ML in Science

University of Glasgow

Extreme Light

GANs for super-resolution fluorescence imaging microscopy (FLIM)

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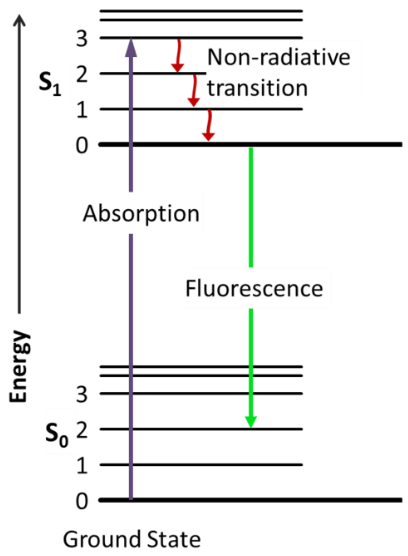
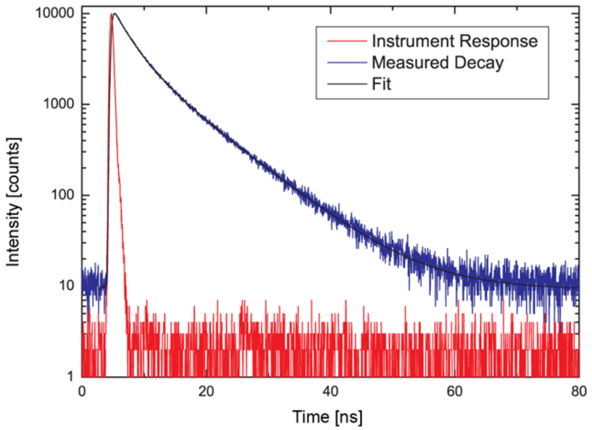
Fluorescence lifetime imaging tells us about protein activity in a cell

- A fluorophore which is excited by a photon will drop to the ground state with a certain probability based on the decay rates through a number of different (radiative and/or nonradiative) decay pathways.
- Fluorophore’s have a signature decay rate.
- By observing the decay rate/lifetime, we can tell what fluorophore is where; by engineering certain fluorophores to certain proteins in vitro, we can tell where a type of protein is.



Jablonski diagram of absorbance, non-radiative decay, and fluorescence. S0 ans s1 are electron energy states[1]



L-Tryptophane dissolved in water - measurement result [2]

