Use for GMM

The folowing import statement is required to avoid a warning when we use the GMM. There is a memory leakge when we use GMM. Do not use it for other entropy approzimations because it slows down the campaign in general.

Note: it causes a problem with the plots. They are created twice.

In [1]:
```
#import os
#os.environ["OMP_NUM_THREADS"] = '1'
```

In [2]:
```
import  MyPlotting as MyPlots
import matplotlib.pyplot as plt
from datastruct import Settings, Experiment, ExperimentStep, DataPoint
from entropy import calc_entropy, default_entropy_options
import numpy as np

from functions_gain_factor import recalculating_entropy
```

9 Reloading Experiments

In [3]:
```
# #Reloading Data
exp_control = Experiment.load('5/test1_control id5c.gz',recalc_yprofs=True)
exp_entropy1 = Experiment.load('5/test1_entropy id5e1.gz', recalc_yprofs=True)
exp_entropy2 = Experiment.load('5/test1_entropy id5e2.gz', recalc_yprofs=True)
exp_on_the_fly1 = Experiment.load('5/test1_on_the_fly1 id5o1.gz', recalc_yprofs=True)
exp_on_the_fly2 = Experiment.load('5/test1_on_the_fly2 id5o2.gz', recalc_yprofs=True)

################################################Use only when you have a GMM version of

###GMM case
# exp_control_gmm = Experiment.load('1/test1_control id1c_gmm.gz',recalc_yprofs=True)
# exp_entropy1_gmm = Experiment.load('1/test1_entropy id1e1_gmm.gz', recalc_yprofs=Tru
# exp_entropy2_gmm = Experiment.load('1/test1_entropy id1e2_gmm.gz', recalc_yprofs=Tru
# exp_on_the_fly1_gmm = Experiment.load('1/test1_on_the_fly1 id1o1_gmm.gz', recalc_ypr
# exp_on_the_fly2_gmm = Experiment.load('1/test1_on_the_fly2 id1o2_gmm.gz', recalc_ypr

#reloaded_exp.creation_time.isoformat()
```

In [ ]:
```
```

In [4]:
```
#Notice now all the outcomes have the same size except for the datax, datay and datady
#last unfitted point
len(exp_entropy1.entropy()) #34
len(exp_entropy1.load_yprofs()) #34
len(exp_entropy1.load_pts()) #34
len(exp_entropy1.getdata()[0]) #35
len(exp_entropy1.meastimes()) #34
```

Out[4]:
```
33
```

Warning

Remember that the maximum time spend in the control data is way greater than for the autonomous cases. Thus, when we are plotting the y-profiles and the histogram for the parameters we should may be truncated the values of control until a time that is closer to max amount of time spend in the autonomous cases.

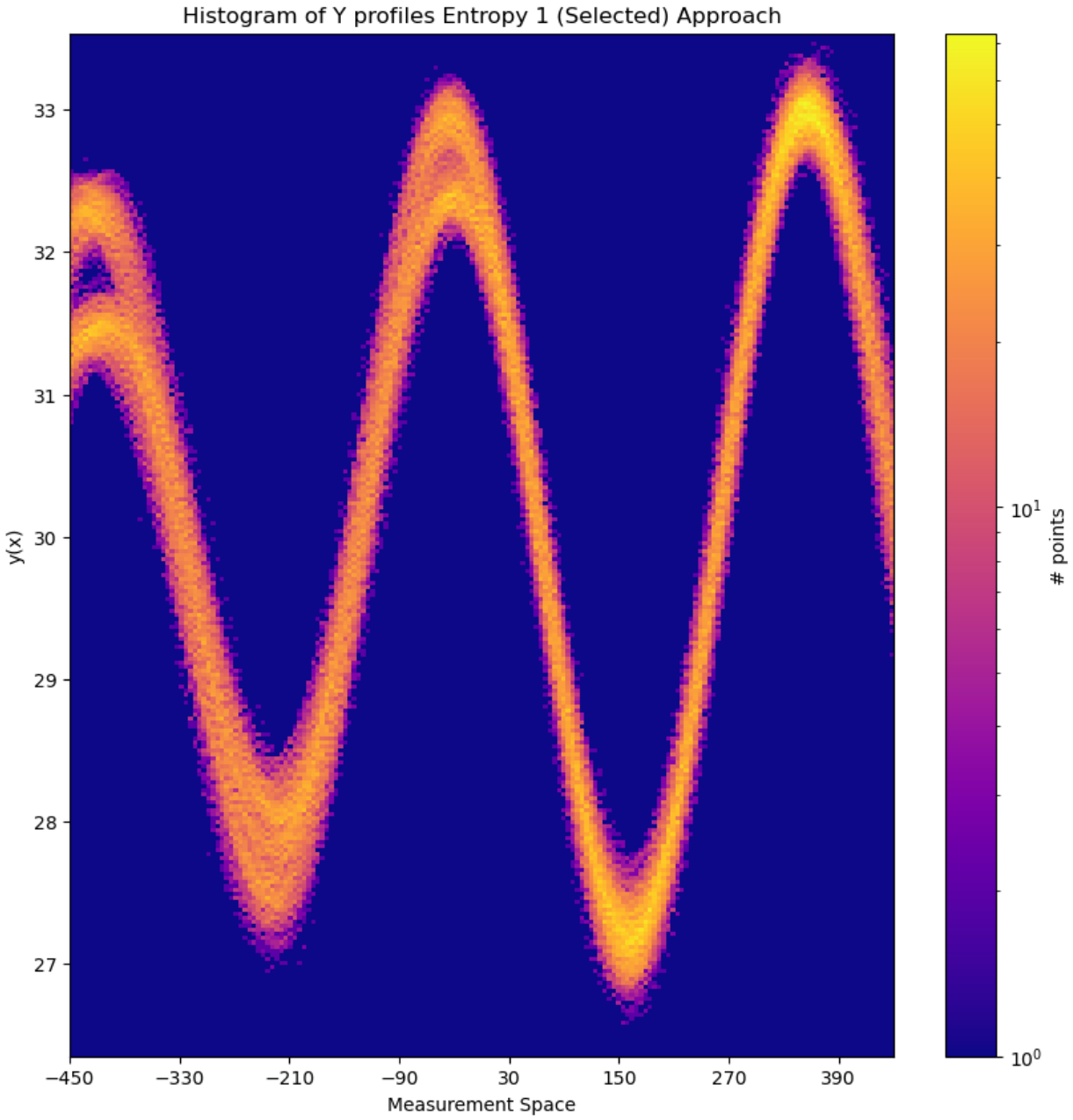
10 Compare to Benchmark

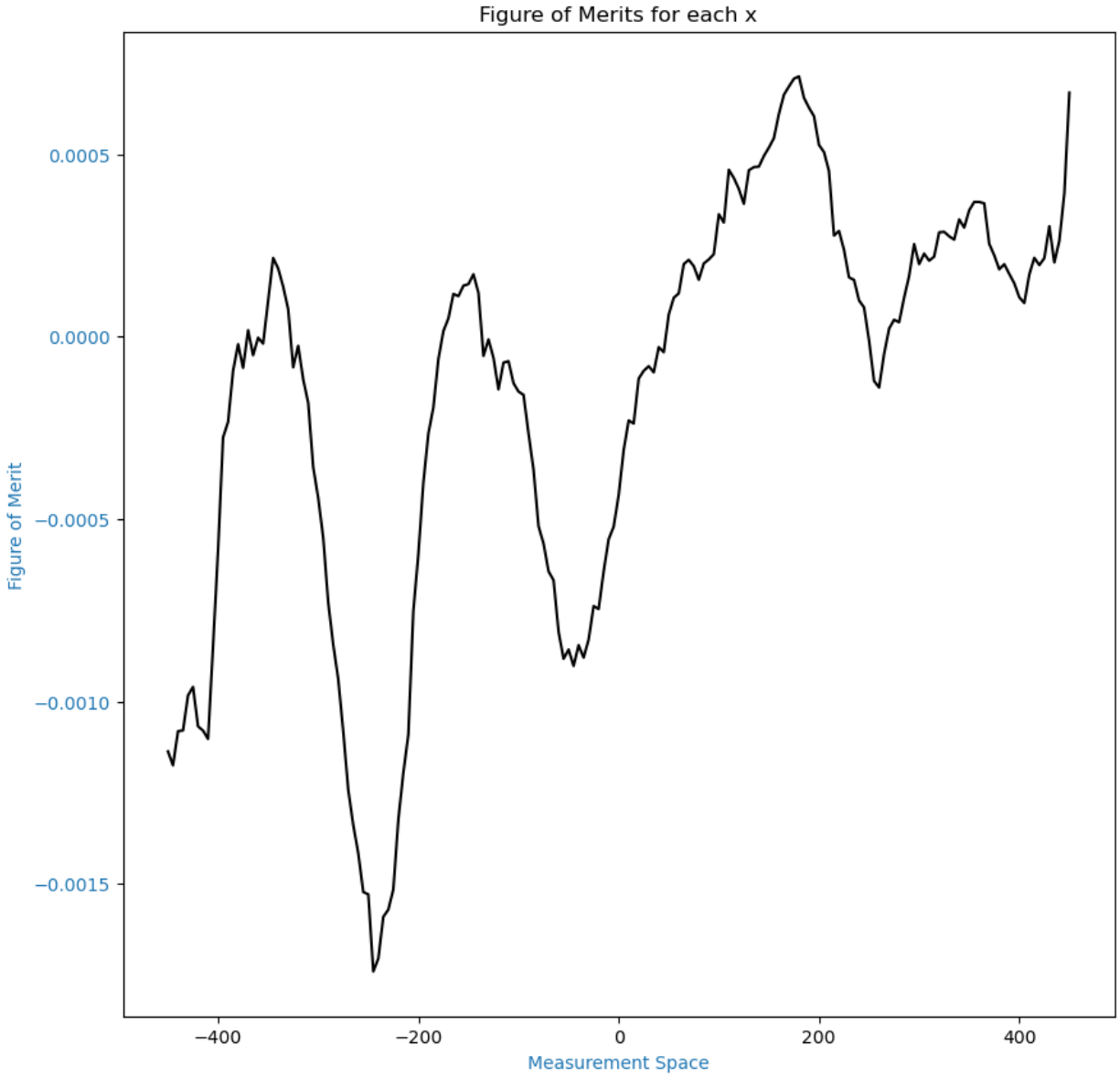
In [5]:
```
# from matplotlib.colors import LogNorm
# from numpy.matlib import repmat

print(exp_entropy1.settings.ground_truth_pars) #{'I0': 30.0, 'A': 15.0, 'phi0': 155.0,
print(exp_on_the_fly1.settings.ground_truth_pars)
```

```
{'I0': 30.0, 'A': 3.0, 'phi0': 155.0, 'T': 401.0, 'sigma': 797.0}
{'I0': 30.0, 'A': 3.0, 'phi0': 155.0, 'T': 401.0, 'sigma': 797.0}
```

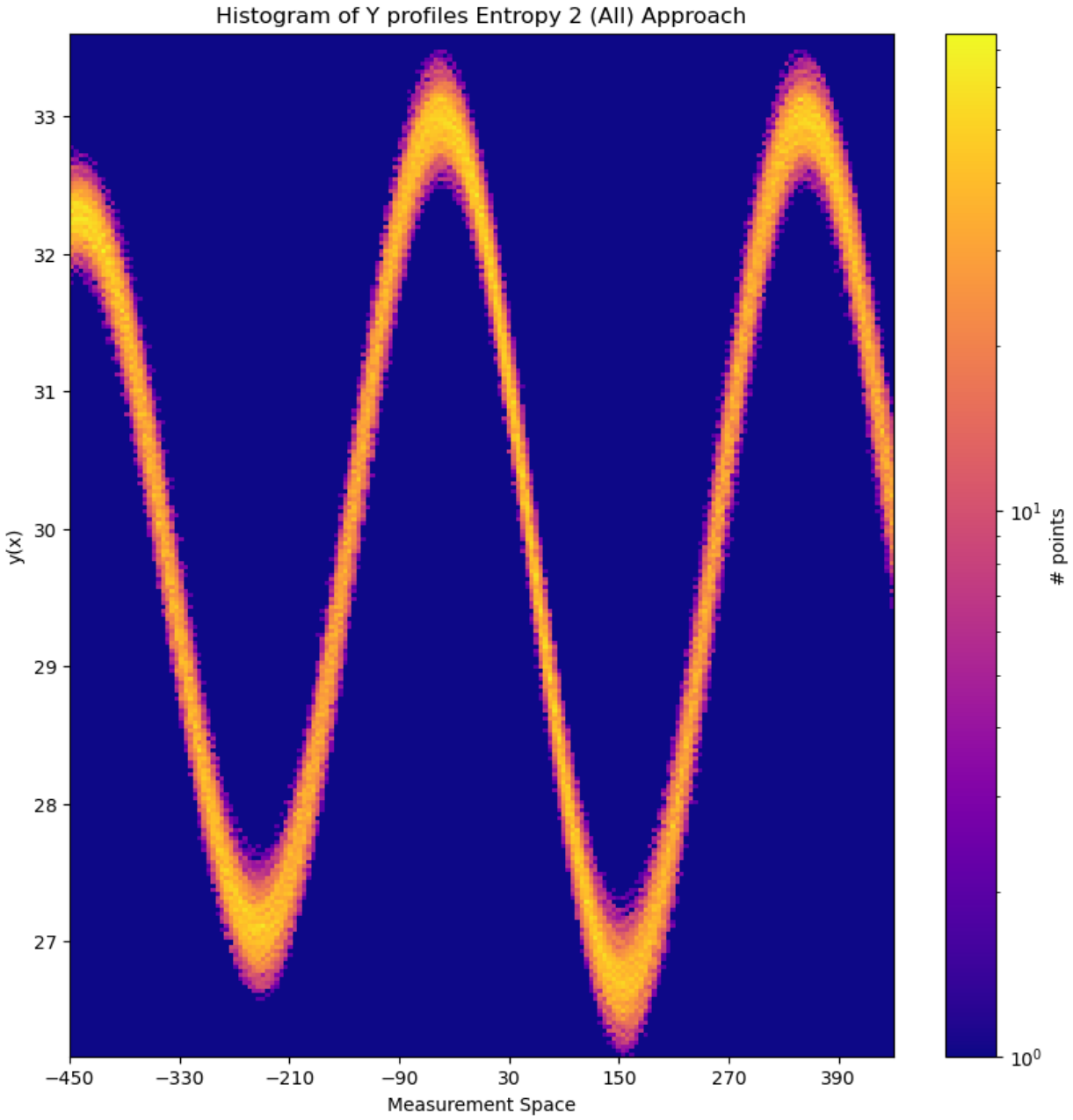
10.1 Y-Profiles Histograms

In [6]:
```
##Plotting the last set of Y-profiles for the different approraches
##If you do not want to plot the figure of merits do not provide them. It still works

#Entropy 1
MyPlots.plot_y_profiles(exp_entropy1.load_yprofs()[-1],exp_entropy1.settings.x,
                        FOM = exp_entropy1.load_FOM()[-1],
                        this_title = "Histogram of Y profiles Entropy 1 (Selected) App

#Entropy 2
MyPlots.plot_y_profiles(exp_entropy2.load_yprofs()[-1],exp_entropy2.settings.x,
                        FOM = exp_entropy2.load_FOM()[-1],
                        this_title = "Histogram of Y profiles Entropy 2 (All) Approach
#On-the Fly 1
MyPlots.plot_y_profiles(exp_on_the_fly1.load_yprofs()[-1],exp_on_the_fly1.settings.x,
                        FOM = exp_on_the_fly1.load_FOM()[-1],
                        this_title = "Histogram of Y profiles On-The_Fly 1 Approach" )
#On-the Fly 1
MyPlots.plot_y_profiles(exp_on_the_fly2.load_yprofs()[-1],exp_on_the_fly2.settings.x,
                        FOM = exp_on_the_fly2.load_FOM()[-1],
                        this_title = "Histogram of Y profiles On-The_Fly 2 Approach" )
#Control Data
MyPlots.plot_y_profiles(exp_control.load_yprofs()[-1],exp_control.settings.x,
                        this_title = "Histogram of Y profiles My Control Evenly Approa
```


