GANs for Biological Image Synthesis

Anton Osokin — INRIA/ENS, France; NRU HSE, Russia

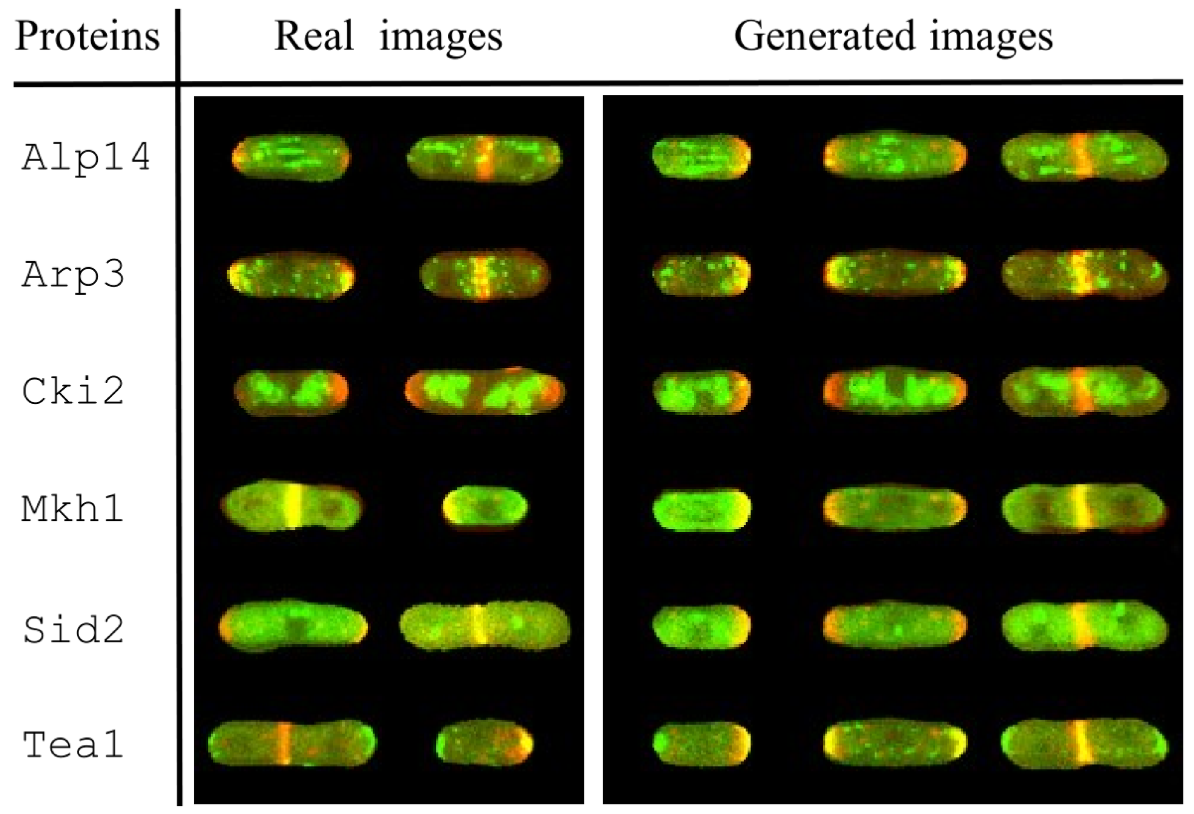
Anatole Chessel — École Polytechnique, France

Rafael Carazo-Salas — University of Bristol, UK

Federico Vaggi — ENS, France; Amazon, USA

Motivation

Generative Adversarial Networks (GANs) [1] to synthesize biological images (fission yeast cells imaged by fluorescence microscopy).



LIN dataset

LIN dataset [2] contains 170,000 cell images each with two fluorescent tags: red and green.

Red shows Bsg4 protein which shows the area of active growth.

Green shows one of other 41 proteins of interest.

There is technology to image up to 3-5 channels at a time, but more than 2 is hard and expensive.

