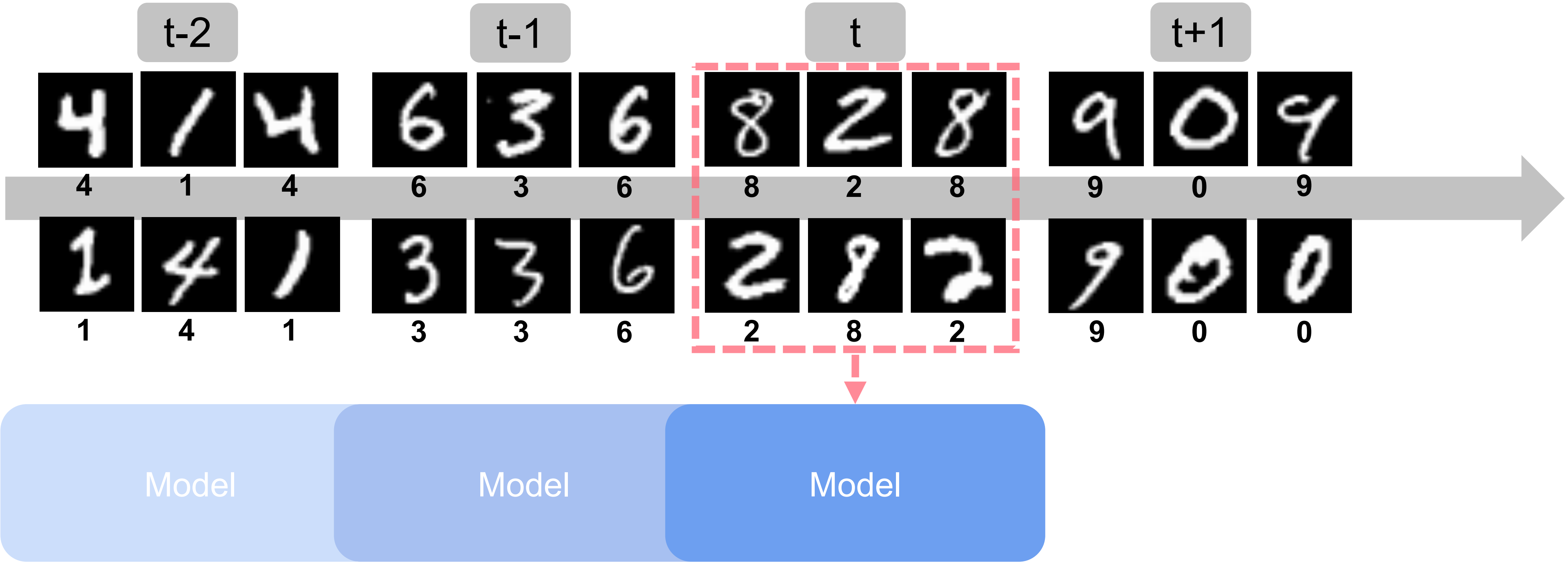
Continual Learning on Noisy Data Streams via Self-Purified Replay

Chris Dongjoo Kim* **Jinseo Jeong*** **Sangwoo Moon** **Gunhee Kim**

(* indicates equal contribution)

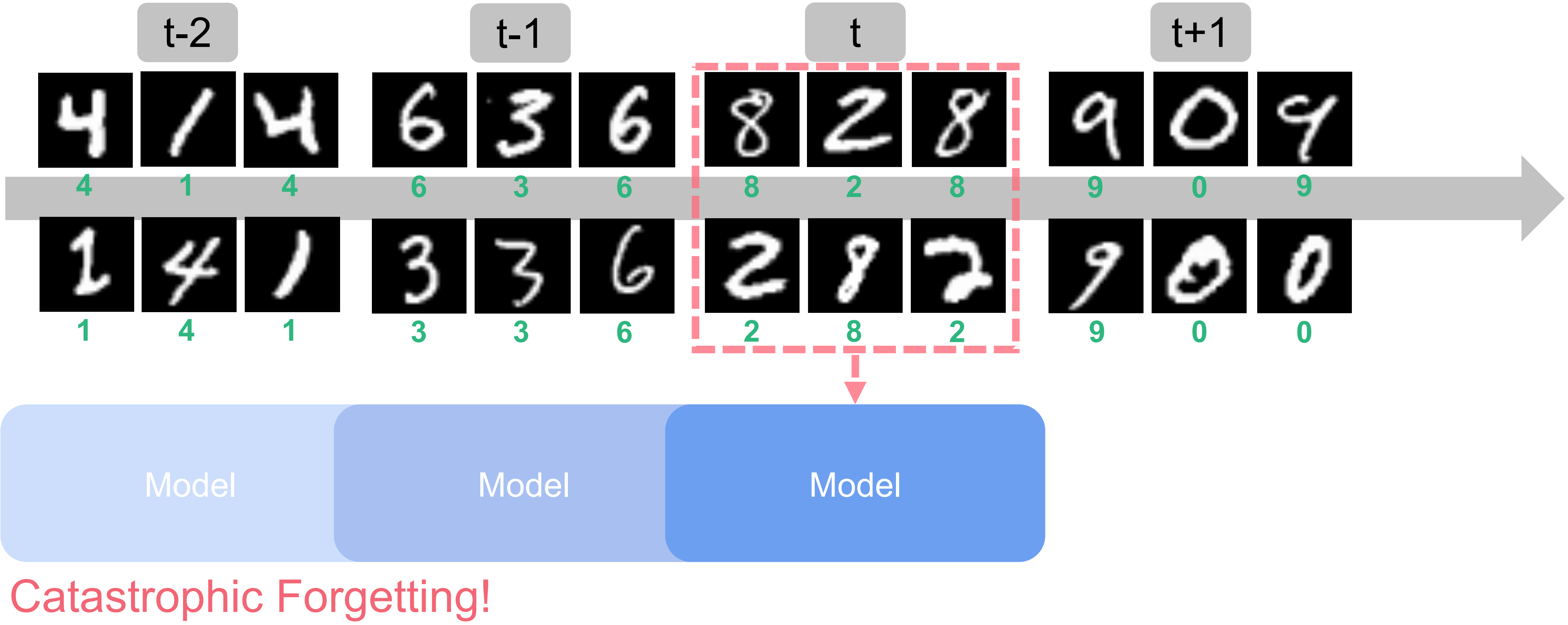
SEOUL NATIONAL UNIV.
VISION & LEARNING

Continual Learning with Noisy Labels

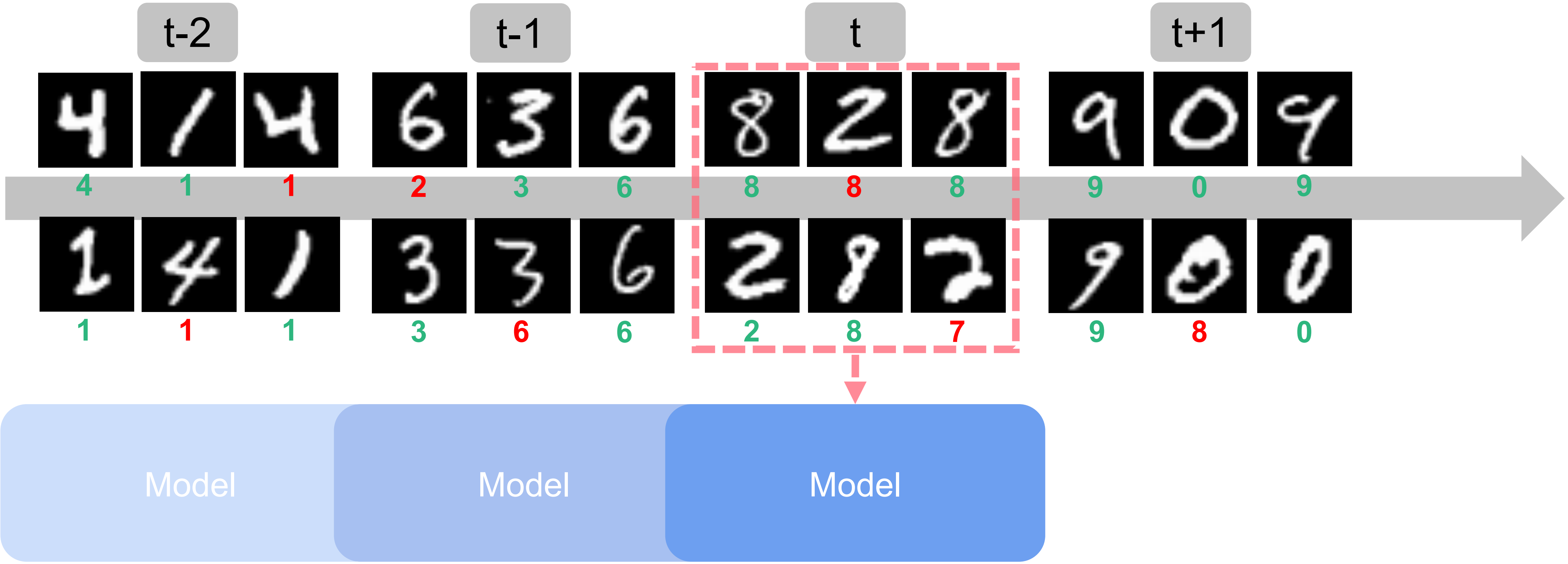


Catastrophic Forgetting!