Histogram of Y profiles Entropy 1 (Selected) Approach
y(x)
33
32
31
30
29
28
27
−450
−330
−210
−90
30
150
270
390
Measurement Space
10^1
10^0
points




```
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:346: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_yprof)
```


Histogram of Y profiles Entropy 2 (All) Approach
y(x)
33
32
31
30
29
28
27
−450
−330
−210
−90
30
150
270
390
Measurement Space
10^1
10^0
points

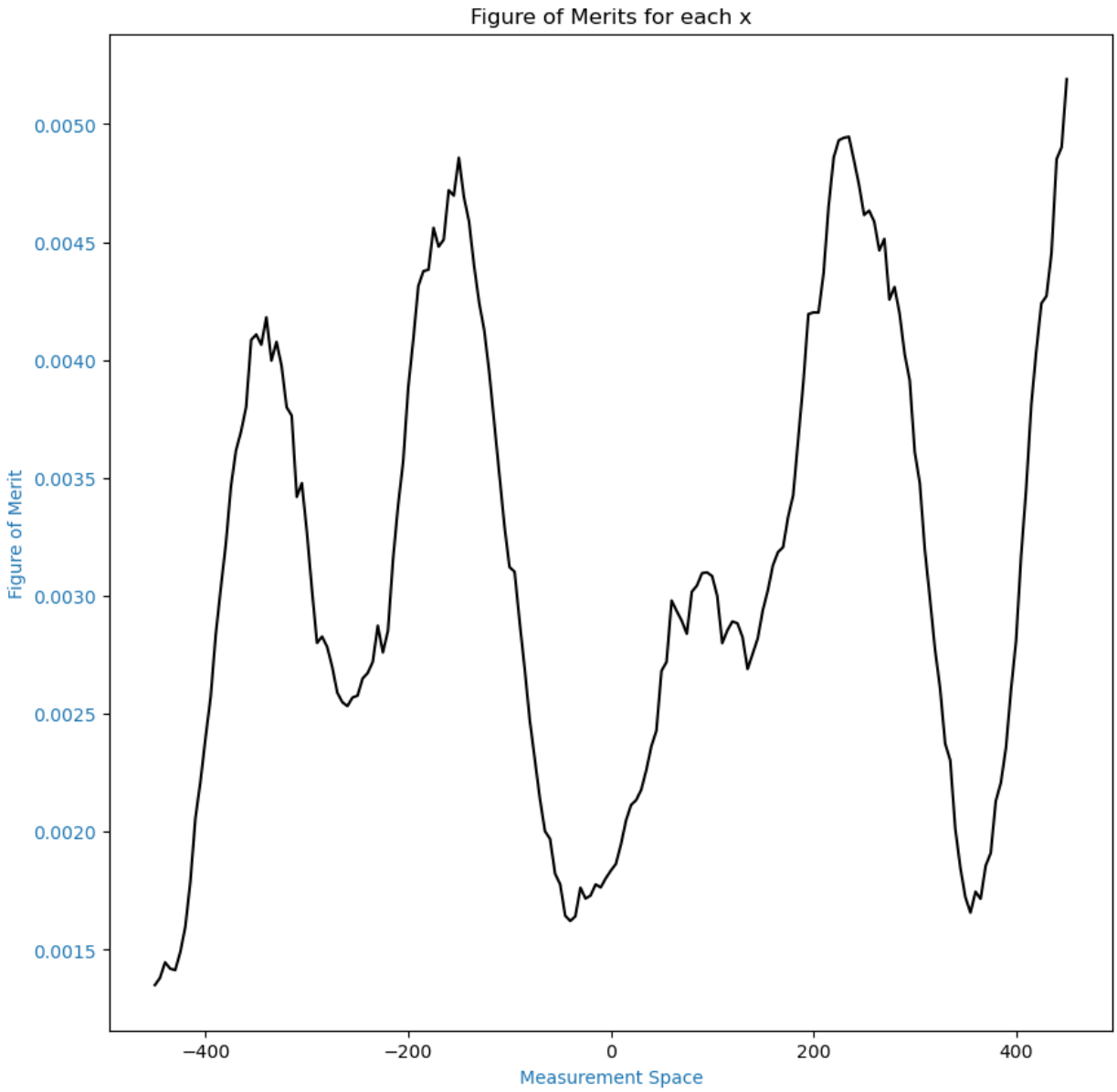
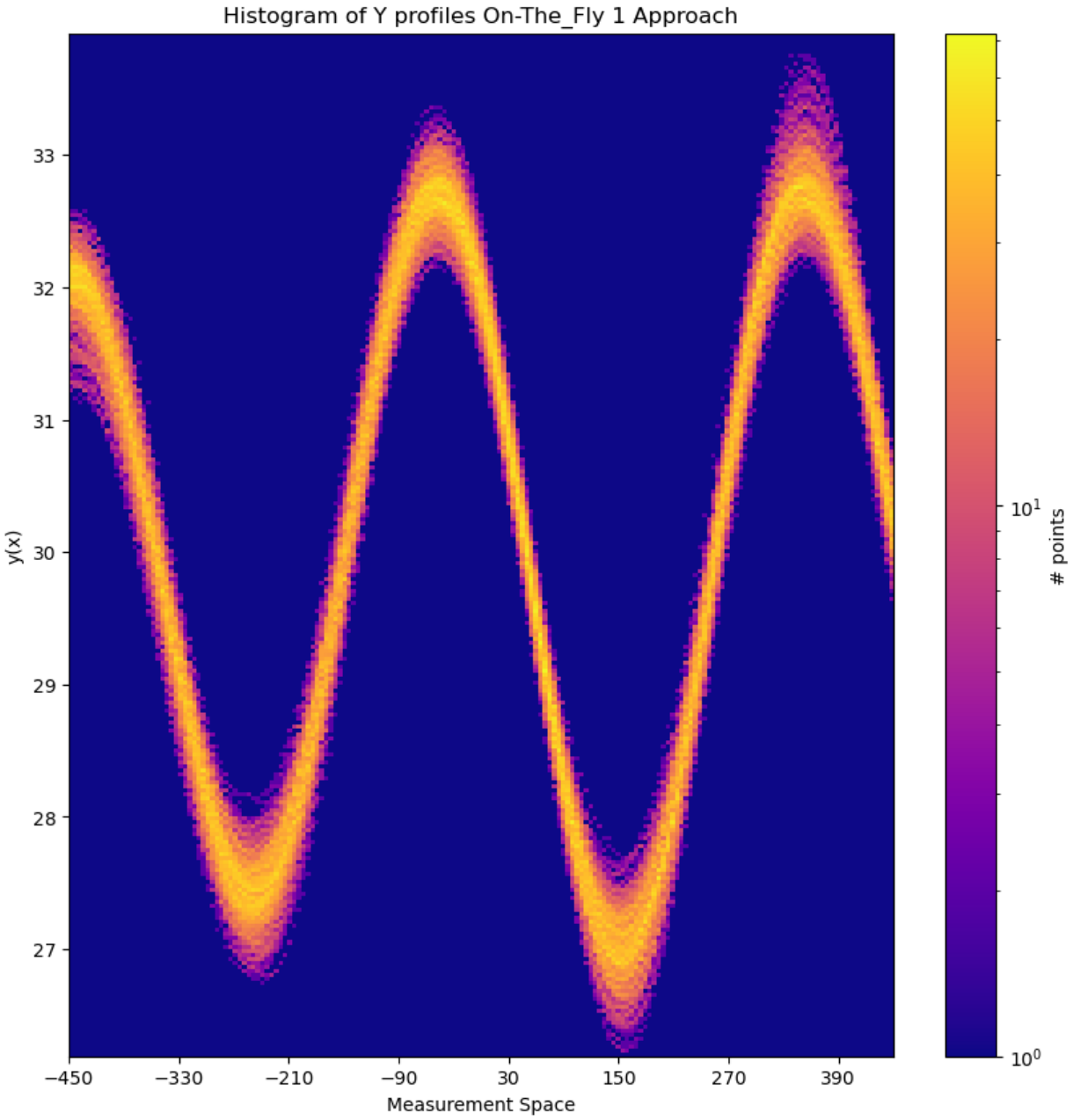


Figure of Merits for each x
Figure of Merit
0.0050
0.0045
0.0040
0.0035
0.0030
0.0025
0.0020
0.0015
−400
−200
0
200
400
Measurement Space


Histogram of Y profiles On-The_Fly 1 Approach
y(x)
33
32
31
30
29
28
27
−450
−330
−210
−90
30
150
270
390
Measurement Space
10^1
10^0
points

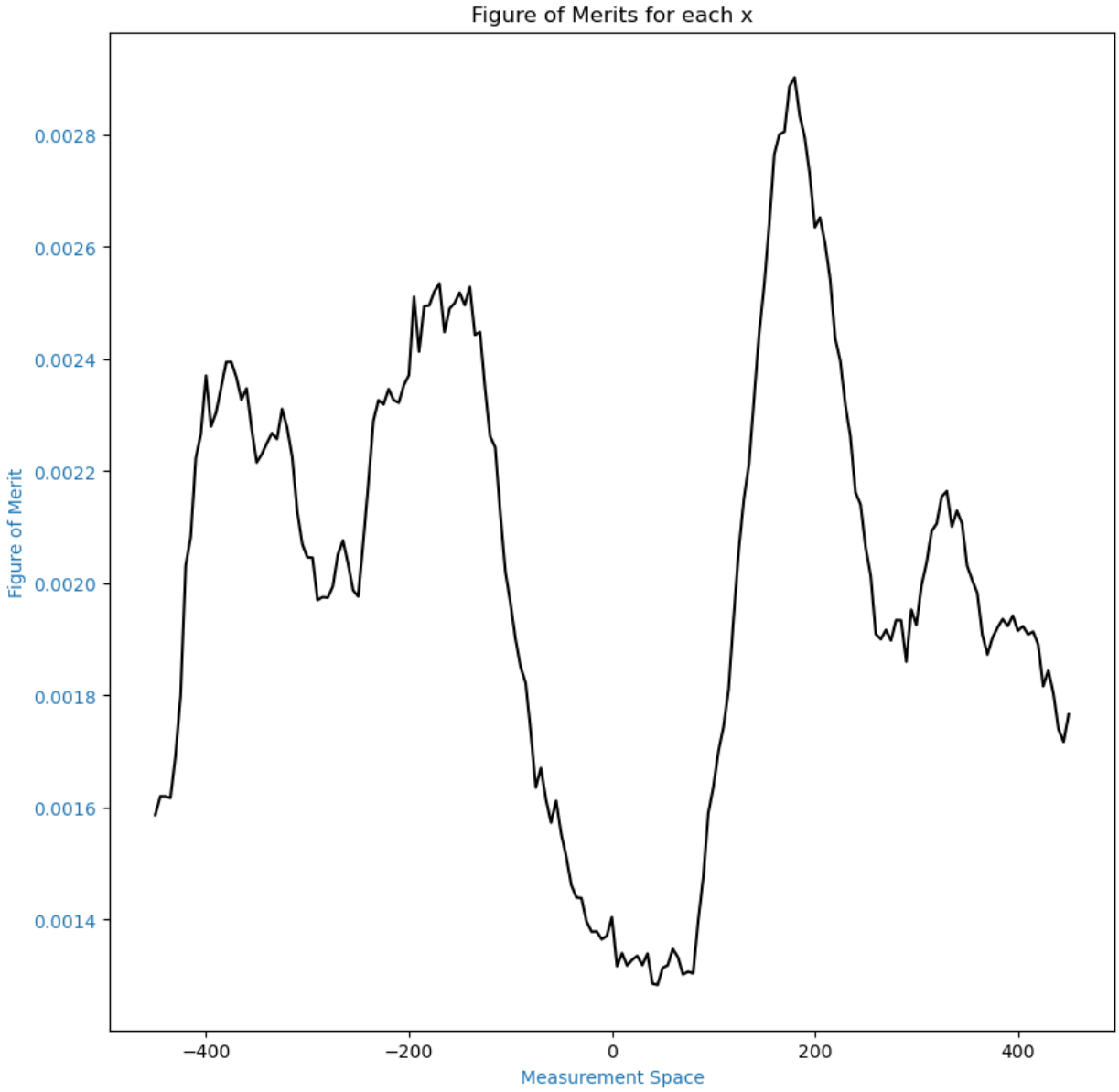
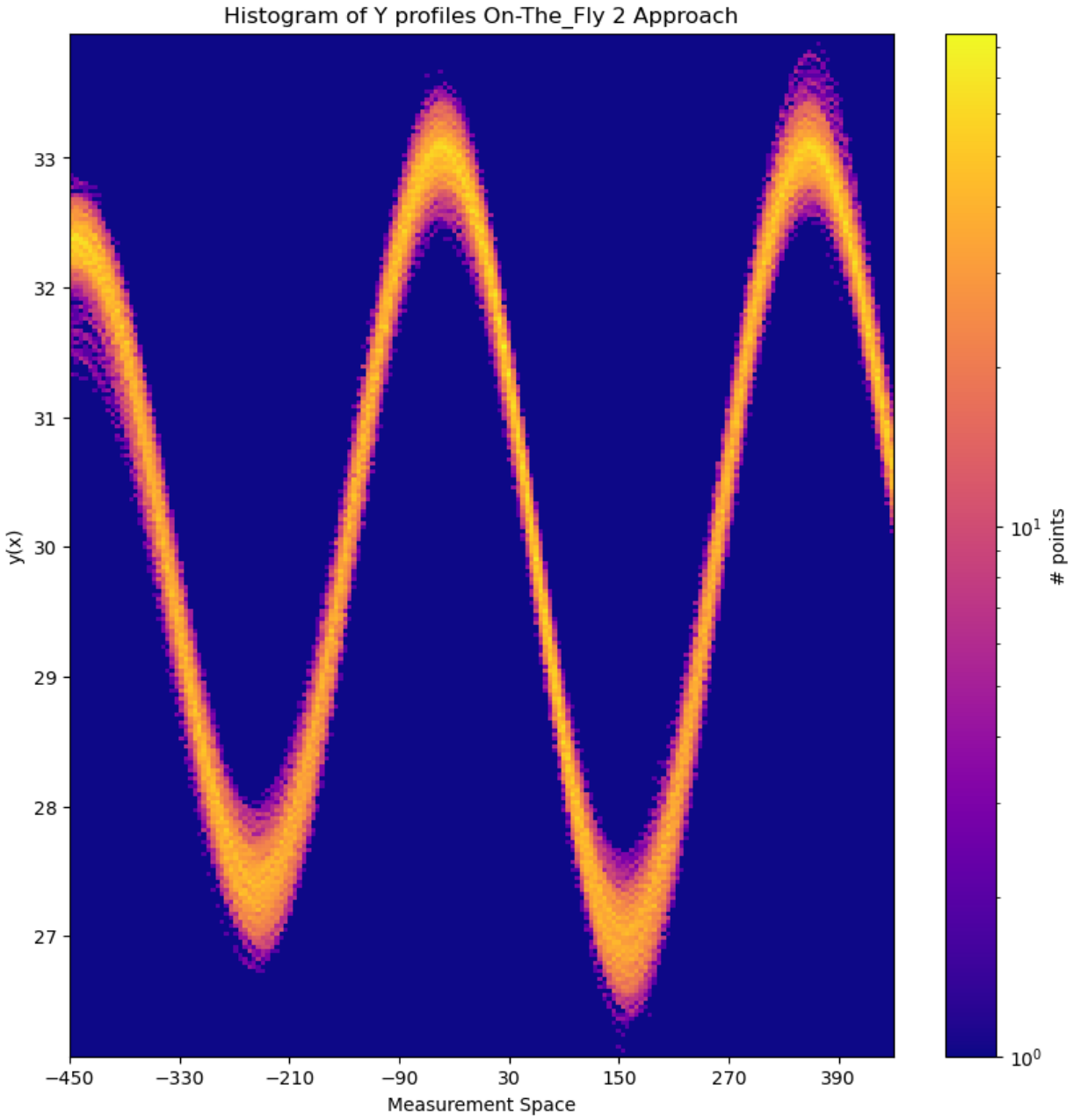


