

Level 4 Project

Week 13

(Week 12/13 Recap)

Original plan for weeks 12 and 13

- **Week 12**

- Finish evaluating best pre-processing method
- Tune autoencoder for dimensionality reduction
- Evaluate t-sne clustering

- **Week 13**

- Visualise t-sne → changed visualisation function + gif function
- Explore methods of segmentation:
 - k-means clustering (2 clusters)
 - contour finding
 - structure similarity
 - blob detection
 - Top-hat transformation?
- Submit status report

T-SNE visualisation in GIF

- Not pictured here because of the size of the GIFs
- <https://drive.google.com/file/d/1SKd2M9Kv6xKsrUxS2M0NC2KuRyV2Ebf6/view?usp=sharing>

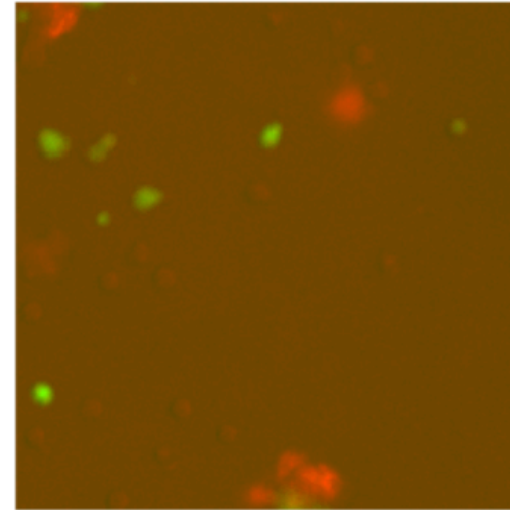
Clipping DMSO dataset values under 255

- low_clip function transforms <255 values to 0
- max_normalise function normalises according to max pixel value of the image
- Performance is very similar to previous, if not slightly worse in terms of loss

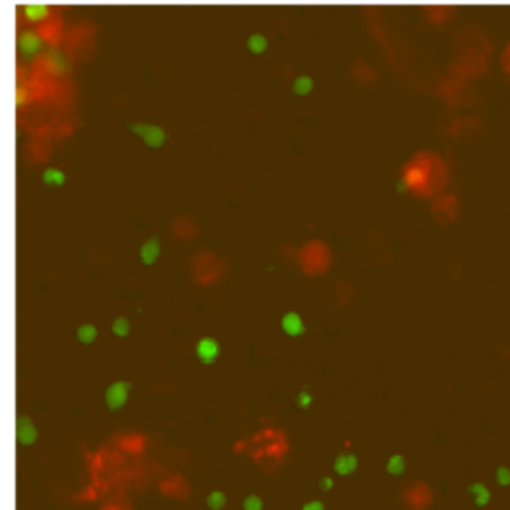
Combining tcell, dc DMSO images into RGB image

- Red channel = dendritic cell
- Green channel = tcell
- Blue channel = empty

original training image



original test image



Summary of all models and outputs

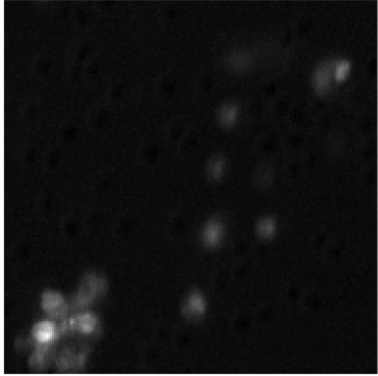
- Available at: https://github.com/leonore/l4-project/blob/master/src/cell_autoencoder.ipynb
 - The important things are the titles and the images
- While doing this I found out that the issue I had been having with poor reconstructions all this time was because unclear documentation in Numpy made me think I was making copies of the dataset, but I was really reusing the array every time.
 - So normalisation over normalisation etc. resulted in a lot of loss.
 - So even 16-bit normalisation gets *some* kind of result but max normalisation still works a lot better.

What I learned from the summary

- Always make a new copy of the data
- Combining the images in a RGB image seems to work better for clustering.

