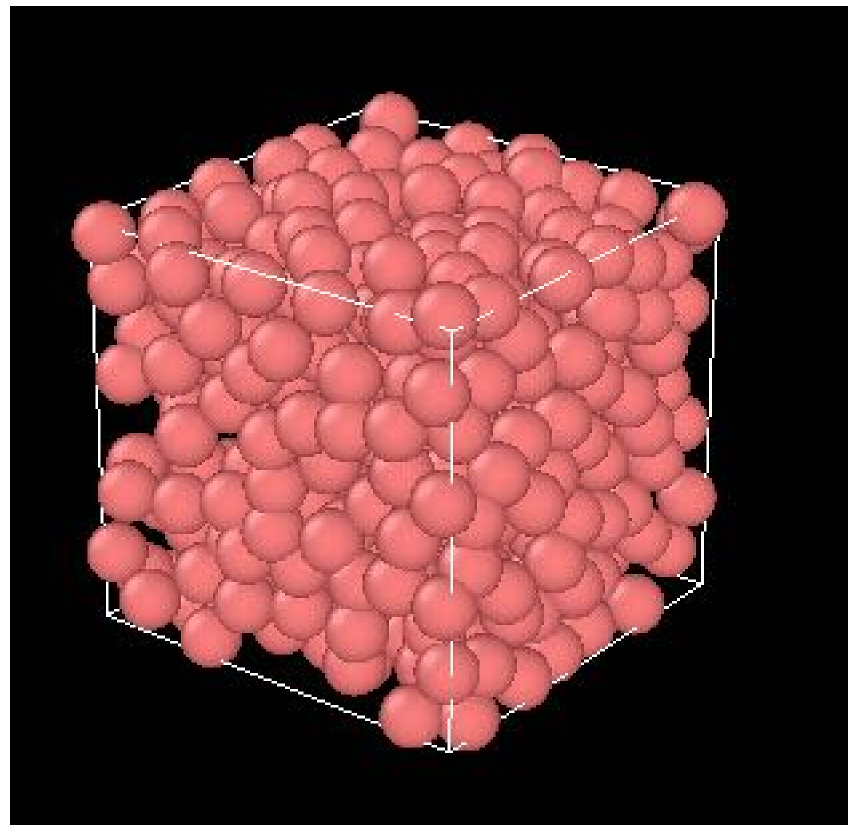
Particle Tracking

Another solvable problem by deep learning?

3D Particle Tracking

We arrange spherical particles into a dense pack, the ground truth would look like the following video

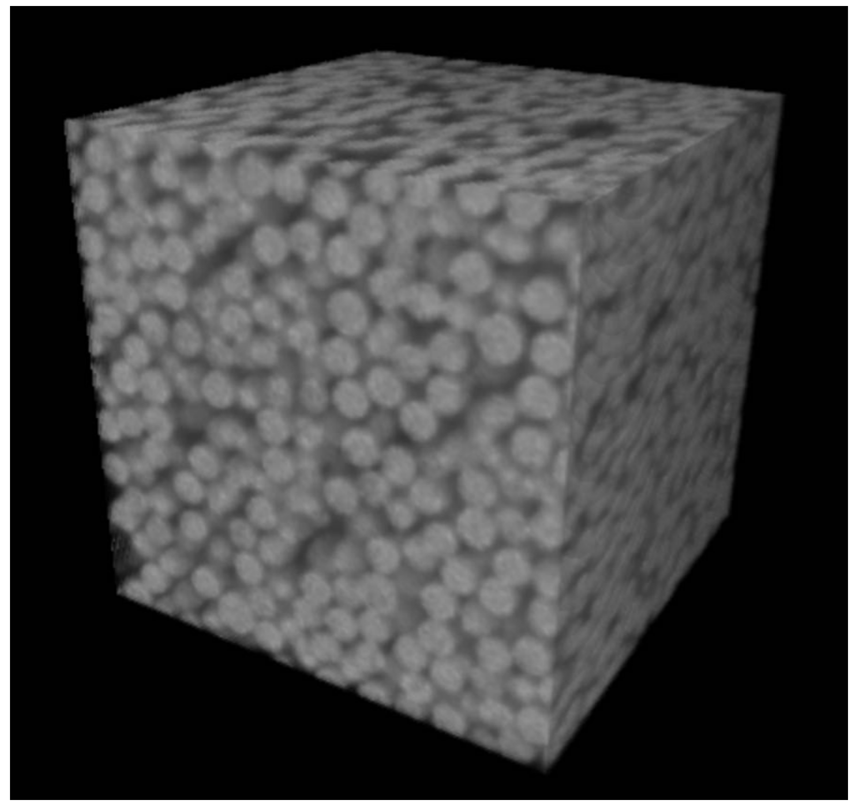


These particles are REAL, they were suspended in a solvent. The whole thing looks like the photo.

