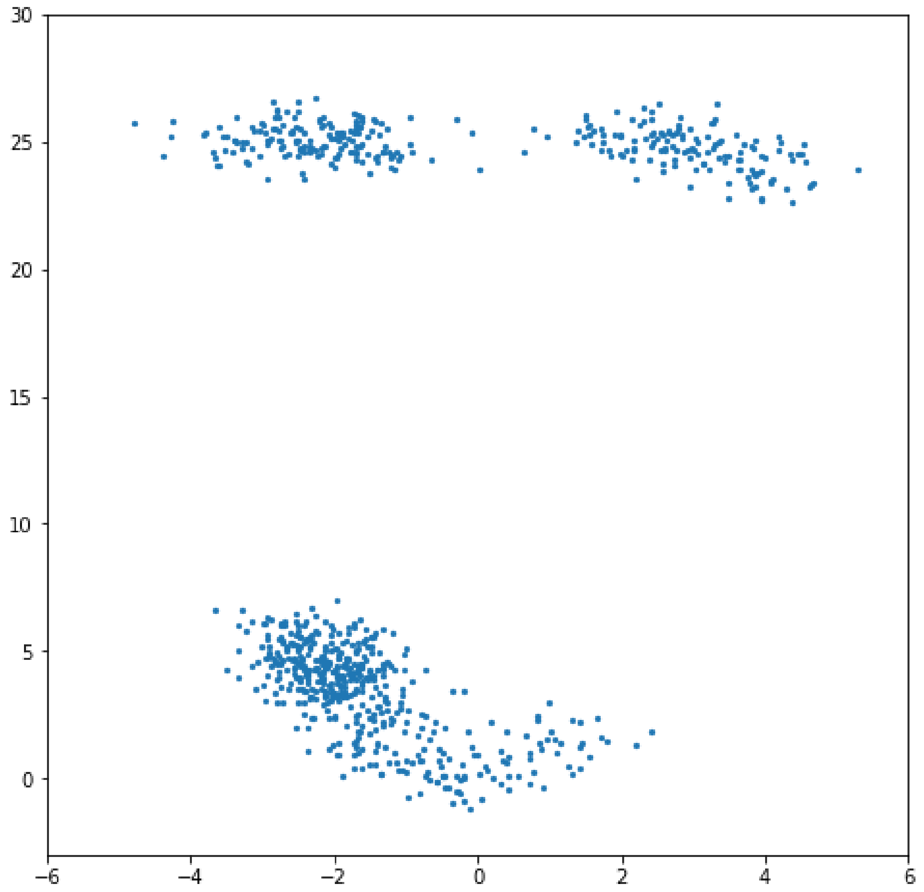
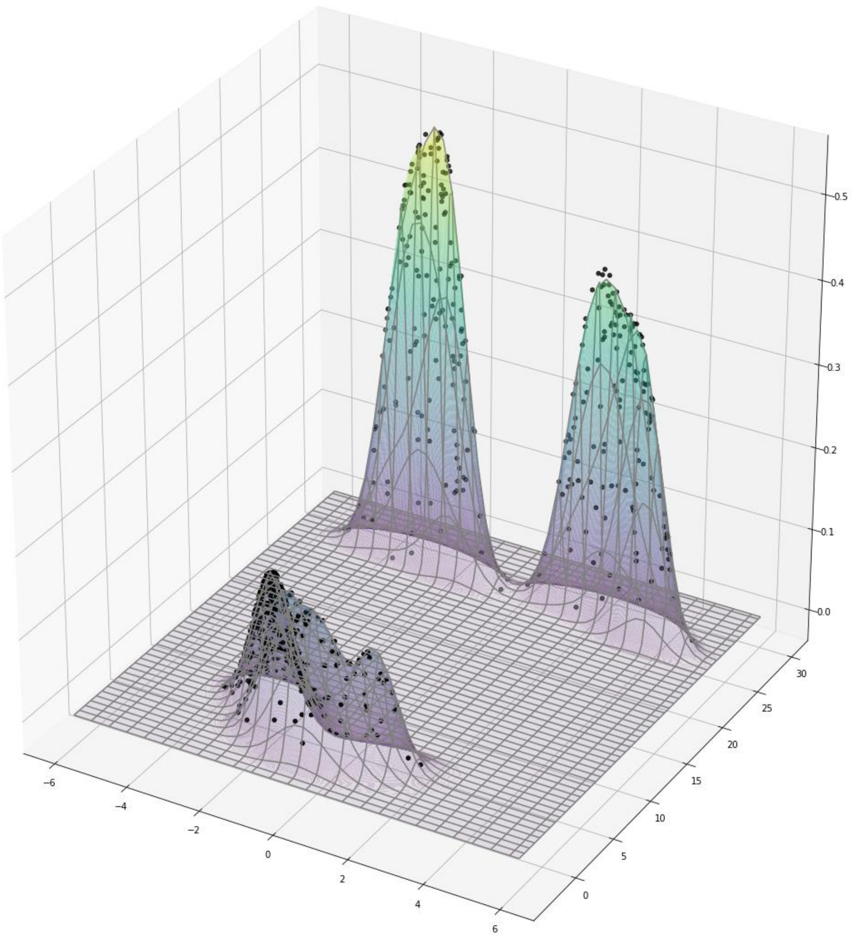
HSMC smiley simulation with 768 particles*