Continual Learning with Noisy Labels



Continual Learning with Noisy Labels

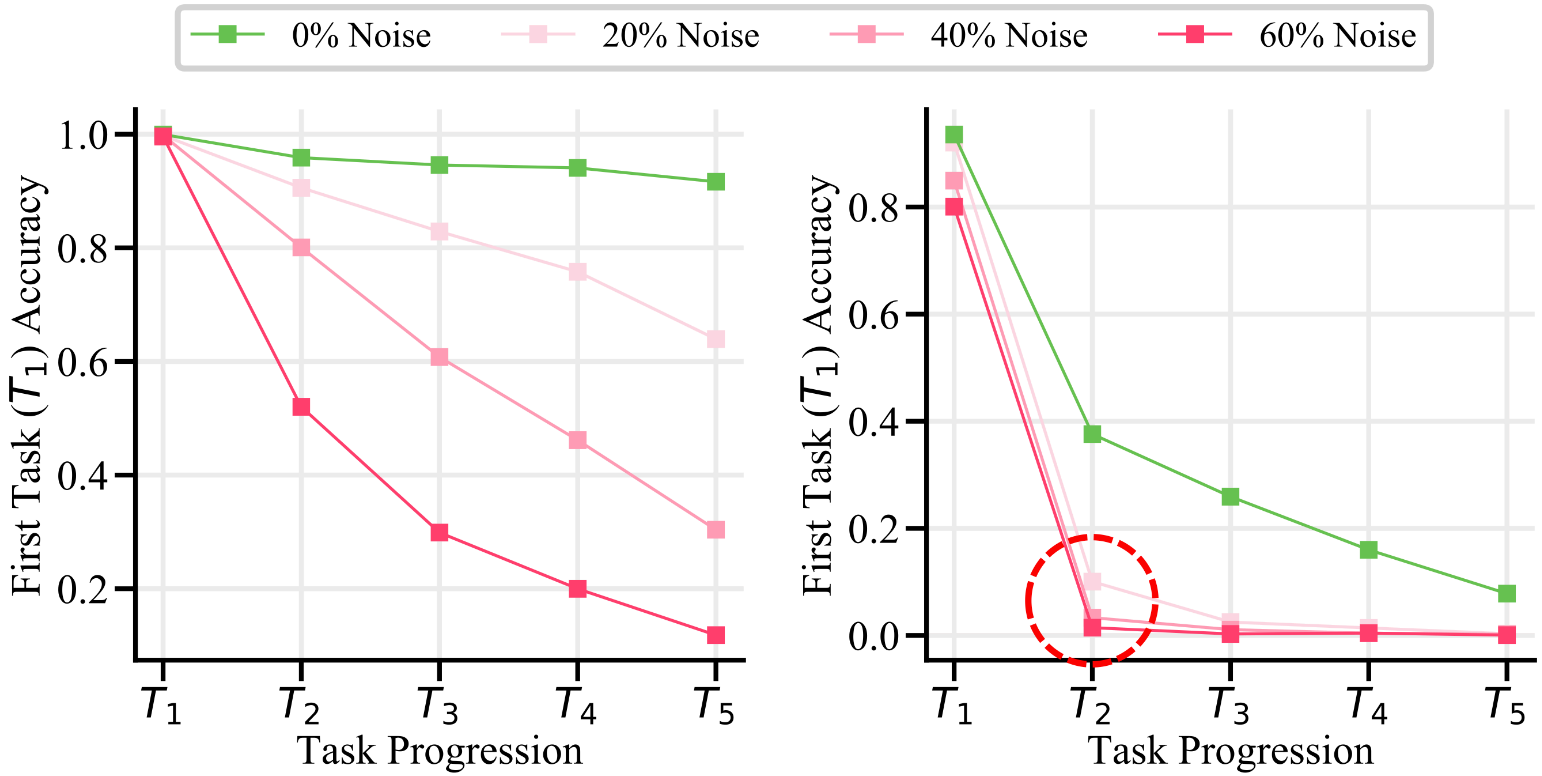


Catastrophic Forgetting!

✓ First work to explore this

Noise Induced Amnesia

- Our empirical investigation exposes a profound worsening of catastrophic forgetting when the data has noisy labels.



(a) MNIST (b) CIFAR-10

Noisy Labeled Continual Learning

Goal. Continually learn from a stream of noisy labeled data.

Subgoal 1.
Reduce forgetting even with noisy labels.

Existing continual learning approaches:
- Relies on correct {x,y} pairings to mitigate forgetting.

✓ Self-Replay

Subgoal 2.
Filter clean data.

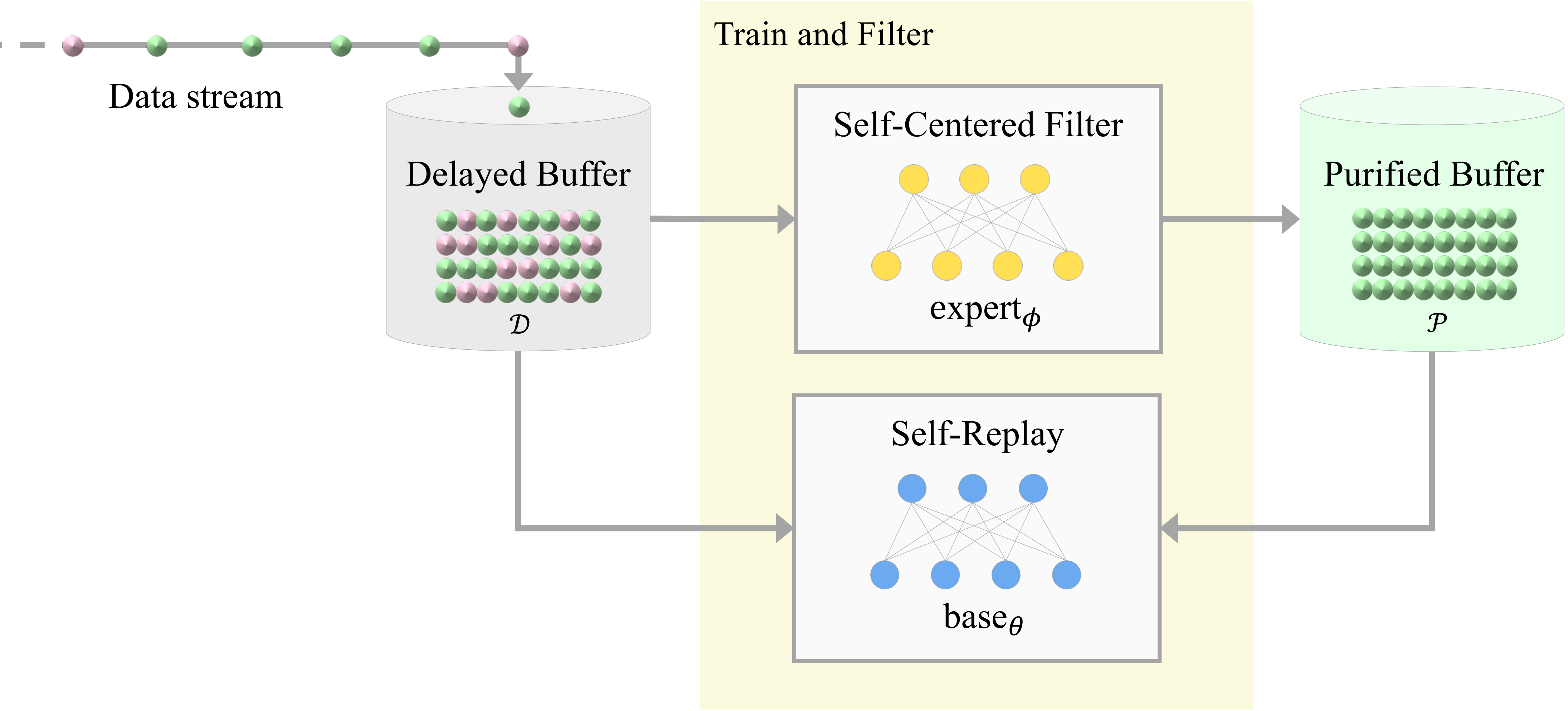
Existing noisy label approaches:
- Difficulty in processing small portion of data.
- Relies on training dynamics.