Goal

- Synthesize multi-channel images given 2-channel data
- Capture randomness of the green given the red
- Learn a latent space to interpolate between cells
- Quantitatively measure quality

Approach

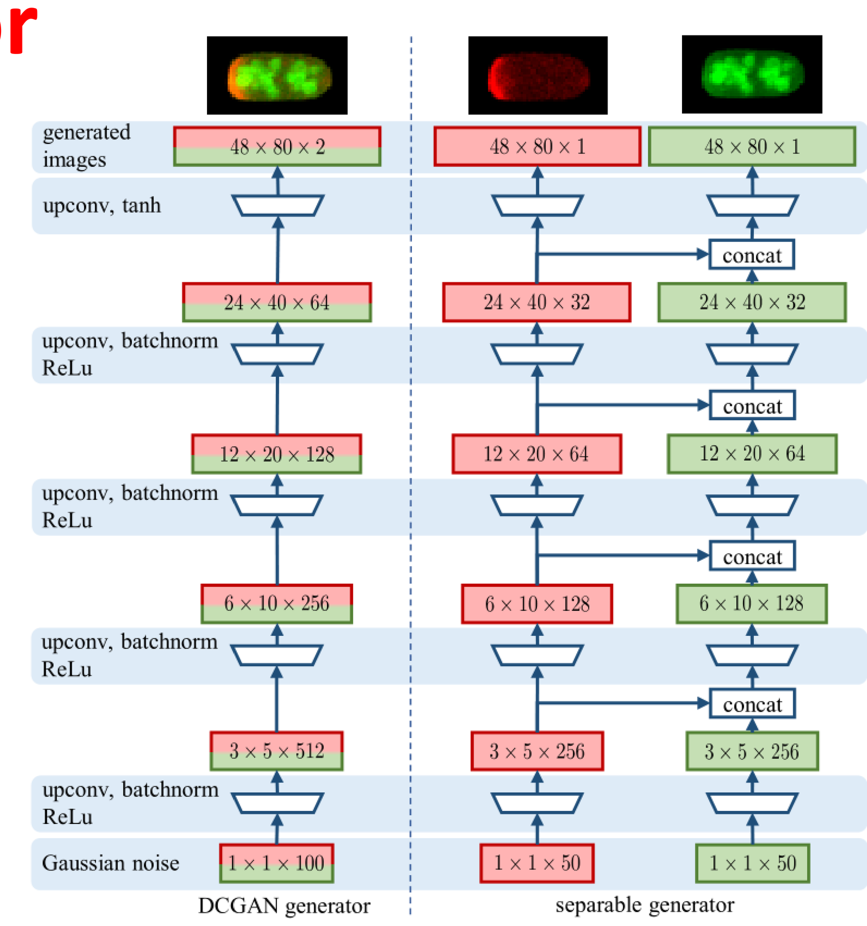
- Separable generator instead of conditioning
- WGAN-GP [3] to avoid mode collapse
- Star-shaped multi-channel model trained on two channel data
- Neural network two-sample test (C2ST) [4] to measure quality
- Interpolation between GAN noise vectors

Separable generator

Based on DCGAN [5]