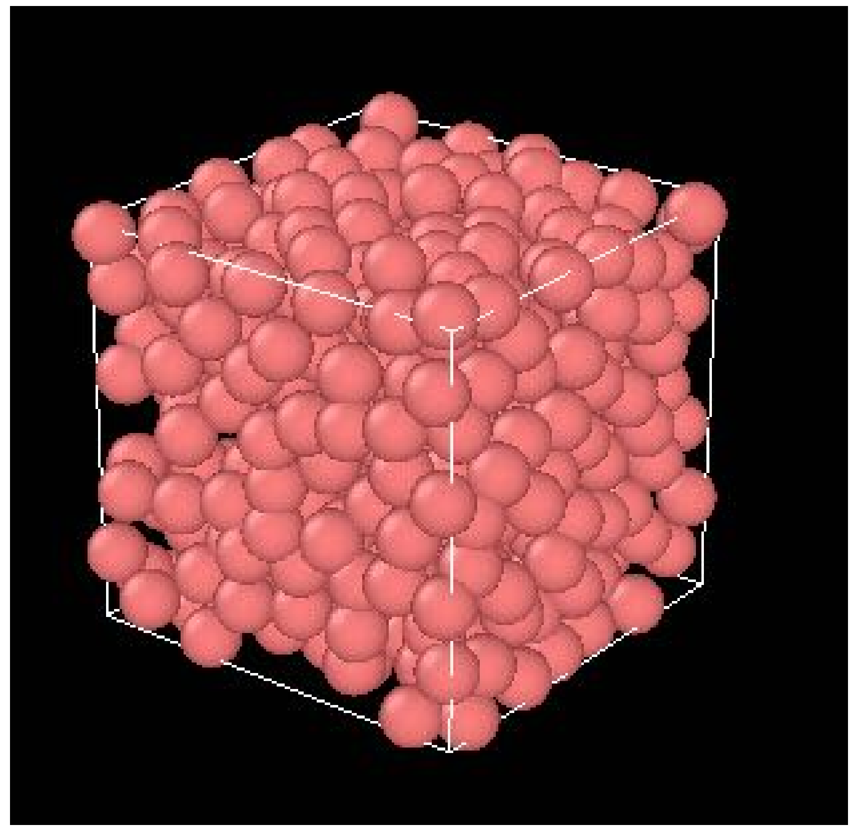
Pusey & Megen 1986 Nature

3D Particle Tracking

Confocal Microscopy

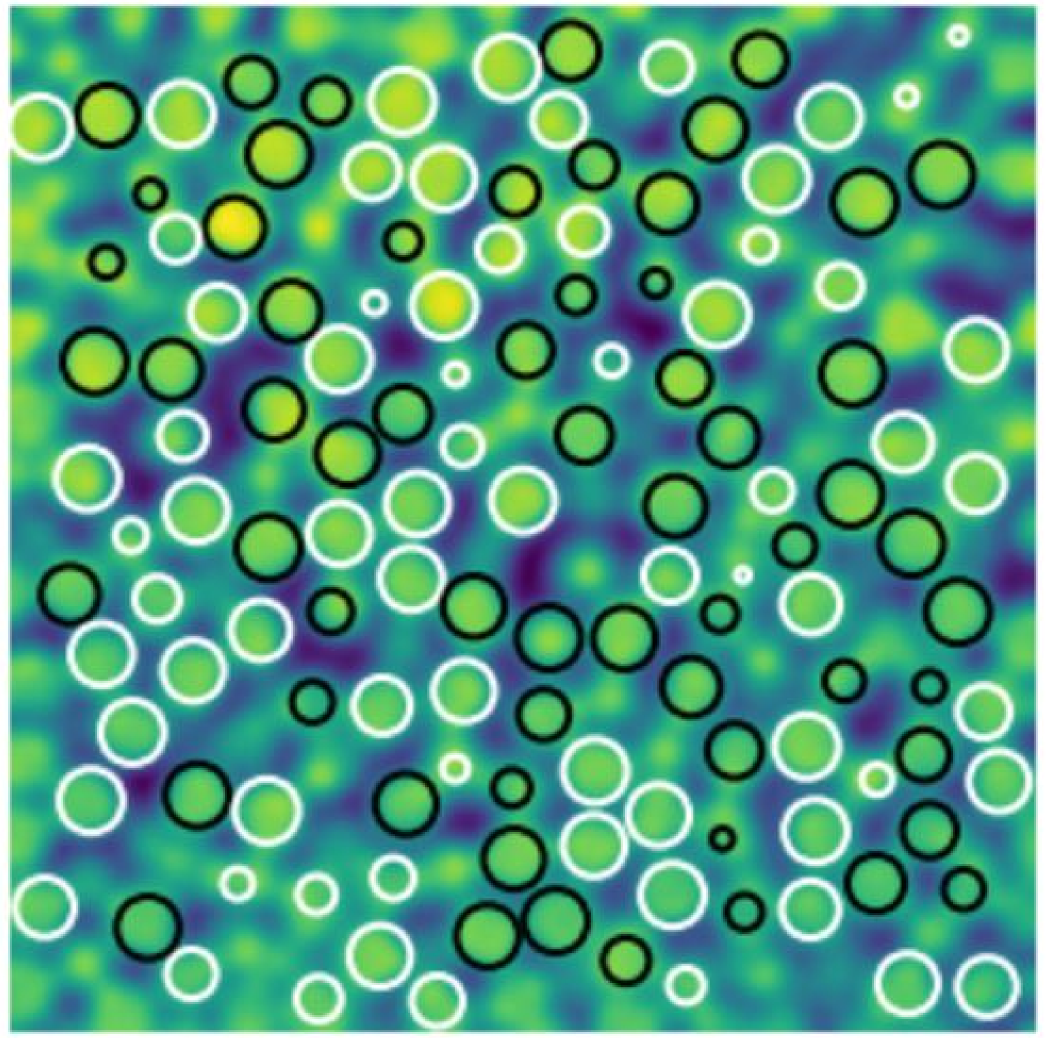


Tracking



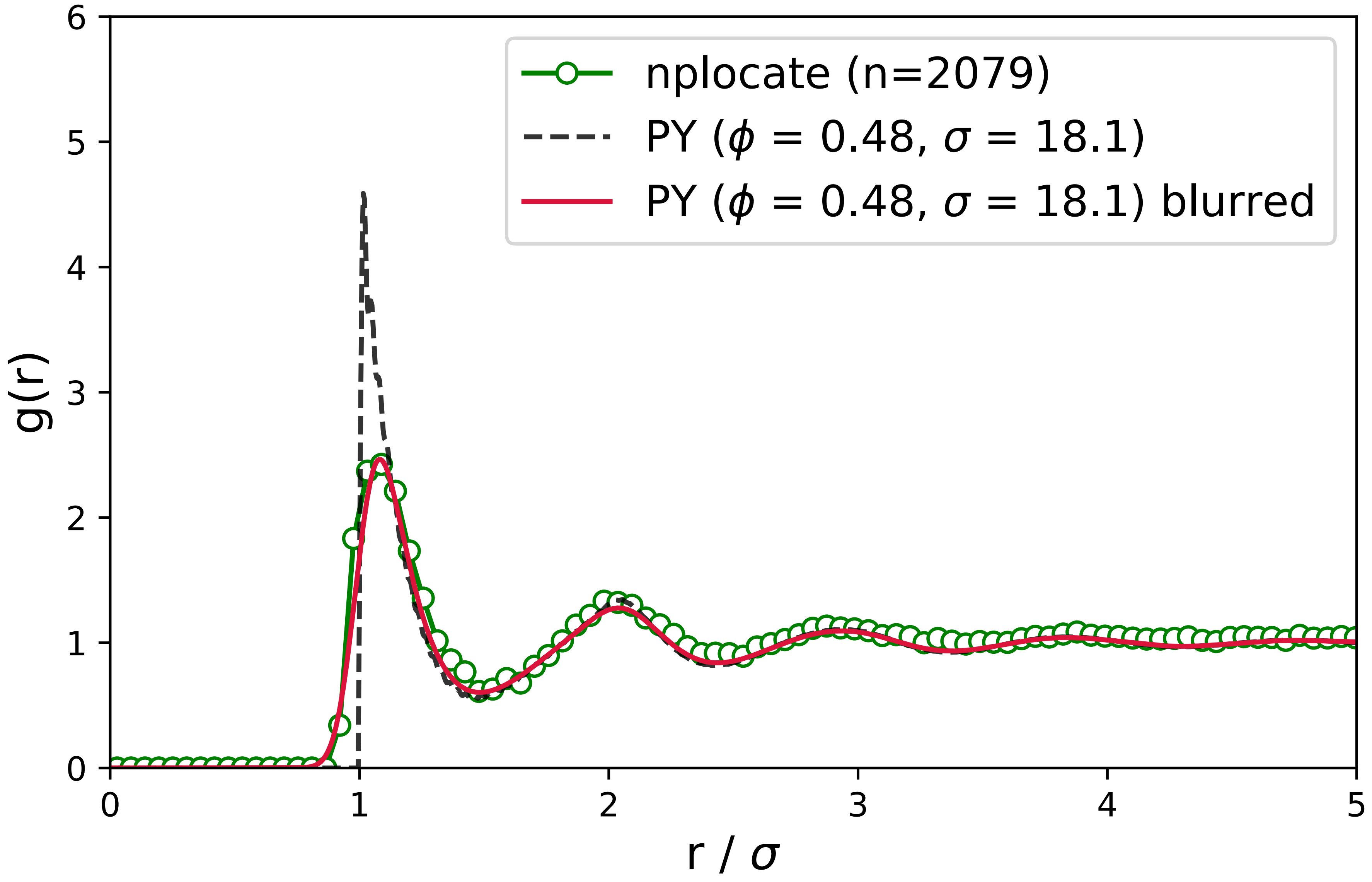
How do We Check the Result

