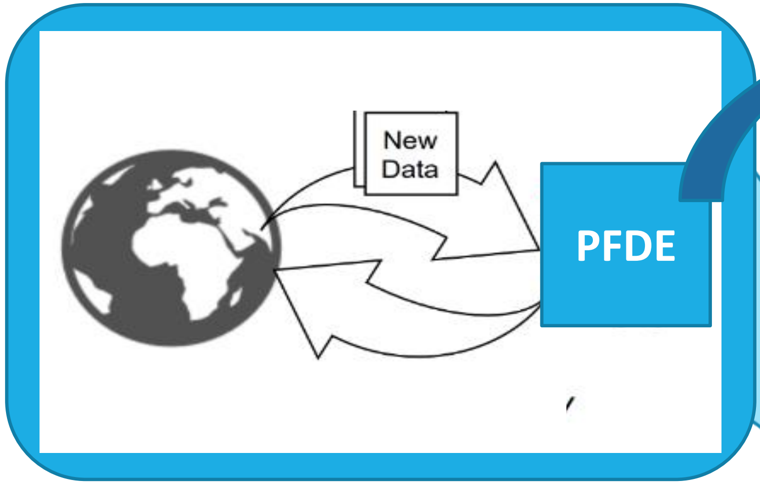

Brain-informed component

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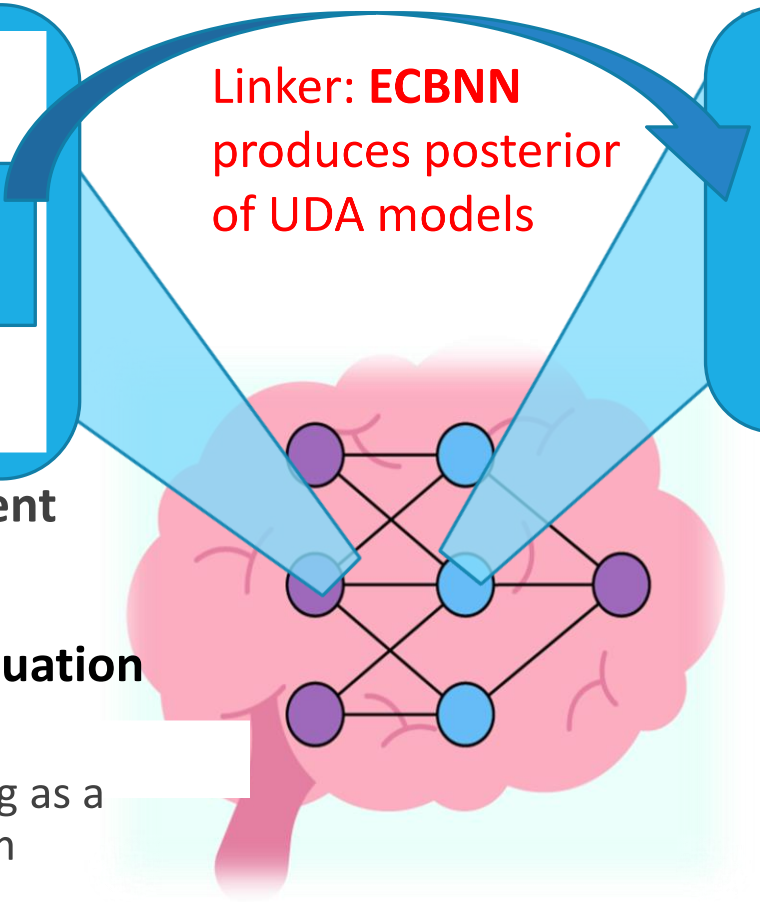
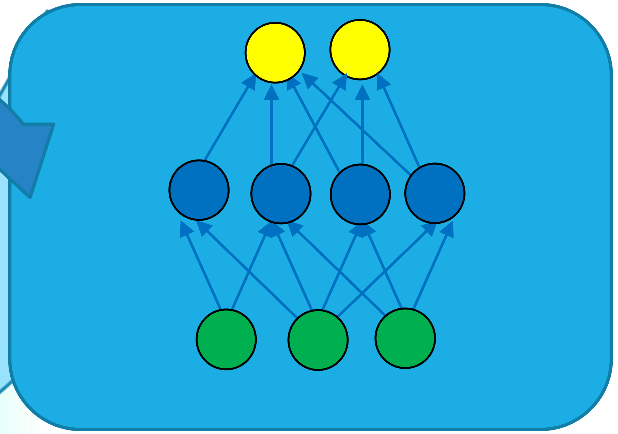