Image segmentation with K-means

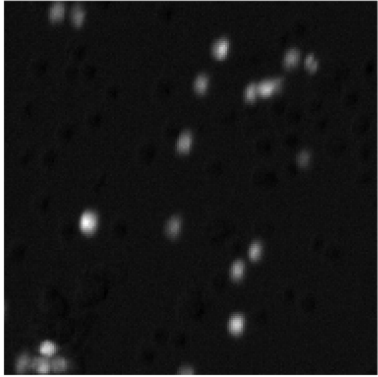
Original Image



Segmented Image when K = 2



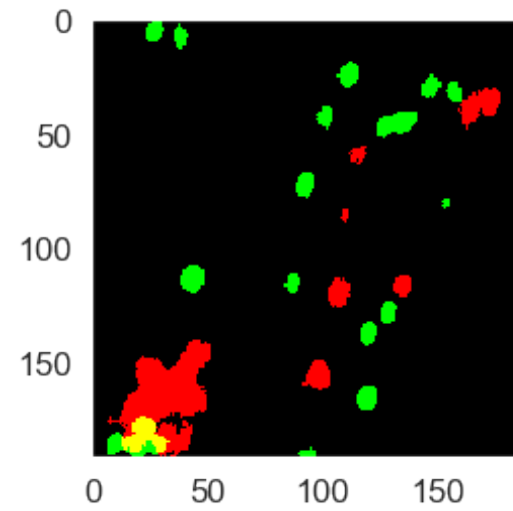
Original Image



Segmented Image when K = 2

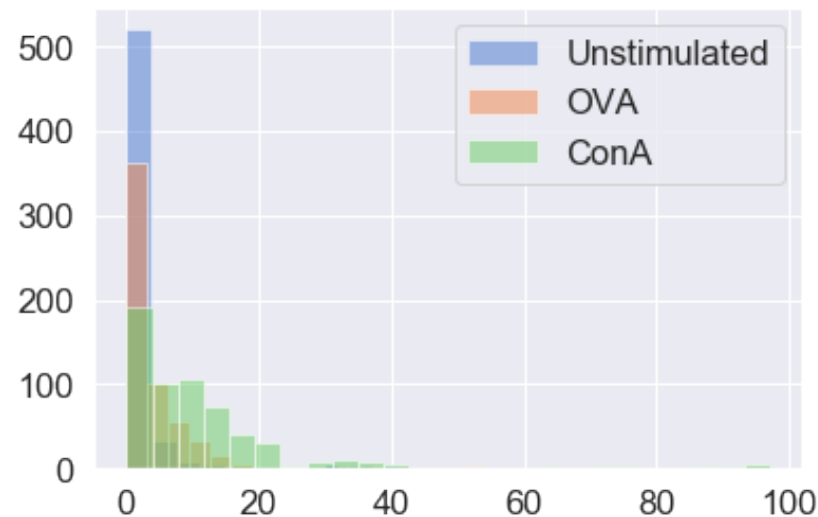


- Works very well for getting masks and direct overlap
- Overlap is shown in yellow below, calculated with intersection over union