Annotate The Image
(circles are tracking results)

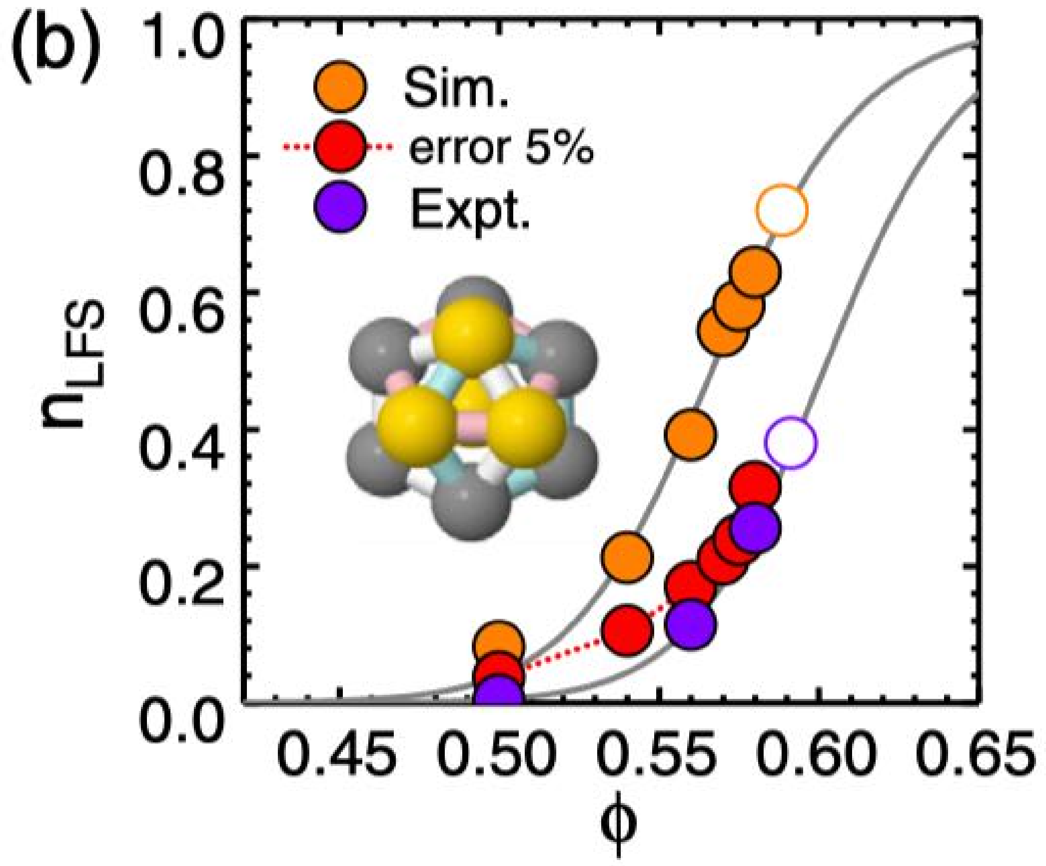


3µm PMMA particle
“my own data”

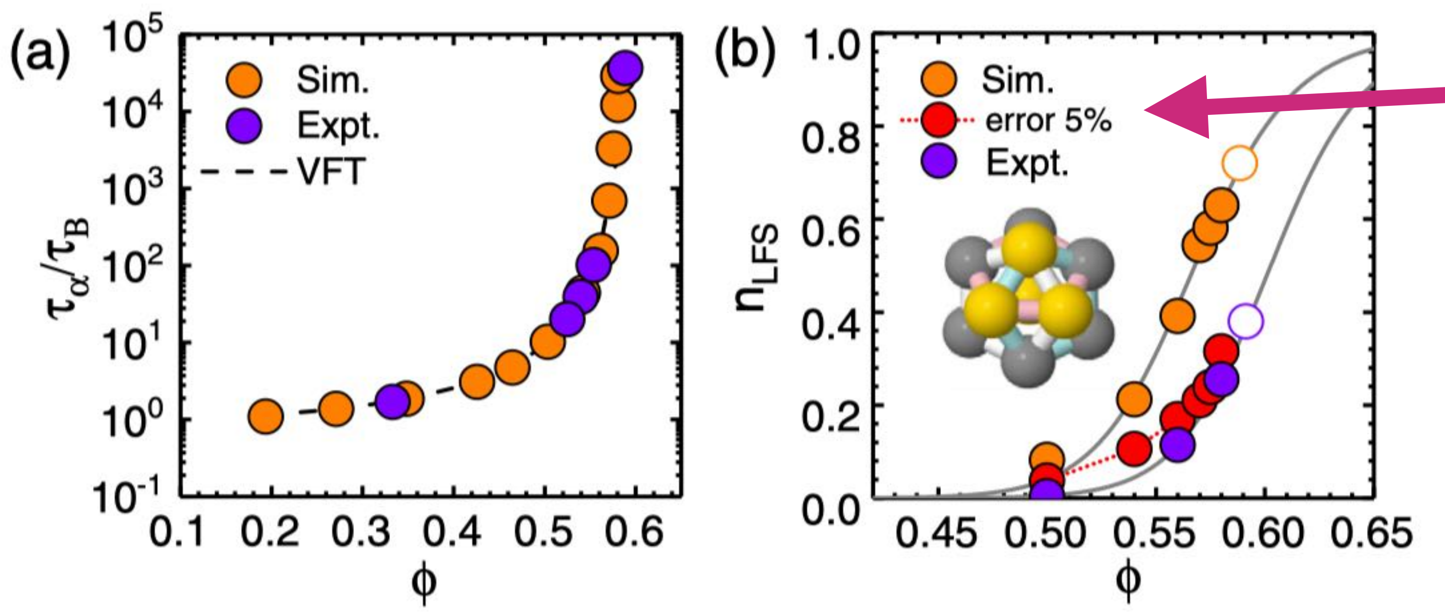
Calculate the Correlation Functions
(compare with the theory)