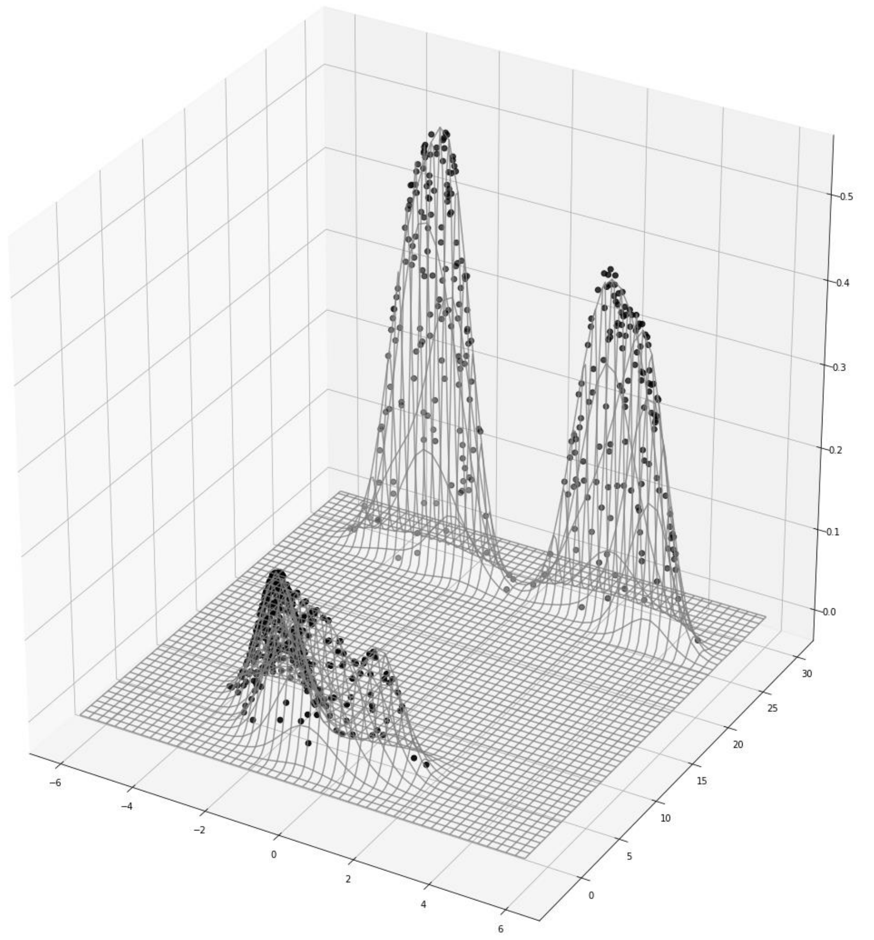
(same as the amount used to generate target)



*4 independent groups of 196 particles

Plotting particles over target density





SMC re-weighting step

$$w_n^{(t)} = f_t(\theta_n)/\hat{f}_{t-1}(\theta_n)$$

leave-one-out kernel density estimate based on previous step's particle cloud , i.e. $(\theta^{(t-1)}, \omega^{(t-1)})$ pairs

vs.

$$w_n^{(t)} = f_t(\theta_n)/f_{t-1}(\theta_n)$$

previous step's exact target distribution (which the particle cloud is supposed to approximate well, but doesn't necessarily if the Markov chain mixes poorly)