Figure of Merits for each x
Figure of Merit
0.0028
0.0026
0.0024
0.0022
0.0020
0.0018
0.0016
0.0014
−400
−200
0
200
400
Measurement Space


Histogram of Y profiles On-The_Fly 2 Approach
y(x)
33
32
31
30
29
28
27
−450
−330
−210
−90
30
150
270
390
Measurement Space
10^1
10^0
points

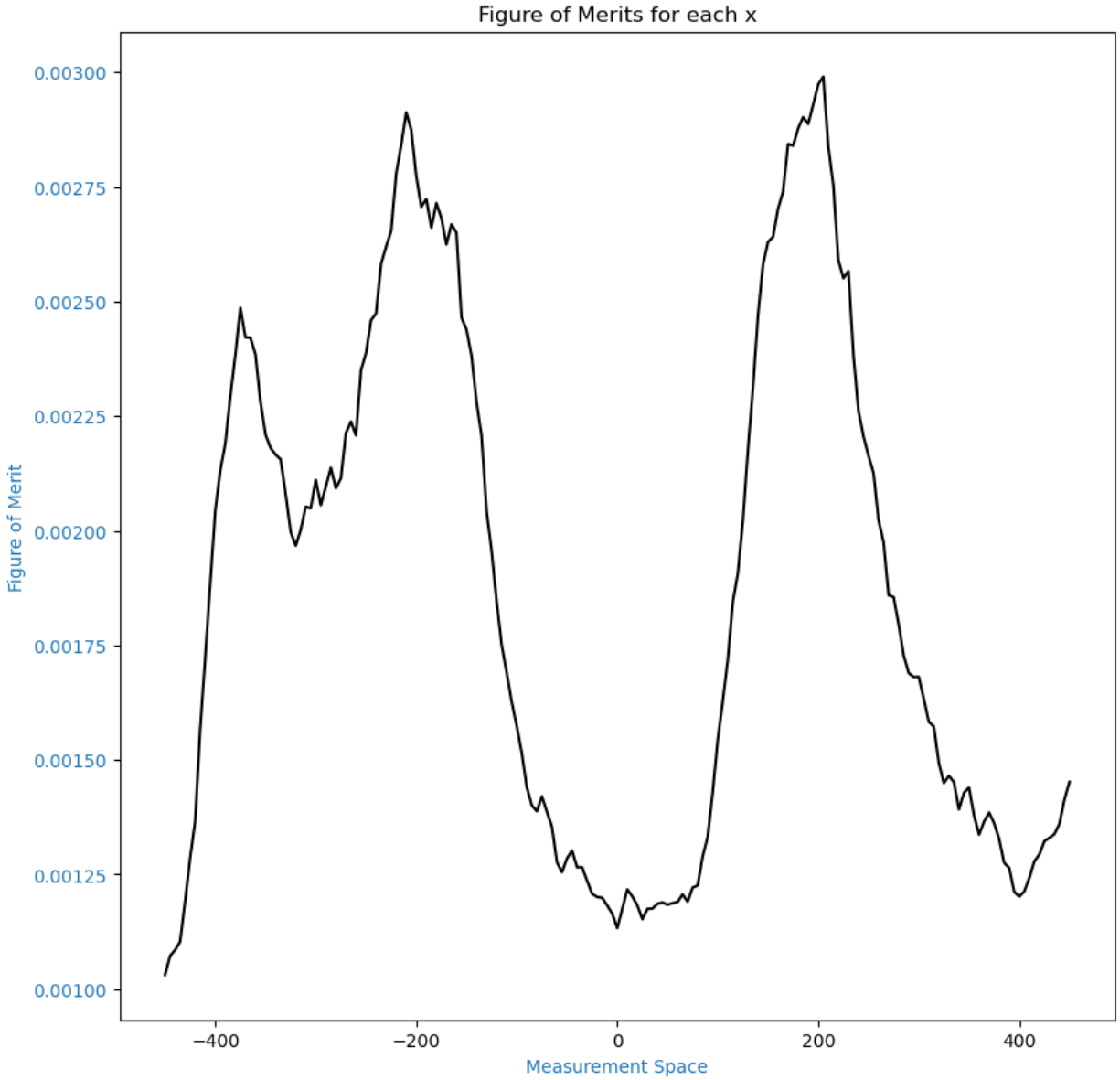
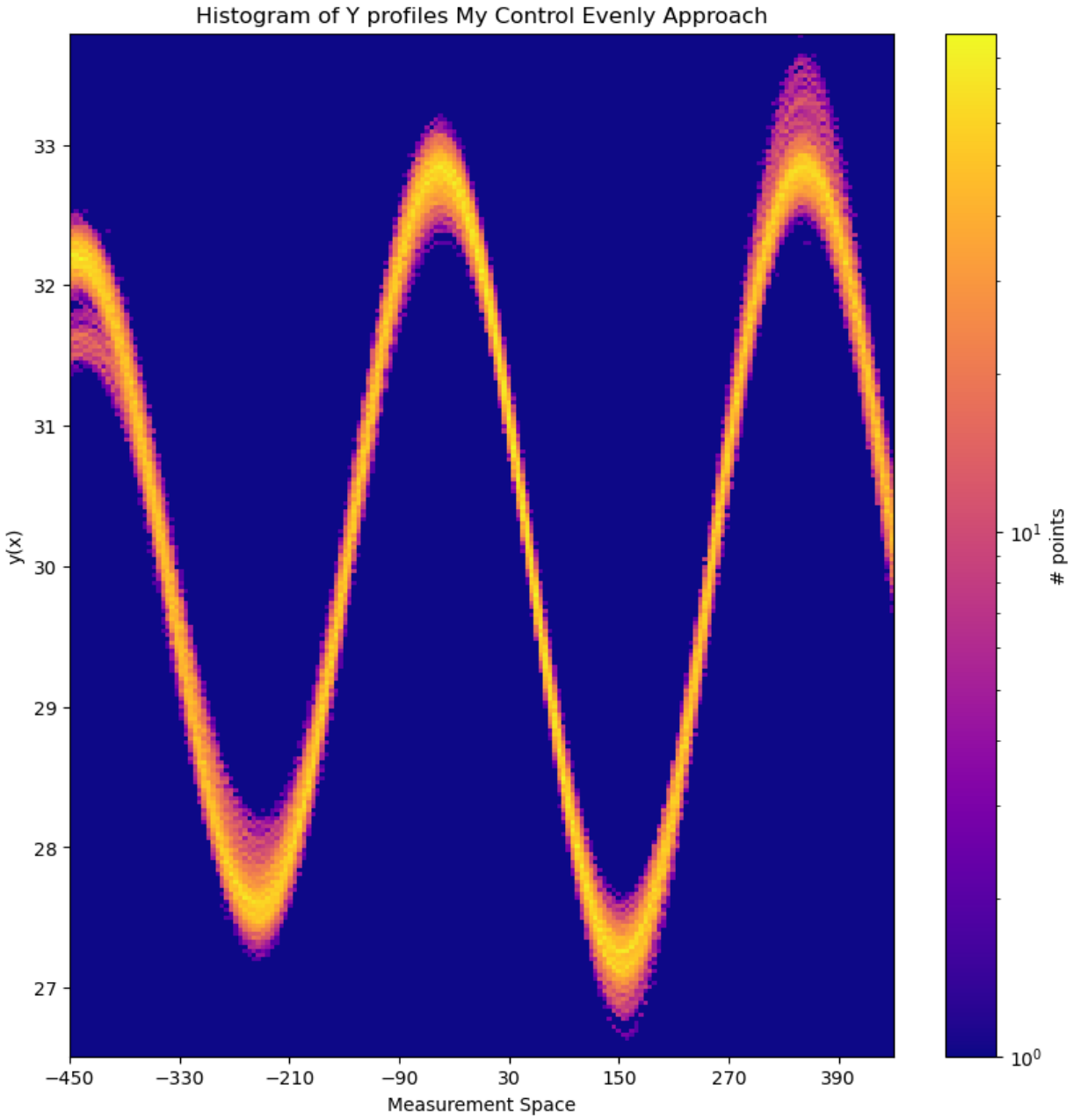


Figure of Merits for each x
Figure of Merit
0.00300
0.00275
0.00250
0.00225
0.00200
0.00175
0.00150
0.00125
0.00100
−400
−200
0
200
400
Measurement Space



In [7]:
```
############################## GMM TO COMPARE Commnet out everything below unless you ha


# #Entropy 1
# MyPlots.plot_y_profiles(exp_entropy1_gmm.load_yprofs()[-1],exp_entropy1_gmm.settings
#                         FOM = exp_entropy1_gmm.load_FOM()[-1],
#                         this_title = "Histogram of Y profiles Entropy 1 (Selected) G

# #Entropy 2
# MyPlots.plot_y_profiles(exp_entropy2_gmm.load_yprofs()[-1],exp_entropy2_gmm.settings
#                         FOM = exp_entropy2_gmm.load_FOM()[-1],
#                         this_title = "Histogram of Y profiles Entropy 2 (All) GMM Ap
# #On-the Fly 1
# MyPlots.plot_y_profiles(exp_on_the_fly1_gmm.load_yprofs()[-1],exp_on_the_fly1_gmm.se
#                         FOM = exp_on_the_fly1_gmm.load_FOM()[-1],
#                         this_title = "Histogram of Y profiles On-The_Fly 1 GMM Appro
# #On-the Fly 1
# MyPlots.plot_y_profiles(exp_on_the_fly2_gmm.load_yprofs()[-1],exp_on_the_fly2_gmm.se
#                         FOM = exp_on_the_fly2_gmm.load_FOM()[-1],
```

```
#                         this_title = "Histogram of Y profiles On-The_Fly 2 GMM Approc
# #Control Data
# MyPlots.plot_y_profiles(exp_control_gmm.load_yprofs()[-1],exp_control_gmm.settings.x
#                         this_title = "Histogram of Y profiles My Control Evenly GMM
```

10.2 Histogram for the Parameters Samples

Getting the Lists for the Parameters The containers total_pts (and similars) stores 2-D arrays on them; each 2-d array represents an iteration. The 2-d array contain the samples for all the parameters n_samples*n_parameters (where the number of samples can change per iteration, but the number of columns is constant). First,based on the columns of each array (each column represents a parameter) we will create lists that represent each parameter where each sub-list inside the list for a given paremeter represents the samples at an iterations, n_iterations*n_samples

Note: 1) Any of the 2-d arays in this_total_pts and this_total_pts2 have as columns representing each parameter. The columns represent respectvily A, I0, T,and phi0. They are in the same order than in the console output from the loop.

2) We Cannot create 2D arrays for each parameter because the number of samples per iteration can change. Thus, we create lists for each parameter.

plottinh_hist() Here we create an auxiliary funtion to plot each of the sublists (that represent the samples at all the iterations for a given parameter) of the output of using the function above.

WARNING: Remember that the number of samples per iteration can change. Thus, a histogram may not be the best way to visualize converge. we have two options.

1. Normalize the number of samples for al iterations.
2. commnet out the line of code mark_outliers() in the main loop. So, we do not rule outliers and then we will have the same number of samples for all iterations.

plottinh_hist()

In [8]:
```
#getting the lists for both approaches. The lists contains lists where each sublists i
#sublists that represent a parameter there are sublists that represent the samples for
#at an iteration.

#Entropy Method
list_par_separated_e1 = MyPlots.getting_list_each_par(exp_entropy1.load_pts()) #This l
list_par_separated_e2 = MyPlots.getting_list_each_par(exp_entropy2.load_pts())
#On-the-fly 1 Method
list_par_separated_o1 = MyPlots.getting_list_each_par(exp_on_the_fly1.load_pts())
#On-the-fly 2 Method
list_par_separated_o2 = MyPlots.getting_list_each_par(exp_on_the_fly2.load_pts())
#Control method
list_par_separated_c = MyPlots.getting_list_each_par(exp_control.load_pts())

#####################################GMM VERSION


# #Entropy Method
```

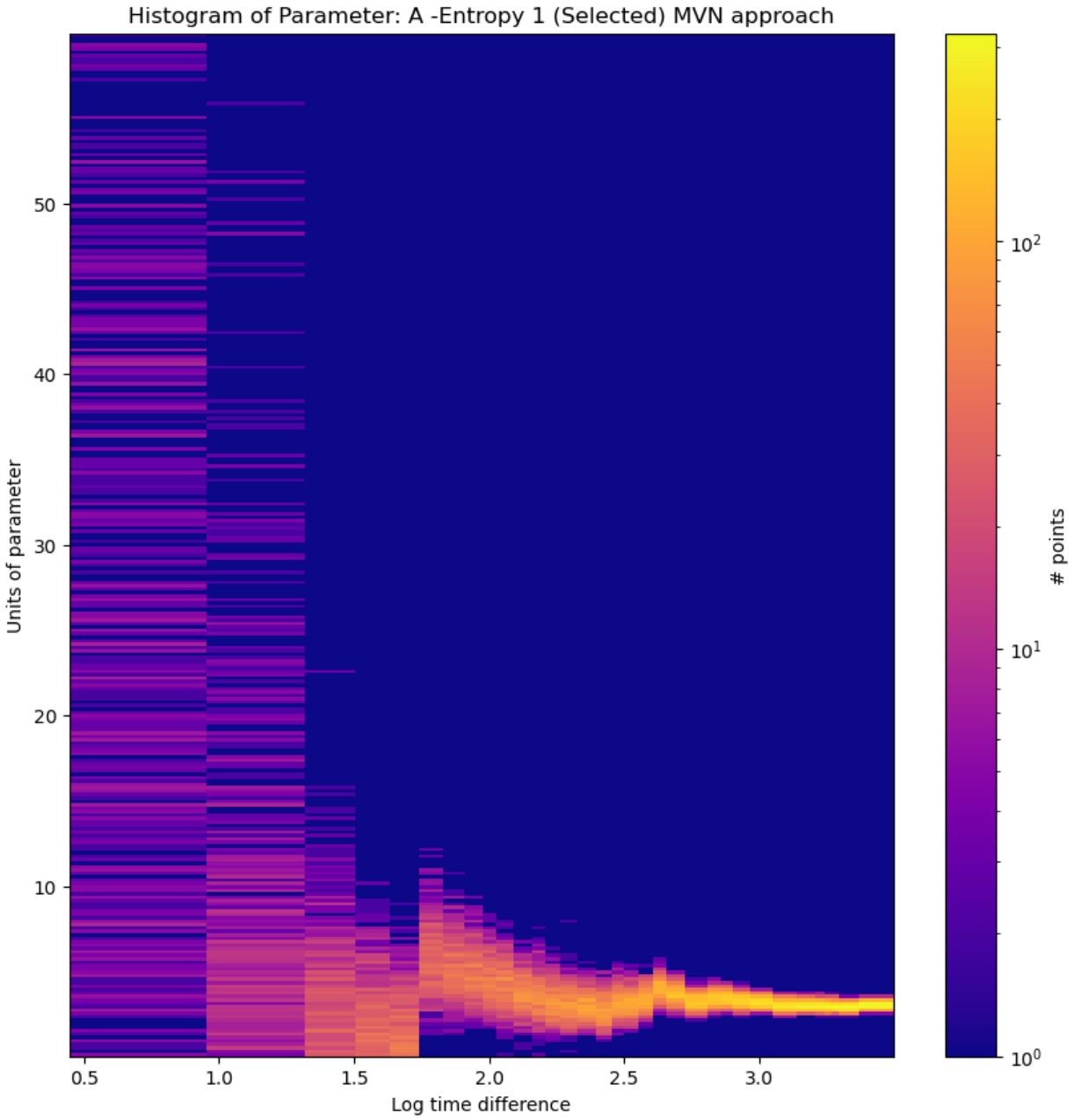
```
# list_par_separated_e1_gmm = MyPlots.getting_list_each_par(exp_entropy1_gmm.load_pts(
# list_par_separated_e2_gmm = MyPlots.getting_list_each_par(exp_entropy2_gmm.load_pts(
# #On-the-fly 1 Method
# list_par_separated_o1_gmm = MyPlots.getting_list_each_par(exp_on_the_fly1_gmm.load_p
# #On-the-fly 2 Method
# list_par_separated_o2_gmm = MyPlots.getting_list_each_par(exp_on_the_fly2_gmm.load_p
# #Control method
# list_par_separated_c_gmm = MyPlots.getting_list_each_par(exp_control_gmm.load_pts())
```

```
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:353: VisibleDeprecationWarning: Creat
ing an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do t
his, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_pts)
```