TCC Results
(compare with the simulation)



Problems with Tracking Error



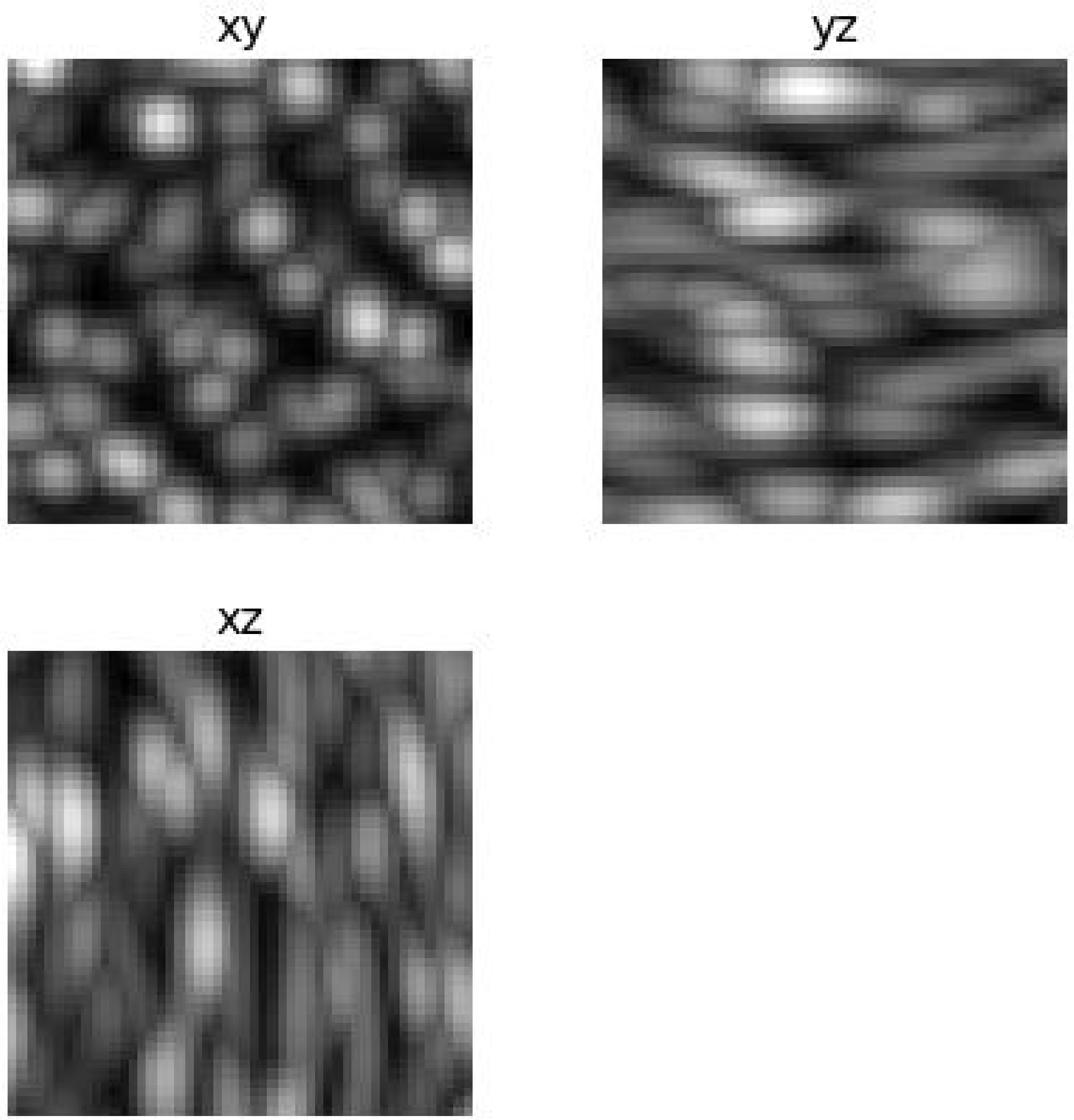
Missing 5% particles

Huge difference in high-order measurement (TCC)

FIG. 1. Dynamical behavior and structural changes upon supercooling hard spheres. (a) Angell plot of structural relaxation time τ_α as a function of the volume fraction. The dashed line is the VFT fit described in the text. (b) The fraction of particles identified in defective icosahedra locally favored structures n_{LFS} increases upon supercooling. The simulation data with errors added to the coordinates (the red symbols) show quantitative agreement with the experiment. Unfilled symbols indicate a volume fraction corresponding to the LFS population in a LFS-rich phase. The grey lines are fits to $n_{\mathrm{LFS}}(\phi)$ (see the SM [25]).

