On Continual Model Refinement in Out-of-Distribution Data Streams


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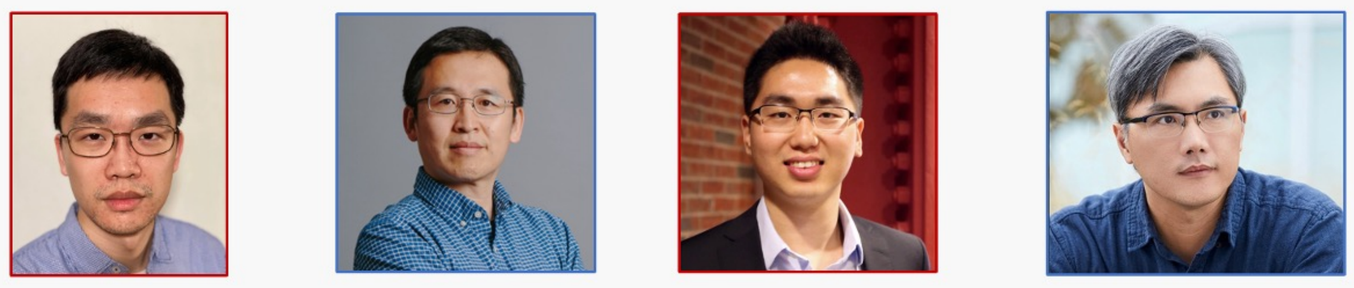
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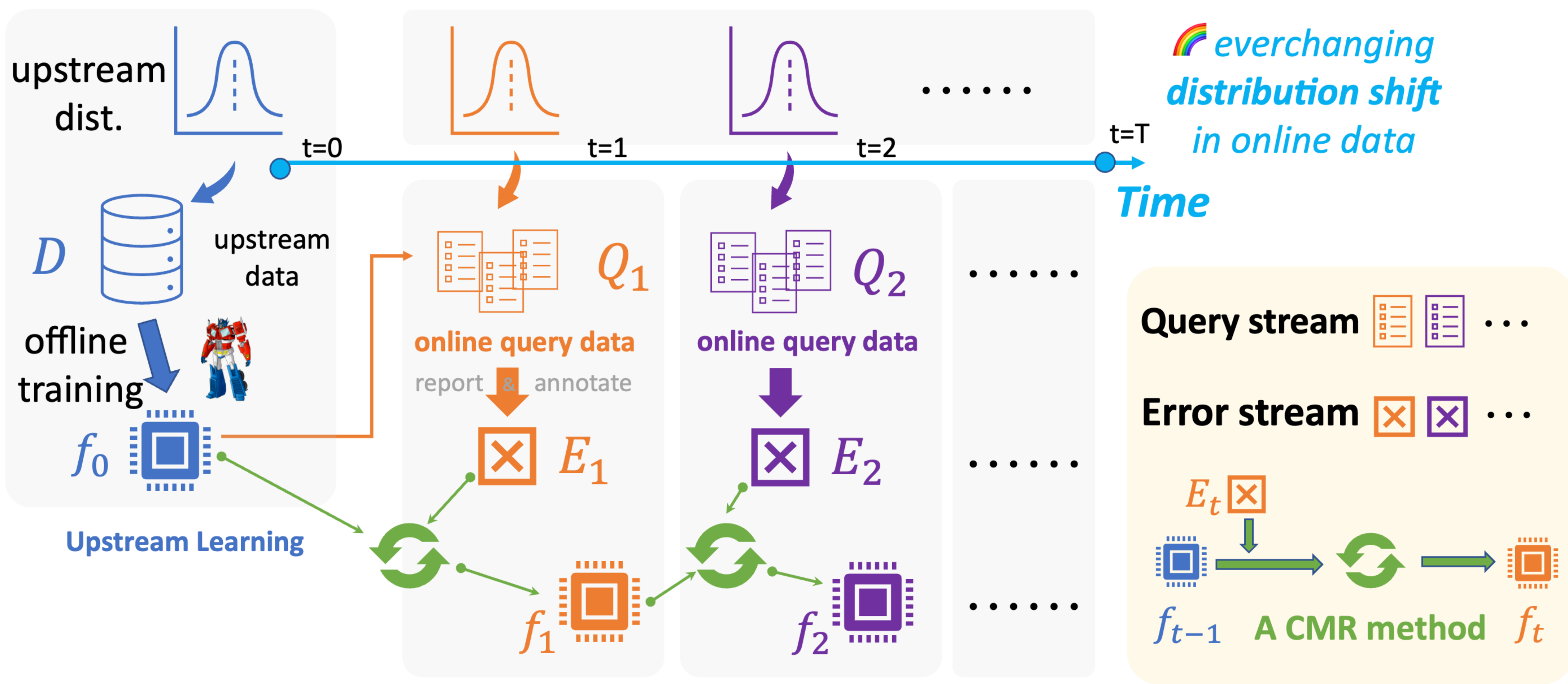
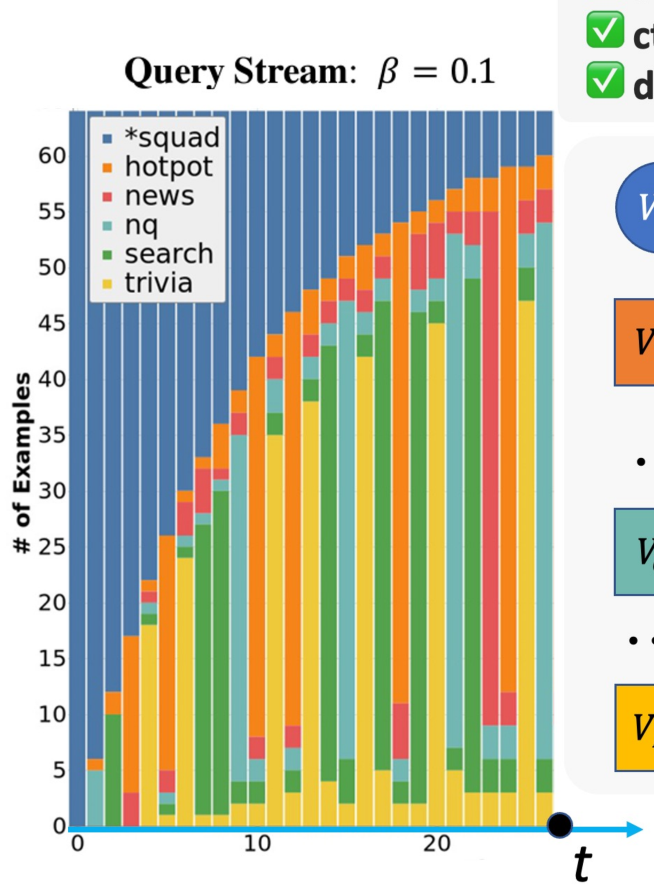
Continual Model Refinement (CMR)



