Algorithm 1 PyTorch-like pseudo-code for CCLoM.

```
# num_classes: number of classes
# batch_size: batch size of real images

def calculating_CCLoM(real_img, real_label, syn_img, syn_label):
    # One-Hot Encoding to real label
    real_label_onehot = torch.zeros((batch_size, num_classes))
    real_label_onehot[torch.arange(batch_size), real_label] = 1

    # One-Hot Encoding to synthetic label
    syn_label_onehot = torch.zeros((ipc * num_classes, num_classes))
    syn_label_onehot[torch.arange(ipc * num_classes), syn_label] = 1

    # True and false sample matrix
    labels = syn_label_onehot @ real_label_onehot.T

    # extract feature representations
    real_feat = model(real_img)
    syn_feat = model(syn_img)
    real_feature_norm = real_feat / real_feat.norm(dim=-1, keepdim=True)
    syn_feature_norm = syn_feat / syn_feat.norm(dim=-1, keepdim=True)

    cos_dist = 1 - syn_feature_norm @ real_feature_norm.T
    cclom = torch.sum(labels * cos_dist) / torch.sum(cos_dist)

    return cclom
```

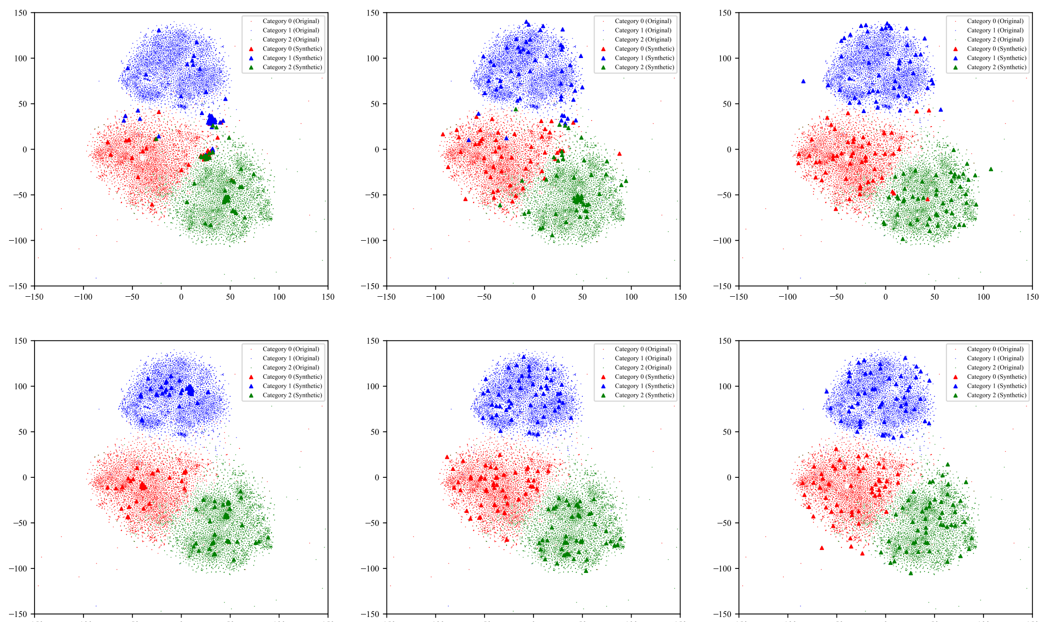

Figure A1: Distributions of synthetic images learned by DC, DSA and DM. The first row represents the distribution without CLoM, while the second row represents the distribution with CLoM using the best combination of options. From left to right are the distributions of DC, DSA, and DM. Best viewed in color.

A APPENDIX

We apply the proposed CLoM to state-of-the-art methods, including IDC (Kim et al., 2022), DiM (Wang et al., 2023), DREAM (Liu et al., 2023) and TM (Cazenavette et al., 2022), and compare the performance in Table A1. For fair comparison, the experiments are conducted under the default parameters provided in original papers. Herein, we utilize well-trained models with diverse initialization parameters and single model architectures ($\mathcal{N}_m = 10, \mathcal{N}_a = 1$) to conduct experiments. The stable performance improvements demonstrate that even with state-of-the-art DD methods, PTMs can still improve the performance of synthetic datasets.

Table A1: The performance comparison to state-of-the-art methods on CIFAR-10. Underline denotes results from the original papers. **Bold entries** are best results.

Method	IPC	CLoM		Method	IPC	CLoM	
		✗	✓			✗	✓
IDC	10	$\underline{67.5}_{\pm 0.5}$	$\mathbf{69.4}_{\pm 0.3}$	DREAM	10	$\underline{69.4}_{\pm 0.4}$	$\mathbf{70.0}_{\pm 0.4}$
	50	$\underline{74.5}_{\pm 0.1}$	$\mathbf{76.3}_{\pm 0.2}$		50	$\underline{74.8}_{\pm 0.1}$	$\mathbf{76.1}_{\pm 0.1}$
DiM	10	$\underline{66.2}_{\pm 0.5}$	$\mathbf{67.3}_{\pm 0.5}$	TM	10	$\underline{65.3}_{\pm 0.7}$	$\mathbf{66.3}_{\pm 0.4}$
	50	$\underline{72.6}_{\pm 0.4}$	$\mathbf{72.7}_{\pm 0.3}$		50	$\underline{71.6}_{\pm 0.2}$	$\mathbf{73.1}_{\pm 0.2}$