✓ Self-Centered Filter

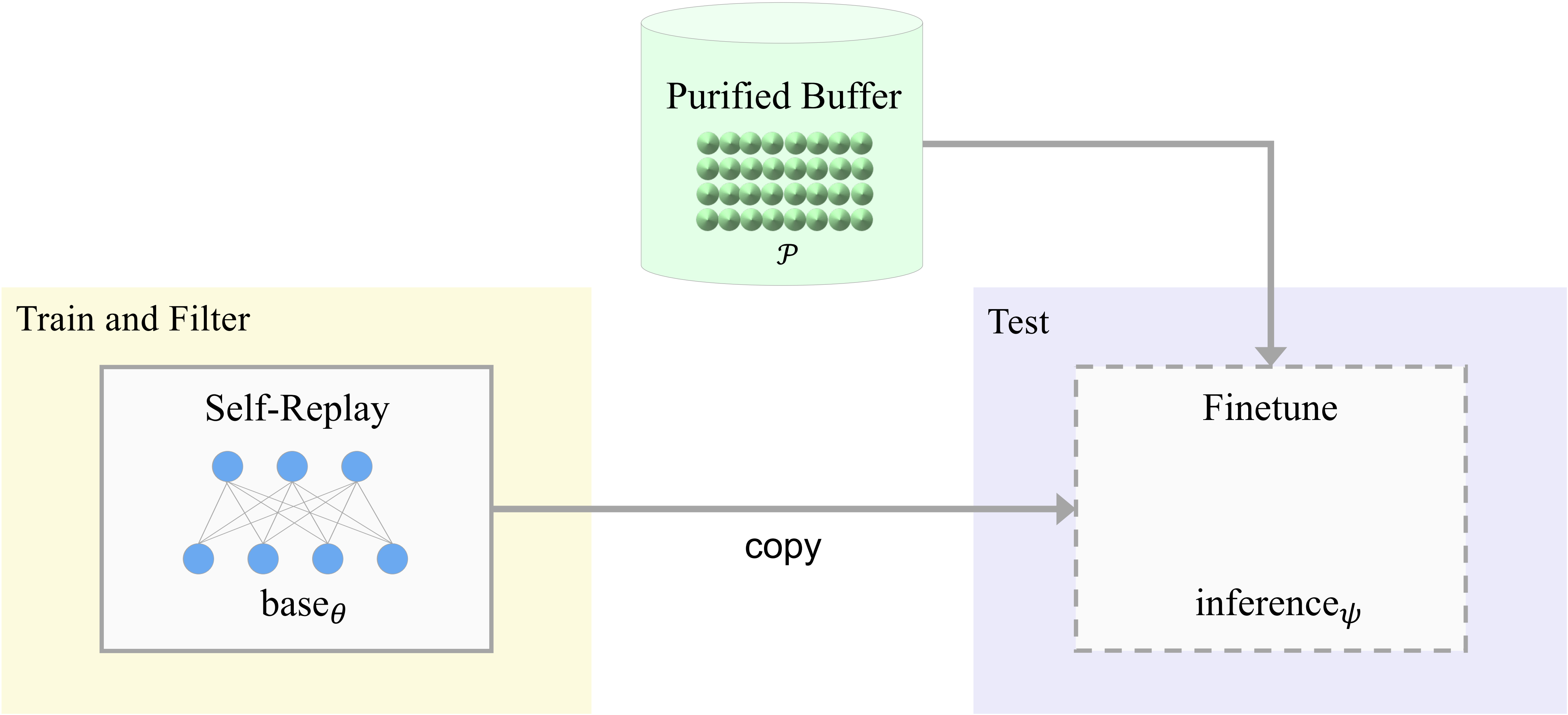
Aljundi et al., *Gradient based sample selection for online continual learning*, NeurIPS, 2020
Kirkpatrick et al., *Overcoming catastrophic forgetting in neural networks*, NeurIPS, 2017
Hayes et al., *Memory efficient experience replay for streaming learning*, ICRA, 2019
Javed et al., *Meta-learning representations for continual learning*, NeurIPS, 2019

Huang et al., *Simple noisy label detection approach for deep neural networks*, ICCV, 2019
Pleiss et al., *Identifying mislabeled data using area under the margin ranking*, NIPS, 2020
Li et al., *Dividemix: Learning with noisy labels as semi-supervised learning*, ICLR, 2020
Zhang et al., *Dualgraph: A graph-based method for reasoning about label noise*, CVPR, 2021

Self-Purified Replay Framework



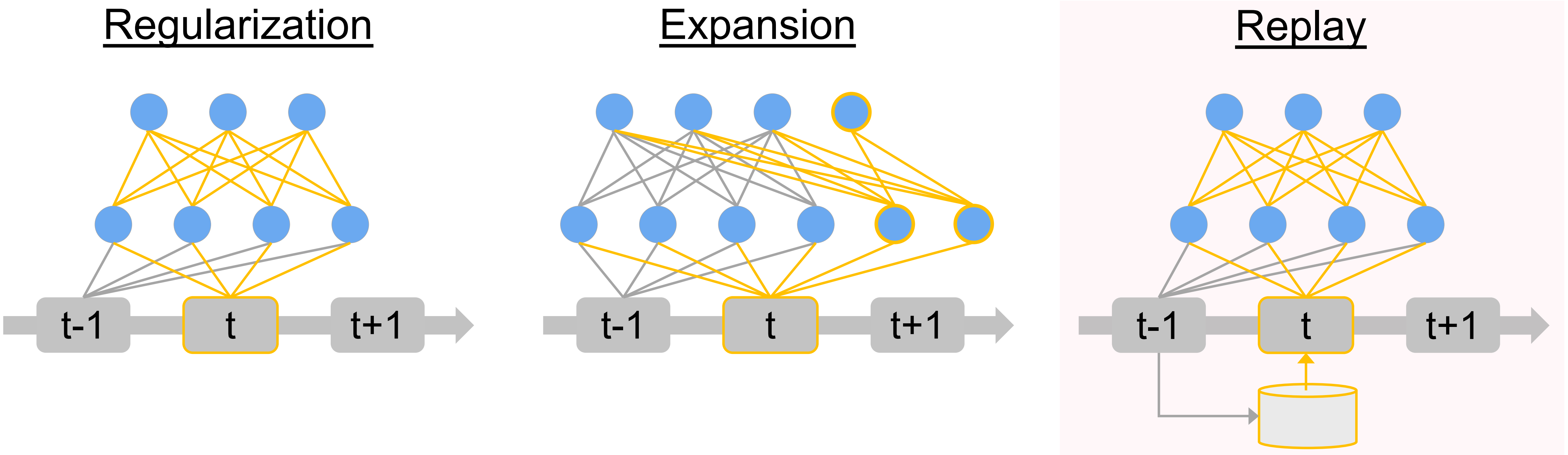
Self-Purified Replay Framework



Self-Replay

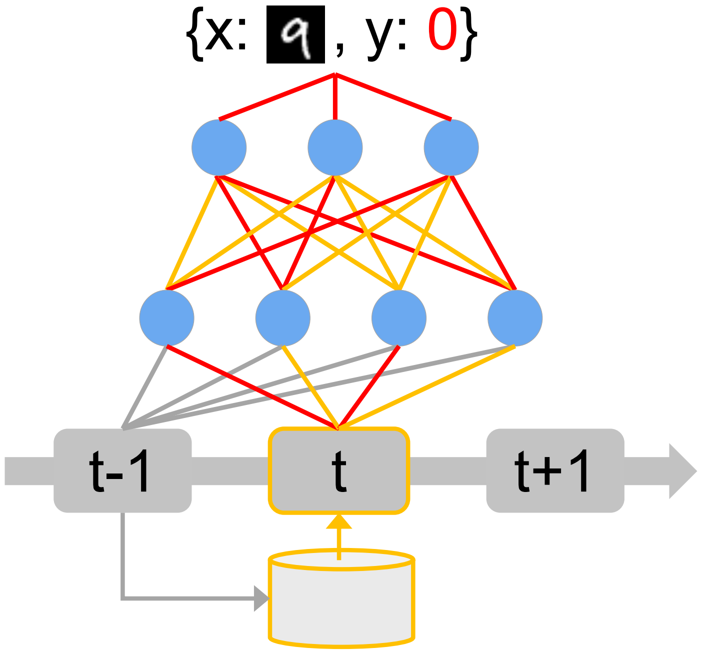
Goal. Reduce the forgetting even with noisy labels.