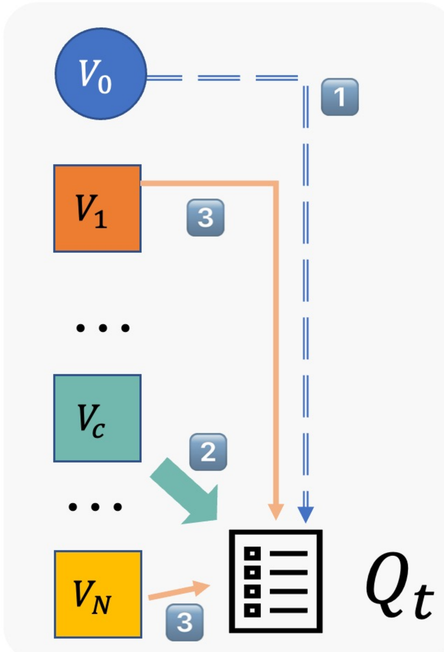
Evaluating CMR: OOD Data Stream

Algorithm 1: Sampling query streams with *controllable non-stationarity* from multiple data clusters.

Input Data Clusters: $V_0, V_1, \ldots, V_N$
Configuration Arguments: $T, b, (\alpha, \beta, \gamma)$.
Output: A query stream $\{Q_1, Q_2, \ldots, Q_T\}$
foreach t *in* range$(1, T)$ **do**
- $b_u = \lfloor b * \alpha^{t-1} \rceil;\ b_o = b - b_u\ ;\ b'_o = \lfloor b_o * \gamma \rceil$
- $c_t \sim P(c|c_{t-1}; \beta)$
- /* The prob. of switching the major OOD data cluster is $1-\beta$, i.e., $P(c_t \neq c_{t-1}) = 1 - \beta$ */
- $V_{\neq c_t} = \bigcup_{\{k \in [1,N] | k \neq c_t\}} V_k$
- 1 $Q_t \leftarrow \text{sample}(V_0, b_u)$
- /* $V_0 \sim \mathcal{U}$; from upstream distribution */
- 2 $Q_t \mathrel{+}= \text{sample}(V_{c_t}, b'_o)$
- /* from the current major OOD data cluster */
- 3 $Q_t \mathrel{+}= \text{sample}(V_{\neq c_t}, b_o - b'_o)$
- /* from non-major data clusters */



