Problem setup: Lifelong Object ReID

Data are presented sequentially in discrete tasks of disjoint classes.
Data from previous tasks are unavailable in successive ones.
The learner must incrementally update.
The test identities are not seen during training.

Continual meta-metric learning vs. Continual metric learning

Continual metric learning is quickly surpassed by continual meta-metric learning.
Re-identification aims to recognize unseen objects. This is the characteristic of few-shot recognition.
Continual metric learning focus on current task.
The DMML loss tends to learn a better representation.
DMML is a more principled approach for continual metric learning.

DwPP vs. DwoPP

The old model has never seen class 1 and so likely produces an output less than 1.
The dominance of the positive class inhibits distillation of negative pair information.

DwPP prediction:
\[ g_c(S_k, \hat{x}; \theta) = \frac{\exp(-d(f_{th}(\hat{x}), u_c))^{1/T}}{\sum_{c' \in C \setminus \{c\}} \exp(-d(f_{th}(\hat{x}), u_{c'}))^{1/T}} \]

DwoPP prediction:
\[ g_c(S_k, \hat{x}, \hat{y}; \theta) = \frac{\exp(-d(f_{th}(\hat{x}), u_c))^{1/T}}{\sum_{c' \in C \setminus \{c\}} \exp(-d(f_{th}(\hat{x}), u_{c'}))^{1/T}} \]

Conclusions

We demonstrate that meta learning approaches perform better than those based on global metric loss optimization for Object ReID.
We propose Distillation without Positive Pairs (DwoPP) as an approach that eliminates positive samples from distillation.
Extensive experiments on newly proposed intra-task object re-identification datasets and the existing LReID benchmark demonstrate the effectiveness of our approach.