Master thesis proposal

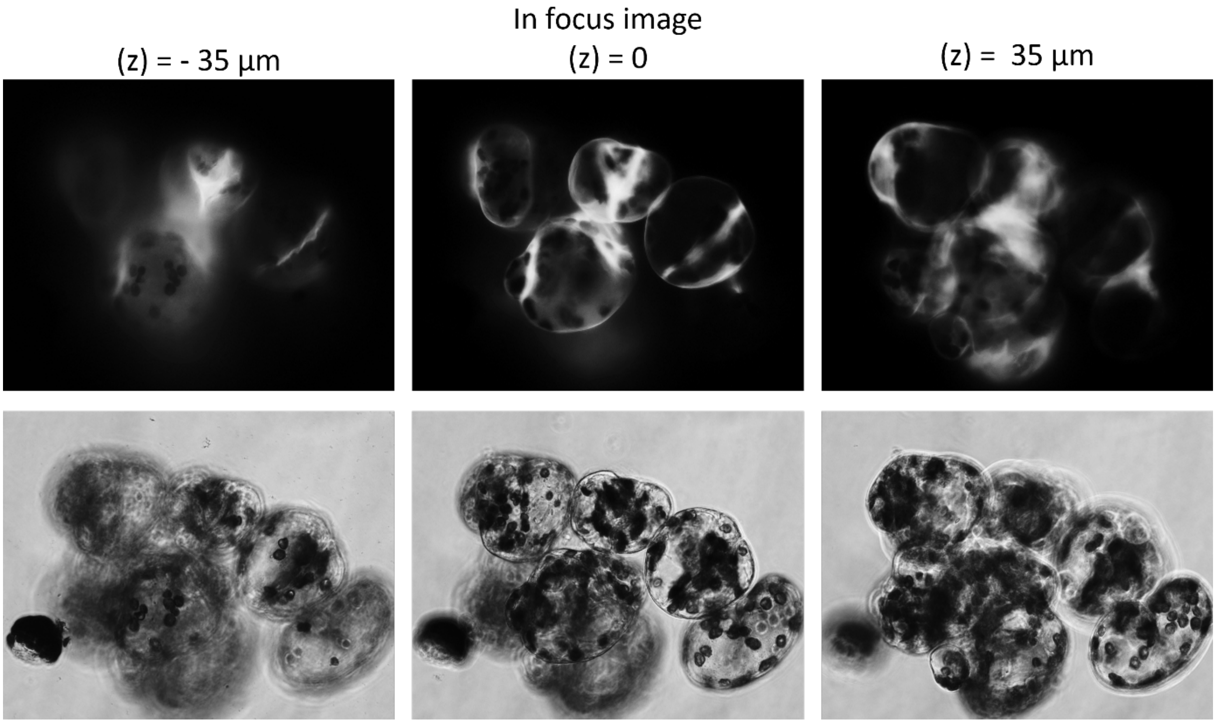

Figure 1: microscopy images of a protoplast cell cluster with different z-focal planes (top: fluorescence image. Bottom: bright field image). Each z level corresponds to a different amount of blur.

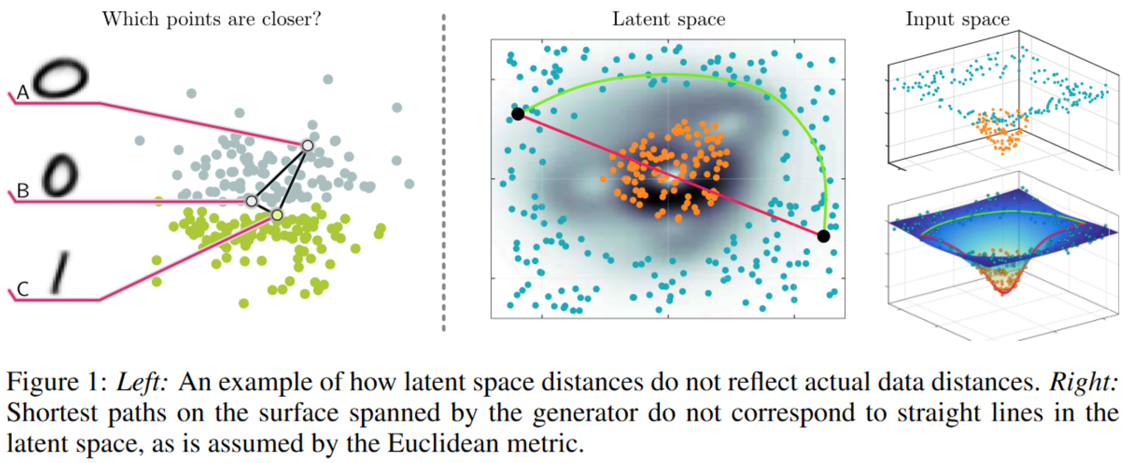

Figure 2: picture from Arvanitidis et al.[1] describing the phenomenon that distances in latent space do not reflect distances in data space

Title: Deep learning techniques for deblurring cell images utilizing (Riemannian/Differential) geometry.

Description:

To predict how a plant will grow, it is important to investigate how division planes in plants form on a single cell level. To build prediction models of the plant cell division and their division planes, we need clear microscopy images. For real microscope setups, such clean images are usually not acquired, as the microscopy images always have a certain level of blur.

We know a blurred image is an in-focus image convolved with a blurring kernel. To get clean non-blurry images, one has to solve the deblurring deconvolution problem. The big issue is that one does not know the blurring kernel. To learn the blurring kernel and deblur images, it has been shown in the literature that Deep Learning is a successful tool.

The goal of this project is to create a deep learning method for deblurring that uses information from the geometry of the (image) data manifold[1, 2] to improve deblurring. For the project, protoplast microscopy data will be provided on which the developed deblurring approach can be tested.

One possible approach is to create an autoencoder of images and find a path in latent space between two blurry versions of an image that has a clean deblurred image in between. The easiest path would be a linear interpolation in latent space. However, the real blurring might not correspond to a linear interpolation in latent space. This is related to the observation that distances in latent spaces do not correspond to distances in data space[1, 2]. In particular, this means that distances in latent spaces do not correspond to distances between images with different level of blur[1, 2]. So we want to embed the data geometry in the learned manifold such that we can find nonlinear paths in latent space that correspond to blurring and deblurring of an image.

Keywords: latent space, deblurring, differential geometry, Riemannian geometry

References:
[1] Arvanitidis, G., Hansen, L. K., & Hauberg, S. (2017). Latent space oddity: on the curvature of deep generative models. arXiv preprint arXiv:1710.11379.

[2] Chadebec, C., Mantoux, C., & Allassonnière, S. (2020). Geometry-aware Hamiltonian variational auto-encoder. arXiv preprint arXiv:2010.11518.