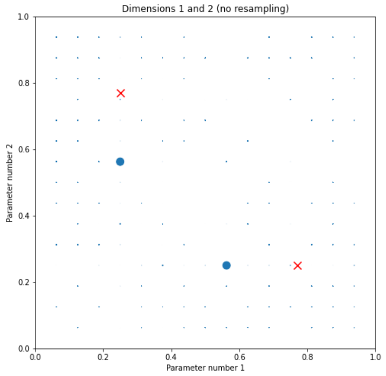
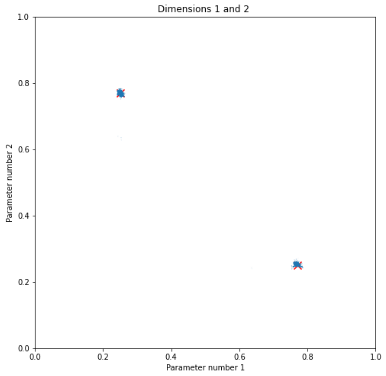
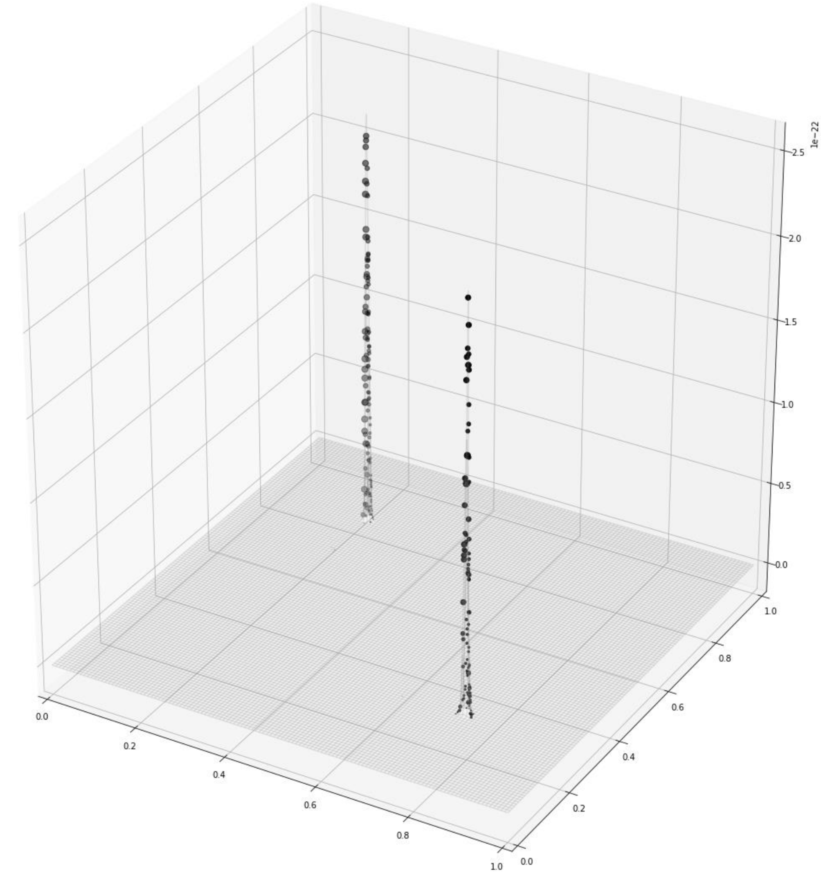
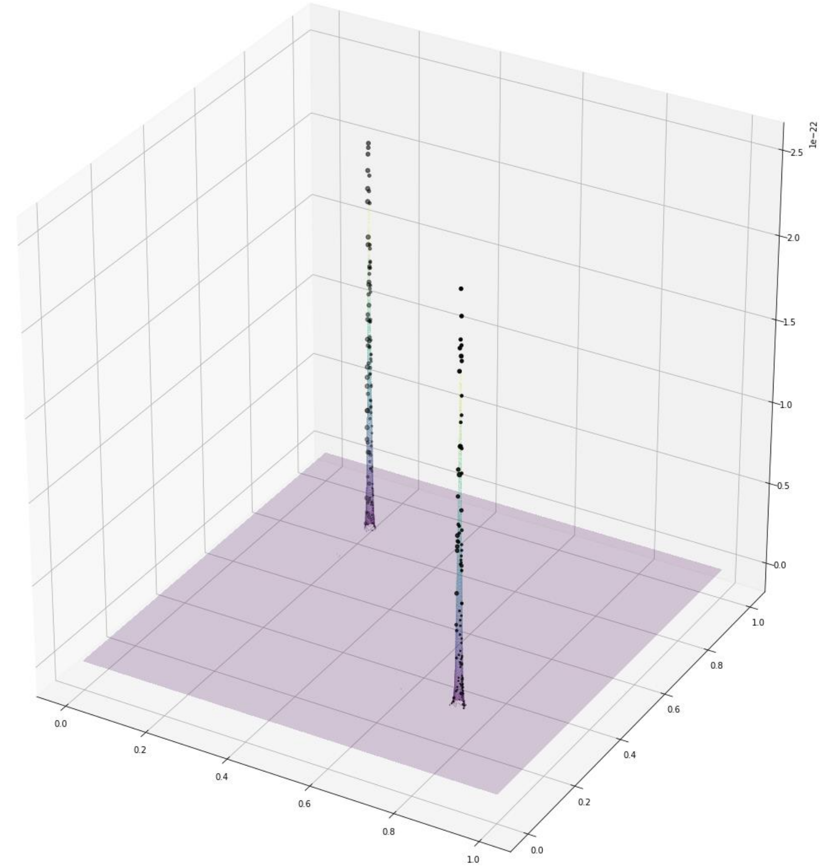
Likelihood vs. distribution plots