Pinchaipat et al. 2017 PRL

Problems with Small Particles



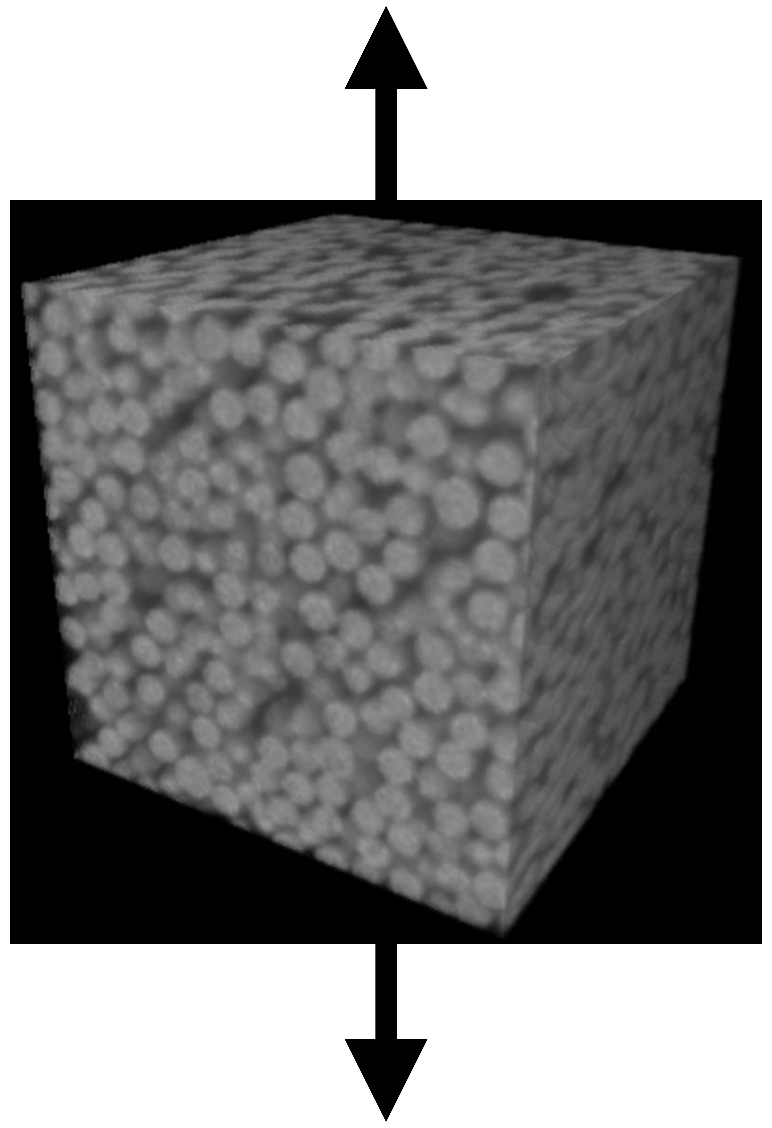
The elongation along z-axis makes tracking difficult

Previous Solutions

	Code available	I Know How to Use
Leocmach & Tanaka 2013 Soft Matter - compare particle with pre-designed kernels - extra *ad-hoc* deconvolution process	✓	✓
Bierbaum et al. 2017 PRX - write down all the possible contributions, analytically - fit the entire image, knowing everything	✓	
Newby et al. 2018 PNAS - Input: image - Output: binary image, highlighting particle centres - Use simulated image to generate training data	✓	

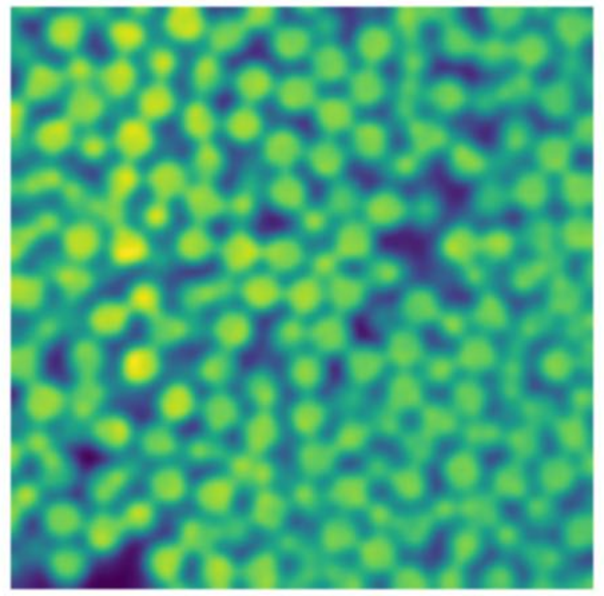
My Heuristic

Particle Shape, S

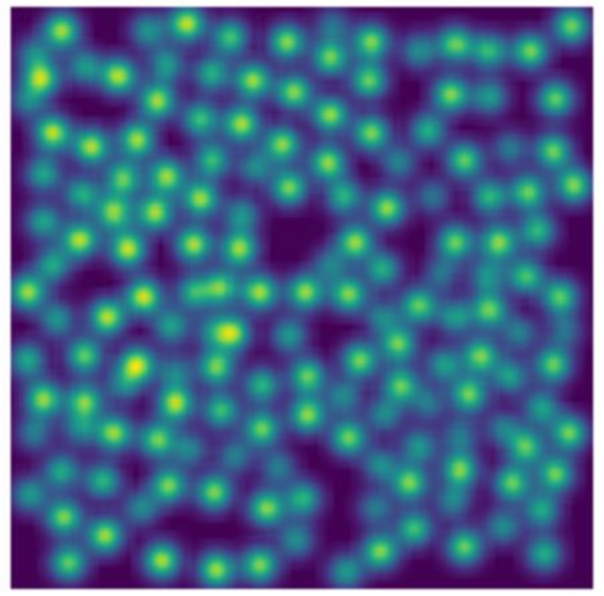


Coordinates, {r}

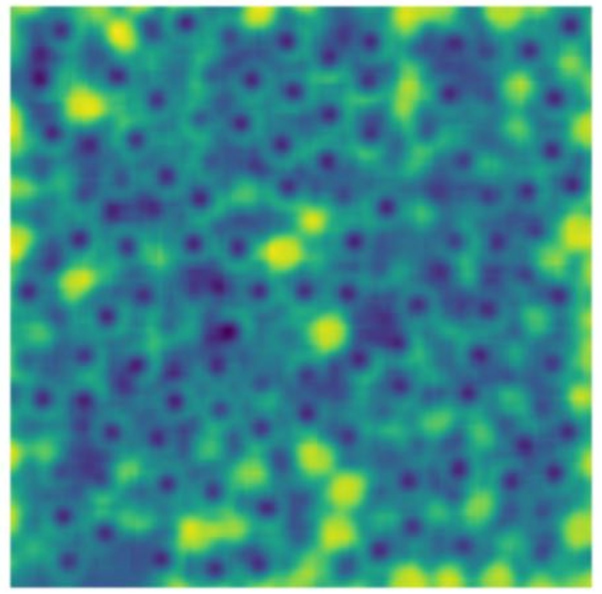
Tracking → {r}
Measurement → S
S + {r} → simulated image
data - simulation → extra particles