In Continual Learning literature, there mainly exist 3 branches to mitigate forgetting.



Self-Replay

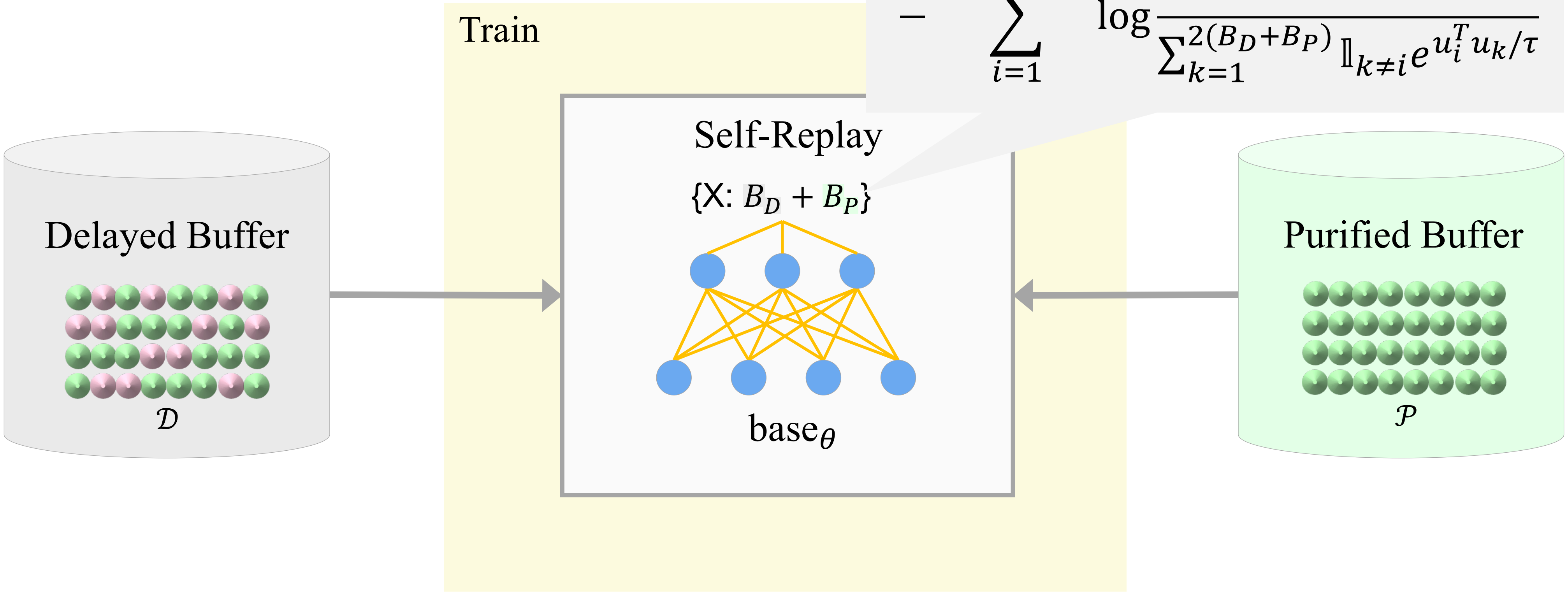
- **Goal.** Reduce the forgetting even with noisy labels.
- **Observation.** Noisy labeled data is only problematic when you learn from both input {x} *and* label {y}. However, if you learn the representation only using {x}, there are no errors.



Self-Replay

- Self-Replay: Self-Supervised replay for continually relevant and rich representations.

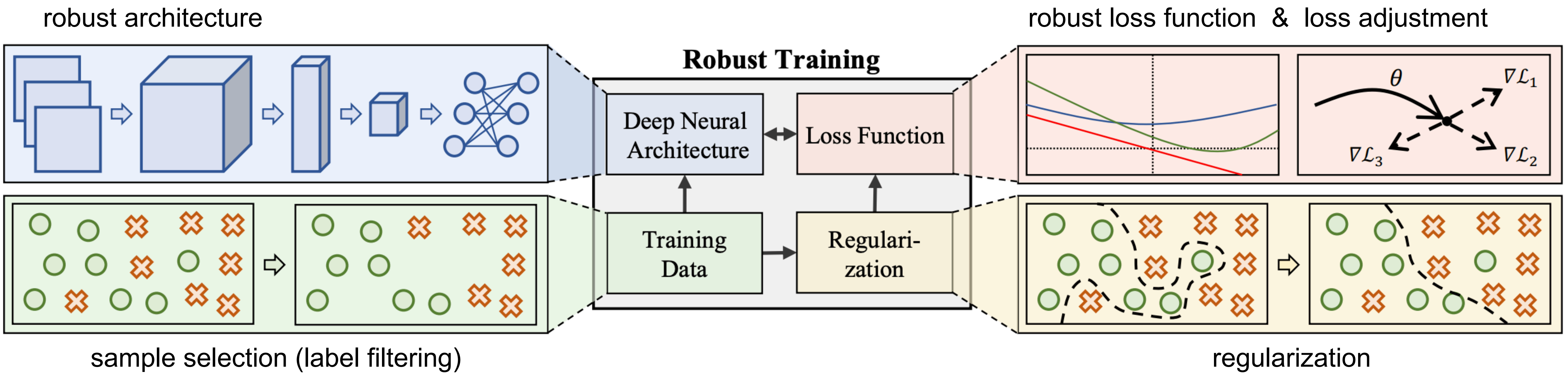
$$-\sum_{i=1}^{2(B_D+B_P)} \log \frac{e^{u_i^T u_j/\tau}}{\sum_{k=1}^{2(B_D+B_P)} \mathbb{1}_{k\neq i} e^{u_i^T u_k/\tau}}$$



Self-Centered Filter

Goal. Filter clean data (using only Delayed Buffer contents).

In the label noise literature, there exist ~4 main high-level perspectives leveraged to design robust models for noisy labels.

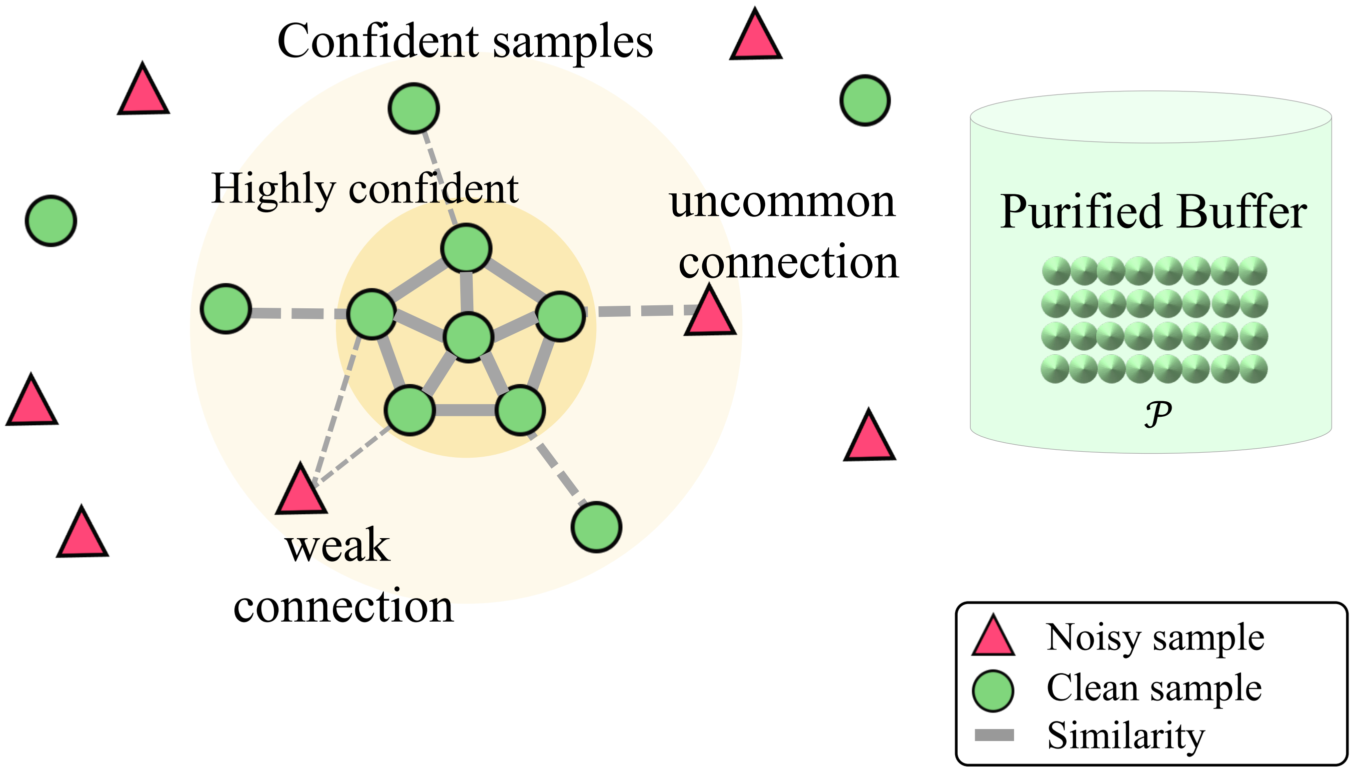


Song et al., *Learning from Noisy Labels with Deep Neural Networks: A Survey*, arxiv: 2007.08199

Self-Centered Filter

Goal. Filter clean data (using only Delayed Buffer contents).