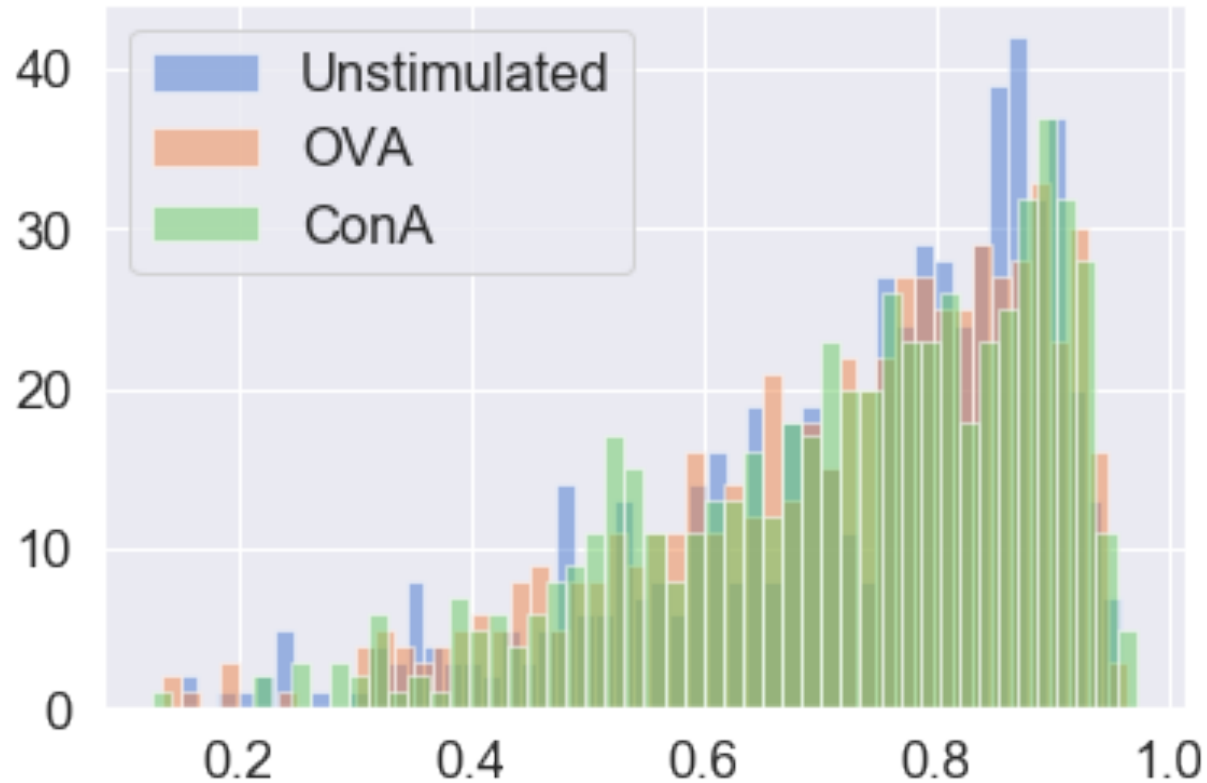


Overlap results with K-means

- Quite spread out, but the mean is maximum for ConA
 - This is in line with what Hannah has told me about ConA driving the most interaction at 60-80% overlap
 - Calculated % is much lower here though
- Sample size issues: both unstimulated and ConA have 9400 samples, but OVA has 1200
 - Results are consistent with a same-sized subsamples:
 - We get more 0% interaction with no stimulation, then OVA, then ConA

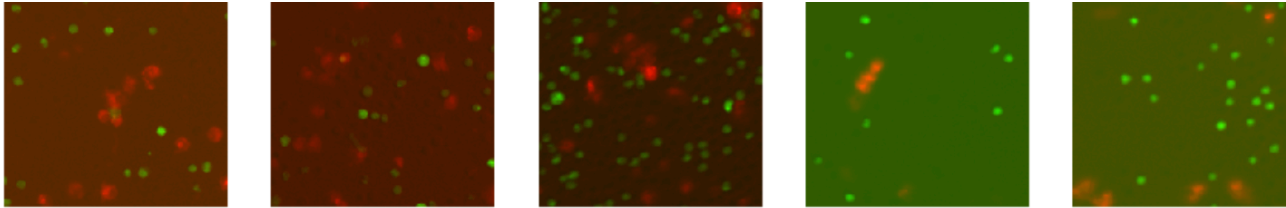


Investigating structural similarity index

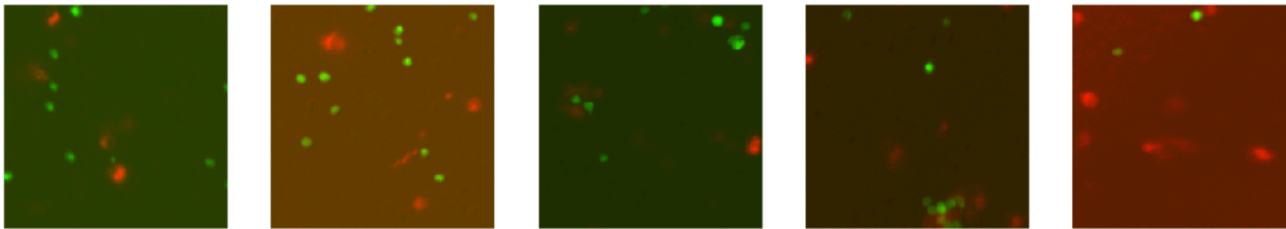


Doesn't seem to be a very promising technique as an interaction detection technique as they are all quite structurally similar (blobs of cells, lots of background)

