OSSGAN: Open-Set Semi-Supervised Image Generation
Supplementary Material

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A. Algorithm of the proposed method

Algorithm 1 shows the algorithm of Softlabel-GAN. The method has a few modifications from supervised GANs, resulting in easily applying to other cGAN architectures instead of BigGAN.

Data: Generator G, Discriminator D, Classifier C, labeled data $\mathcal{D}_t$, unlabeled data $\mathcal{D}_u$, total number of iteration T
Result: Trained G and D
initialize $\{\theta_G, \theta_D, \theta_C\}$
for $t \leftarrow 1$ **to** T **do**
  Sample Batch $(\boldsymbol{x}, \boldsymbol{y}) \sim \mathcal{D}_t, \boldsymbol{u} \sim \mathcal{D}_u, (\boldsymbol{z}, \boldsymbol{y}^f) \sim q(\boldsymbol{z}, \boldsymbol{y})$
  Calculate $\mathcal{L}_D$ using Eq. 9
  $\theta_D, \theta_C \leftarrow \mathrm{AdamOptimizer}(\mathcal{L}_D, \{\theta_D, \theta_C\})$

  Sample Batch $(\boldsymbol{z}, \boldsymbol{y}) \sim q(\boldsymbol{z}, \boldsymbol{y})$
  Calculate $\mathcal{L}_G$ using Eq. 10
  $\theta_G \leftarrow \mathrm{AdamOptimizer}(\mathcal{L}_G, \theta_G)$
end

Algorithm 1: Open-Set Semi-Supervised GAN.

B. Intuitive illustration

As fig. A shows, while the cross-entropy loss makes the entropy smaller, the entropy regularization makes the entropy larger. The cross-entropy loss affects close-set samples stronger, resulting in the clear separation between the closed- and open-set samples.

C. Comparison with additional threshold-based methods

In addition to comparison with threshold-based methods with ad-hoc labeling schemes in Sec. 6, we further compare our OSSGAN with threshold-based methods with Montre-Carlo Dropout uncertainty estimation in fig. B.

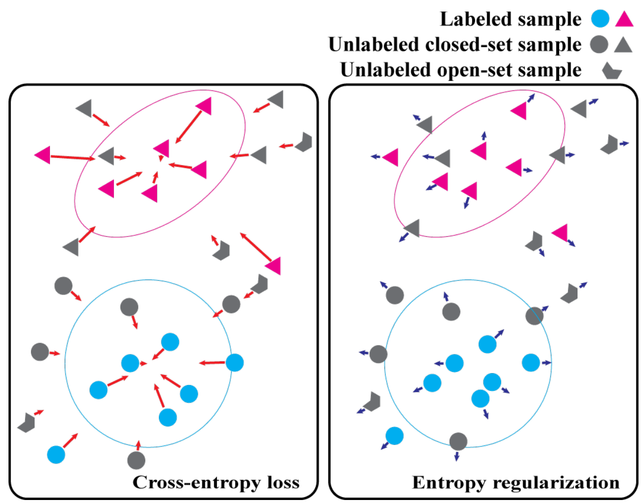


Figure A. Intuitive illustration about how does our method work.

OpensetGAN-MC and RejectGAN-MC indicate OpensetGAN with MC Dropout and RejectGAN with MC Dropout, respectively. As fig. B shows, RejectGAN-MC performs on par with OSSGAN in only a few cases with the easy configuration and the best threshold. In other cases, it is still difficult to achieve better performance for threshold-based methods with MC Dropout. These results show that threshold-based methods can not work for our complex task regardless of the quality of quantified confidence.

D. More examples

Figure C provides generated examples from the compared methods. Our method produces plausible images while the other methods fail to produce plausible images. S^3GAN produces images respecting the given condition but lacking the plausibility of images.

We provide more generated examples of OSSGAN on ImageNet with 50 classes in fig. D.

We also conduct experiments on ImageNet. The experiments have the number of closed-set classes of 100, the ratio of the labeled samples in closed-set class samples of

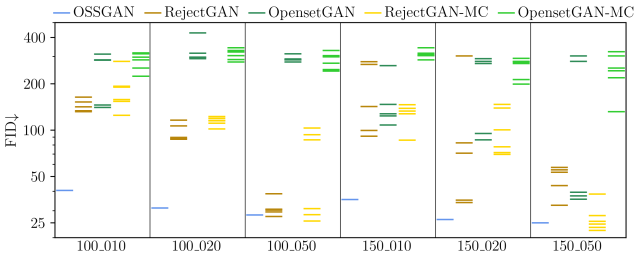


Figure B. Comparison of OSSGAN and threshold-based methods. We only report the constant scores for OSSGAN, as it does not employ a threshold. For OpensetGAN and RejectGAN, the optimal thresholds are investigated in the range from 0 to 1. The range for OpensetGAN-MC and RejectGAN-MC is from 0.000001 to 0.0001 The threshold-based methods fail in most cases due to the difficulty of selecting a threshold. The data configuration of 100_010 indicates 100 closed classes and 10% labeled samples. The same notations are applicable to other data configurations.

Figure C. Visual comparison of class-conditional image synthesis results on Tiny ImageNet with 50 classes. Our method produces plausible images while respecting the given condition.