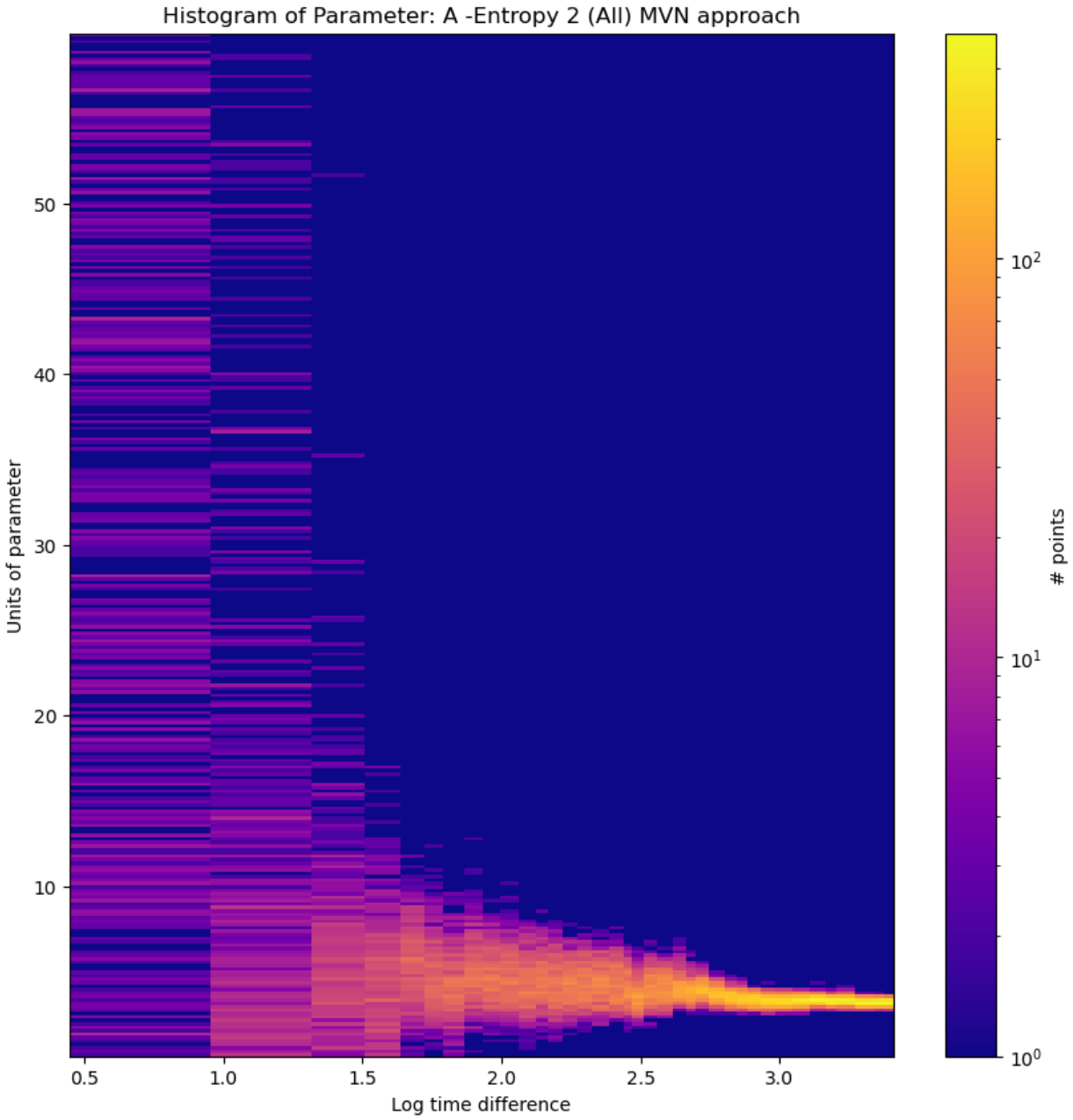
In [9]:

```
aux_list = [list_par_separated_e1[0],list_par_separated_e2[0], list_par_separated_o1[0
            list_par_separated_o2[0], list_par_separated_c[0]]

list_times = [exp_entropy1.totaltimes(), exp_entropy2.totaltimes(), exp_on_the_fly1.to
             exp_on_the_fly2.totaltimes(), exp_control.totaltimes()]

names_for_approaches = ["Entropy 1 (Selected) MVN", "Entropy 2 (All) MVN","On-the fly
                        "Control-45 even MVN"]
par_name = "A"



# specify y-edges for all three histograms
y_min, y_max = MyPlots.finding_max_min(aux_list)

for i in range(len(aux_list)):
    MyPlots.plotting_hist_logtime(aux_list[i], names_for_approaches[i], par_name, y_mi



#################GMM VERSION COMMNENT OUT IF YOU DO NOT HAVE A GMM VERSION

# aux_list = [list_par_separated_e1_gmm[0],list_par_separated_e2_gmm[0], list_par_sepa
#             list_par_separated_o2_gmm[0], list_par_separated_c_gmm[0]]

# names_for_approaches = ["Entropy 1 (Selected) GMM", "Entropy 2 (All) GMM","On-the fl
#                         "Control-45 even GMM"]
# par_name = "A"



# # specify y-edges for all three histograms
# y_min, y_max = MyPlots.finding_max_min(aux_list)

# for i in range(len(aux_list)):
#     MyPlots.plotting_hist(aux_list[i], names_for_approaches[i], par_name, y_min, y_m
```

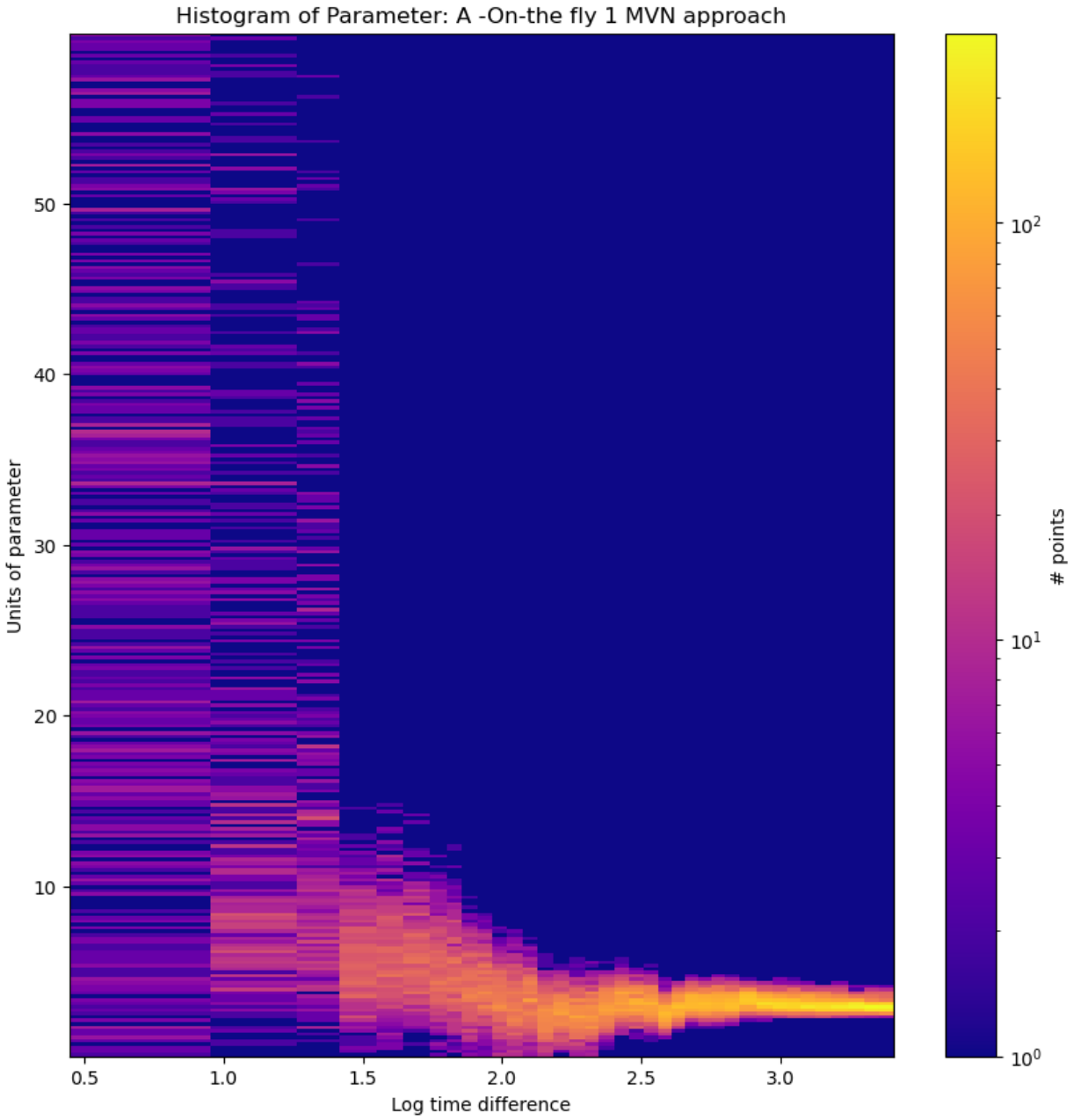
```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.74272769
 1.83050944 1.91008283 1.97943661 2.0269083  2.08881828 2.16061222
 2.21074595 2.26186185 2.32921544 2.39594841 2.45579197 2.50125804
 2.55219229 2.6052847  2.65510974 2.72418739 2.80734028 2.86072328
 2.90388007 2.96602687 3.0492519  3.1411309  3.20713195 3.24442994
 3.26798023 3.29415742 3.36996744 3.4985517 ]
```



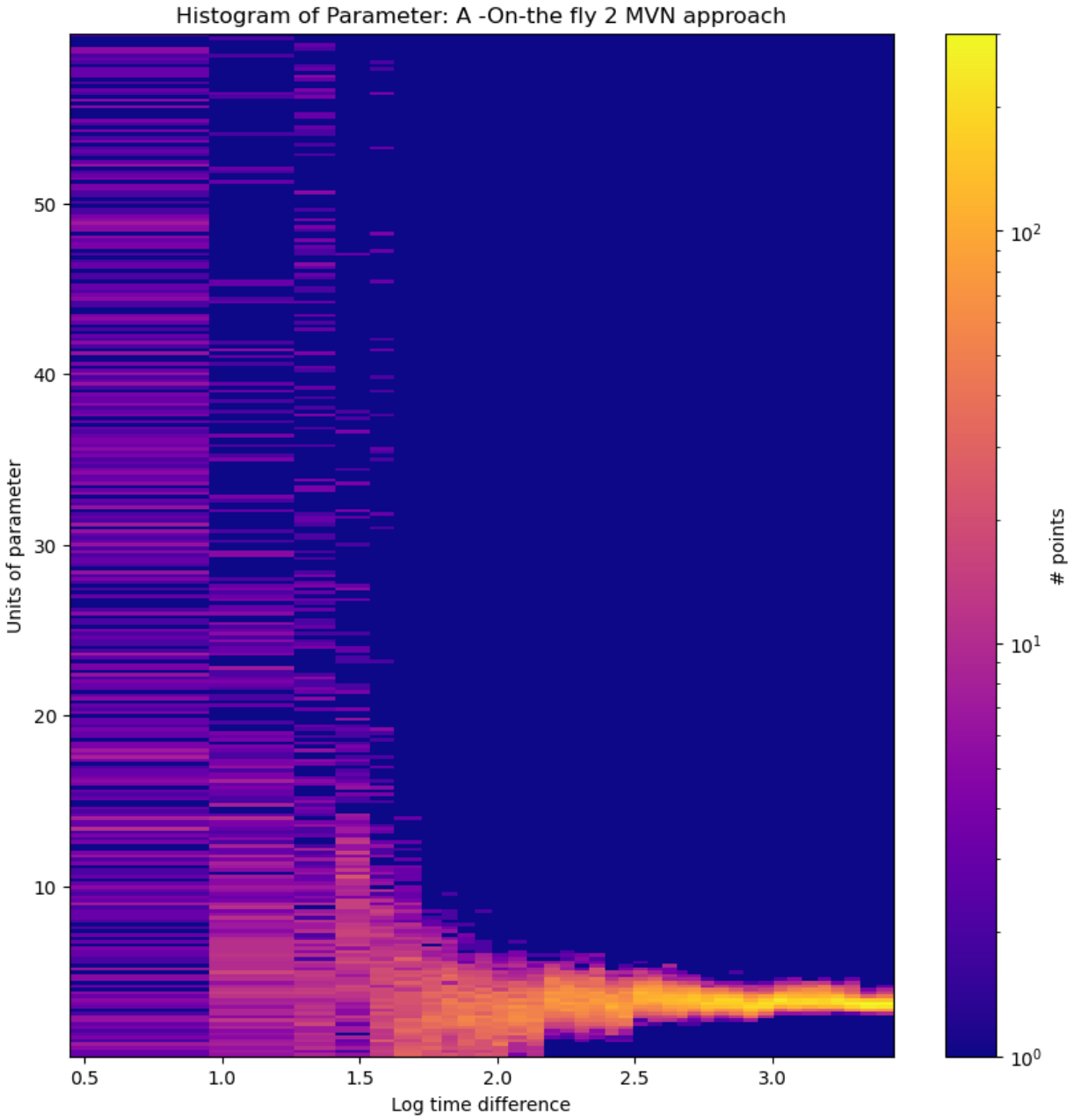

```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.72044998
 1.78944125 1.86551887 1.93368955 1.99505089 2.06220452 2.12181476
 2.16869847 2.21762037 2.27296752 2.32546545 2.38789077 2.43996251
 2.47011073 2.51051997 2.55720065 2.61467453 2.66339217 2.69702697
 2.74562125 2.80238    2.84492702 2.88532973 2.93216611 2.98475581
 3.0442753  3.1081969  3.16564268 3.20220066 3.27005994 3.34112851
 3.37471937 3.40931831]
```