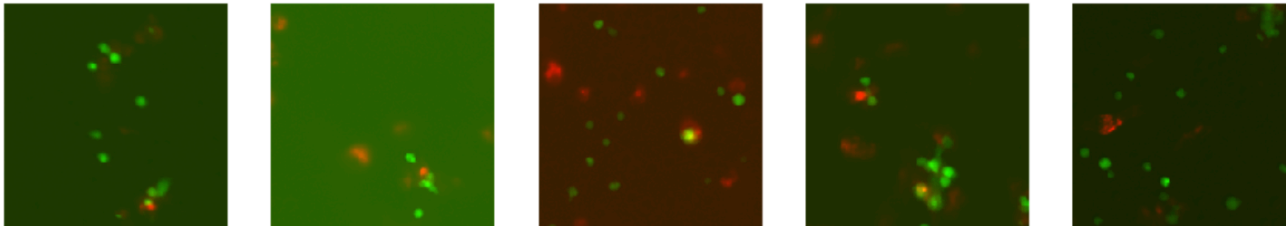
Combining K-Means + autoencoder



```
plot_range(ova, rn=9)
```

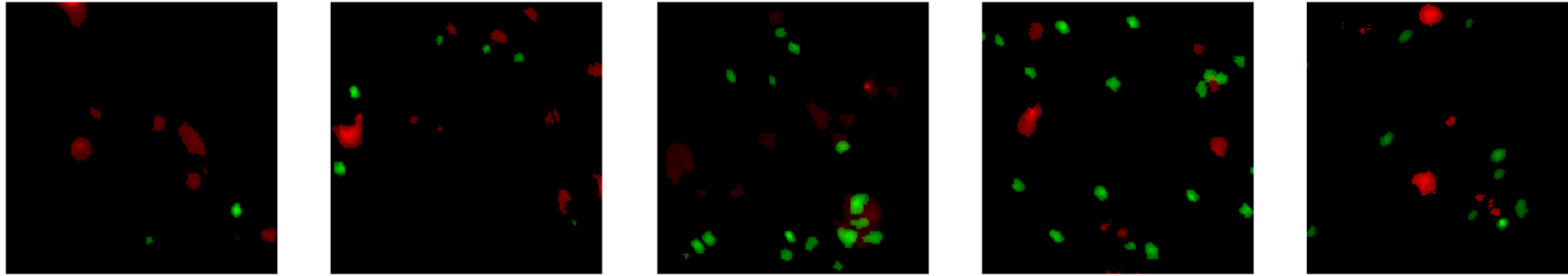


```
plot_range(cona, rn=9)
```



- Making a dataset with the images, but their background is masked out with the masks obtained through K-Means
- This is because as you can see, the images seem to be very dependent on the shade of the background

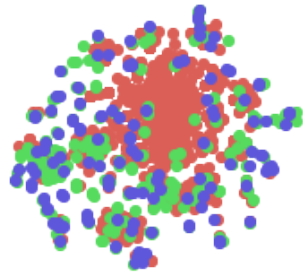
Combining K-Means + autoencoder



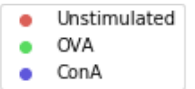
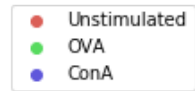
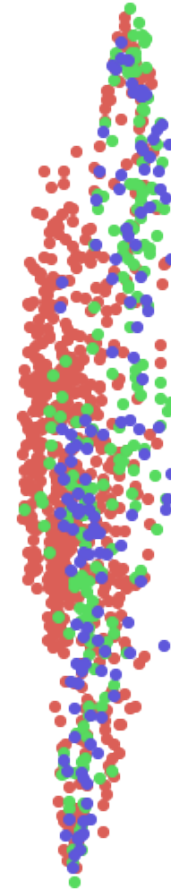
- As you can see the shades are much more consistent.
- And the clustering results are much more promising:
 - One main cluster but very tight “unstimulated” cluster within it
 - Some outliers which can come from empty images, images that suffer from the pre-processing, etc.

Combining K-Means + autoencoder

t-sne



UMAP



Next steps

- I want to re-investigate using a UNet like structure for detecting masks in unseen images and be able to differentiate between dendritic cells and t-cells.
 - It seems that this is Hannah mentioned at the beginning of the semester: how software struggles with dendritic cells, but not t-cells as they are blobs.
 - What do you think?
- Full plan is in status report