0.2, and the usage ratio in open-set class samples of 0.1. Our OSSGAN achieves an IS of 22.11 and FID of 45.42, improving over S^3GAN with an IS of 18.79 and FID of 51.96, RandomGAN with an IS of 11.04 and FID of 99.00, and BigGAN with an IS of 4.31 and FID of 182.90. The qualitative results of OSSGAN and S^3GAN are shown in

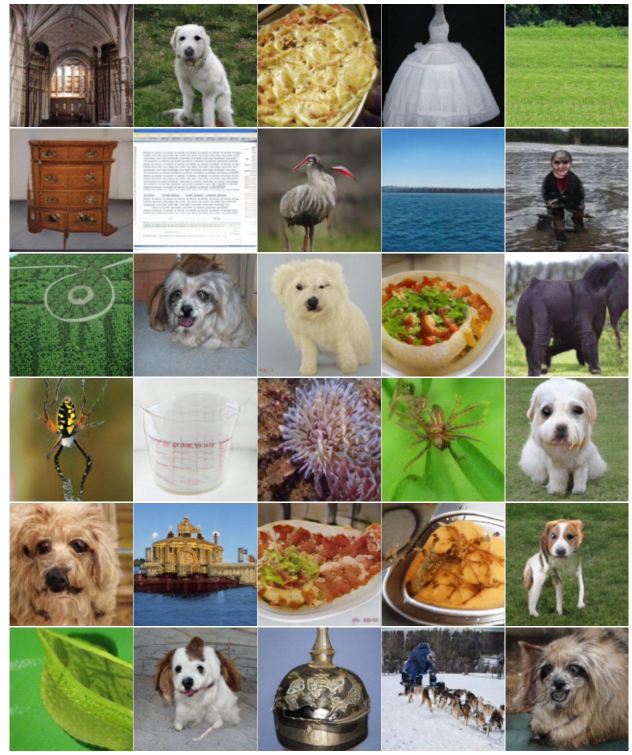
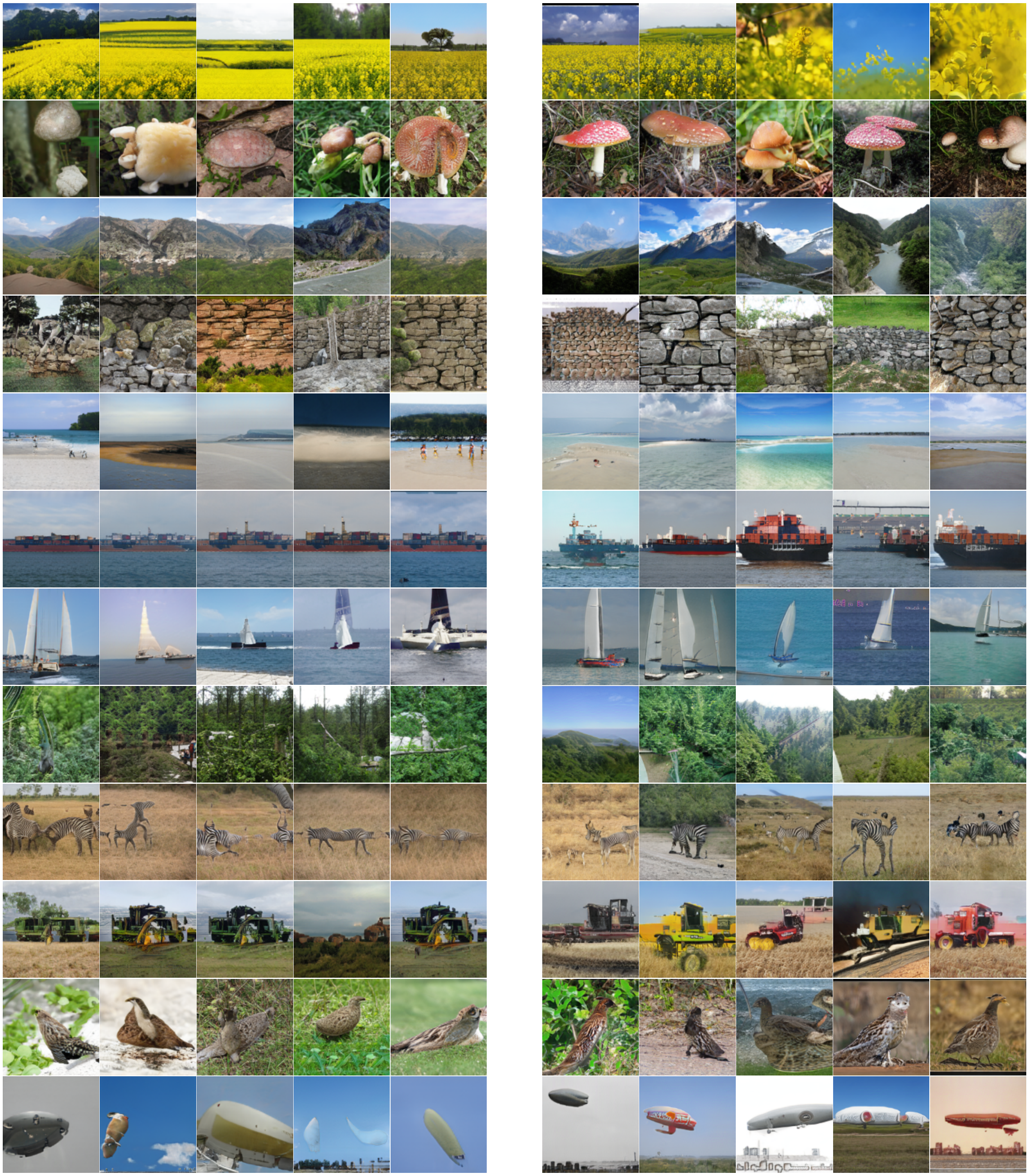


Figure D. More examples synthesized by OSSGAN on ImageNet with 50 classes.

fig. E. In contrast to S^3GAN sometimes generate While S^3GAN sometimes generates almost the same images repeatedly, OSSGAN generates diverse and plausible images.



(a) S^3GAN (b) OSSGAN

Figure E. Qualitative comparison of class-conditional image synthesis results on ImageNet with 100 classes. Our method produces diverse images.