Offline estimation: random times <= 100
Uniform prior distribution, data chunksize = 20
1 particle group
HMC: Cov^-1, L=10, eta=0.0100000000
> n=15.00^2; N=100; 2d sum of squared cosines

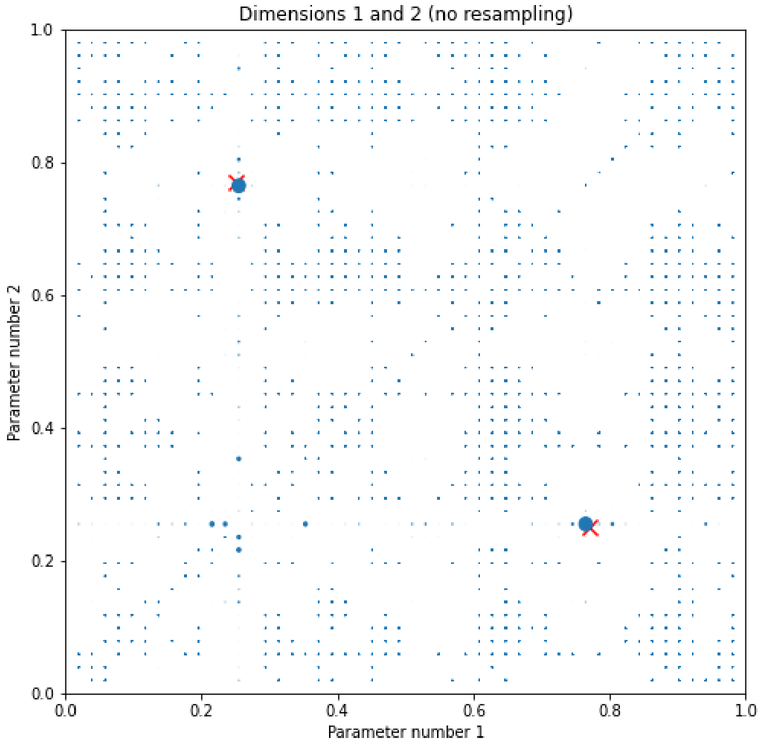
* Total resampler calls: 3.
* Percentage of HMC steps: 100.0%.
* Hamiltonian Monte Carlo: 84% mean particle acceptance rate.

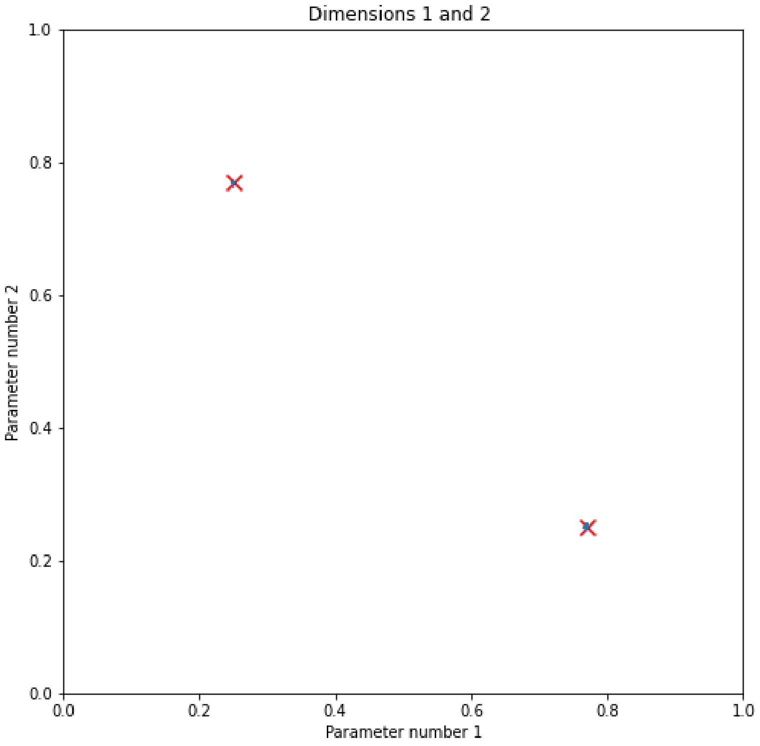
Adaptive measurement choice

$$t^{(k)} \propto \frac{1}{occupation\_rate^{(k-1)} \times {ESS^{(k-1)}}/{N\_particles}}$$