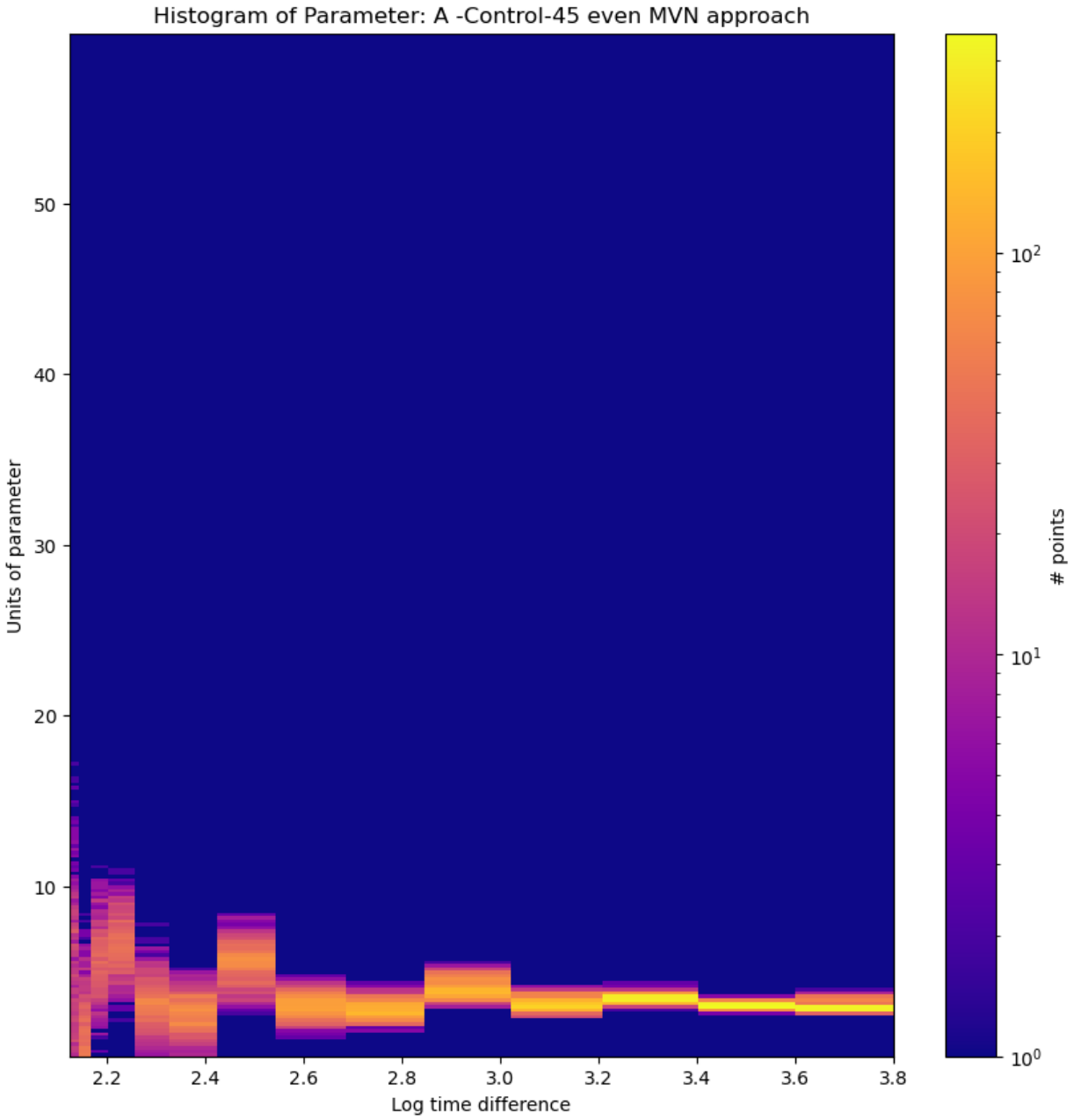

```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.54711242 1.64324682
 1.74073877 1.80318351 1.85558475 1.91122789 1.96316759 2.01948022
 2.07340611 2.12741956 2.18306767 2.24275265 2.29775704 2.34720704
 2.4017414  2.45838616 2.51061901 2.56065071 2.60915022 2.65718061
 2.7047217  2.75214743 2.79919776 2.85347019 2.91548412 2.97237346
 3.02585956 3.07448248 3.12540436 3.18373907 3.24244474 3.30106135
 3.35582976 3.40698161]
```




```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.53667585 1.62472148
 1.72604662 1.79625765 1.8555356  1.92029574 1.98081054 2.03966319
 2.10436084 2.17107604 2.22637098 2.27846113 2.33570388 2.38956964
 2.4404791  2.49502846 2.54789818 2.60138809 2.65034166 2.69200149
 2.73983251 2.78879424 2.83924197 2.89328811 2.94809892 3.00221855
 3.05284095 3.10758895 3.16302443 3.21012688 3.26139188 3.31927847
 3.37794914 3.43913074]
```



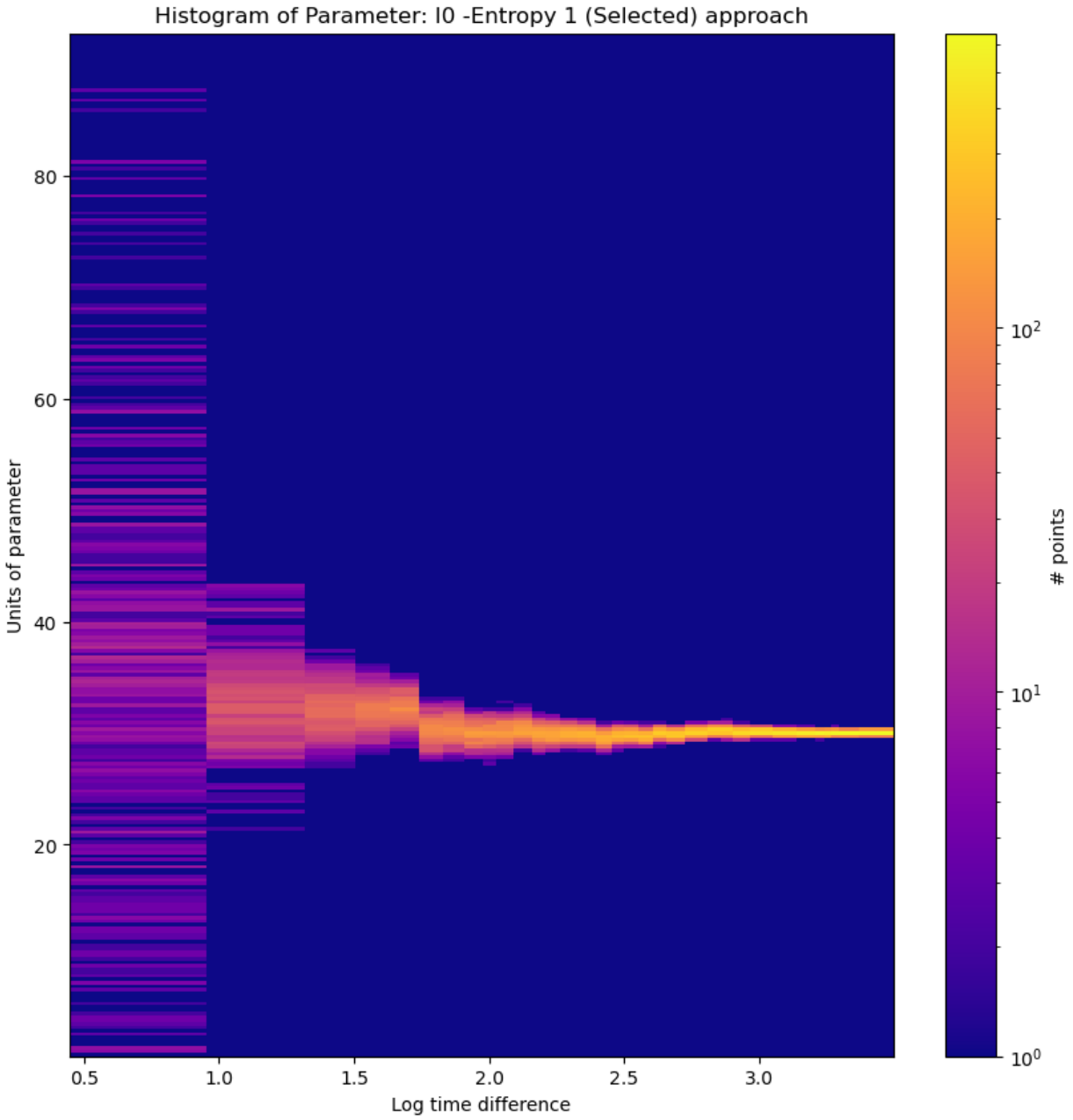

```
my x edges
[2.12400496 2.14307285 2.16713147 2.203179   2.25542118 2.32797081
 2.42377446 2.54362306 2.68585652 2.84696932 3.02270427 3.209021
 3.40261866 3.60105122 3.80139375]
```



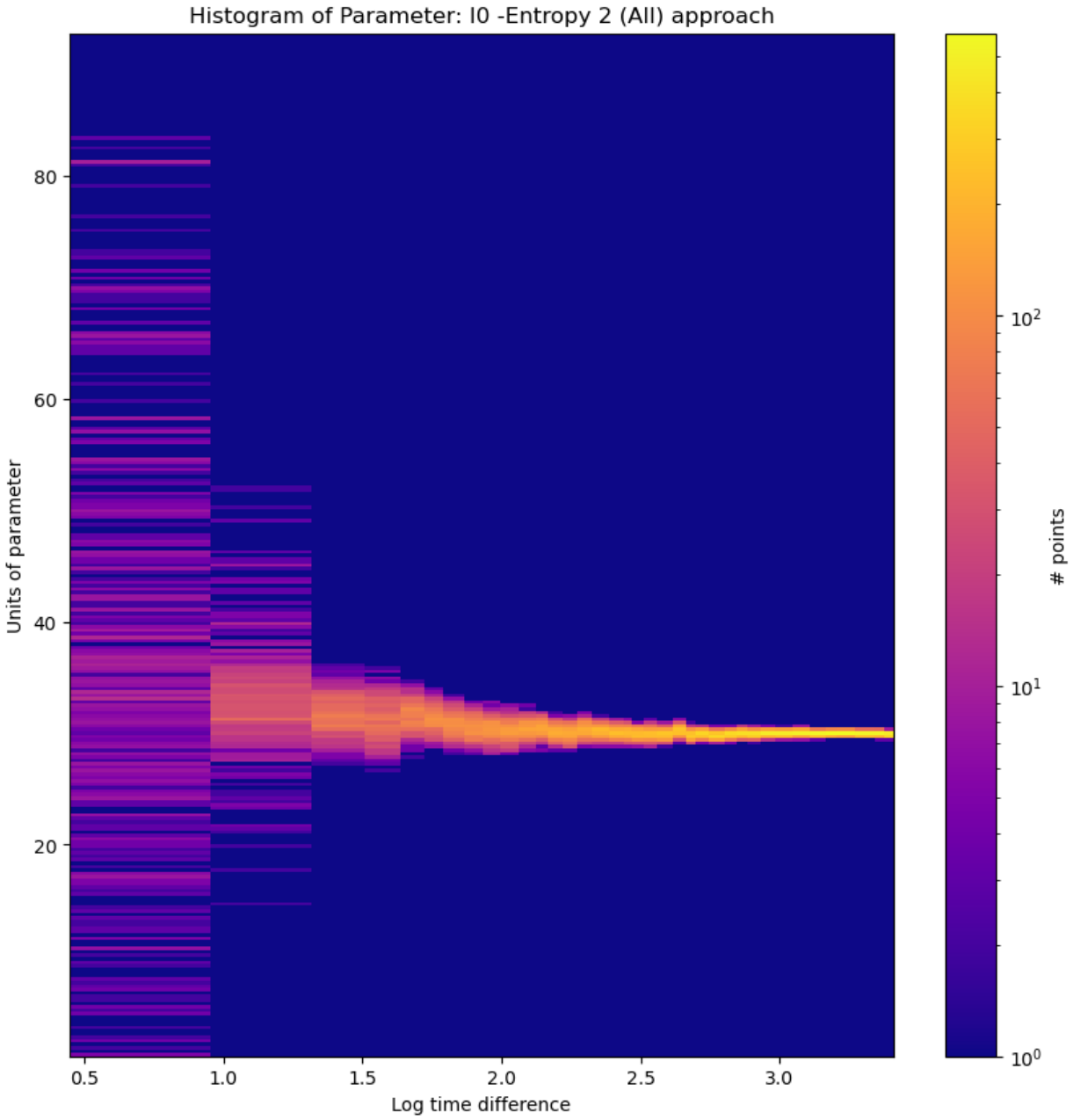
In [10]:
```
aux_list = [list_par_separated_e1[1],list_par_separated_e2[1], list_par_separated_o1[1
            list_par_separated_o2[1], list_par_separated_c[1]]

list_times = [exp_entropy1.totaltimes(), exp_entropy2.totaltimes(), exp_on_the_fly1.to
             exp_on_the_fly2.totaltimes(), exp_control.totaltimes()]


names_for_approaches = ["Entropy 1 (Selected)", "Entropy 2 (All)","On-the fly 1","On-t
                        "Control-45 even"]
par_name = "I0"



# specify y-edges for all three histograms

#WARNING: If you are plotting the GMM versions, you will need to include the values us
#values below
y_min, y_max = MyPlots.finding_max_min(aux_list)
```

```
for i in range(len(aux_list)):
    MyPlots.plotting_hist_logtime(aux_list[i], names_for_approaches[i], par_name, y_mi



################GMM VERSION COMMNENT OUT IF YOU DO NOT HAVE A GMM VERSION

# aux_list = [list_par_separated_e1_gmm[1],list_par_separated_e2_gmm[1], list_par_sepa
#             list_par_separated_o2_gmm[1], list_par_separated_c_gmm[1]]

# names_for_approaches = ["Entropy 1 (Selected) GMM", "Entropy 2 (All) GMM","On-the fl
#                         "Control-45 even GMM"]
# par_name = "I0"



# # specify y-edges for all three histograms
# y_min, y_max = MyPlots.finding_max_min(aux_list)

# for i in range(len(aux_list)):
#     MyPlots.plotting_hist(aux_list[i], names_for_approaches[i], par_name, y_min, y_m
```

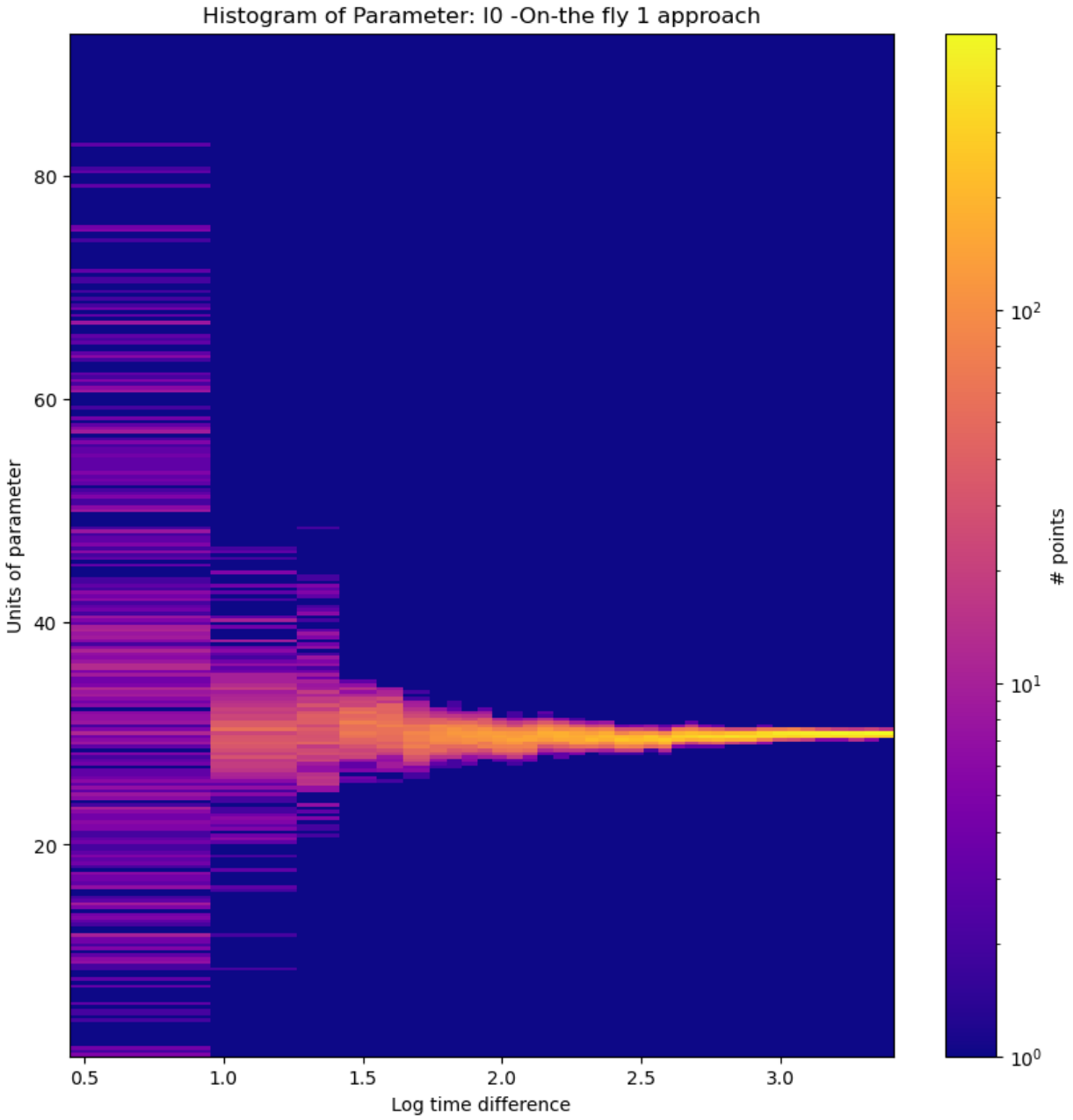
```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.74272769
 1.83050944 1.91008283 1.97943661 2.0269083  2.08881828 2.16061222
 2.21074595 2.26186185 2.32921544 2.39594841 2.45579197 2.50125804
 2.55219229 2.6052847  2.65510974 2.72418739 2.80734028 2.86072328
 2.90388007 2.96602687 3.0492519  3.1411309  3.20713195 3.24442994
 3.26798023 3.29415742 3.36996744 3.4985517 ]
```



