Generative Adversarial Networks (GANs): Recent Progress

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BigGAN (Brock, Donahue, Simonyan 2019)
- class-conditional

SS-GAN (Chen et al. 2019)
- unsupervised
Generative Adversarial Networks (GANs): Recent Progress

Conditioning reduces the diverse generation problem to a per-class problem
Unsupervised models are considerably less powerful
This work: How to close the gap between conditional and unsupervised GANs?
Proposed methods: Overview

- Replace ground-truth labels with synthetic/inferred labels
  ➔ No changes in the GAN architecture required
- Infer labels for the real data using self-supervised and semi-supervised learning techniques
Proposed methods: Pre-training

1. Learn a semantic representation $F$ of the data using self-supervision by rotation prediction (Gidaris et al. 2018)
2. Clustering or semi-supervised learning on the representation $F$
3. Train GAN with inferred labels
Proposed methods: Co-training

- Semi-supervised classification head on discriminator
Improve pre- and co-training methods

- Rotation-self supervision *during GAN training* (Chen et al. 2019)
Clustering (SS) is unsupervised SOTA (FID 22.0)

- $S^2$ GAN (20%) and $S^3$ GAN (10%) match BigGAN (100%)
- $S^3$ GAN (20%) outperforms BigGAN (100%) (SOTA)
Samples: BigGAN (our implementation) vs proposed

BigGAN (100%)

S^3GAN (10%)
Results

S³GAN (10%) 256 x 256 px
Code, pretrained models and Colabs:

github.com/google/compare_gan

Check out our **poster #13** tonight 6:30-9:00 pm!