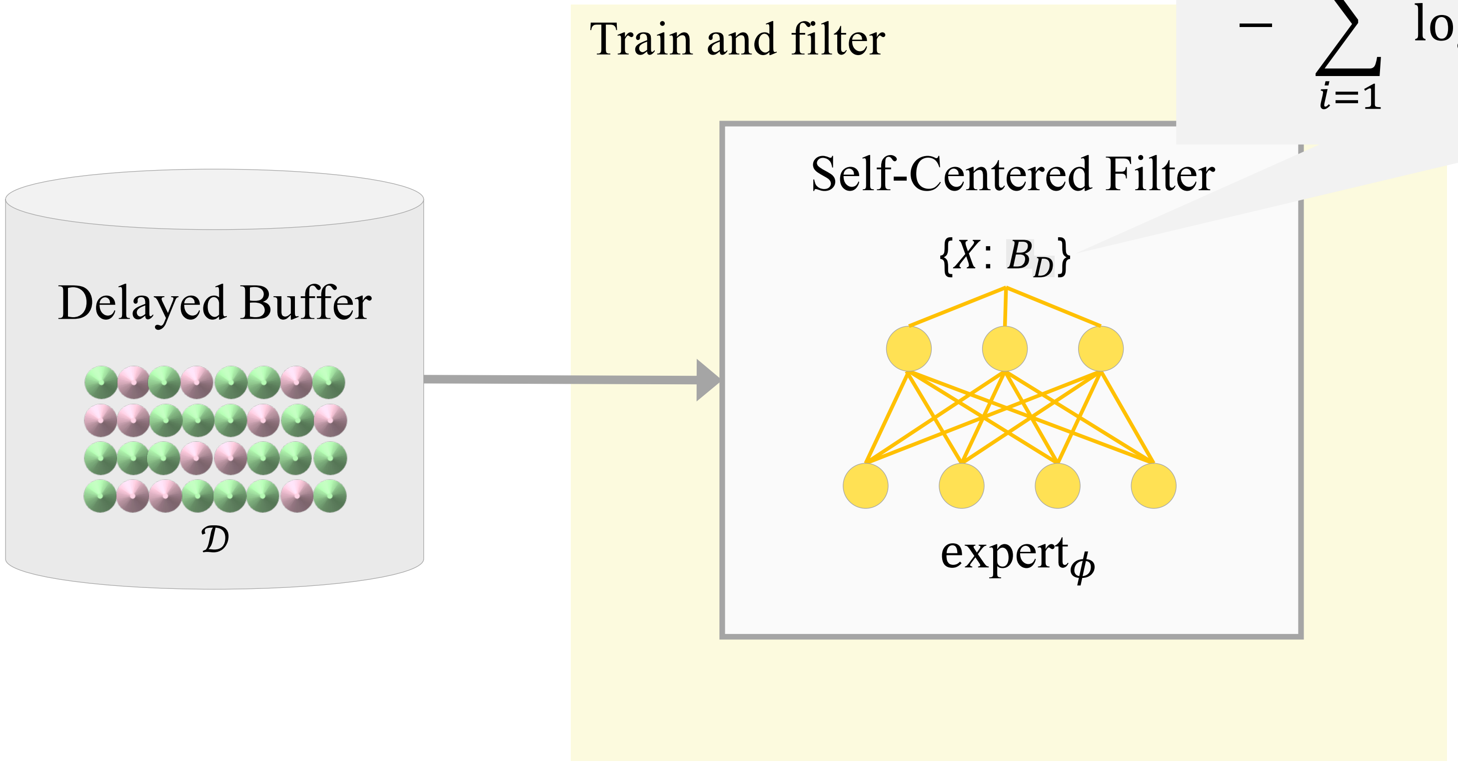
1. Representation learning
2. Centrality scoring
3. Probabilistic discrimination
4. Stochastic ensembles



Self-Centered Filter

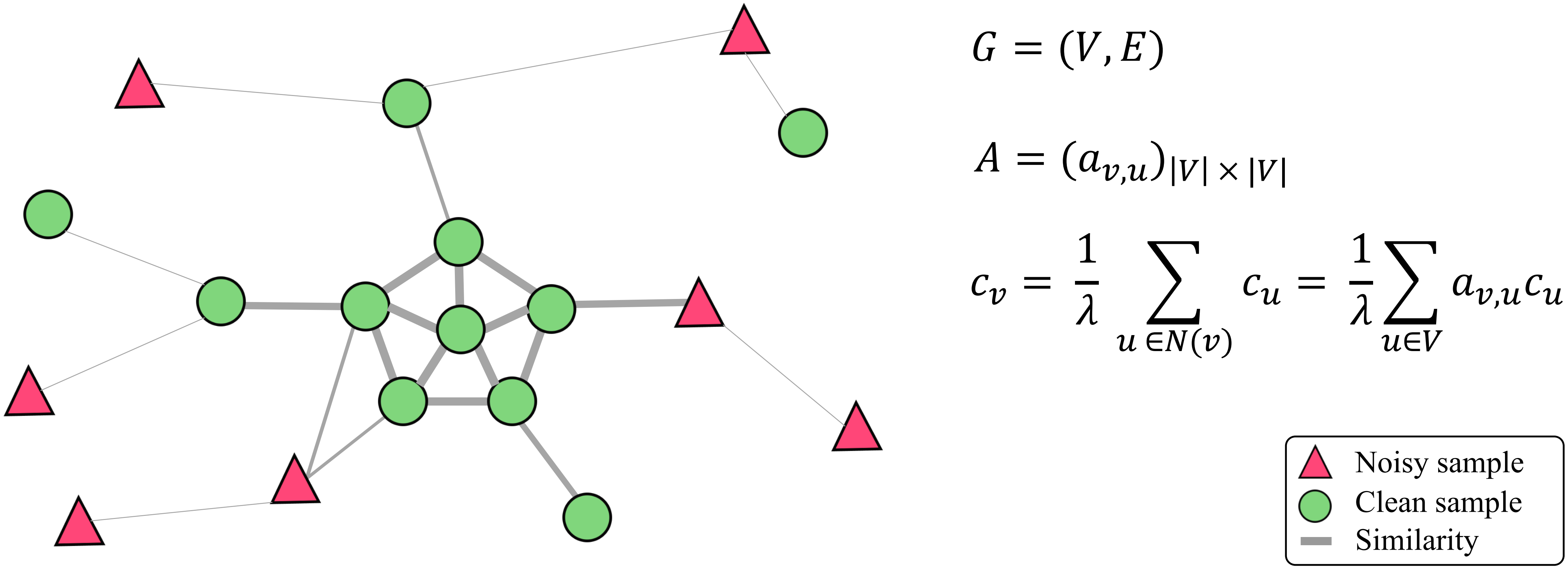
- Step 1. Representation learning

$$- \sum_{i=1}^{2(B_D)} \log \frac{e^{u_i^T u_j/\tau}}{\sum_{k=1}^{2(B_D+B_P)} \mathbb{1}_{k\neq i}\, e^{u_i^T u_k/\tau}}$$



