27/12/25

Conceptualization Draft Thesis

∴ Focus not on tailored intances but SEMANTIC instances

NEW Generator needed

Assumes temporal coherence

$$D_{\tau} \approx D_{\tau+1} \Rightarrow \text{previous representation is partially reusable}$$

If each distribution has:

- internally inseparable heuristic classes
- or completely different feature-heuristic relationships

then:

- memory replay preserves noise
- retraining reinforces contradictions
- forgetting is unavoidable

This is why OCL is used with images, words, data with SEMANTIC meaning

So continual learning requires distribution-wise learnability

Reasonable separability

The generator is a precondition for viability

$$\mathbb{E}[\text{intra-class distance}] < \mathbb{E}[\text{inter-class distance}]$$

Possibly:

- Only for some regions
- Only probabilistically
- Only after nonlinear transformation

Enough for contrastive objectives to converge and distance-based voting to outperform chance

If this condition fails,
then the framework is not viable regardless of:

- Network depth
- Memory size
- Retraining schedule

No-free-lunch situation

$Pr(w|\phi) \approx$ uniform

What we want to avoid

Next steps thesis:

NSGA-II instead of GA generator !
↳ Optimize several objectives
Pareto again

For an online continual learning framework, generating semanthic-preserving instances is far more important than generating merely tailored or hard instances, because semantic stability is the true precondition for representation learning and continual adaptation

- Focus in developing a new generator D_{sem} designed to preserve semantic structure across distributions.

$\forall h \in H, \exists \mu_h \in \mathbb{R}^d$ such that $\mathbb{E}_{I \sim D_K \mid w(I)=h}[g_\theta(\phi(I))] \approx \mu_h \ \forall K$

stable centroid

* Variability is mostly intra-class, not inter-class

Different distributions D_K do not move that centroid arbitrarily

MLP learns $g_\theta : \mathbb{R}^f \to \mathbb{R}^{d'}$
f = no. features

geometric transformation

with Centroid Stability
same heuristic across D_K $\Rightarrow$ same regions in embedding space

Distance-based reasoning

with Fixed Centroids
- Nearest Neighbors are meaningful across time
- Memory Buffer stores prototypes
- Shepard Weights decay around semantic centers

$D_T \to D_{T+1}$ but $\mu_h^{(t)} \approx \mu_h^{(t+1)}$