Image



Simulation



Difference

My Naive Machine Learning Approaches

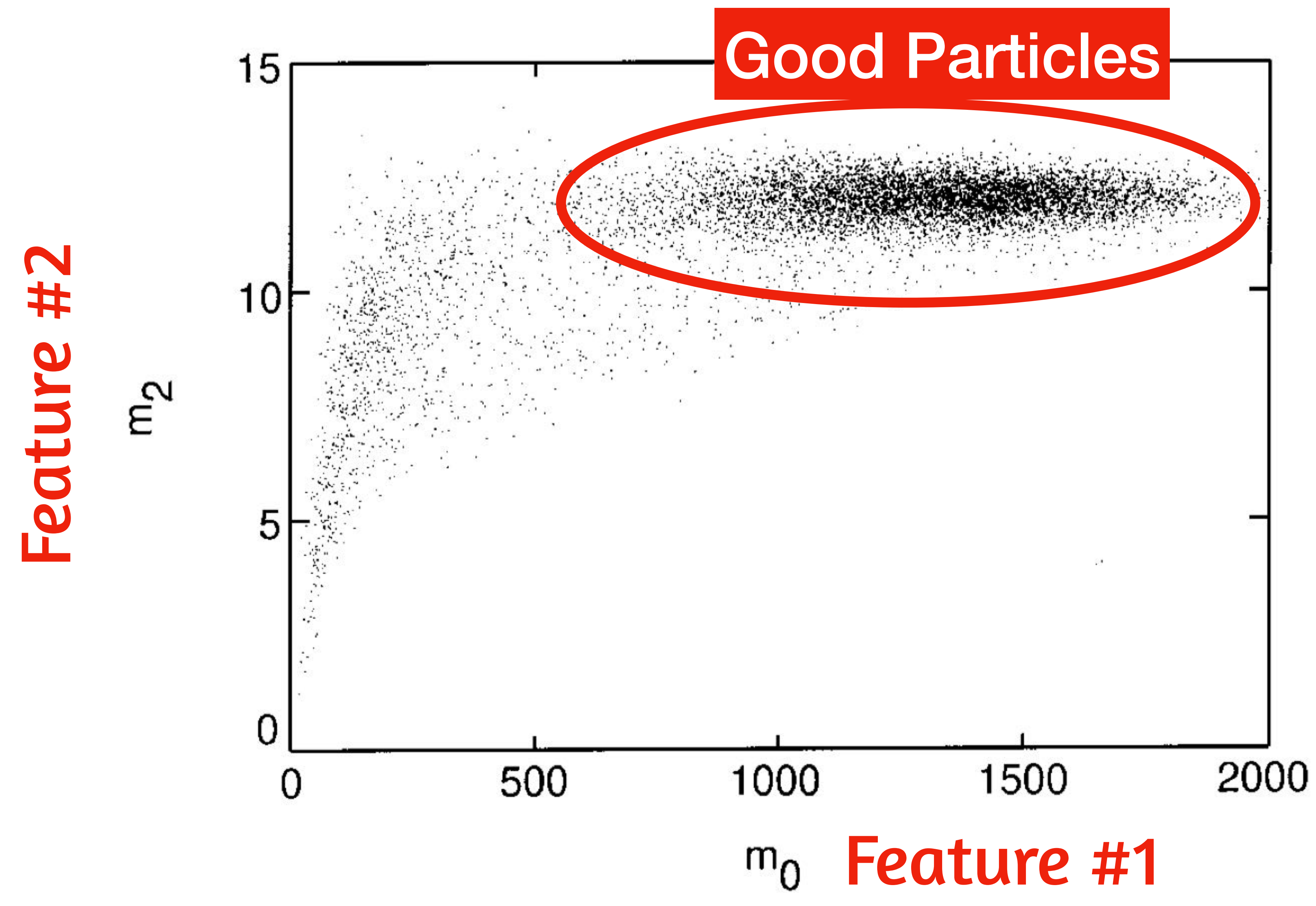


FIG. 2. Clustering of colloidal images in the (m_0, m_2) plane. 15,000 images of $\sigma = 0.325\ \mu m$ radius spheres.