Self-Centered Filter

- Step 2. Centrality scoring



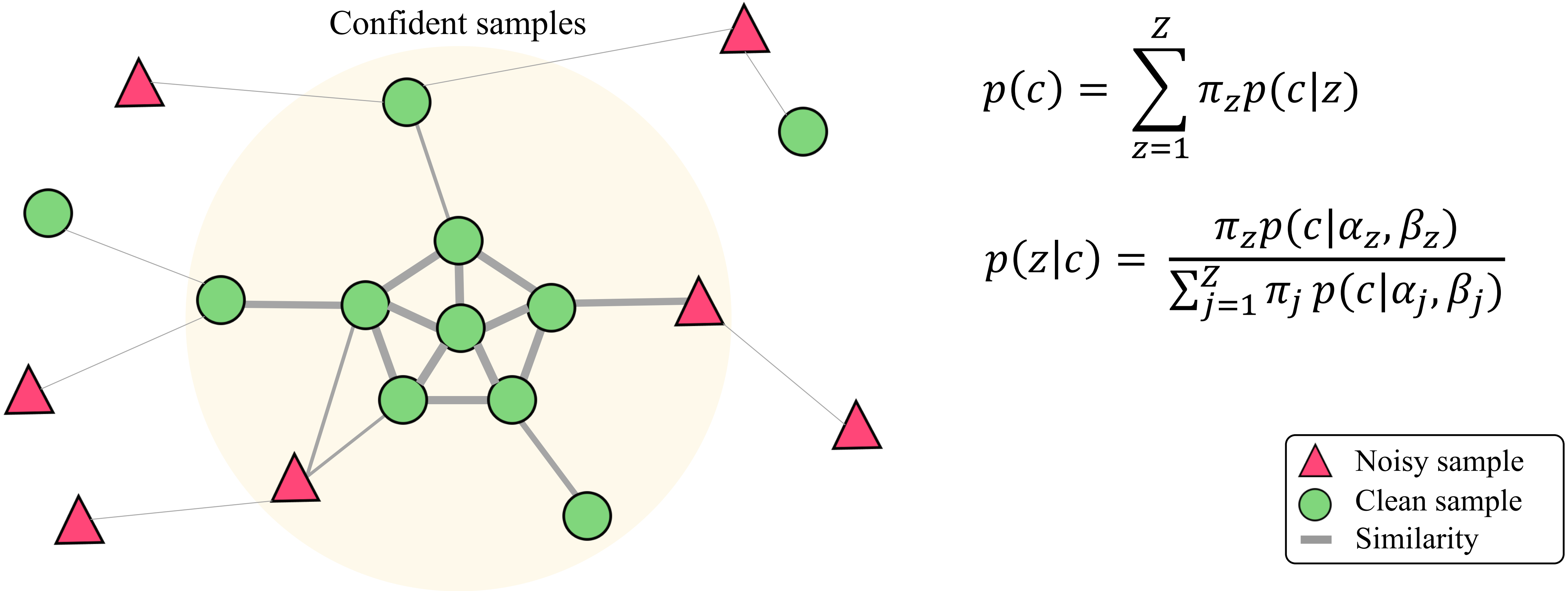
$$G = (V, E)$$

$$A = (a_{v,u})_{|V| \times |V|}$$

$$c_v = \frac{1}{\lambda} \sum_{u \in N(v)} c_u = \frac{1}{\lambda} \sum_{u \in V} a_{v,u} c_u$$

Self-Centered Filter

- Step 3. Probabilistic discrimination

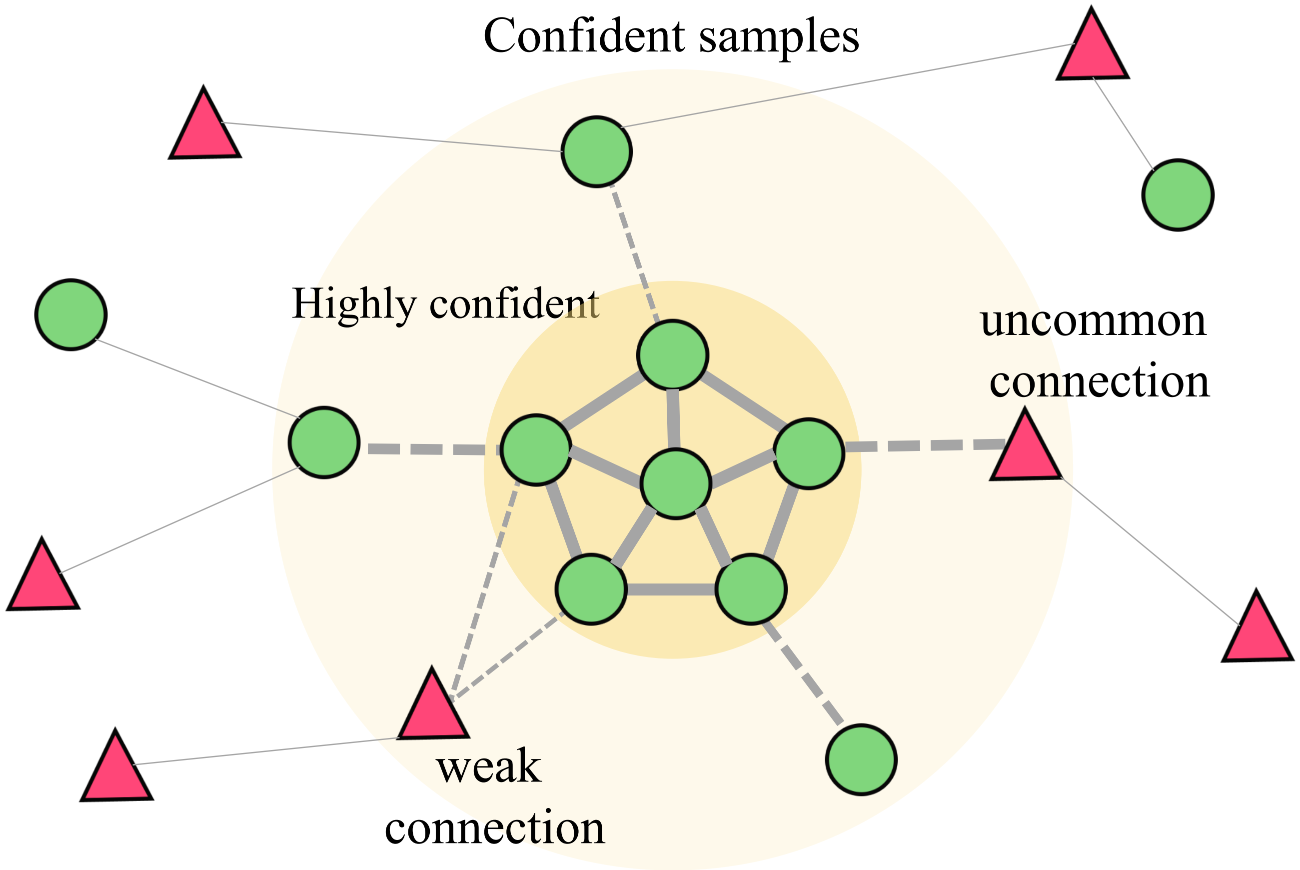


$$p(c) = \sum_{z=1}^{Z} \pi_z p(c|z)$$

$$p(z|c) = \frac{\pi_z p(c|\alpha_z, \beta_z)}{\sum_{j=1}^{Z} \pi_j \, p(c|\alpha_j, \beta_j)}$$

Self-Centered Filter

- Step 4. Stochastic Ensembles



$$p(z|D_l) \propto \int_{\mathrm{A}} p(z|\mathrm{cent}(\mathrm{A}))dp(\mathrm{A}|D_l)$$

$$p(\mathrm{A}|D_l)$$
$$= \prod_{d_i, d_j \in D_l} \mathrm{Bern}\left(\mathrm{A}_{ij}|\mathrm{ReLU}\left(\frac{d_i \cdot d_j}{\|d_i\| \cdot \|d_j\|}\right)\right)$$

Experiments

- **Task-free setting**: no task labels during training or test time.
- **Online Learning**: data stream processed just once.