✅ boundary-agnostic
✅ ctrl. non-stationarity
✅ diverse OOD mixture



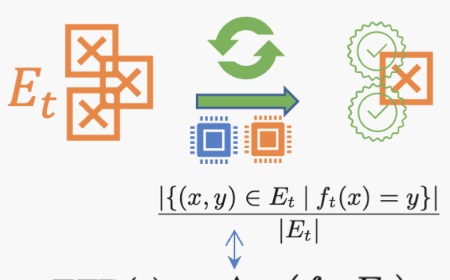
Methods ↓ Metrics →	$\overline{\text{EFR}}$	UKR$^{(T)}$	OKR$^{(T)}$
Frozen Upstream ($f_t \equiv f_0$)	0.00	80.27	36.13
● Continual Fine-Tuning	97.36	66.21	77.73
■ Online L2Reg.	97.18	71.09	83.59
▲ Online EWC	97.49	68.55	85.74
✚ Exp. Replay	97.07	72.46	87.30
◆ MaxLoss	97.43	75.00	84.77
▶ MIR	97.08	75.78	87.50
Offline Refining ($f_0 \rightarrow f_T$)	*95.62*	*83.78*	*93.75*

all can fix the errors pretty well (on average)

forget upstream knowledge

forget online knowledge

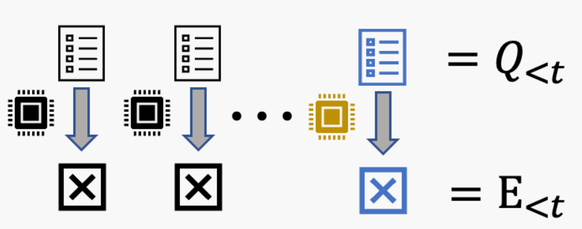
Error Fixing Rate (EFR)



$\text{EFR}(t) =: \textbf{Acc}(f_t, E_t)$

Cumulative Success Rates (CSR)

$\textbf{CSR}(t) =: 1 - |E_{<t}| / |Q_{<t}|$



Upstream Knowledge Retention (UKR)

$\textbf{UKR}(t) =: \text{Acc}(f_t, D)$ test

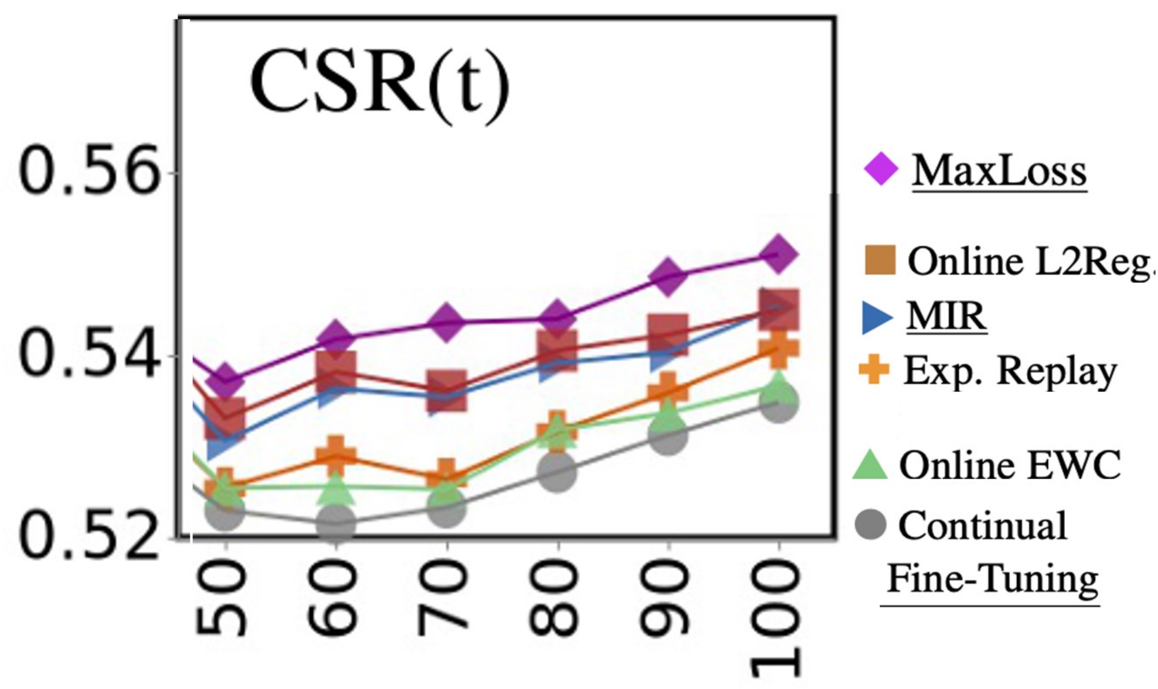
Online Knowledge Retention (OKR)