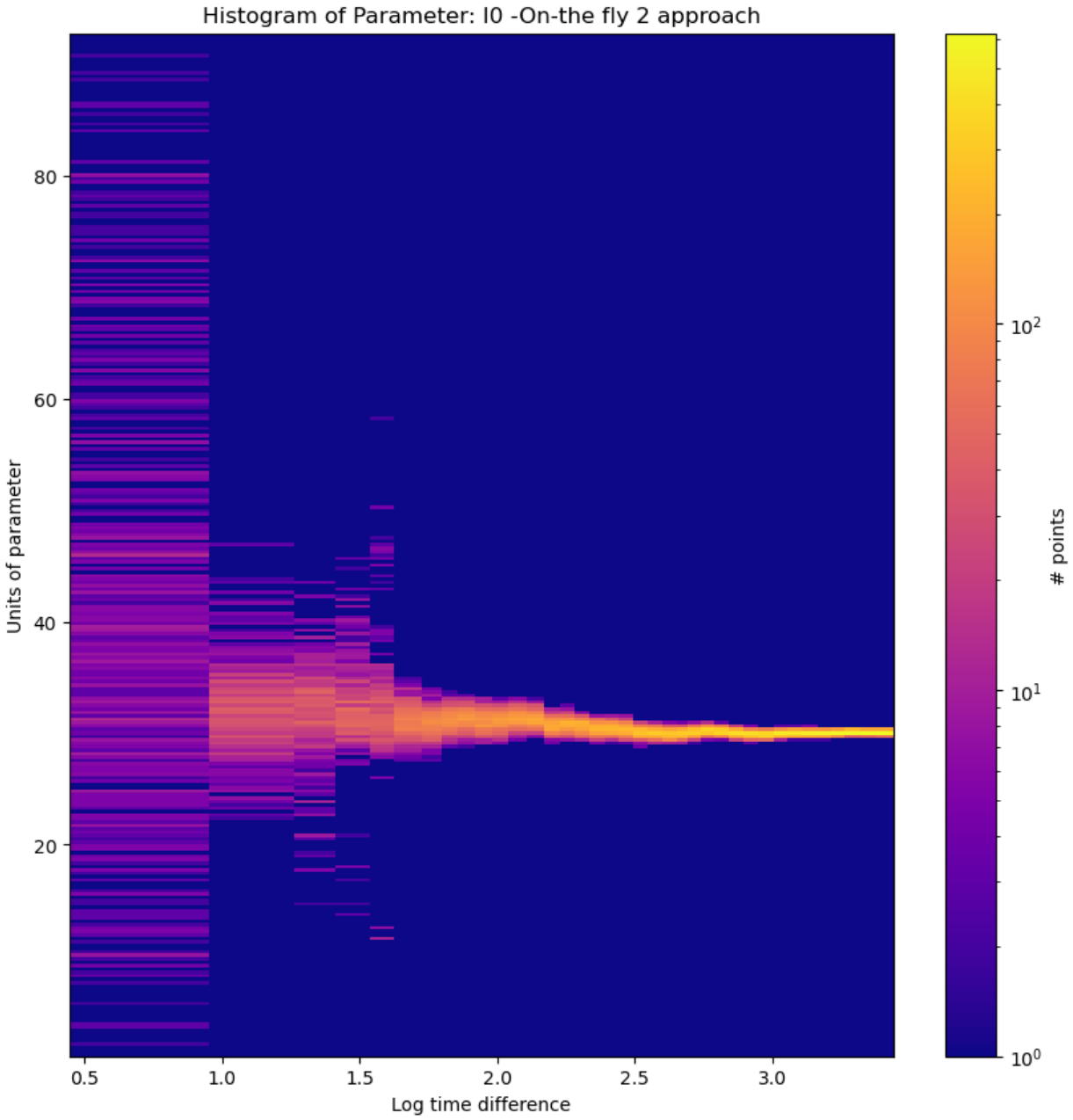

```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.72044998
 1.78944125 1.86551887 1.93368955 1.99505089 2.06220452 2.12181476
 2.16869847 2.21762037 2.27296752 2.32546545 2.38789077 2.43996251
 2.47011073 2.51051997 2.55720065 2.61467453 2.66339217 2.69702697
 2.74562125 2.80238    2.84492702 2.88532973 2.93216611 2.98475581
 3.0442753  3.1081969  3.16564268 3.20220066 3.27005994 3.34112851
 3.37471937 3.40931831]
```



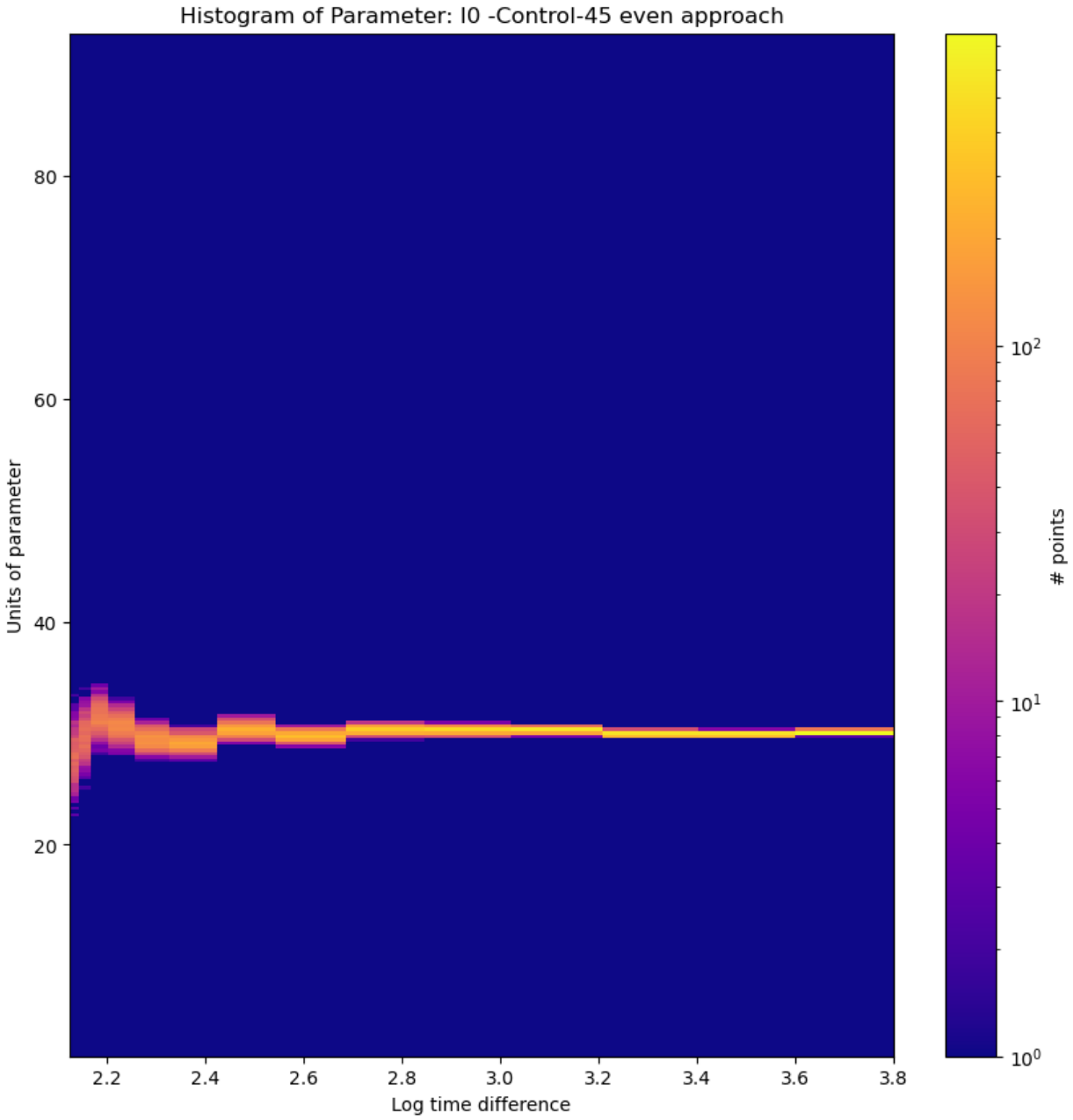

```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.54711242 1.64324682
 1.74073877 1.80318351 1.85558475 1.91122789 1.96316759 2.01948022
 2.07340611 2.12741956 2.18306767 2.24275265 2.29775704 2.34720704
 2.4017414  2.45838616 2.51061901 2.56065071 2.60915022 2.65718061
 2.7047217  2.75214743 2.79919776 2.85347019 2.91548412 2.97237346
 3.02585956 3.07448248 3.12540436 3.18373907 3.24244474 3.30106135
 3.35582976 3.40698161]
```




```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.53667585 1.62472148
 1.72604662 1.79625765 1.8555356  1.92029574 1.98081054 2.03966319
 2.10436084 2.17107604 2.22637098 2.27846113 2.33570388 2.38956964
 2.4404791  2.49502846 2.54789818 2.60138809 2.65034166 2.69200149
 2.73983251 2.78879424 2.83924197 2.89328811 2.94809892 3.00221855
 3.05284095 3.10758895 3.16302443 3.21012688 3.26139188 3.31927847
 3.37794914 3.43913074]
```



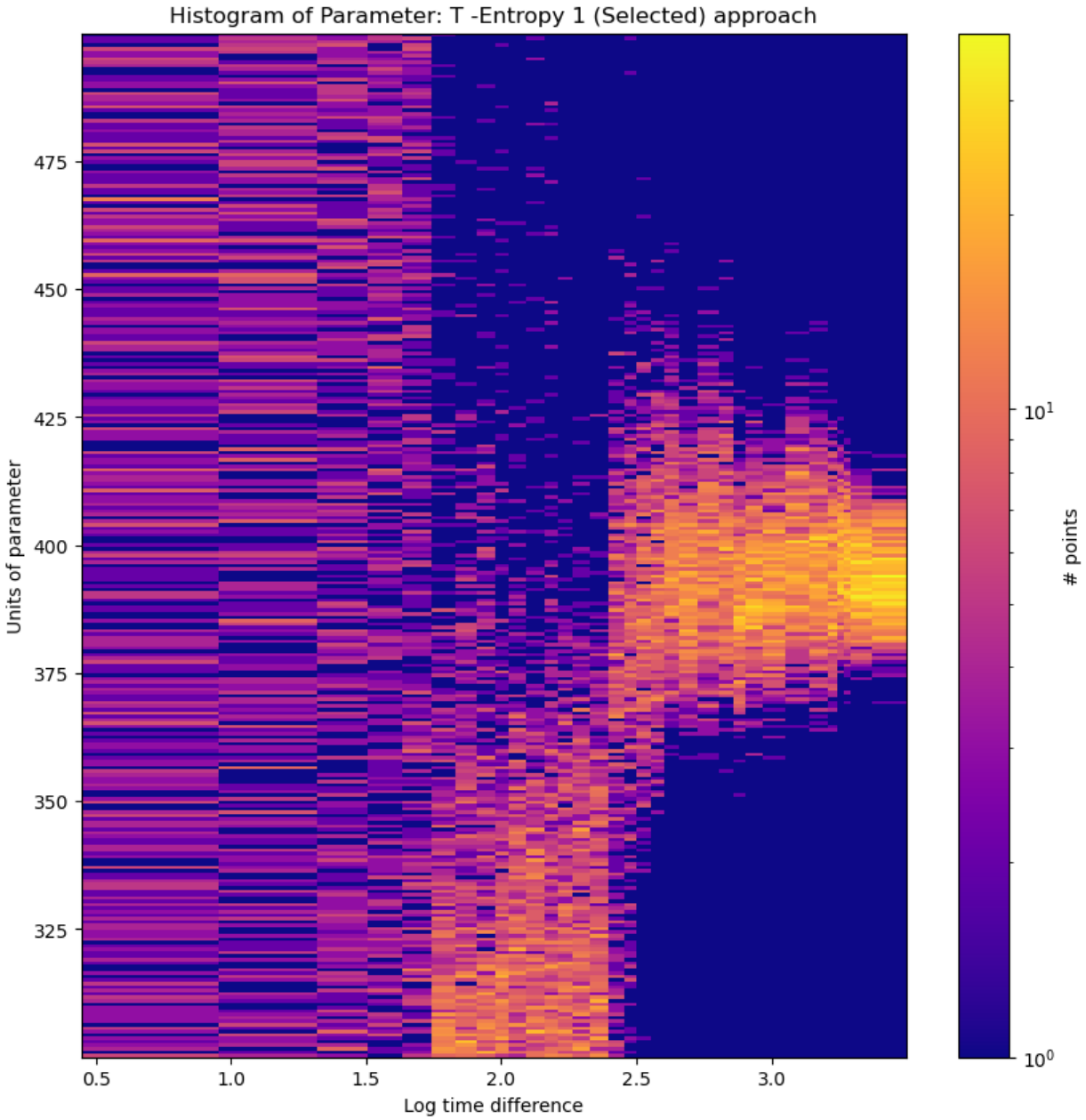

```
my x edges
[2.12400496 2.14307285 2.16713147 2.203179   2.25542118 2.32797081
 2.42377446 2.54362306 2.68585652 2.84696932 3.02270427 3.209021
 3.40261866 3.60105122 3.80139375]
```