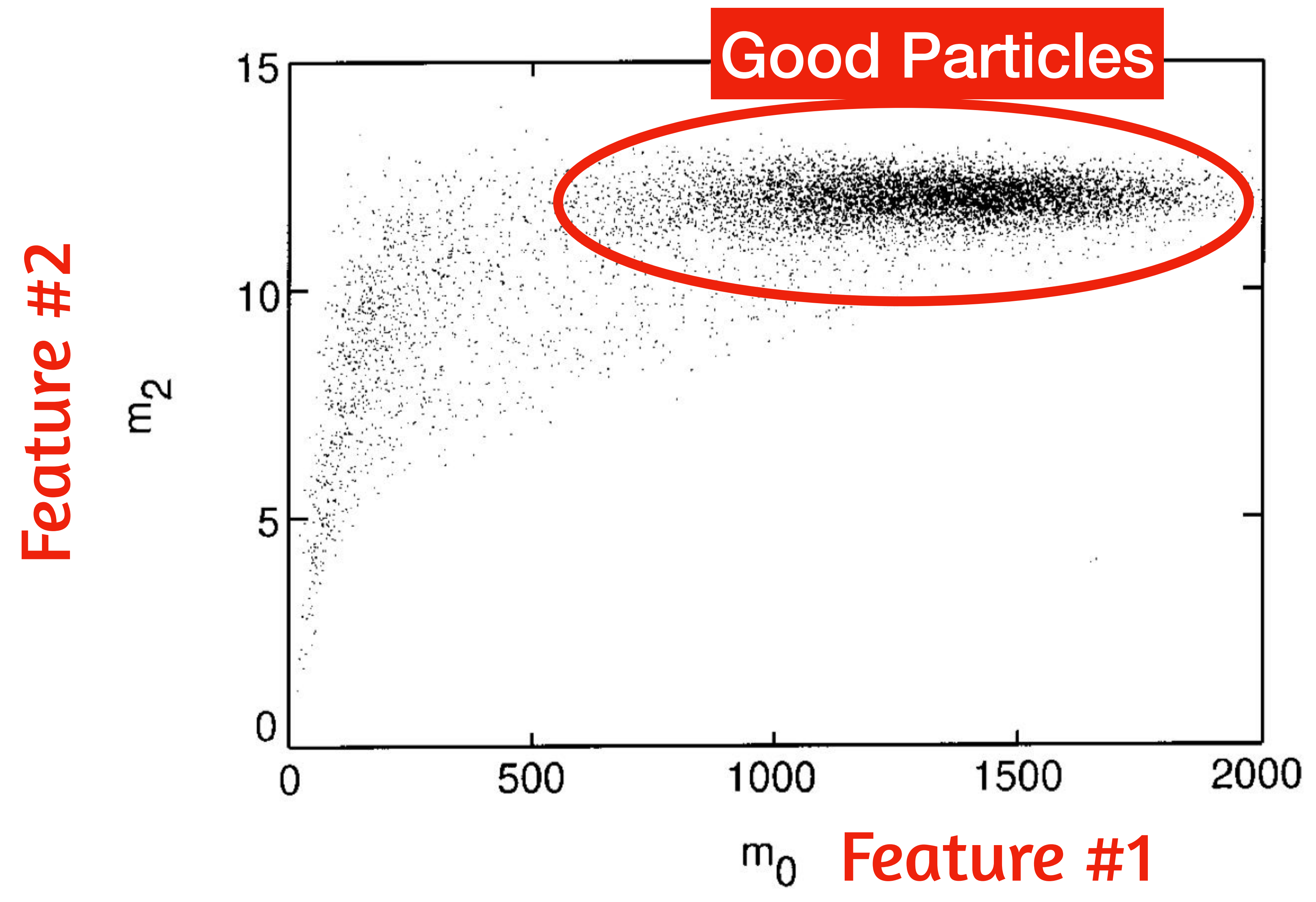
Crocker & Grier 1996

Anna Karenina principle:

(particles)
All happy families are alike;

(particles)
each unhappy family is unhappy in its own way.

My Naive Machine Learning Approaches



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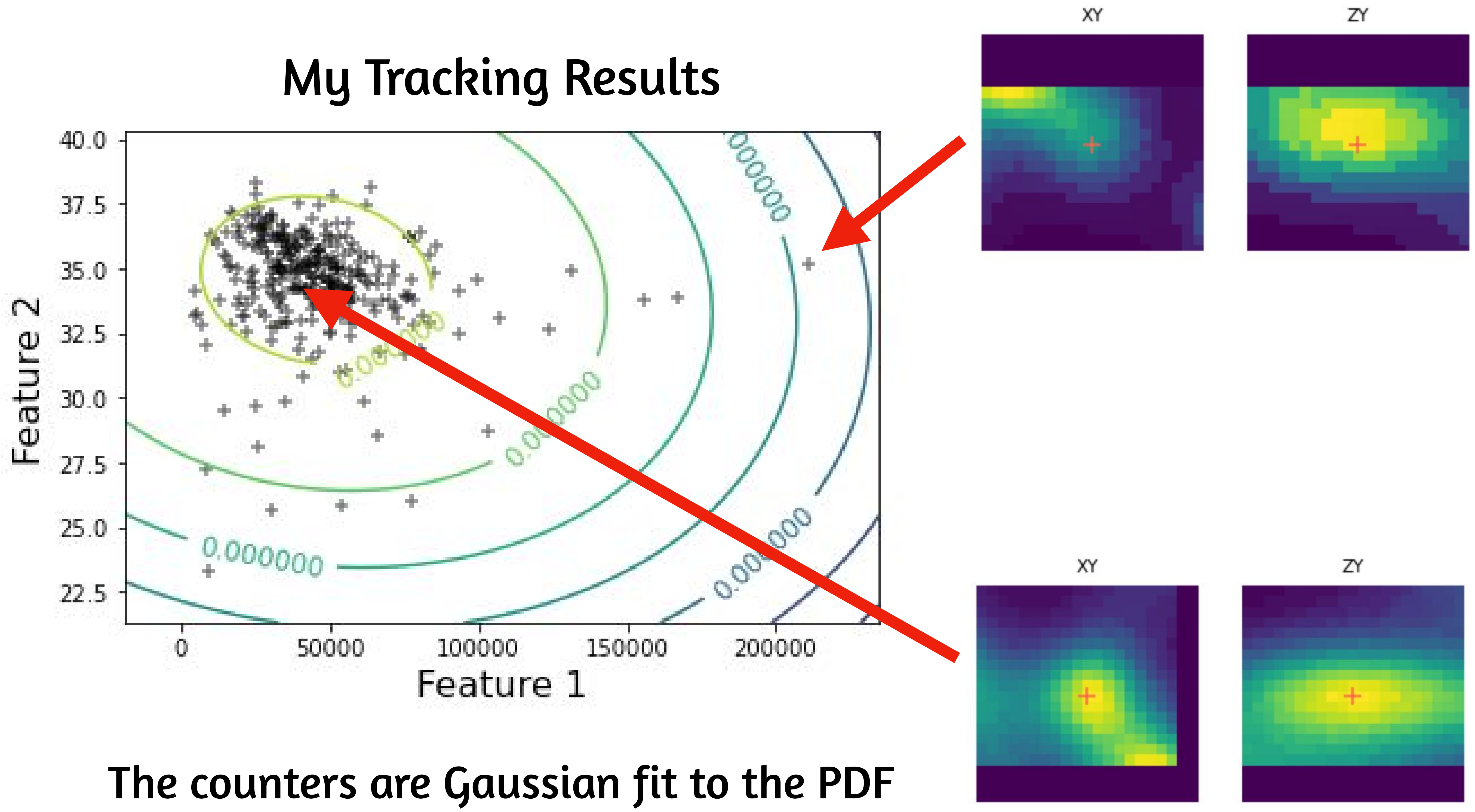
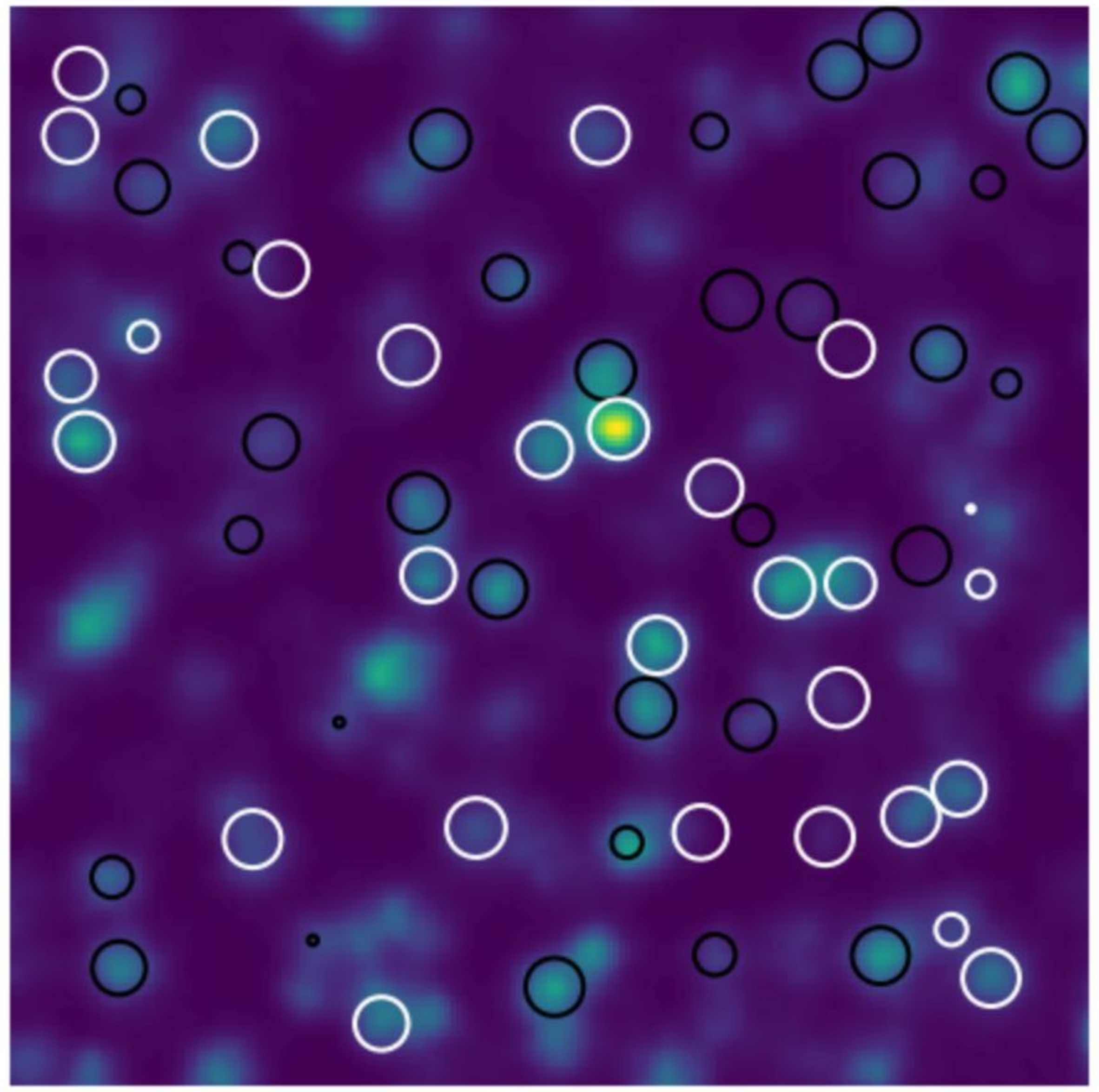
Crocker & Grier 1996