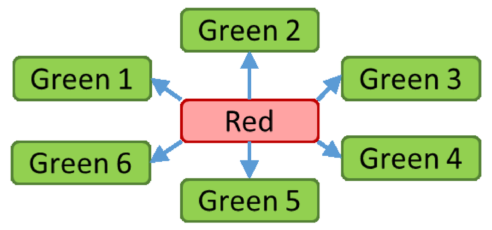
Red and green noise

Red and green towers



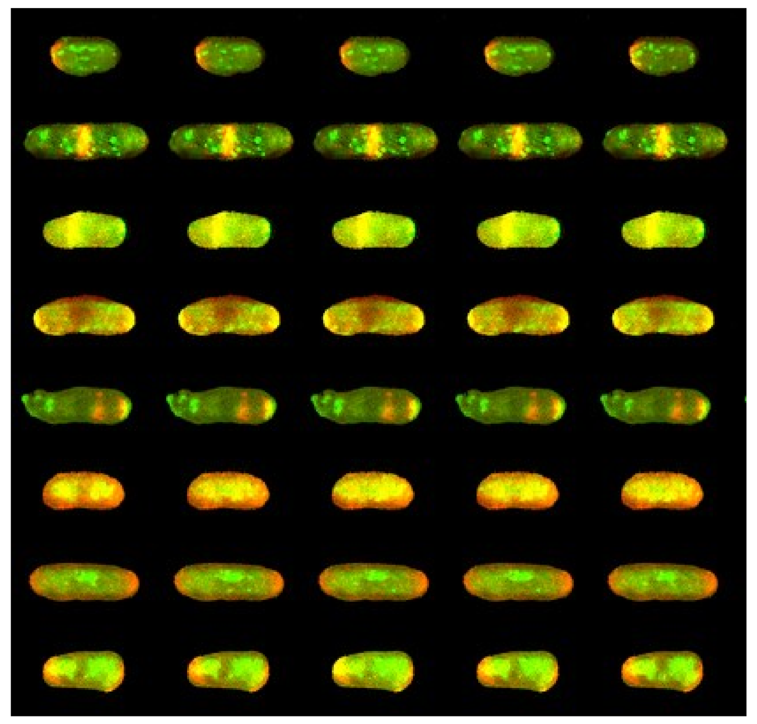
Star-shaped model

Adaptation for multiple greens

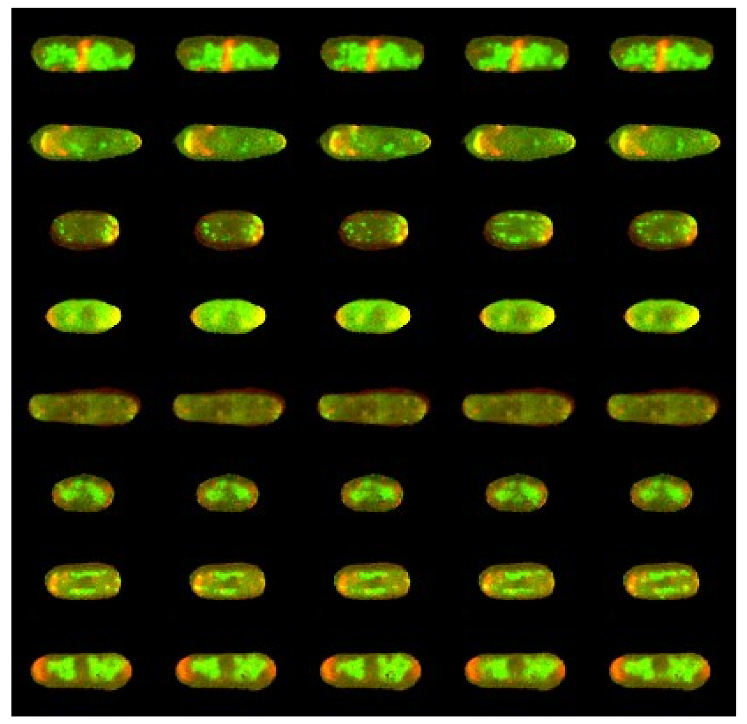


Fighting mode collapse