Task-specific component

Adaptive AI

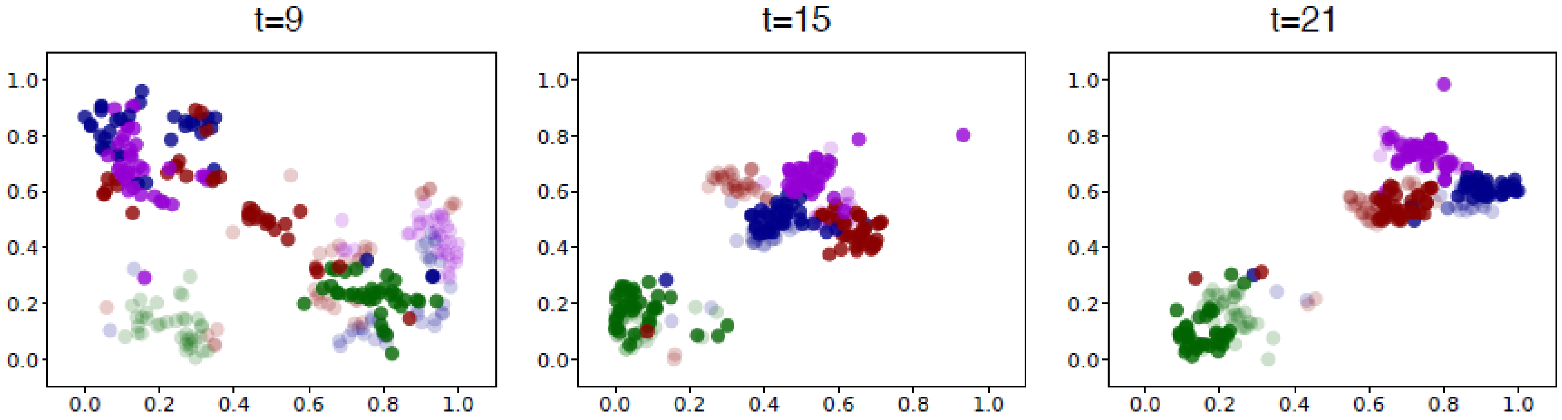
- Unsupervised domain adaptation (UDA) models for streaming data

Extrapolative continuous-time Bayesian neural network (ECBNN) as a bridge

Temporal-domain invariance for streaming data

Major challenge:

- Impractically aligning over partial observation of the stream leads to poor alignment quality
  - This work propose to align over the entire data generation mechanism (represented by PFDE)
  - Though such operation is intractable, we provide an analytical upper bound for achieving the temporal-domain invariance (Theorem 2)



Alignment are gradually improved during real-time testing!

Internal predictive modelling as a stochastic dynamical system

Our particle filter differential equation (PFDE)
(Theorem 1)

$$\boxed{\left(\log w(t)^{(j)}\right)'' = \left(\log p(\theta(t)^{(j)}|\theta(t-\tau)^{(j)})\right)''}$$

Internal predictive modelling as a stochastic dynamical system

Our particle filter differential equation (PFDE) (Theorem 1)

$$\left(\log \underbrace{\boxed{w(t)^{(j)}}}_{\text{Importance weight}}\right)'' = \left(\log \underbrace{\boxed{p(\theta(t)^{(j)} | \theta(t-\tau)^{(j)})}}_{\text{Transition distribution}}\right)''$$

Internal predictive modelling as a stochastic dynamical system

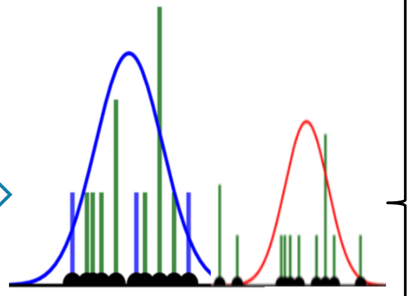
Our particle filter differential equation (PFDE) (Theorem 1)

$$\left(\log \boxed{w(t)^{(j)}}\right)'' = \left(\log \boxed{p(\theta(t)^{(j)}|\theta(t-\tau)^{(j)})}\right)''$$