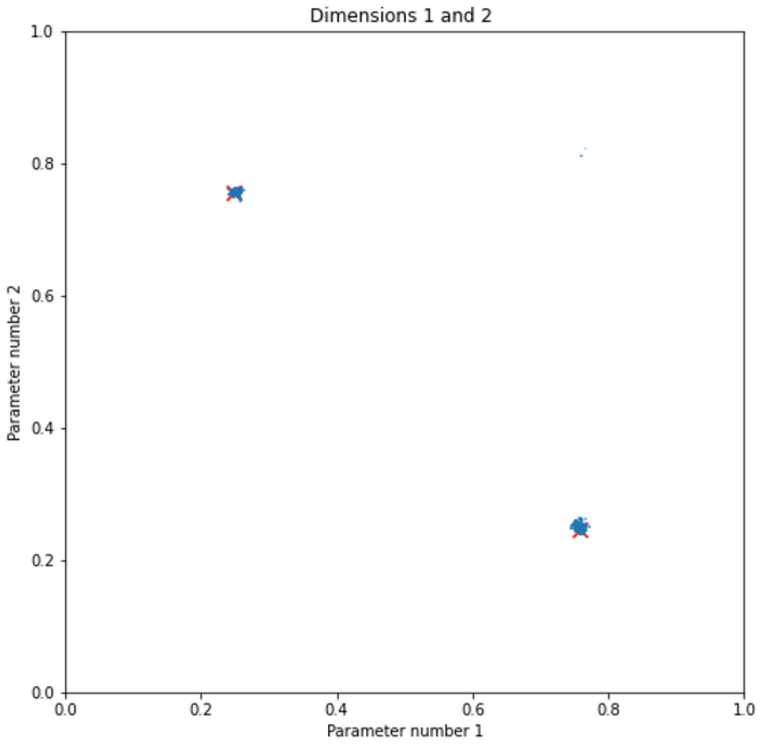
(to increase times between resampler calls)

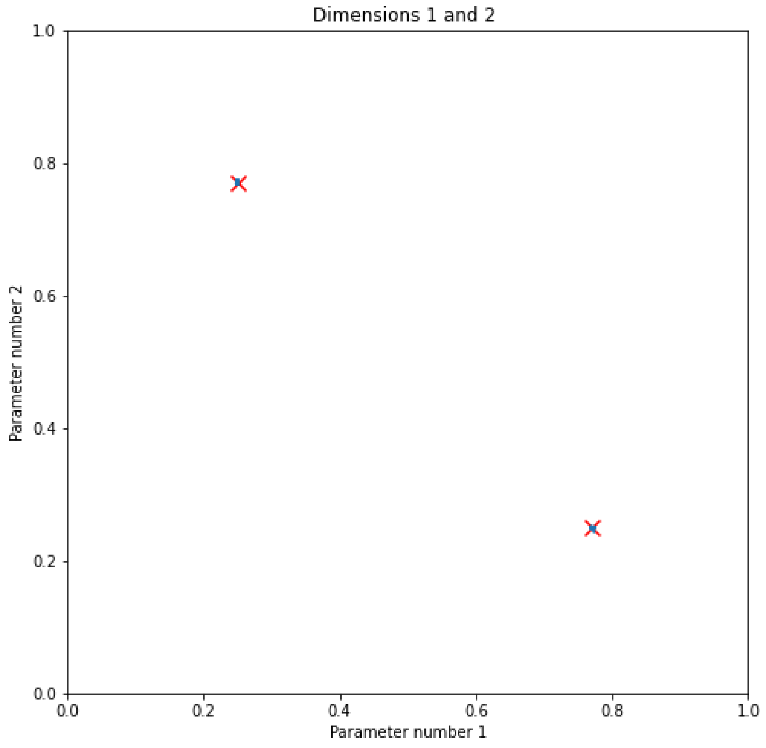
Start with S^{dim} grid, double partitions when less than $T\%$ particles in different divisions (in these graphs S=50, T=10)





Offline (L) vs. adaptive (R) estimation





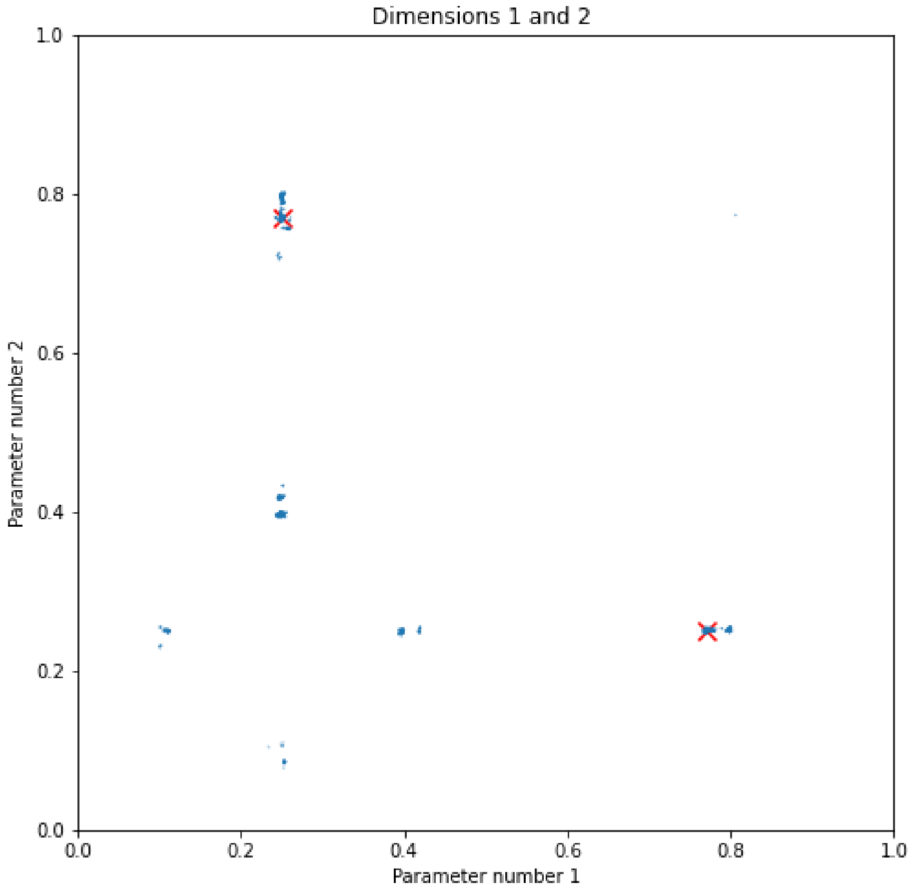
- 2d sum of squared cosines, single group/run (selected best across several for both)
- Resampling threshold = 100
- 100 measurements/updates, 15^2 particles
- HMC: Cov^-1, L=10, eta=0.01*N(1,V=0.25)
- MH: S=Cov, factor=0.0010
- Offline estimation: random times <= 100
- Adaptive estimation: times from ~ 1 to 1800