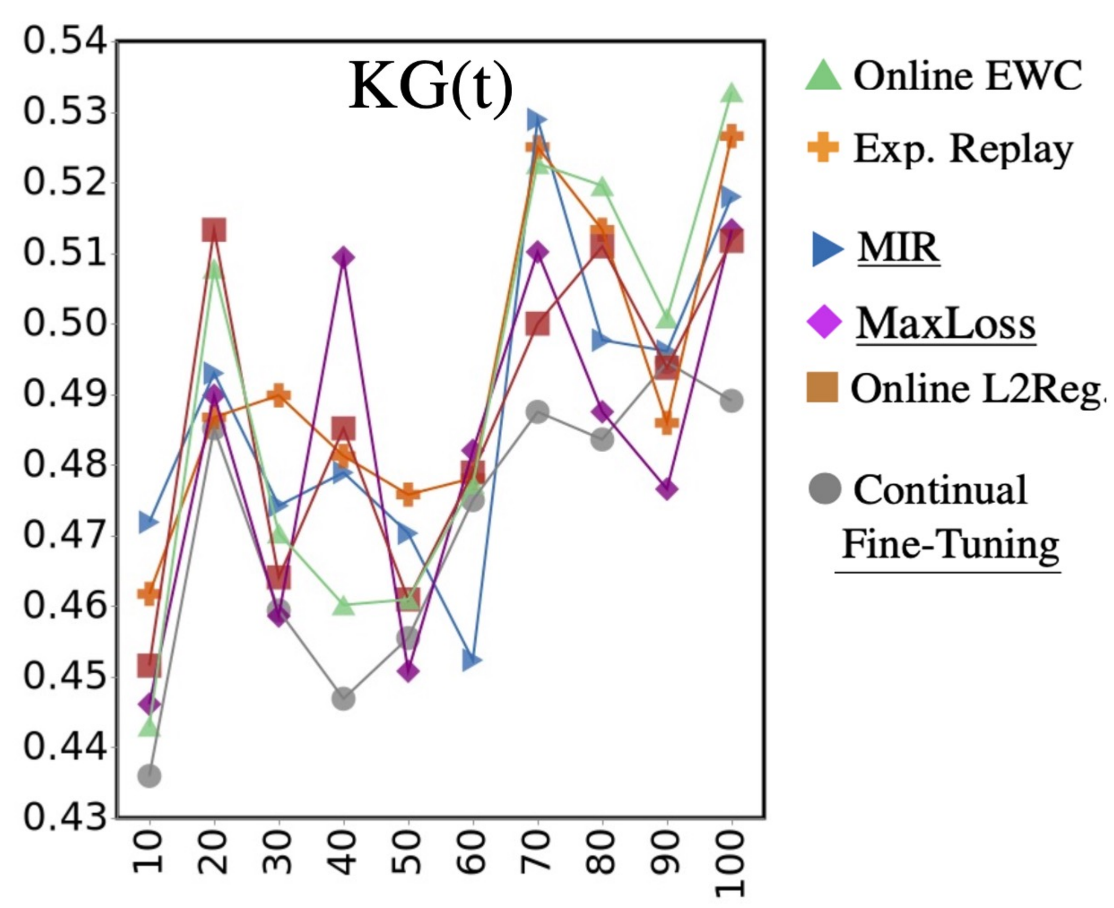
$\textbf{OKR}(t) =: \text{Acc}(f_t, Q_{<t})$ test

Knowledge Generalization (KG)

$\textbf{KG}(t) =: \text{Acc}(f_t, H)$

t=T test

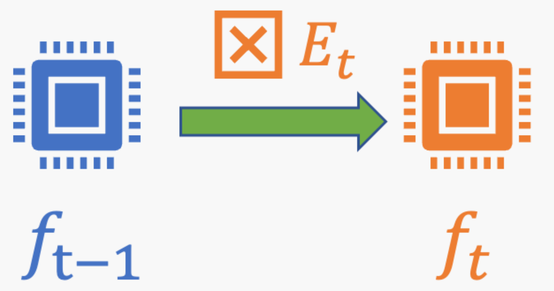




CMR Methods: Regularization | Replay

$$\mathcal{L}_{\text{total}}(t) = \mathcal{L}_{\text{Error}}(t) + \lambda \mathcal{L}_{\text{Reg}}(t)$$