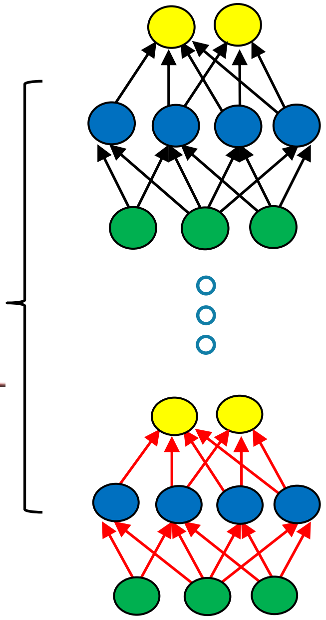
Importance weight

Transition distribution

Solve PFDE at time t



Model Posterior at time t



Model parameters of UDA

Quantitative results on streaming rotating digits

Accuracy (%) on Streaming Rotating MNIST→USPS

Method	MNIST Source	USPS Target	USPS OOD
Source-Only	97.8	28.8	24.9
DANN [27]	97.7	45.9	33.0
ADDA [28]	97.3	52.0	34.3
CIDA [30]	97.5	46.5	31.1
DSAN [29]	96.1	46.8	33.0
EDA [11]	**97.9**	45.5	31.9
ECBNN (Ours)	97.1	**60.9**	**38.5**

Ablation study (Accuracy (%))

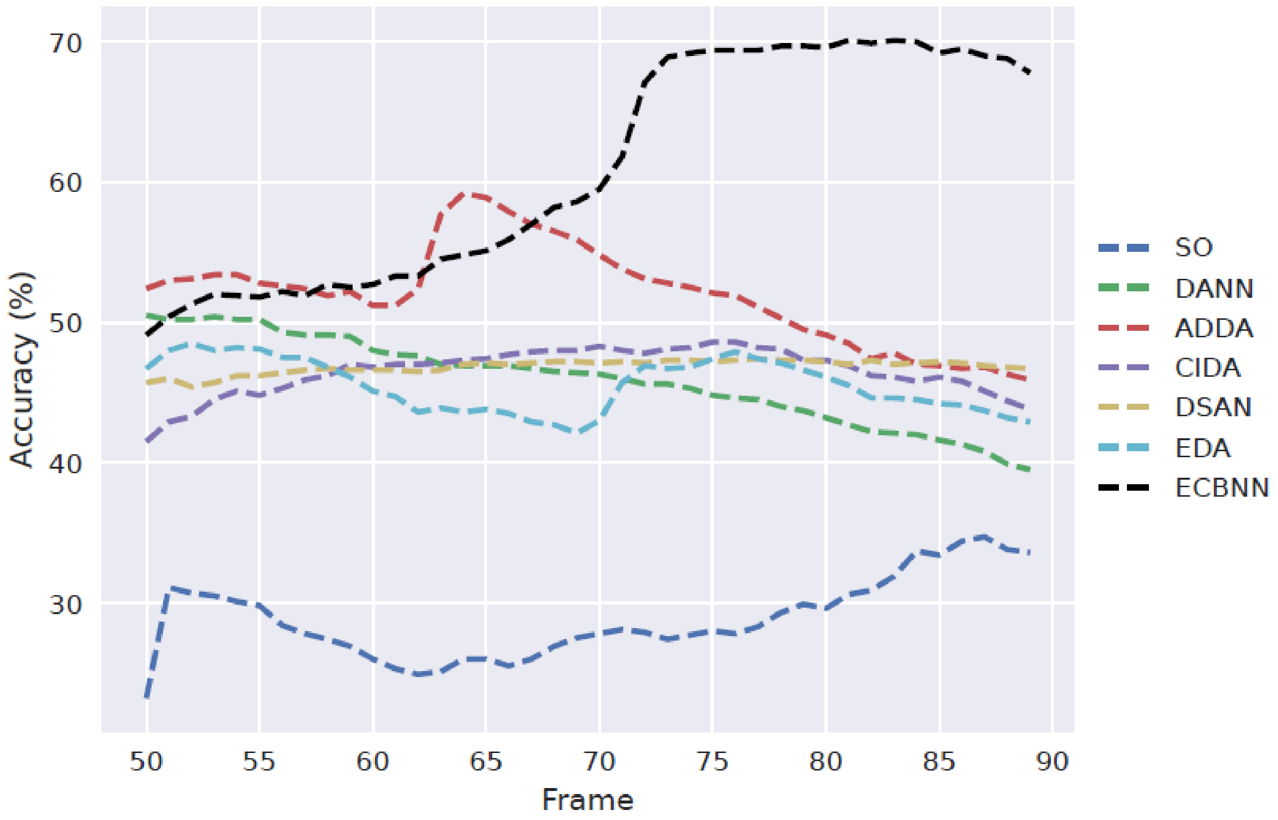
Method	Target Domain ↑	Out-of-Domain ↑
ECBNN (ours)	60.9	38.5
w/o $\widetilde{l_i}$	53.6 (-7.3)	29.9 (-8.6)
w/o $\widetilde{l_i}$ & w/o l_{de}	43.2 (-17.5)	28.0 (-9.5)