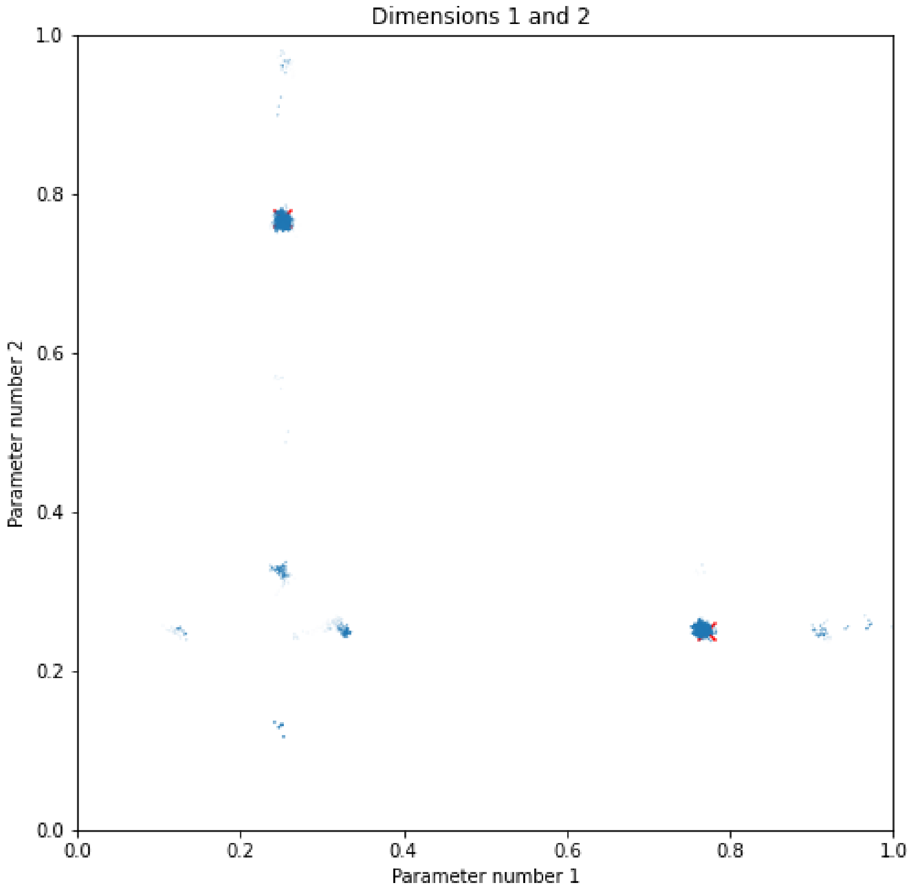
* Total resampler calls: 12.
* Percentage of HMC steps: 100.0%.
* Hamiltonian Monte Carlo: 95% mean particle acceptance rate.

* Total resampler calls: 17.
* Percentage of HMC steps: 45.4%.
* Hamiltonian Monte Carlo: 87% mean particle acceptance rate.
* Metropolis-Hastings: 38% mean particle acceptance rate.

Offline (L) vs. adaptive (R) estimation

5 independent particle groups





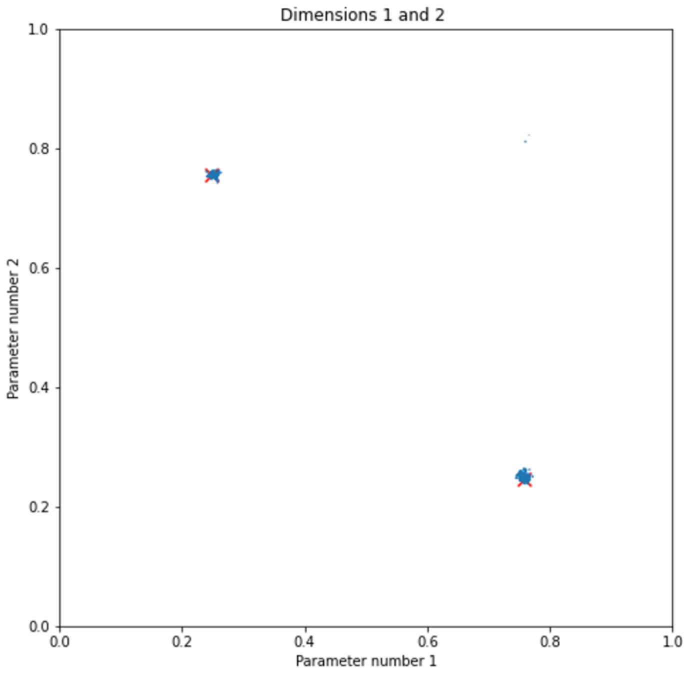
$$t_{(k)} = \frac{1}{occupation\_rate_{(k-1)} \times {ESS_{(k-1)}}/{N\_particles}}$$