● Continual Fine-Tuning

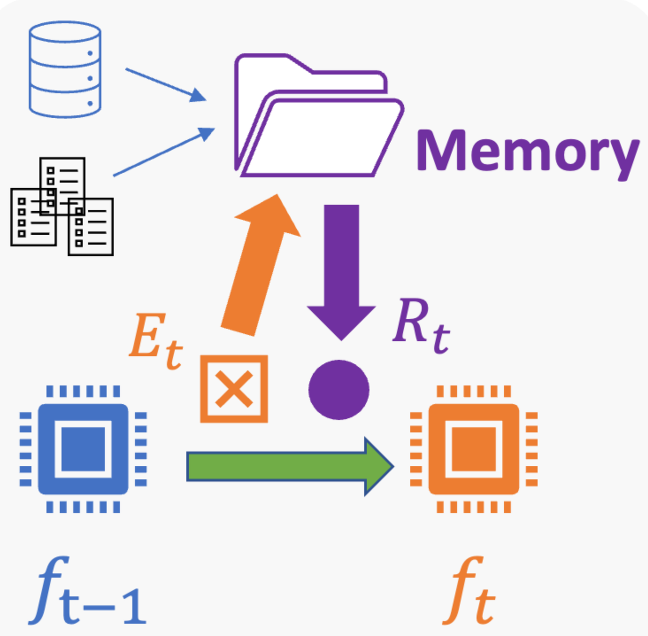


■ Online L2Reg.

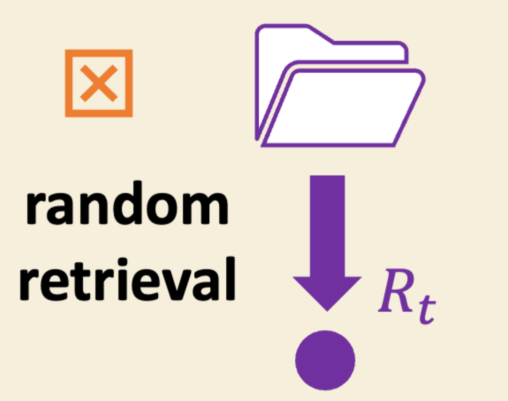
$$\mathcal{L}_{\text{L2Reg}}(t) = \sum_i \left(\theta_t^i - \theta_{t-1}^i\right)^2$$

▲ Online EWC

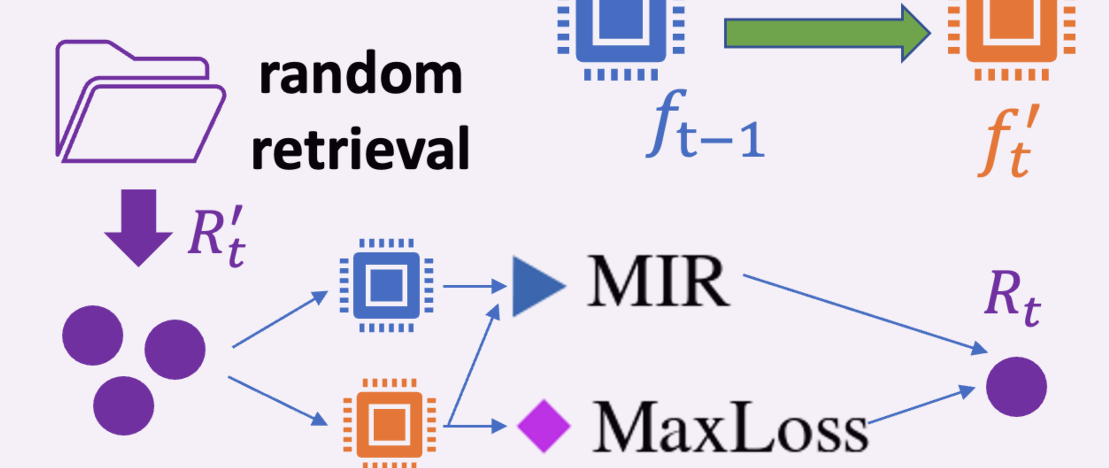
$$\mathcal{L}_{\text{EWC}}(t) = \sum_{j=1}^{t-1} \left(\frac{1}{2} \sum_i F_{ii}^{(j)} \left(\theta_t^i - \theta_{t-1}^i\right)^2 \right)$$



✚ Exp. Replay



Conditional Replay



The typical CL setup
- boundary-aware
- pre-defined data streams
- disallowing revisiting the past dist.
- single dist. to learn in a period

CMR: a more realistic CL setup
- boundary-agnostic
- dynamic streams of pred. errors
- allowing revisiting the past dist.
- diverse mixtures of OOD data

https://cmr-nlp.github.io/