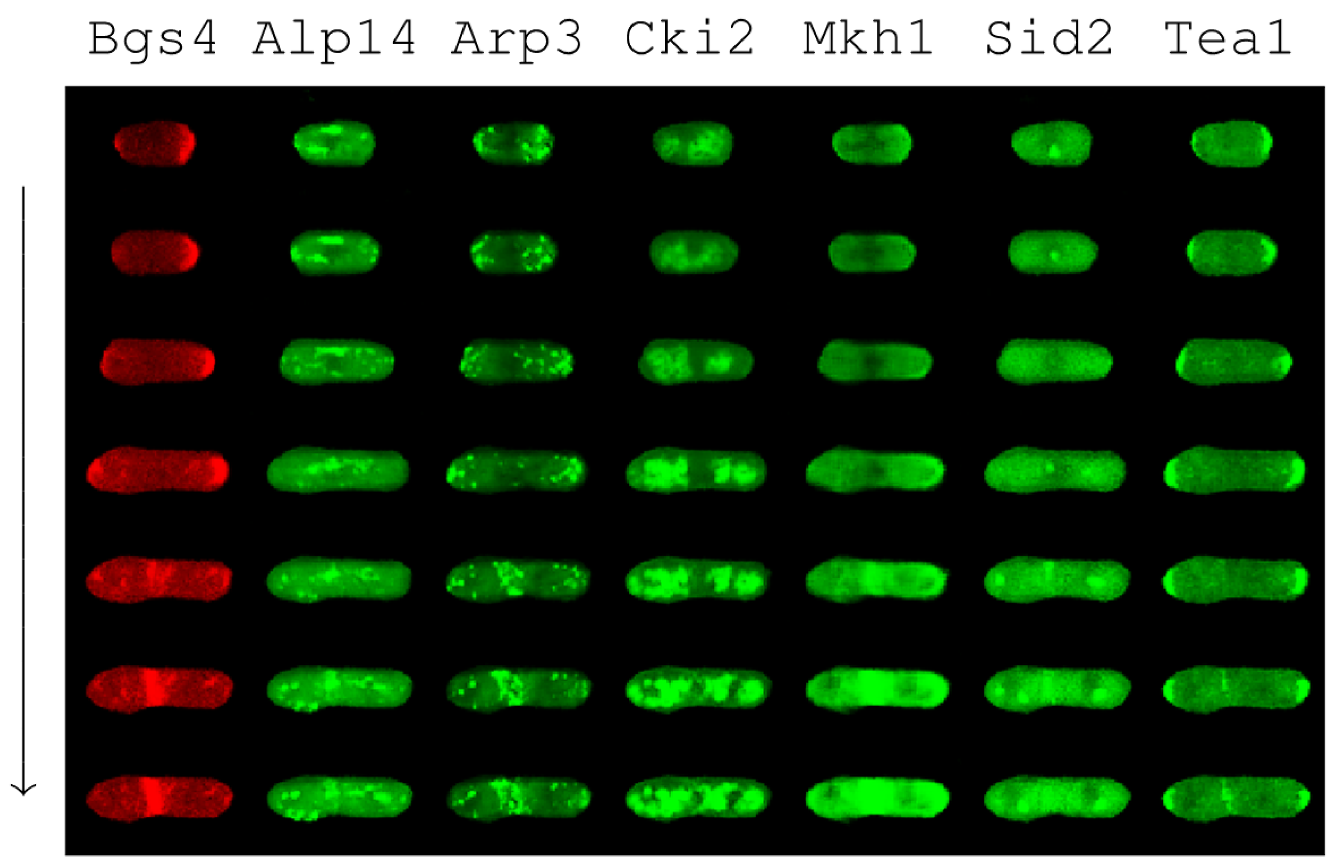
Separable GAN



Separable Wasserstein GAN



Interpolating cell growth cycle



Quantitative evaluation: two-sample test

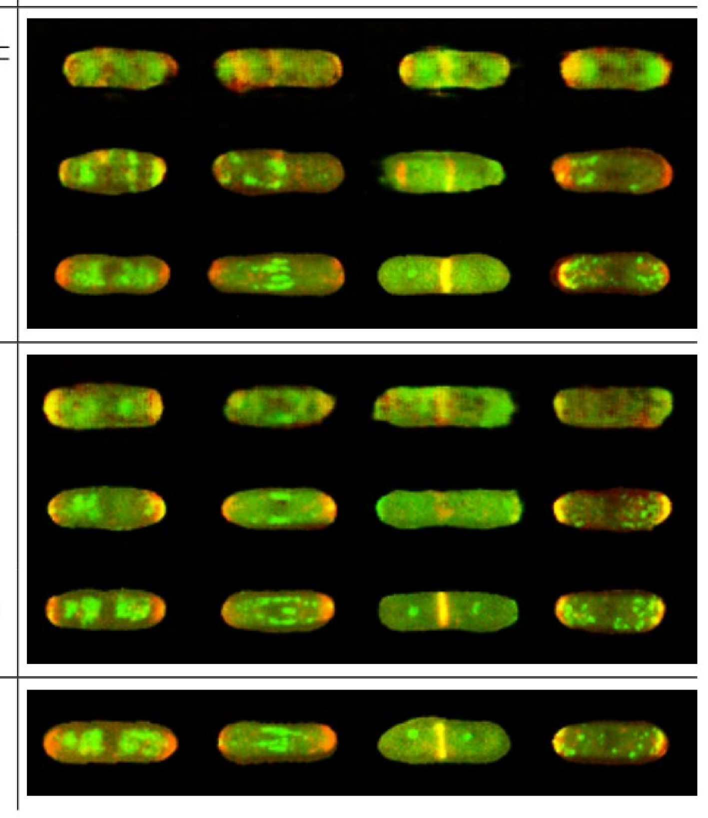
With a model fixed, one trains a network to classify real vs fake.