$$random\ times \leq 100$$

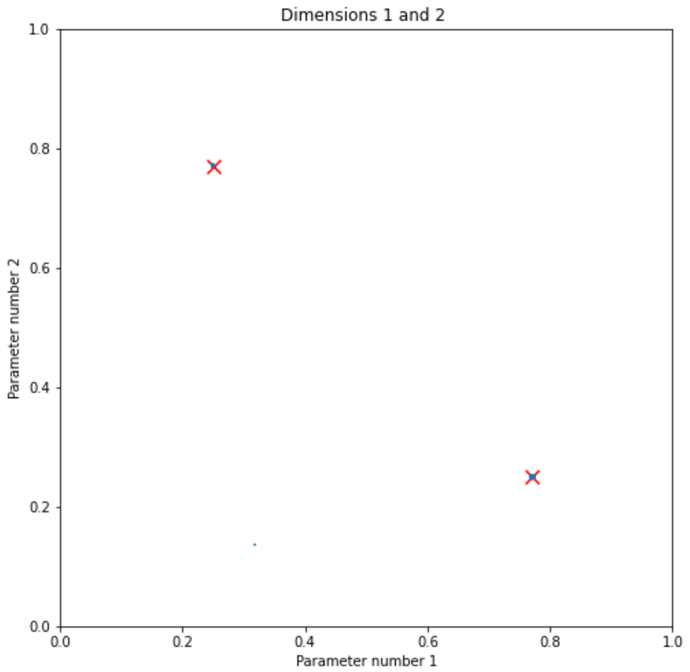
Offline (L/C) vs. adaptive (R) estimation

Attempting to mimic adaptive strategy by increasing maximum evolution time (selected good runs among 3 for all):

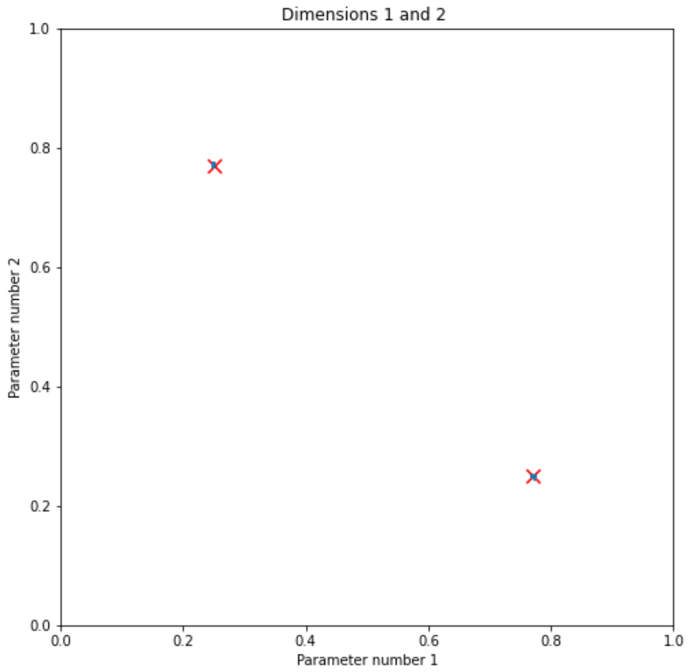
$$t_{max}^{(k)} = (\mathrm{k}//groupsize{+}1) \times increment$$