GANs started to see popular use in SR around 2016/2017

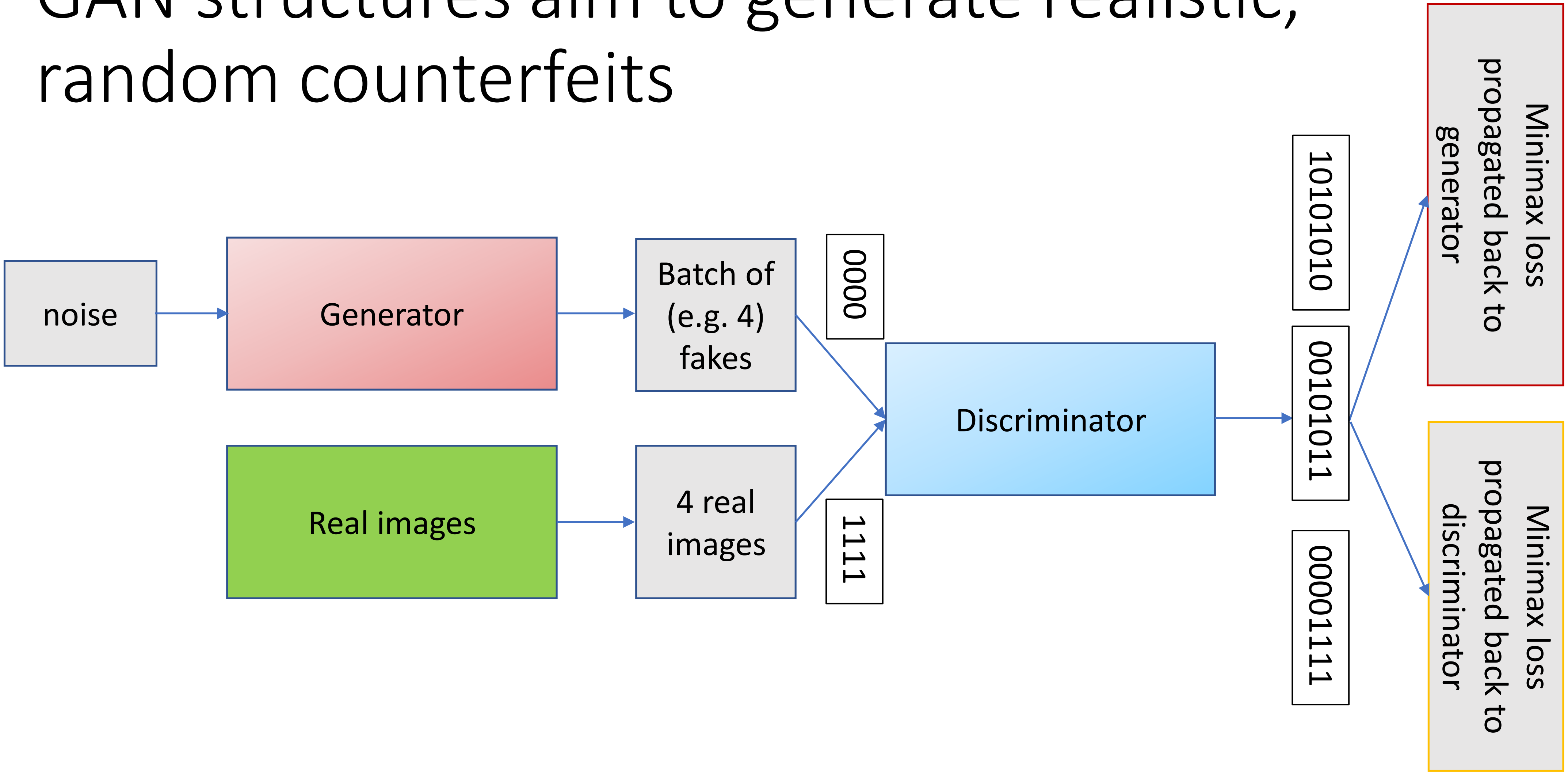
Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, Wenzhe Shi; The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 4681-4690