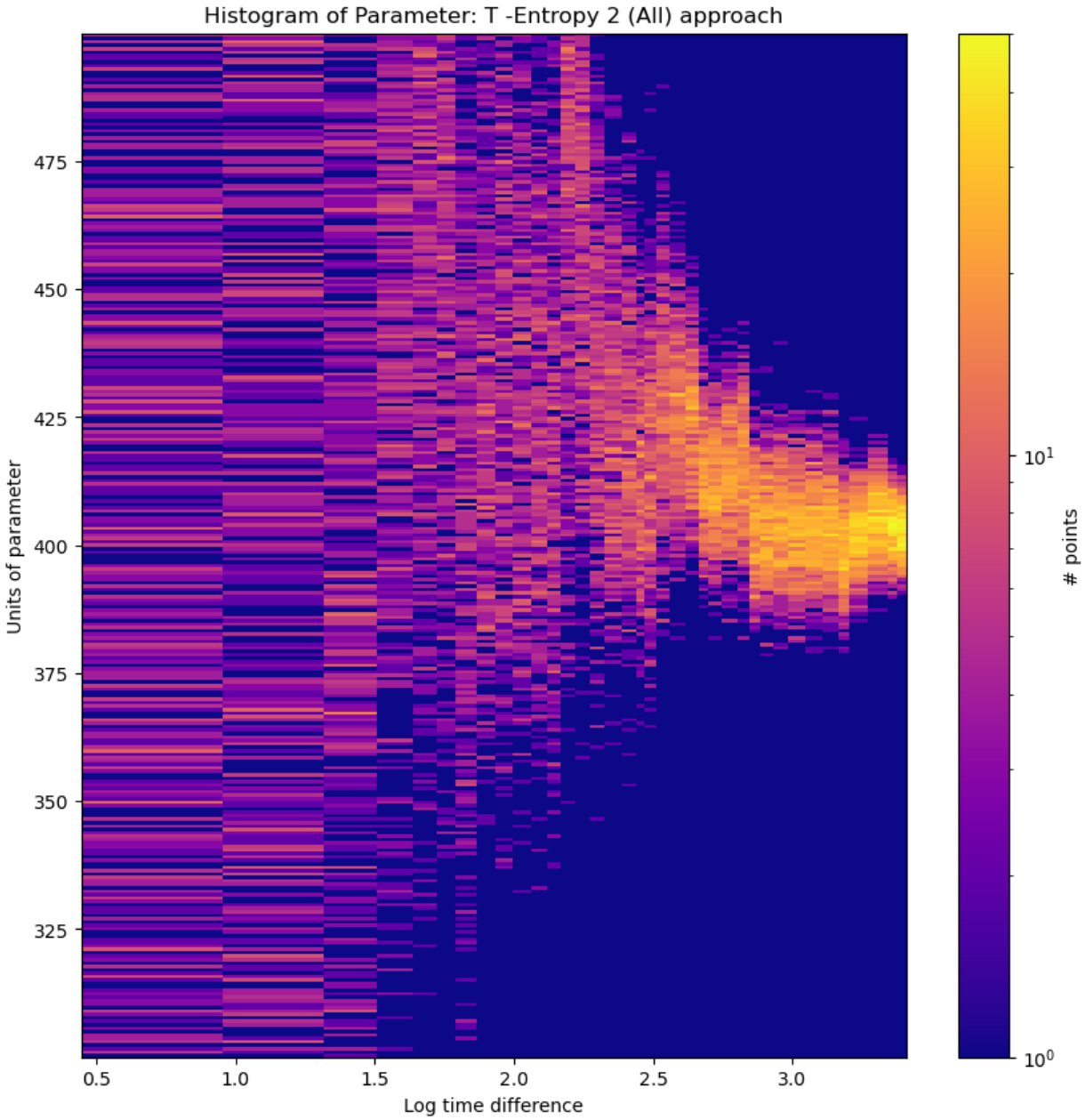
In [11]:
```
#Plotting histograms for T
aux_list = [list_par_separated_e1[2],list_par_separated_e2[2], list_par_separated_o1[2
            list_par_separated_o2[2], list_par_separated_c[2]]

list_times = [exp_entropy1.totaltimes(), exp_entropy2.totaltimes(), exp_on_the_fly1.to
             exp_on_the_fly2.totaltimes(), exp_control.totaltimes()]


names_for_approaches = ["Entropy 1 (Selected)", "Entropy 2 (All)","On-the fly 1","On-t
                        "Control-45 even"]
par_name = "T"



# specify y-edges for all three histograms
y_min, y_max = MyPlots.finding_max_min(aux_list)

for i in range(len(aux_list)):
    MyPlots.plotting_hist_logtime(aux_list[i], names_for_approaches[i], par_name, y_mi
```

```
################GMM VERSION COMMNENT OUT IF YOU DO NOT HAVE A GMM VERSION

# aux_list = [list_par_separated_e1_gmm[2],list_par_separated_e2_gmm[2], list_par_sepa
#             list_par_separated_o2_gmm[2], list_par_separated_c_gmm[2]]

# names_for_approaches = ["Entropy 1 (Selected) GMM", "Entropy 2 (All) GMM","On-the fl
#                         "Control-45 even GMM"]
# par_name = "T"



# # specify y-edges for all three histograms
# y_min, y_max = MyPlots.finding_max_min(aux_list)

# for i in range(len(aux_list)):
#     MyPlots.plotting_hist(aux_list[i], names_for_approaches[i], par_name, y_min, y_m
```

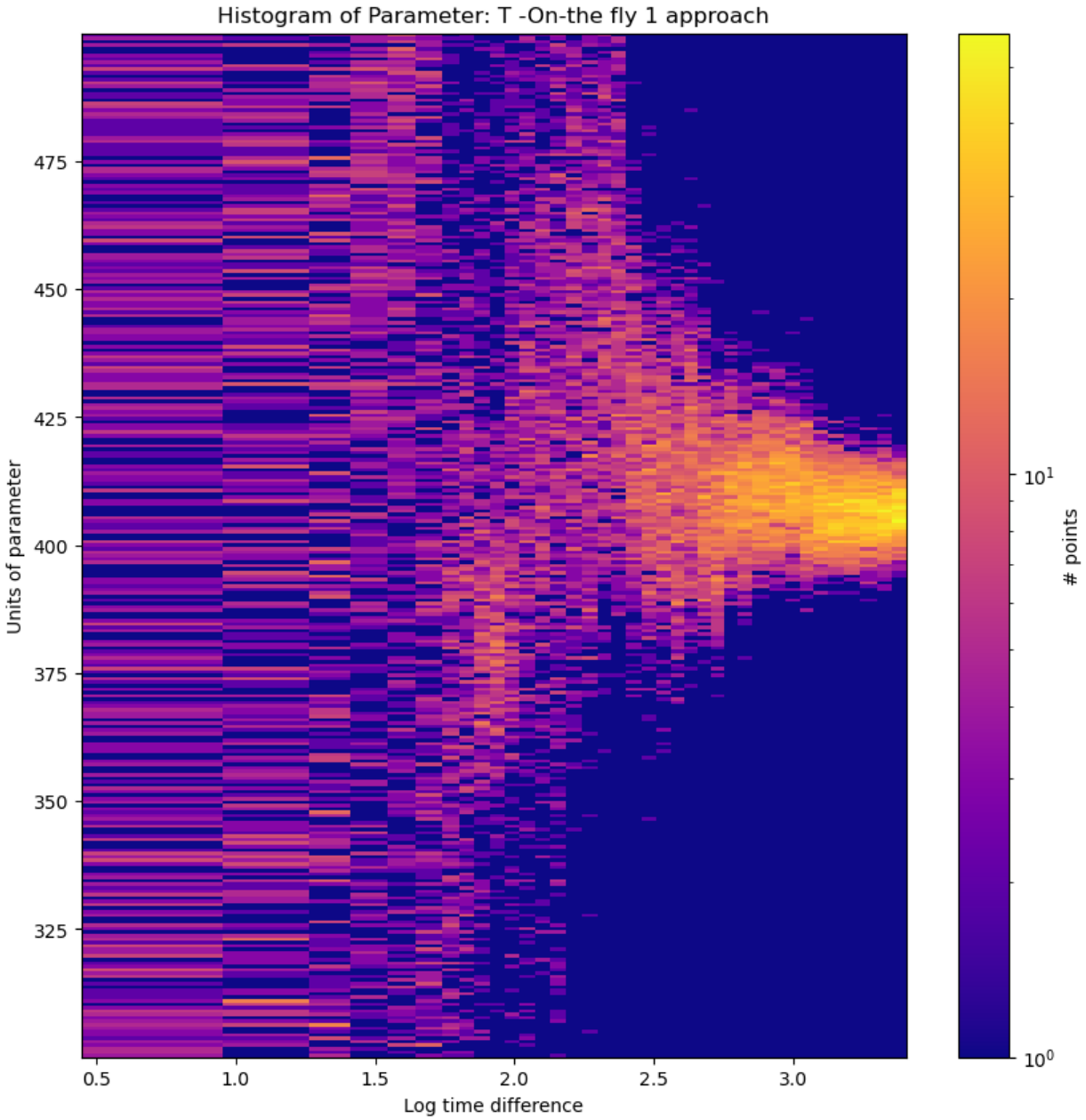
```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.74272769
 1.83050944 1.91008283 1.97943661 2.0269083  2.08881828 2.16061222
 2.21074595 2.26186185 2.32921544 2.39594841 2.45579197 2.50125804
 2.55219229 2.6052847  2.65510974 2.72418739 2.80734028 2.86072328
 2.90388007 2.96602687 3.0492519  3.1411309  3.20713195 3.24442994
 3.26798023 3.29415742 3.36996744 3.4985517 ]
```



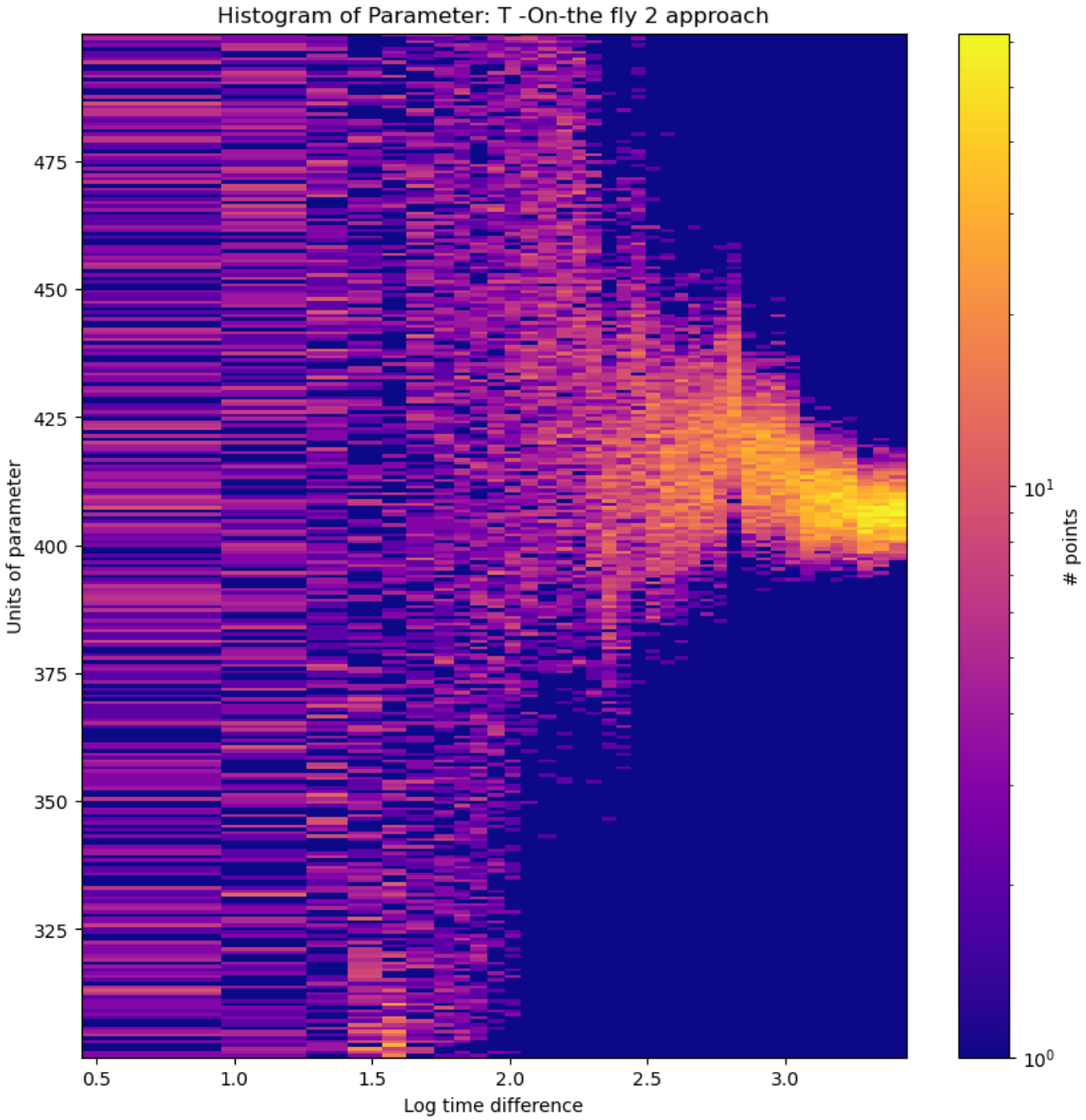

```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.72044998
 1.78944125 1.86551887 1.93368955 1.99505089 2.06220452 2.12181476
 2.16869847 2.21762037 2.27296752 2.32546545 2.38789077 2.43996251
 2.47011073 2.51051997 2.55720065 2.61467453 2.66339217 2.69702697
 2.74562125 2.80238    2.84492702 2.88532973 2.93216611 2.98475581
 3.0442753  3.1081969  3.16564268 3.20220066 3.27005994 3.34112851
 3.37471937 3.40931831]
```



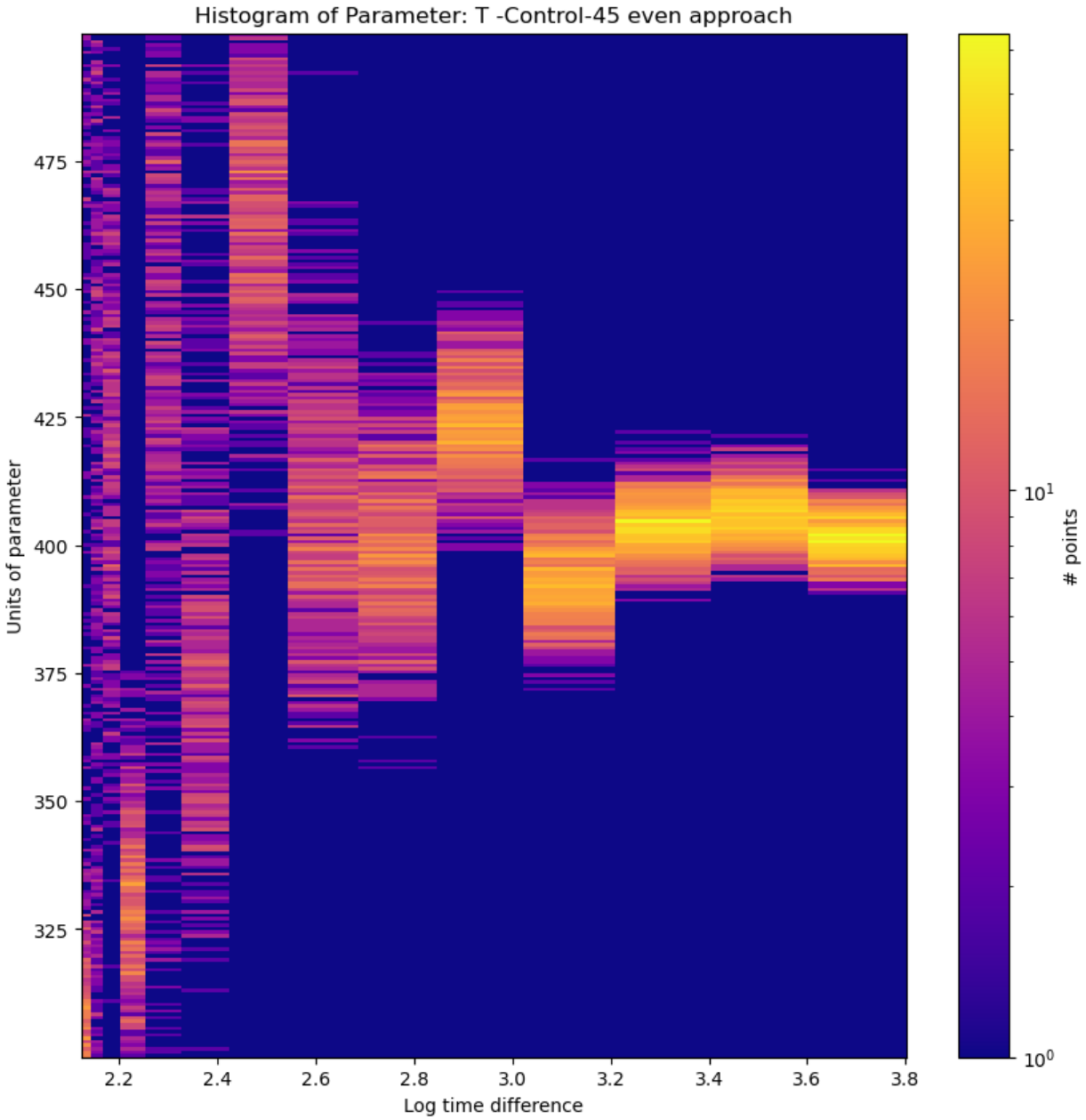

```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.54711242 1.64324682
 1.74073877 1.80318351 1.85558475 1.91122789 1.96316759 2.01948022
 2.07340611 2.12741956 2.18306767 2.24275265 2.29775704 2.34720704
 2.4017414  2.45838616 2.51061901 2.56065071 2.60915022 2.65718061
 2.7047217  2.75214743 2.79919776 2.85347019 2.91548412 2.97237346
 3.02585956 3.07448248 3.12540436 3.18373907 3.24244474 3.30106135
 3.35582976 3.40698161]
```




```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.53667585 1.62472148
 1.72604662 1.79625765 1.8555356  1.92029574 1.98081054 2.03966319
 2.10436084 2.17107604 2.22637098 2.27846113 2.33570388 2.38956964
 2.4404791  2.49502846 2.54789818 2.60138809 2.65034166 2.69200149
 2.73983251 2.78879424 2.83924197 2.89328811 2.94809892 3.00221855
 3.05284095 3.10758895 3.16302443 3.21012688 3.26139188 3.31927847
 3.37794914 3.43913074]
```




```
my x edges
[2.12400496 2.14307285 2.16713147 2.203179   2.25542118 2.32797081
 2.42377446 2.54362306 2.68585652 2.84696932 3.02270427 3.209021
 3.40261866 3.60105122 3.80139375]
```