$t_{max} = 100$



$t_{max}^{(k)} = (\mathrm{k}//20{+}1) \times 100$

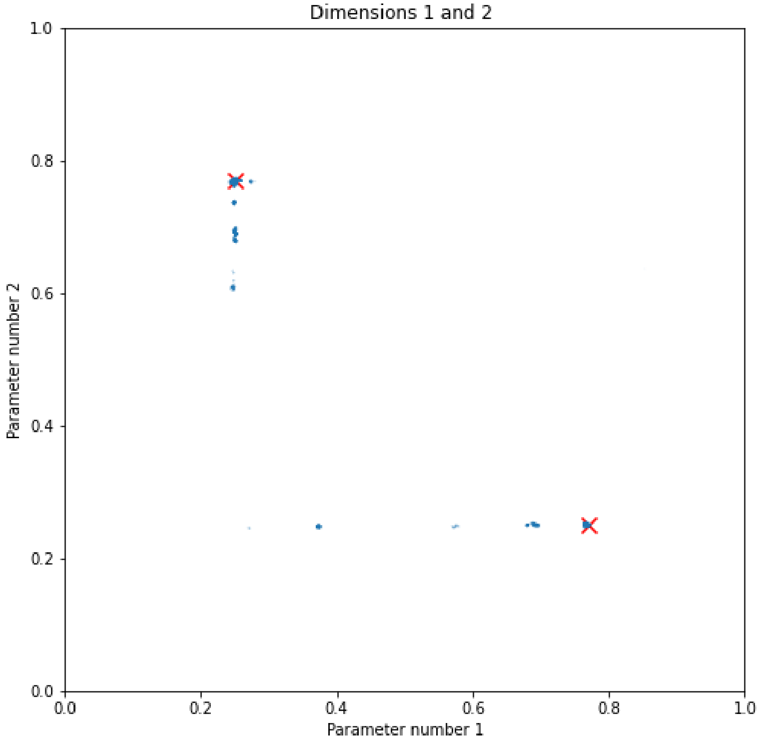


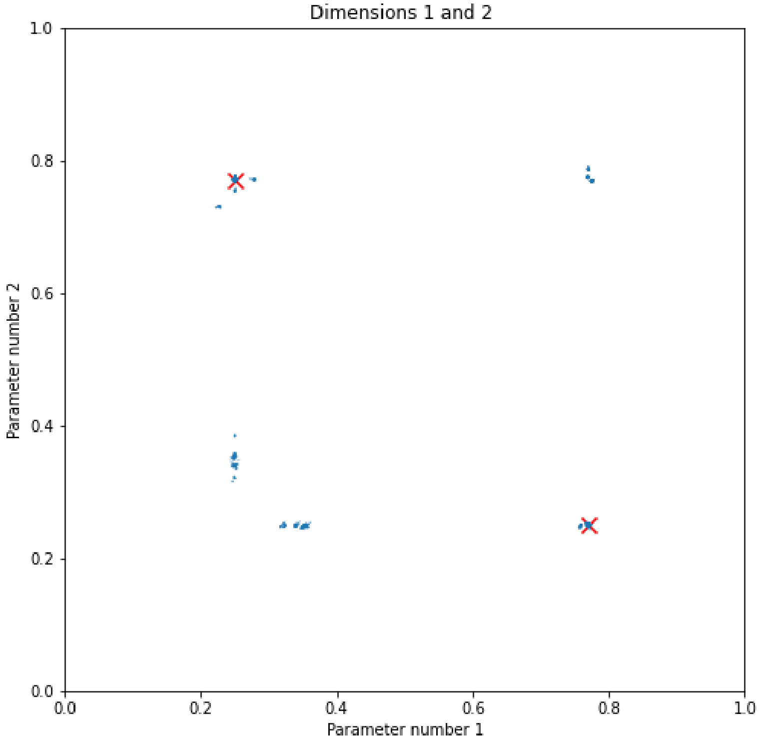
$$t_{(k)} = \frac{1}{occupation\_rate_{(k-1)} \times {}^{ESS_{(k-1)}}\!/_{N\_particles}}$$

(then choose randomly from $[0, t_{max}[$)

Offline (L) vs. adaptive (R) estimation

For 5 independent particle groups:



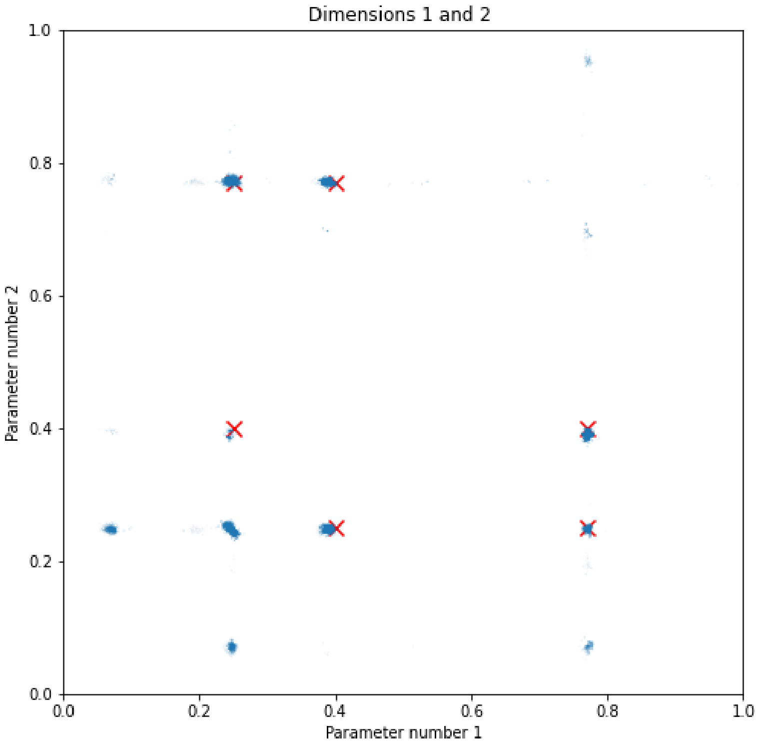


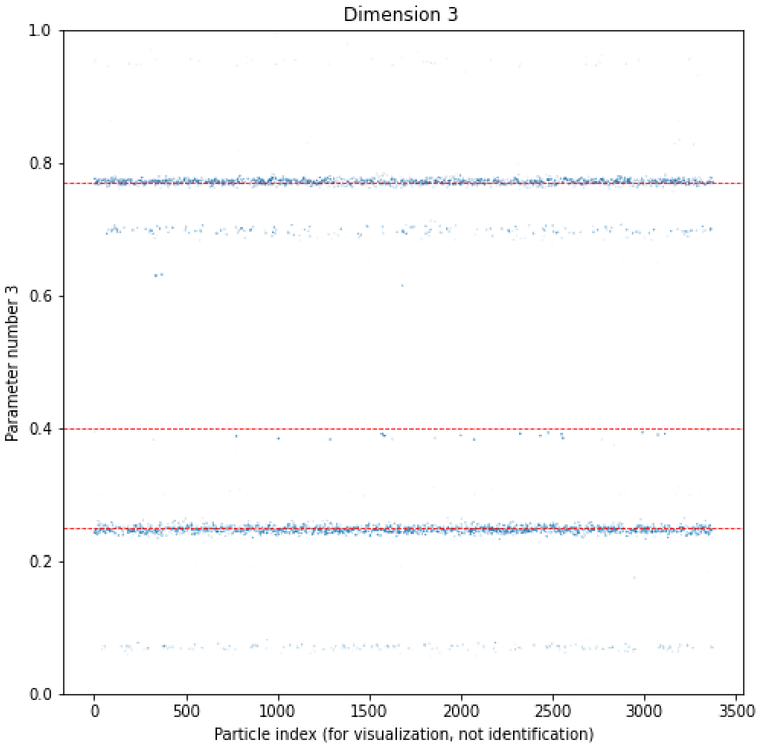
$$t_{max}^{(k)} = (\mathrm{k}//20+1) \times 100$$

$$t_{(k)} = \frac{1}{occupation\_rate_{(k-1)} \times {ESS_{(k-1)}}/{N\_particles}}$$

Adaptive estimation: 3d

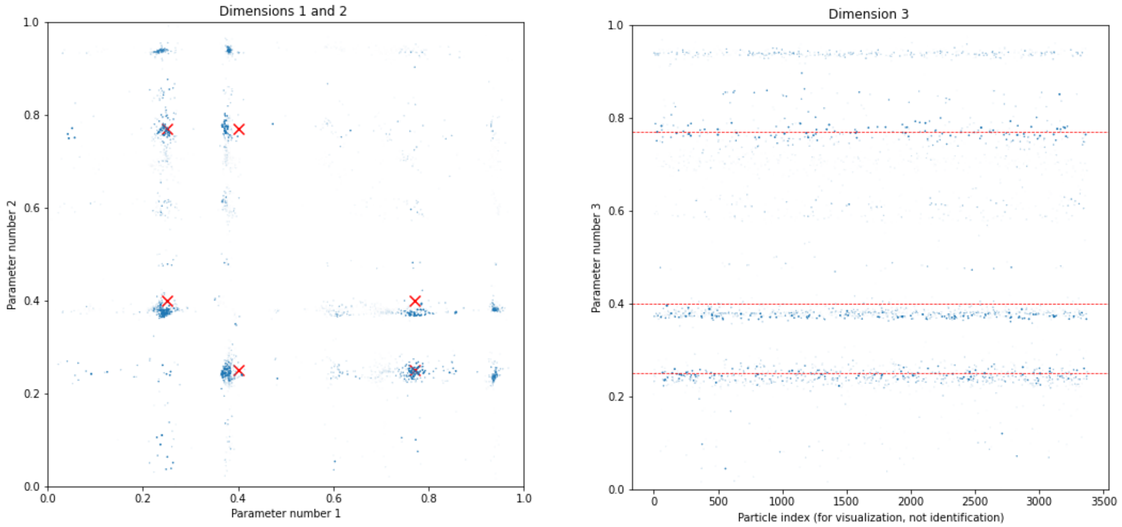
Times work very differently for higher dimensionality parameter space (because the downtrend in particle density is too steep due to the volume increasing too fast with the dimensionality?)
Works better if taking fractional roots of the spatial occupation (here square), but hard to tune (sides and threshold for occupation estimate, powers for computing the times’ denominators, proportionality factor)