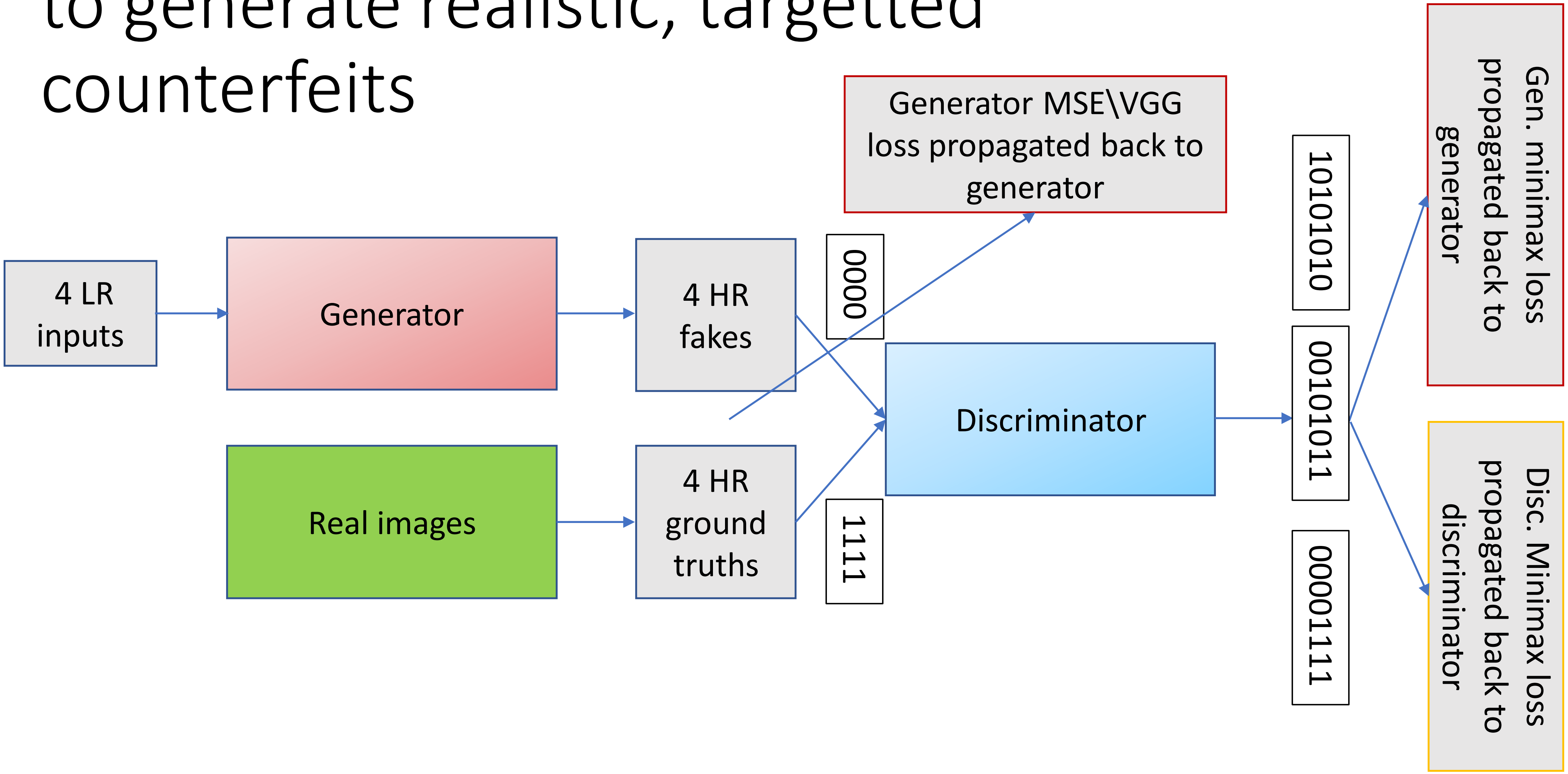
Abstract

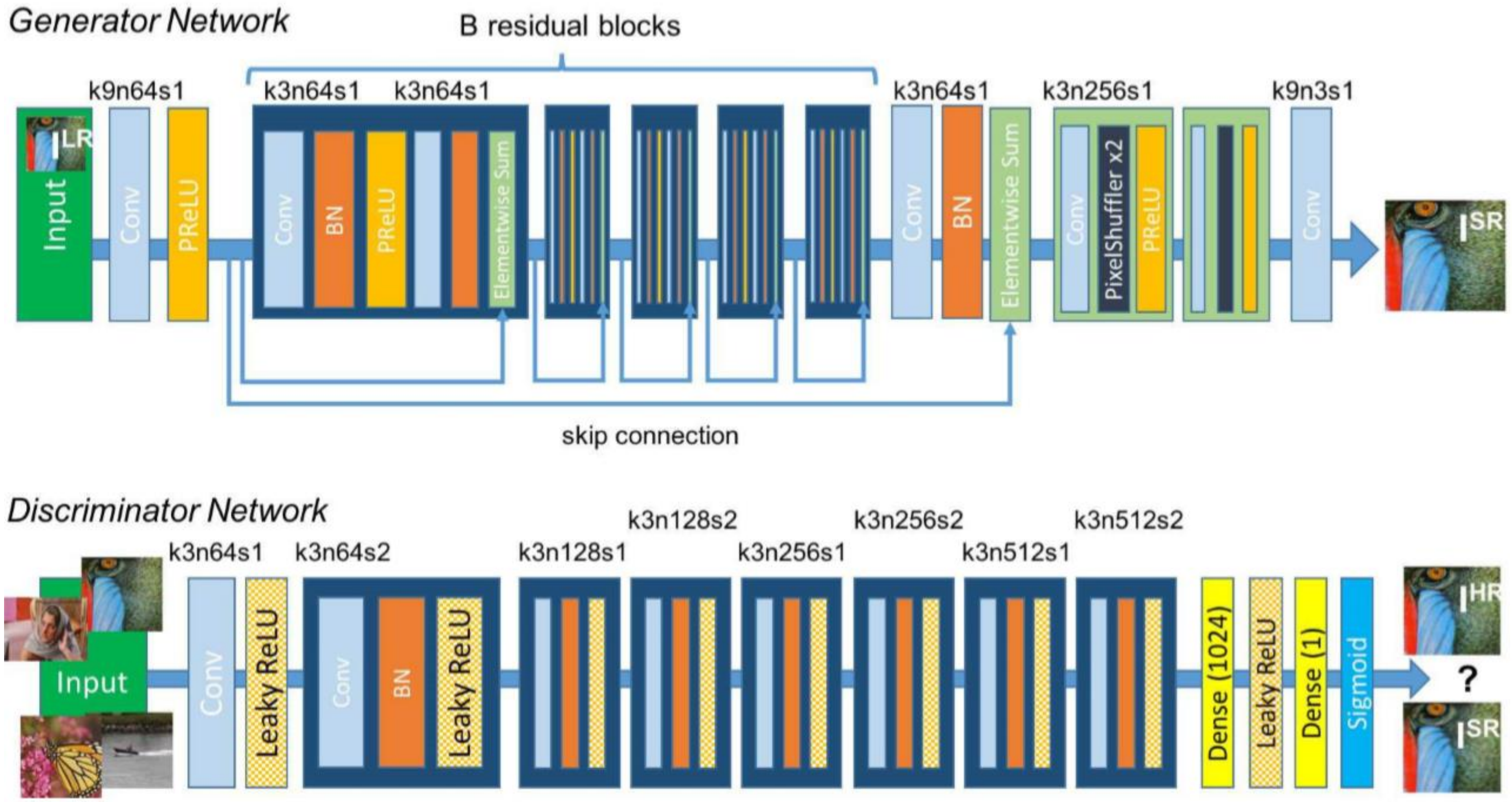
Despite the breakthroughs in accuracy and speed of single image super-resolution using faster and deeper convolutional neural networks, one central problem remains largely unsolved: how do we recover the finer texture details when we super-resolve at large upscaling factors? The behavior of optimization-based super-resolution methods is principally driven by the choice of the objective function. Recent work has largely focused on minimizing the mean squared reconstruction error. The resulting estimates have high peak signal-to-noise ratios, but they are often lacking high-frequency details and are perceptually unsatisfying in the sense that they fail to match the fidelity expected at the higher resolution. In this paper, we present SRGAN, a generative adversarial network (GAN) for image super-resolution (SR). To our knowledge, it is the first framework capable of inferring photo-realistic natural images for 4x upscaling factors. To achieve this, we propose a perceptual loss function which consists of an adversarial loss and a content loss. The adversarial loss pushes our solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images. In addition, we use a content loss motivated by perceptual similarity instead of similarity in pixel space. Our deep residual network is able to recover photo-realistic textures from heavily downsampled images on public benchmarks. An extensive mean-opinion-score (MOS) test shows hugely significant gains in perceptual quality using SRGAN. The MOS scores obtained with SRGAN are closer to those of the original high-resolution images than to those obtained with any state-of-the-art method.

Traditional (unsupervised/random input) GAN structures aim to generate realistic, random counterfeits