Aljundi et al., *Gradient based sample selection for online continual learning*, NIPS, 2020
Lee et al., *A neural dirichlet process mixture model for task-free continual learning*, ICLR, 2020

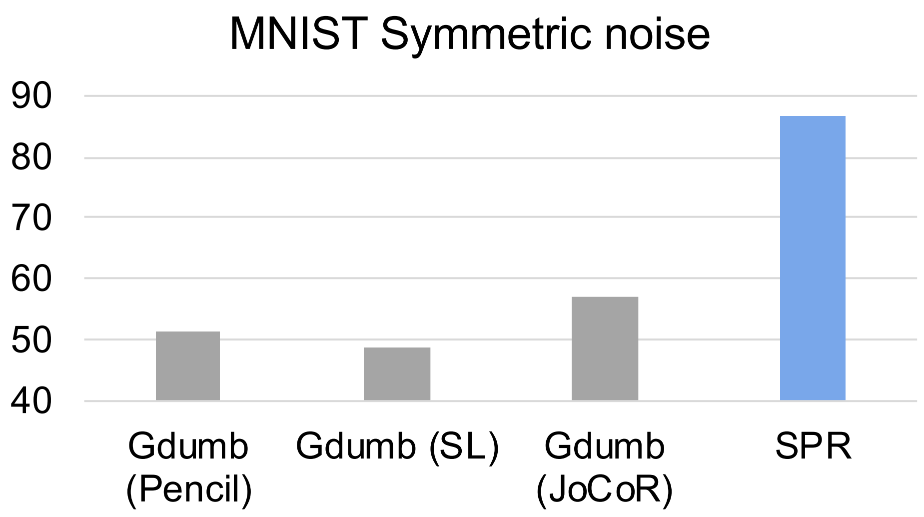
Experimental Settings

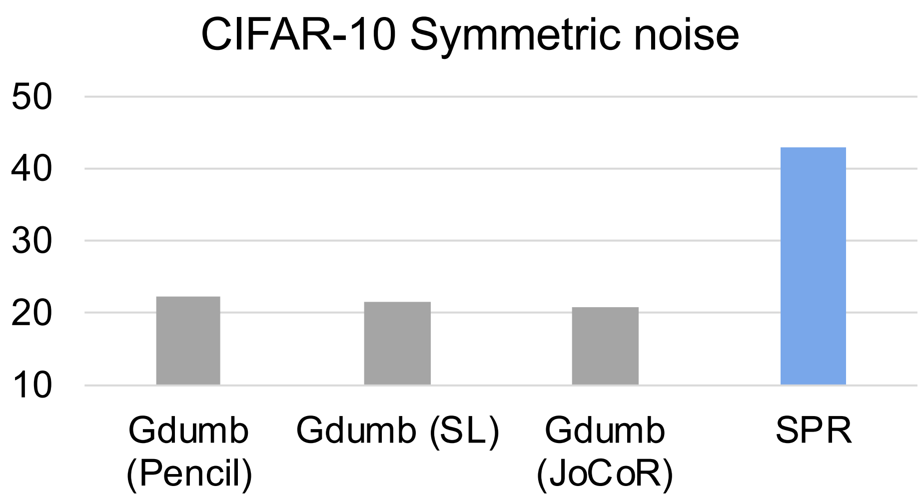
- Four datasets, {MNIST, CIFAR10, CIFAR100, WebVision}
- 5~20 tasks each.
- Symmetric, Asymmetric with {20%, 40%, 60%} noise, Real Noise.
- 22 baseline combinations.

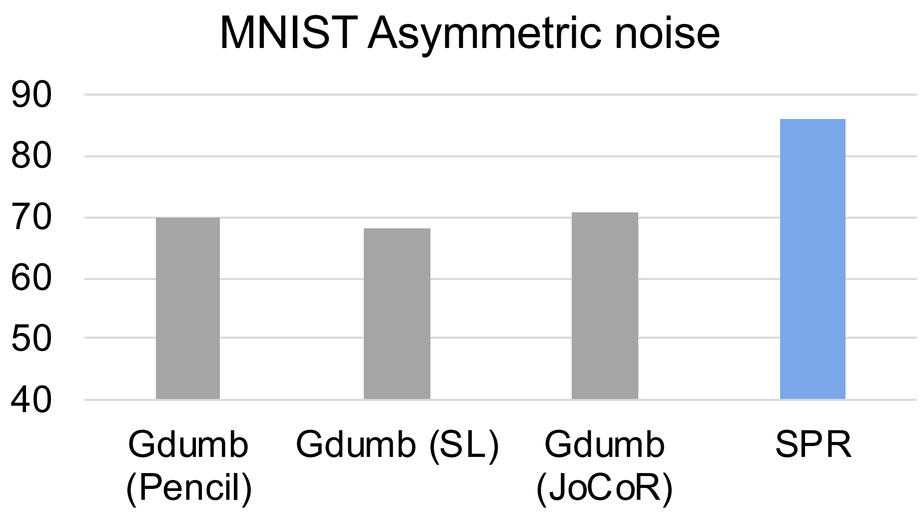
Aljundi et al., *Online continual learning with maximally interfered retrieval*, NeurIPS, 2019
Kim et al., *Imbalanced continual learning with partitioning reservoir sampling*, ECCV, 2020
Vitter et al., *Random sampling with a reservoir*, ACM TOMS, 1985
Prabhu et al., *Gdumb: A simple approach that questions our progress in continual learning*, ECCV, 2019

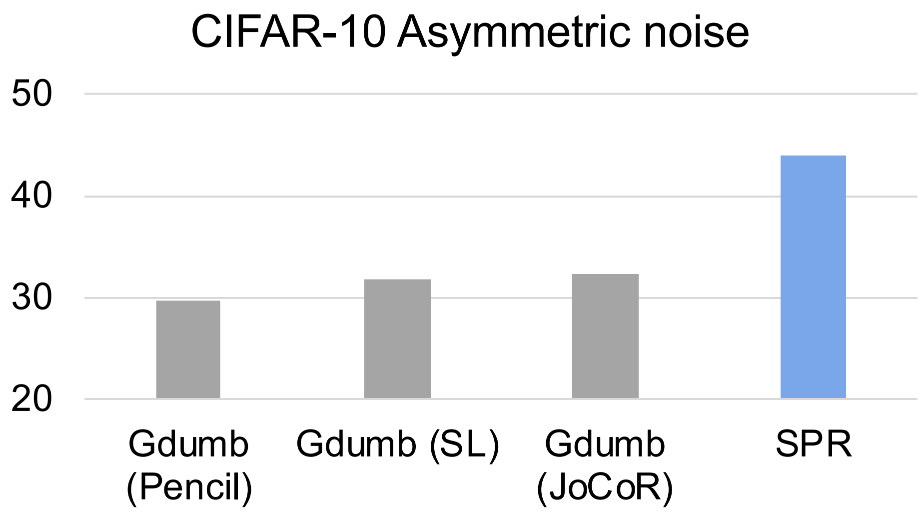
Ren et al., Learning to reweight examples for robust deep learning, ICML, 2018
Pleiss et al., *Identifying mislabeled data using area under the margin ranking*, NIPS, 2020
Li et al., *Symmetric cross entropy for robust learning with noisy labels*, ICCV, 2019
Chen et al., *Understanding and utilizing deep neural networks trained with noisy labels*, ICCV, 2019
Yi et al., Probabilistic end-to-end noise correction for learning with noisy labels, CVPR, 2019
Wei et al., *Combatting noisy labels by agreement: A joint training method with co-regularization*, CVPR, 2020