Test accuracy is taken as a similarity measure.

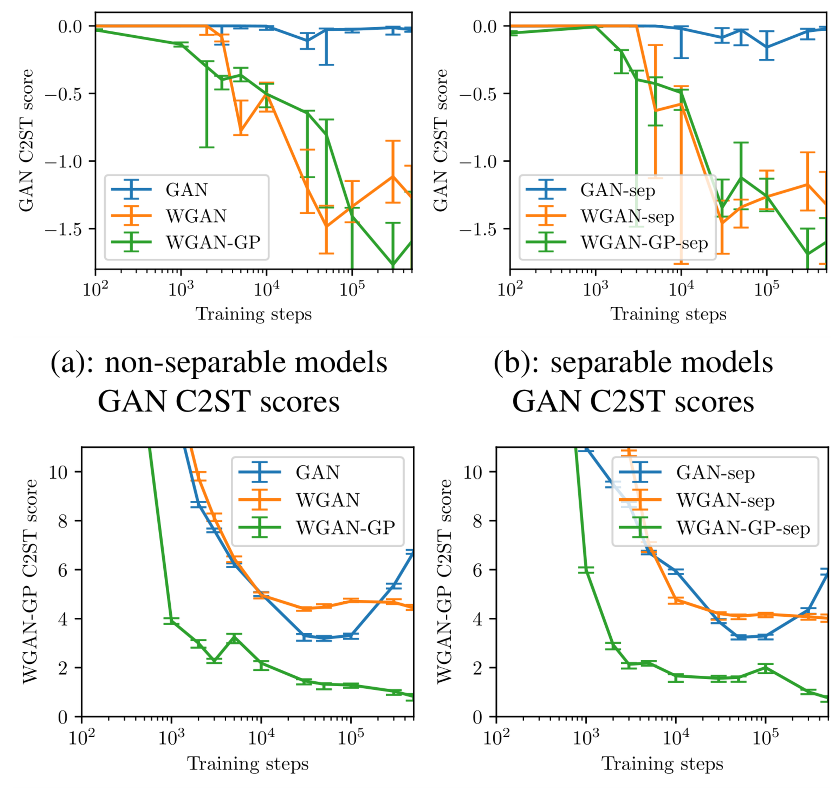
Correlation of C2ST and quality

	Steps	C2ST
sep. GAN	1k	11.0± 0.1
	5k	6.7± 0.1
	50k	3.2± 0.1
sep. WGAN-GP	1k	6.0± 0.1
	5k	2.2± 0.1
	50k	**1.6± 0.1**
Real	-	−0.7 ±0.6