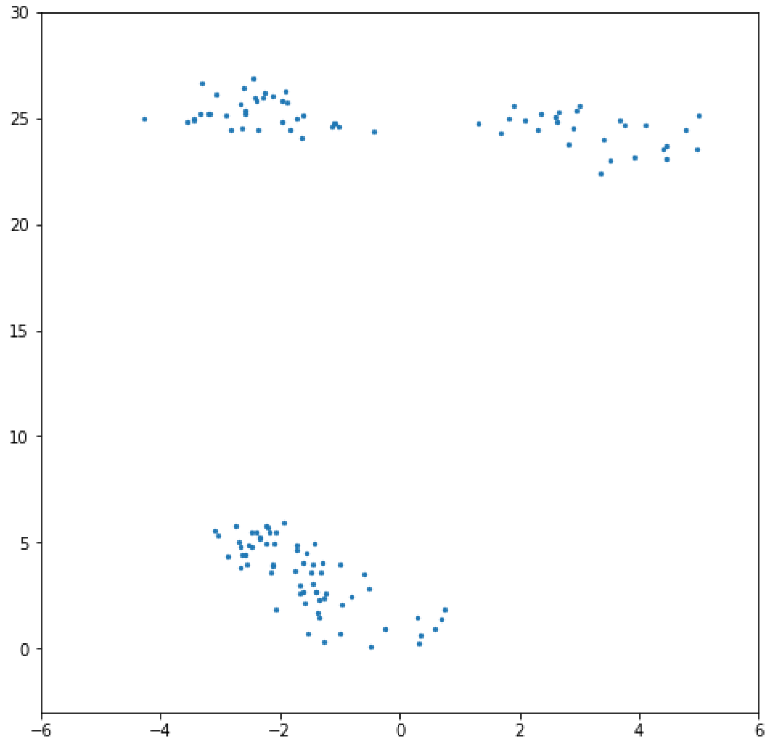
Helpful if the Markov transitions are insufficient to reach the steady state for some step's target, which can affect the subsequent targets' samples (since they depend on each other in sequential Monte Carlo)

Leave one out not to overvalue specific (discrete) particle locations?

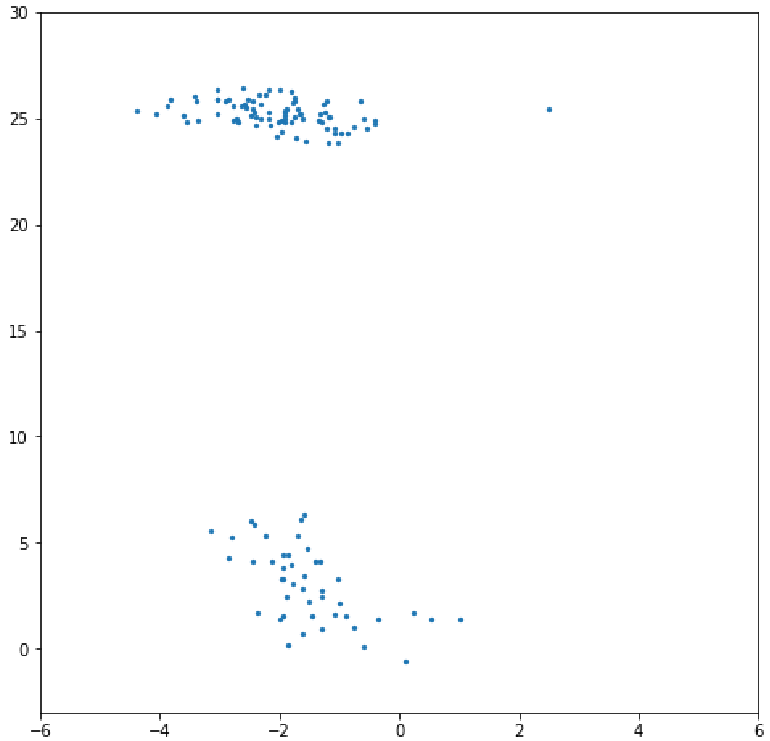
Remi Daviet, Inference with Hamiltonian Sequential Monte Carlo Simulators, 2018

SMC re-weighting step

$$w_n^{(t)} = f_t(\theta_n)/\hat{f}_{t-1}(\theta_n)$$



$$w_n^{(t)} = f_t(\theta_n)/f_{t-1}(\theta_n)$$



With few particles available, the classic (non-KDE) approach tends not to cover modes as fairly (e.g. “right eye”)