$\widetilde{l_i}$: upper bound of temporal-domain-invariant loss

l_{de} : PFDE loss

ECBNN can effectively "learn" from testing data in real-time!

Frame-wise accuracy on Streaming Rotating USPS testing set



ECBNN can adapt with much lower latency during real-time testing stage!

Run time (s) for model adaptation and Accuracy (%) on OuluVS2 Dataset

Method	Run time	Target
Source-Only	-	46.0
DANN [27]	-	71.5
ADDA [28]	-	69.3
CIDA [30]	-	63.0
DSAN [29]	-	66.4
EDA [11]	0.23	70.3
ECBNN (Ours)	**0.01**	**75.3**

Thanks!
Q&A on poster

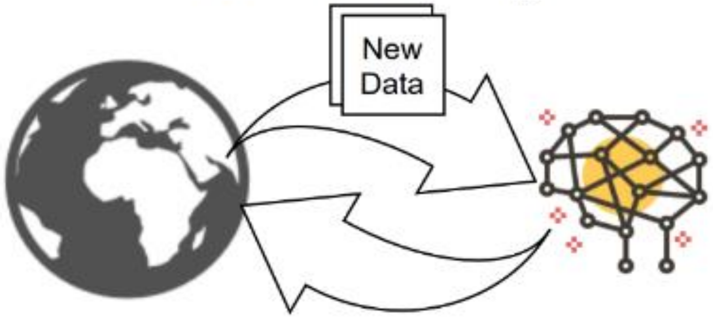
Reference

Huang, H., Xue, F., Wang, H., & Wang, Y. (2020, November). Deep graph random process for relational-thinking-based speech recognition. In *International Conference on Machine Learning* (pp. 4531-4541). PMLR.

Huang, H., Liu, H., Wang, H., Xiao, C., & Wang, Y. (2021, July). STRODE: Stochastic Boundary Ordinary Differential Equation. In *International Conference on Machine Learning* (pp. 4435-4445). PMLR.

Huang, H., Gu X., Wang, H., Xiao, C., Liu, H., & Wang, Y. (2022, Dec). Extrapolative Bayesian Neural Network for Real-time Streaming Domain Adaptation. In *Advances in Neural Information Processing Systems*.

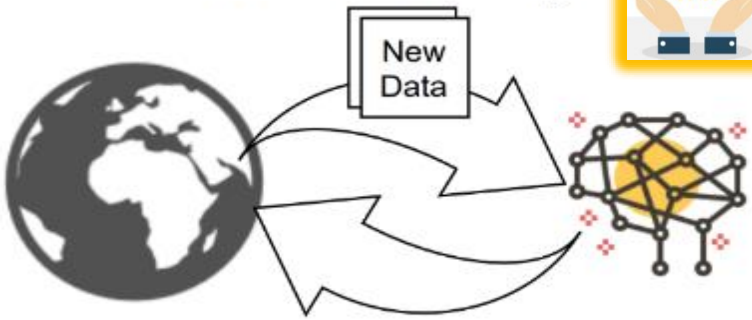
Adapt/learn



Deploy

Adaptive AI

Real-time adapt



Real-time deploy

Adaptive Brain-informed AI