Samples



Comparing different C2ST



(a): non-separable models GAN C2ST scores

(b): separable models GAN C2ST scores

(e): non-separable models WGAN-GP C2ST scores

(f): separable models WGAN-GP C2ST scores

C2ST for real vs real of different classes

test	Alp14	Arp3	Cki2	Mkh1	Sid2	Tea1	Fim1	Tea4
Alp14	0.1 ± 0.2	12.5 ± 0.3	8.1 ± 0.3	12.5 ± 0.5	9.5 ± 0.2	10.9 ± 0.3	15.6 ± 0.3	11.4 ± 0.3
Arp3	14.4 ± 0.2	0.8 ± 0.4	16.2 ± 0.2	11.5 ± 0.4	20.5 ± 0.3	13.2 ± 0.2	**3.7 ± 0.2**	18.3 ± 0.3
Cki2	8.6 ± 0.2	15.9 ± 0.3	-0.2 ± 0.3	13.7 ± 0.4	12.0 ± 0.3	15.8 ± 0.3	18.5 ± 0.4	16.0 ± 0.5
Mkh1	12.3 ± 0.4	12.2 ± 0.6	13.6 ± 0.3	-0.2 ± 0.4	12.4 ± 0.6	13.3 ± 0.6	15.1 ± 0.5	14.9 ± 0.8
Sid2	9.0 ± 0.3	19.5 ± 0.4	11.8 ± 0.5	13.4 ± 0.9	-0.6 ± 0.3	12.6 ± 0.3	23.9 ± 0.4	7.7 ± 0.6
Tea1	11.3 ± 0.3	11.5 ± 0.5	15.9 ± 0.3	14.4 ± 0.6	13.1 ± 0.1	-0.1 ± 0.4	14.5 ± 0.5	**6.9 ± 0.5**
Fim1	16.3 ± 0.2	**2.8 ± 0.3**	18.4 ± 0.2	14.5 ± 0.3	23.4 ± 0.3	15.1 ± 0.2	-0.2 ± 0.3	20.8 ± 0.5
Tea4	9.7 ± 0.6	15.8 ± 0.7	14.0 ± 0.9	13.9 ± 0.9	6.2 ± 0.4	**5.9 ± 0.3**	19.5 ± 0.7	-0.5 ± 0.7

C2ST for evaluating different conditional WGAN-GP

	real images	one-class non-separable	one-class separable	multi-channel non-separable	multi-channel separable	star-shaped
separable red/green	-	✗	✓	✗	✓	✓
class conditioned	-	✗	✗	✓	✓	✓
Alp14	0.1 ± 0.2	**0.6 ± 0.3**	1.2 ± 0.2	3.2 ± 0.4	2.3 ± 0.5	**0.6 ± 0.3**
Arp3	0.8 ± 0.4	**1.2 ± 0.3**	2.4 ± 0.4	3.2 ± 0.4	4.2 ± 0.4	2.1 ± 0.5
Cki2	-0.2 ± 0.3	**0.3 ± 0.5**	1.0 ± 0.3	2.5 ± 0.3	3.6 ± 0.5	1.2 ± 0.3
Mkh1	-0.2 ± 0.4	0.8 ± 0.6	**0.5 ± 0.4**	4.6 ± 0.5	6.6 ± 0.5	2.4 ± 0.6
Sid2	-0.6 ± 0.3	**0.8 ± 0.4**	1.0 ± 0.5	4.5 ± 0.5	3.2 ± 0.6	1.1 ± 0.6
Tea1	-0.1 ± 0.4	**0.8 ± 0.5**	**0.8 ± 0.5**	4.4 ± 0.3	2.8 ± 0.5	1.1 ± 0.4
6 proteins	-0.1 ± 0.2	**0.8 ± 0.2**	1.1 ± 0.2	3.7 ± 0.1	3.8 ± 0.2	1.4 ± 0.1

References

[1] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D.Warde-Farley, S.Ozair, A.Courville, Y. Bengio. Generative adversarial nets. In NIPS, 2014

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[3] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville. Improved training of Wasserstein GANs. arXiv:1704.00028v2, 2017.

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[5] A. Radford, L. Metz, and S. Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. In ICLR, arXiv:1511.06434v2, 2016