Overall Accuracy

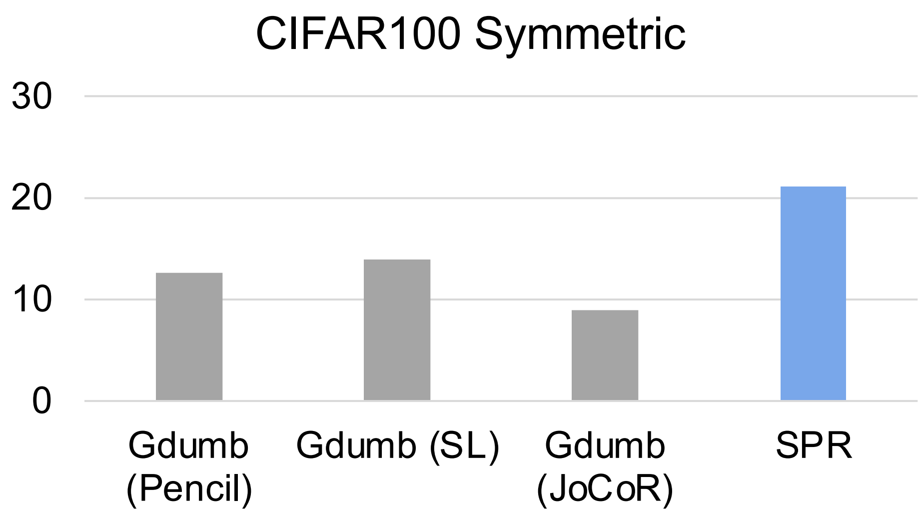


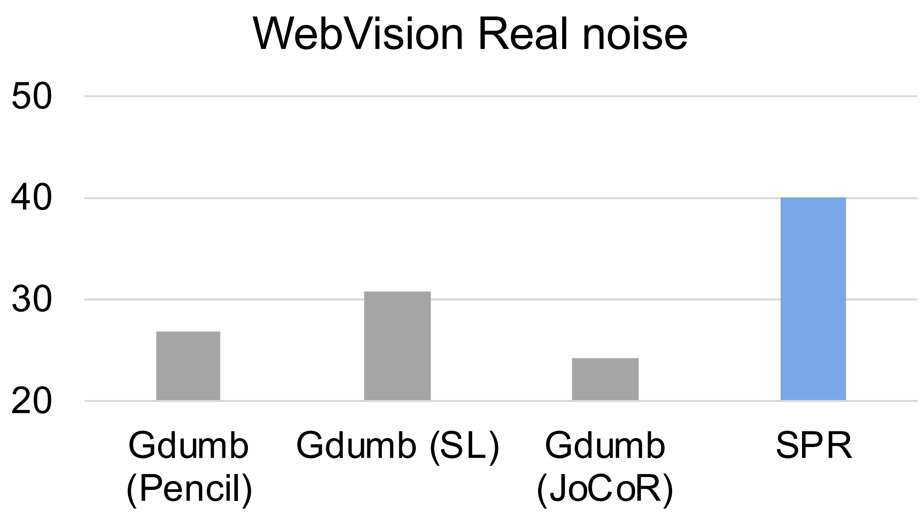


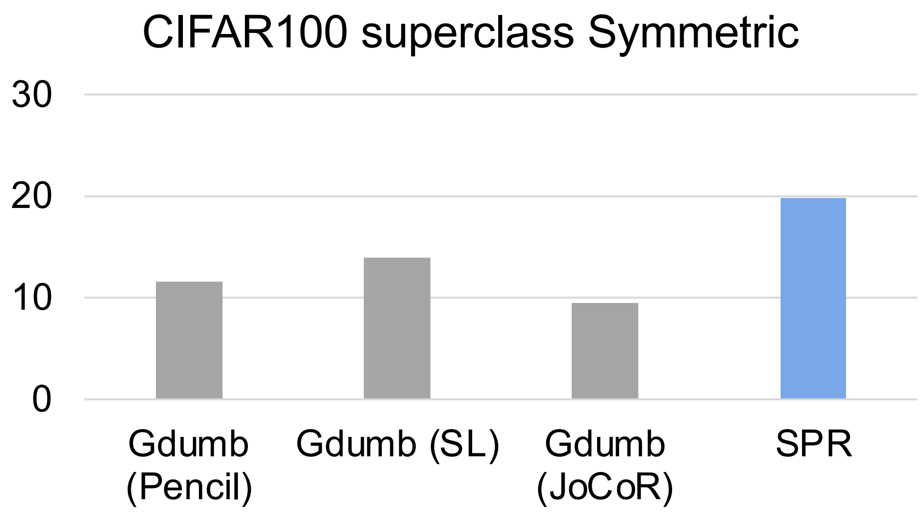




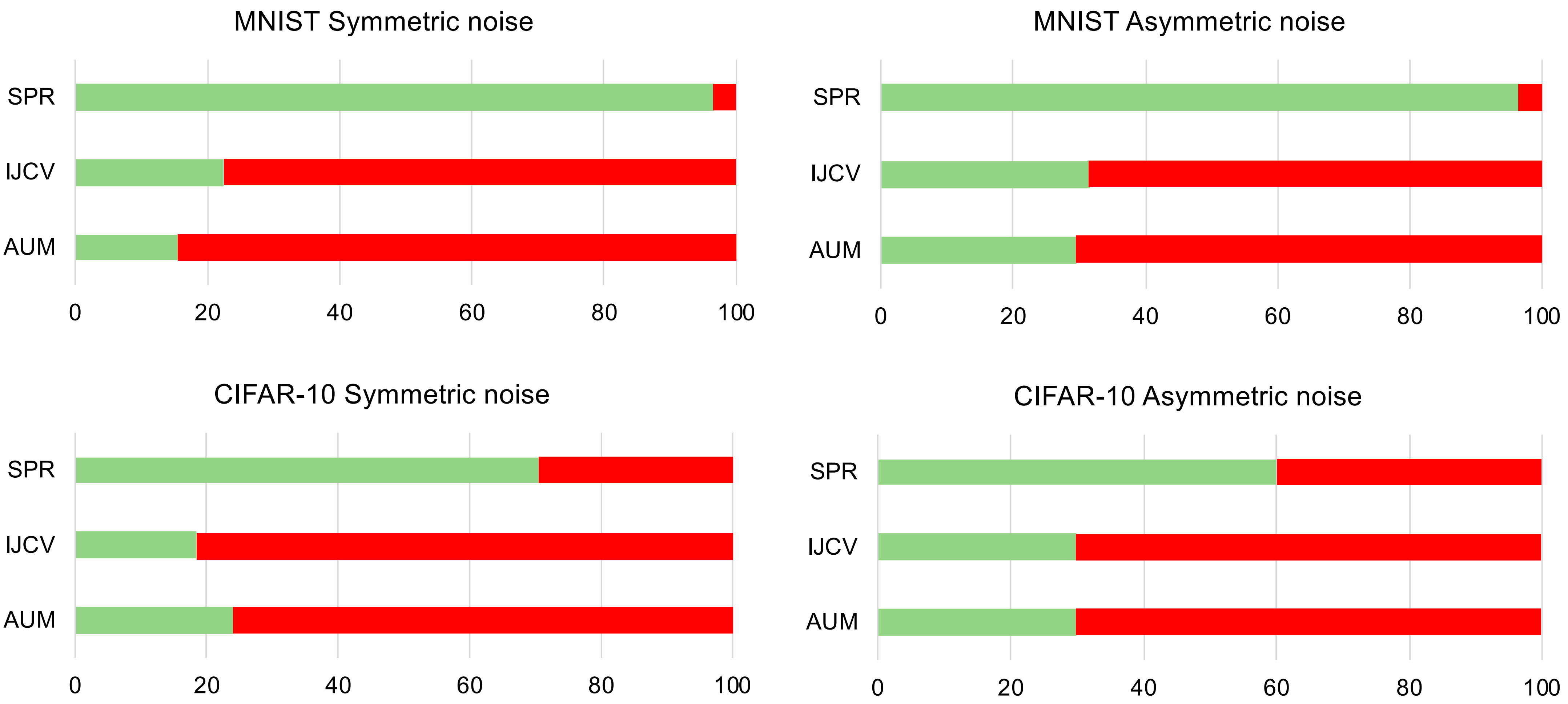
Overall Accuracy



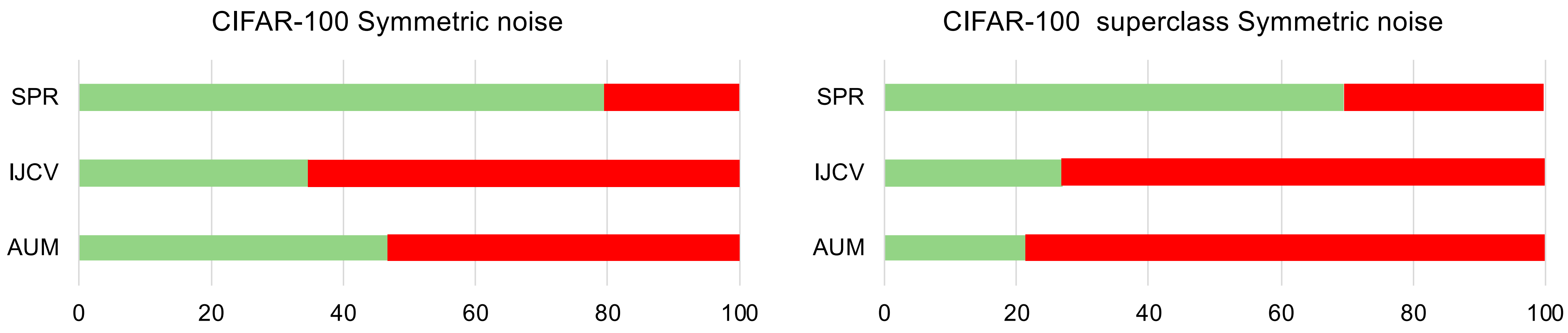




Filtered Percentage



Filtered Percentage



Concluding Remarks

- Explore a novel problem of continual learning from noisy labeled data streams (Clearly showing the problem arising due to data imbalances)
- Devise a novel framework *Self-Purified Replay that include Self-Replay and the Self-Centered Filter* as a viable solution.
- Extensive experiments and analysis to study the effectiveness and limitation of SPR.

Thank you

source code at:
https://vision.snu.ac.kr/projects/SPR