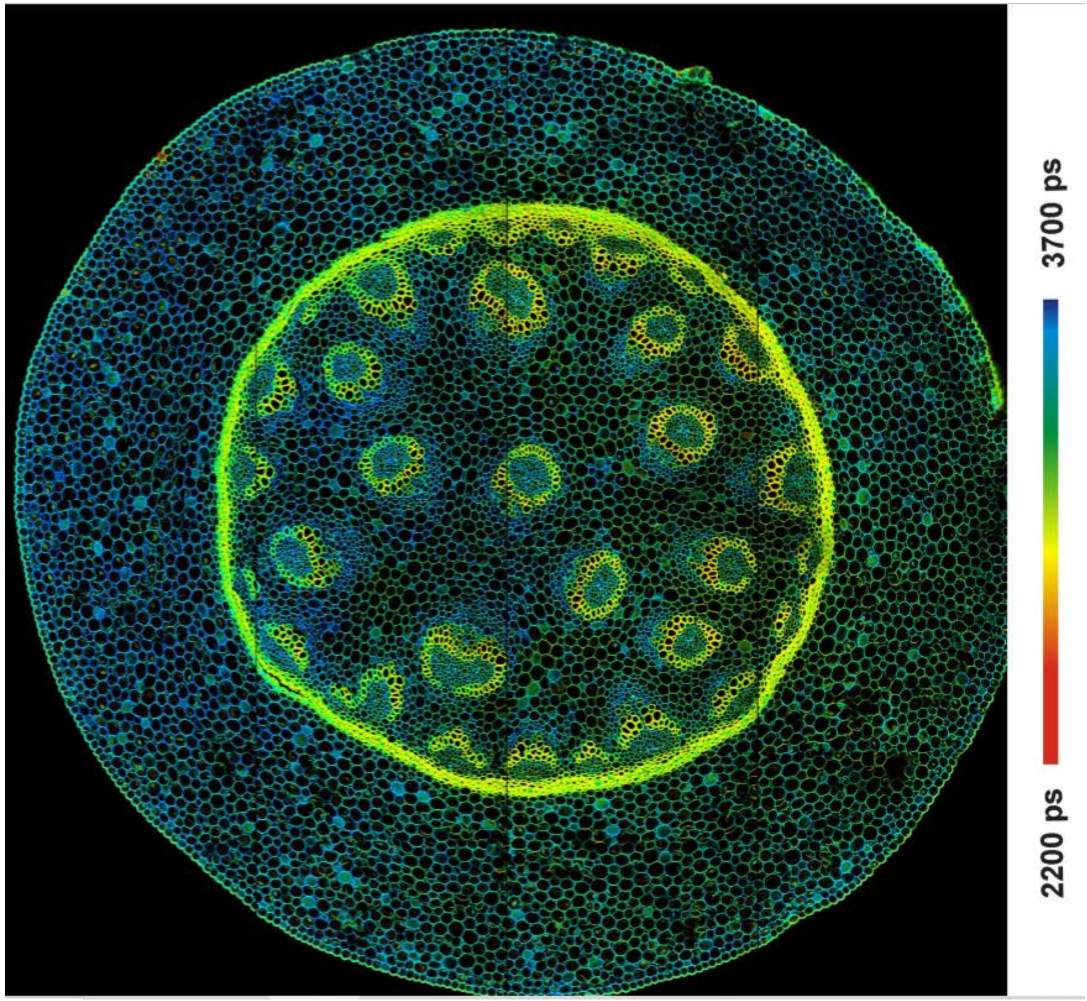
SRGAN (supervised) GAN structures aim to generate realistic, targetted counterfeits





Original SRGAN architecture [3]. The generator is a fully convolutional residual network (the residual property helps with the vanishing gradient problem). The discriminator is a CNN with some dense layers at the end. The discriminator follows the generator.

Final goal



Mosaic FLIM of a Convallaria sample [4]. The complete mosaic has 2048 x 2048 pixels, each pixel holding 256 time channels. To get good SNR, this image takes around 16 minutes to acquire normally, however acquisition time scales (mostly) linearly with pixel count. So, if e.g. only 1/16th of the pixels were needed, and the rest were inferred using a GAN, acquisition time could be reduced 16-fold.

References

1. Wikipedia Commons *Fluorescence* https://cs.wikipedia.org/wiki/Fluorescence
2. PicoQuant *Measurements of the fluorescence lifetime*. URL: https://www.picoquant.com/applications/category/life-science/time-resolved-fluorescence
3. Ledig, C., Theis, L., Huszár, F., Caballero, J., Cunningham, A., Acosta, A., ... & Shi, W. (2017). Photo-realistic single image super-resolution using a generative adversarial network. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4681-4690).
4. Studier, H., Weisshart, K., Holub, O., & Becker, W. (2014, February). Megapixel FLIM. In *Multiphoton Microscopy in the Biomedical Sciences XIV* (Vol. 8948, p. 89481K). International Society for Optics and Photonics.