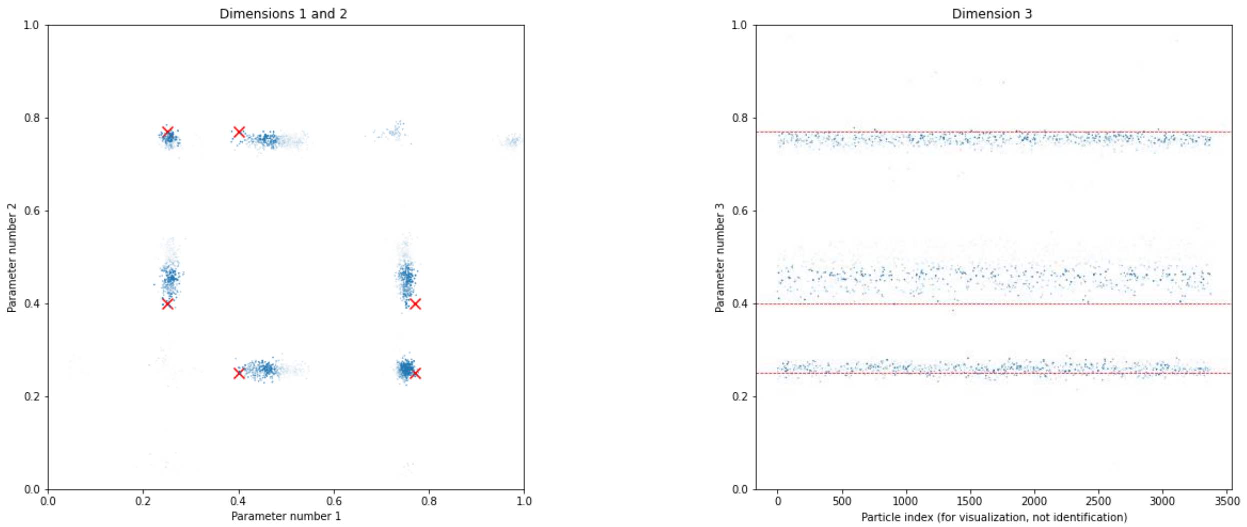




Offline (L) vs. adaptive (R) estimation

Testing with scarce data/particles to evaluate information quality:



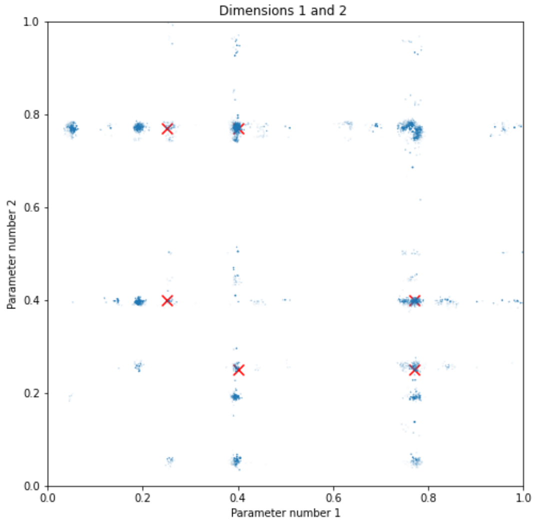


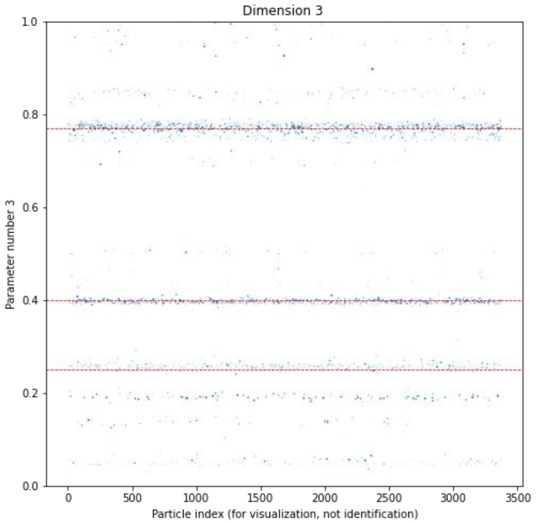
$random\ times \leq 100$

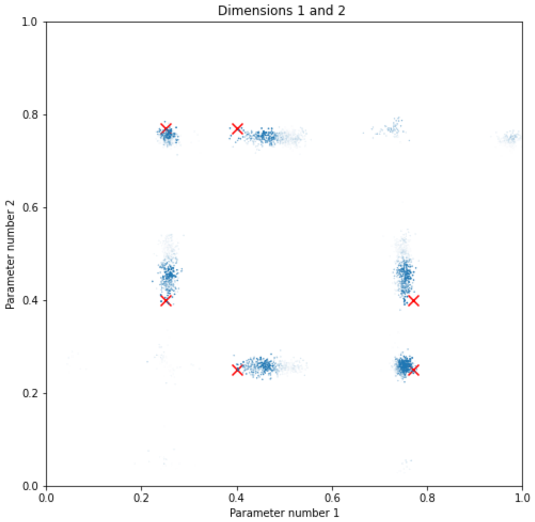
$$t_{(k)} = \frac{1}{occupation\_rate_{(k-1)}{}^{2} \times {ESS_{(k-1)}}/{N\_particles}}$$

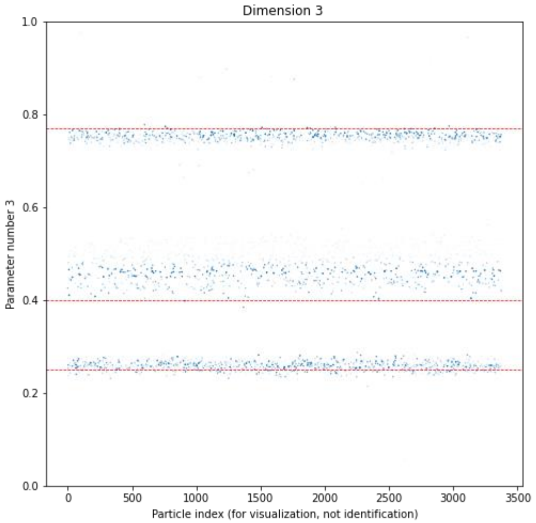
Offline (L) vs. adaptive (R) estimation, 3d

Again using increasing times (vs. random with fixed maxima) also in the adaptive case (all else equal):









$$t_{max}^{(k)} = (\mathrm{k}//20+1) \times 50$$

$$t_{(k)} = \frac{1}{occupation\_rate_{(k-1)}{}^{1/2} \times {}^{ESS_{(k-1)}}\big/_{N\_particles}}$$