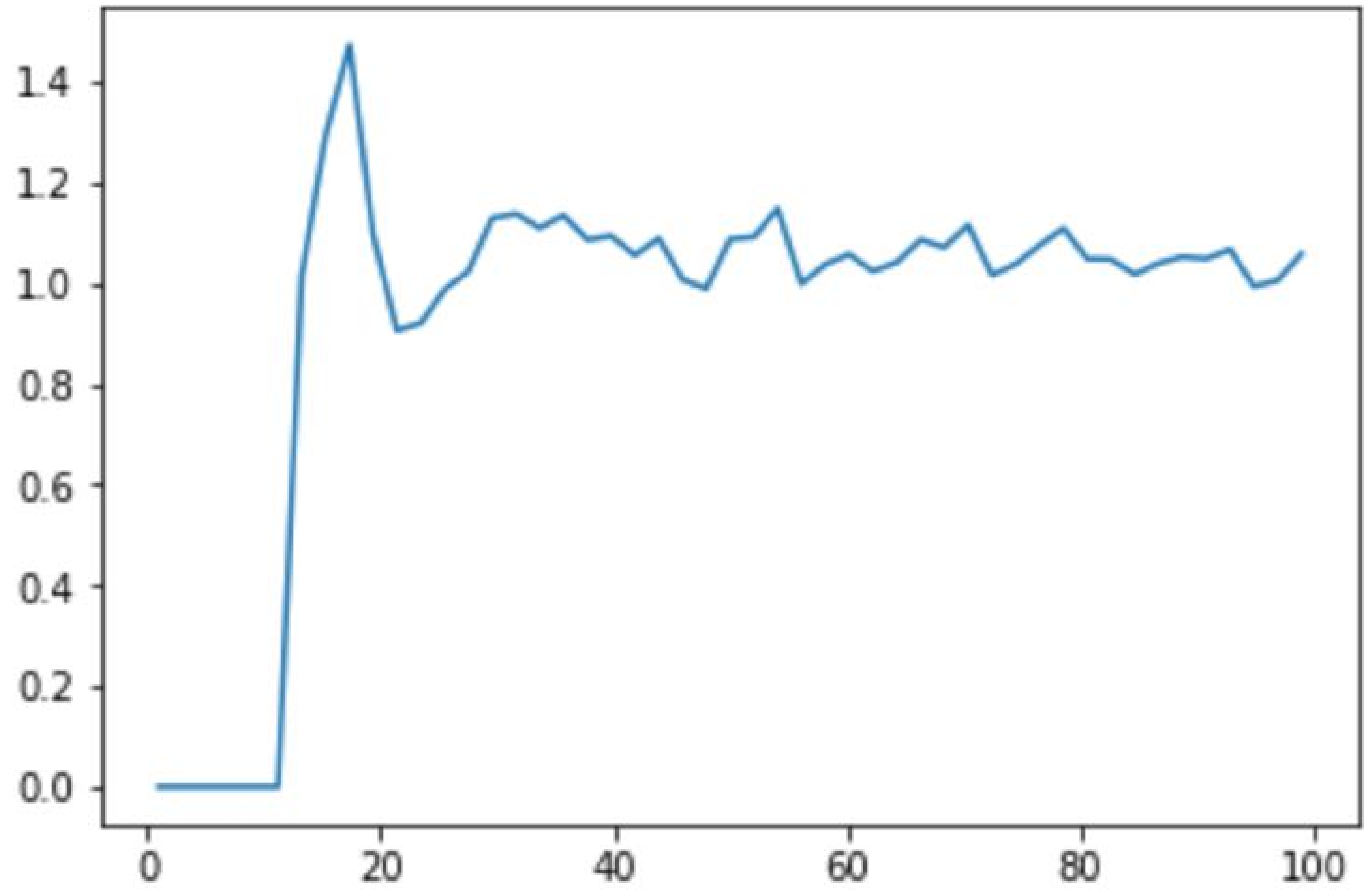


The counters are Gaussian fit to the PDF

It is not enough

After all the work, we still get pretty rubbish results





My thoughts

After all the work, we still get pretty rubbish results

Following Newby's approach, maybe start with a trial 3D U-Net

The images are HUGE, may need to chopping the image, map & reduce

The code should be really easy to use

```
data = preprocess(image)
result = track(data)
refined = refine(result)
```