Abstract:

Since their introduction by Goodfellow et al. in 2014, generative adversarial models seem to have completely transformed Computer Vision and Graphics. In this talk I will address three questions: (1) What did we do before the GAN era (and was it really that different)? (2) Is the way we train GANs in line with the theory (and can we do it better)? (3) How is information about object transformations encoded in a pre-trained generator?

I will start by showing that Contrastive Divergence (CD) learning (Hinton â2002), the most widely used method for learning distributions before GANs, is in fact also an adversarial procedure. This settles a long standing debate regarding the objective that this method actually optimizes, which arose due to an unjustified approximation in the original derivation. Our observation explains CDâs great empirical success.

Going back to GANs, I will challenge the common practice for stabilizing training using spectral-normalization. Although theoretically motivated by the Wasserstein GAN formulation, I will show that this heuristic works for different reasons and can be significantly improved upon. Our improved approach leads to state-of-the-art results in many common tasks, including super-resolution and image-to-image-translation.

Finally, I will address the task of revealing meaningful directions in the latent space of a pre-trained GAN. I will show that such directions can be computed in closed form directly from the generator's weights, without the need of any training or optimization as done in existing works. I will particularly discuss nonlinear trajectories that have natural endpoints and allow controlling whether one transformation is allowed to come on the expense of another (e.g. zoom-in with or without allowing translation to keep the object centered).

* These are joint works with Omer Yair, Idan Kligvasser, Nurit Spingarn, and Ron Banner.