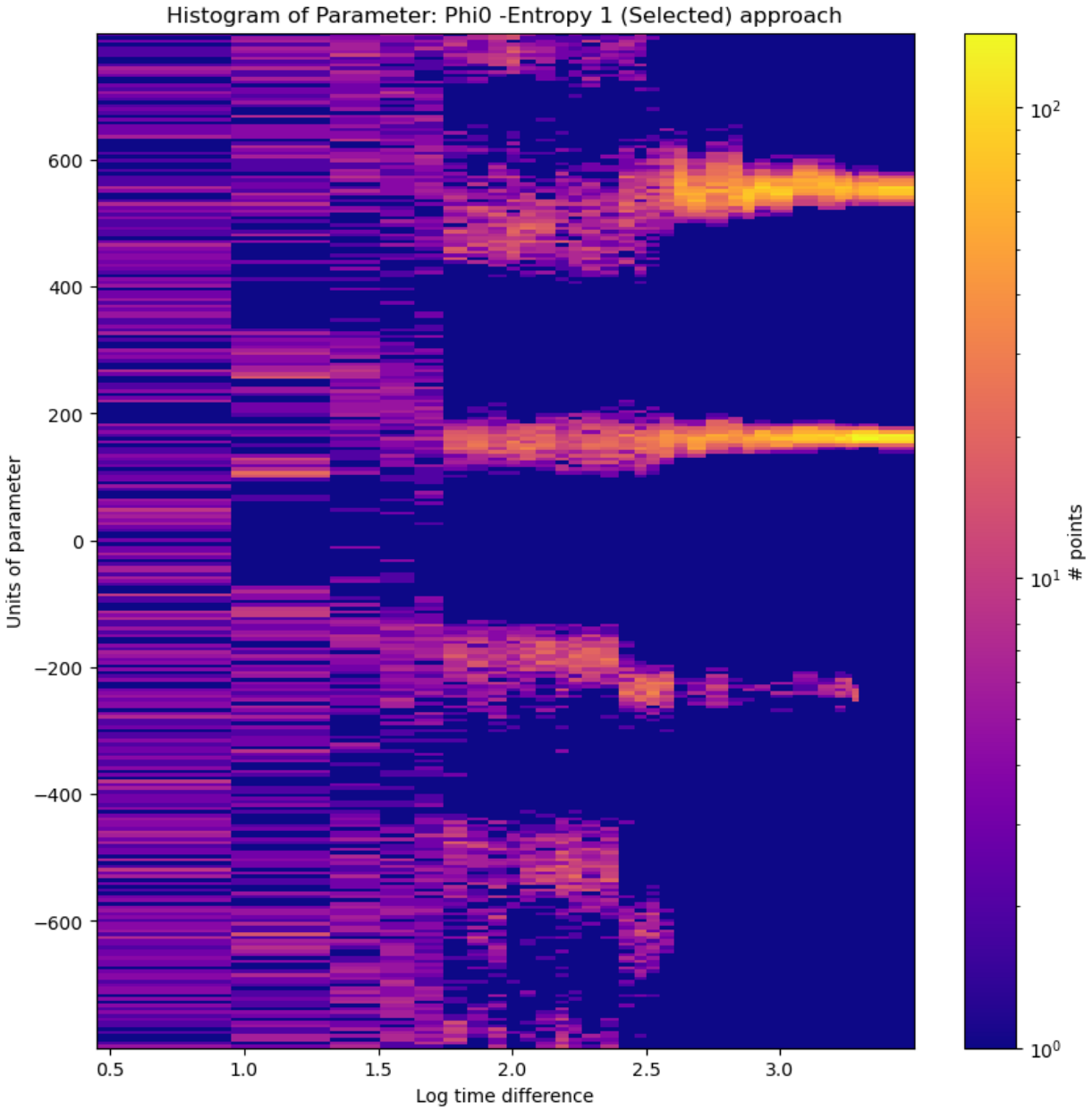


In [ ]:

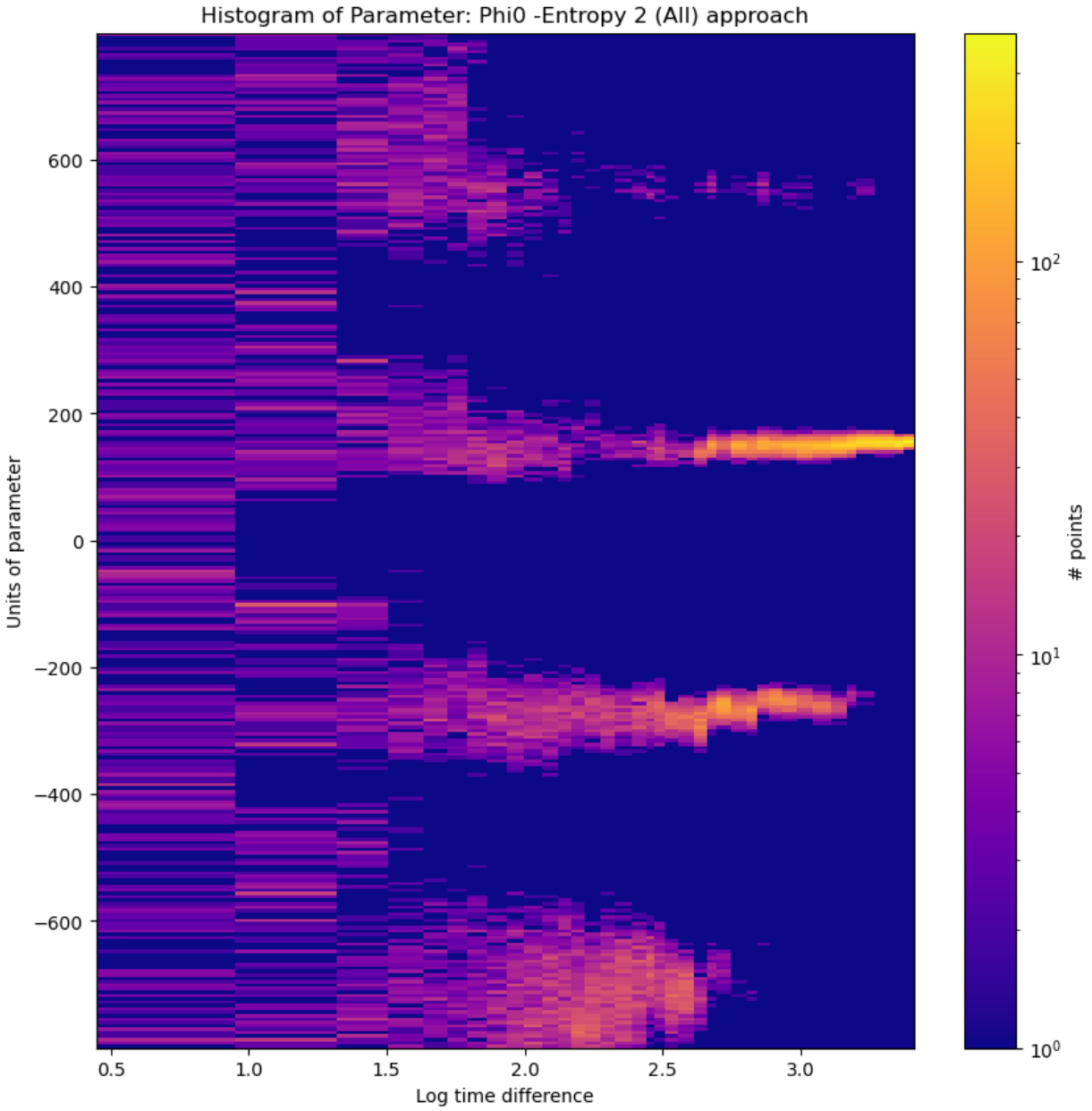
In [12]:
```
#Plotting histograms for Phi0
aux_list = [list_par_separated_e1[3],list_par_separated_e2[3], list_par_separated_o1[3
            list_par_separated_o2[3], list_par_separated_c[3]]

list_times = [exp_entropy1.totaltimes(), exp_entropy2.totaltimes(), exp_on_the_fly1.to
             exp_on_the_fly2.totaltimes(), exp_control.totaltimes()]


names_for_approaches = ["Entropy 1 (Selected)", "Entropy 2 (All)","On-the fly 1","On-t
                        "Control-45 even"]
par_name = "Phi0"



# specify y-edges for all three histograms
y_min, y_max = MyPlots.finding_max_min(aux_list)
```

```
for i in range(len(aux_list)):
    MyPlots.plotting_hist_logtime(aux_list[i], names_for_approaches[i], par_name, y_mi



################GMM VERSION COMMNENT OUT IF YOU DO NOT HAVE A GMM VERSION

# aux_list = [list_par_separated_e1_gmm[3],list_par_separated_e2_gmm[3], list_par_sepa
#             list_par_separated_o2_gmm[3], list_par_separated_c_gmm[3]]

# names_for_approaches = ["Entropy 1 (Selected) GMM", "Entropy 2 (All) GMM","On-the fl
#                         "Control-45 even GMM"]
# par_name = "Phi0"



# # specify y-edges for all three histograms
# y_min, y_max = MyPlots.finding_max_min(aux_list)

# for i in range(len(aux_list)):
#     MyPlots.plotting_hist(aux_list[i], names_for_approaches[i], par_name, y_min, y_m
```

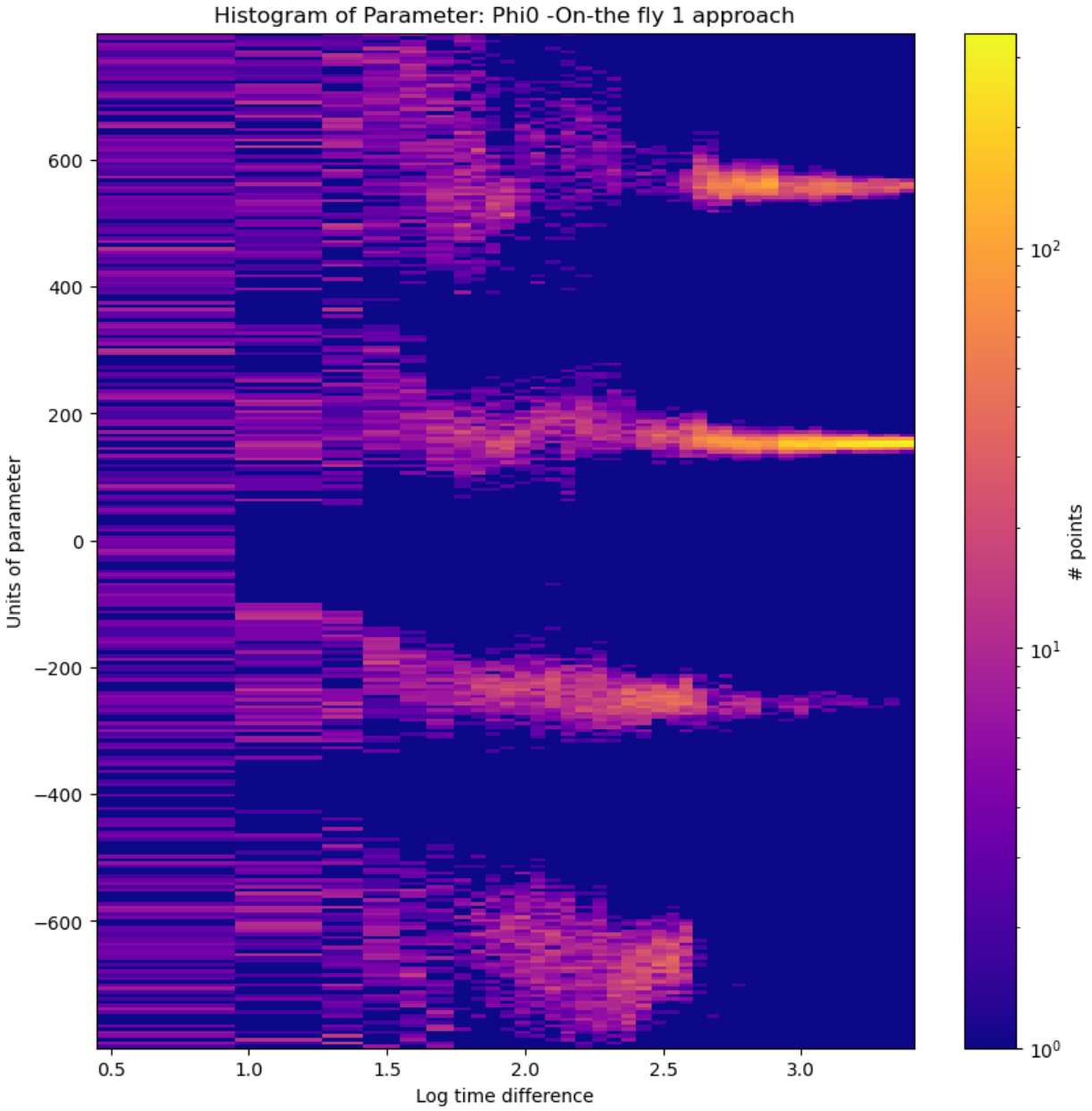
```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.74272769
 1.83050944 1.91008283 1.97943661 2.0269083  2.08881828 2.16061222
 2.21074595 2.26186185 2.32921544 2.39594841 2.45579197 2.50125804
 2.55219229 2.6052847  2.65510974 2.72418739 2.80734028 2.86072328
 2.90388007 2.96602687 3.0492519  3.1411309  3.20713195 3.24442994
 3.26798023 3.29415742 3.36996744 3.4985517 ]
```



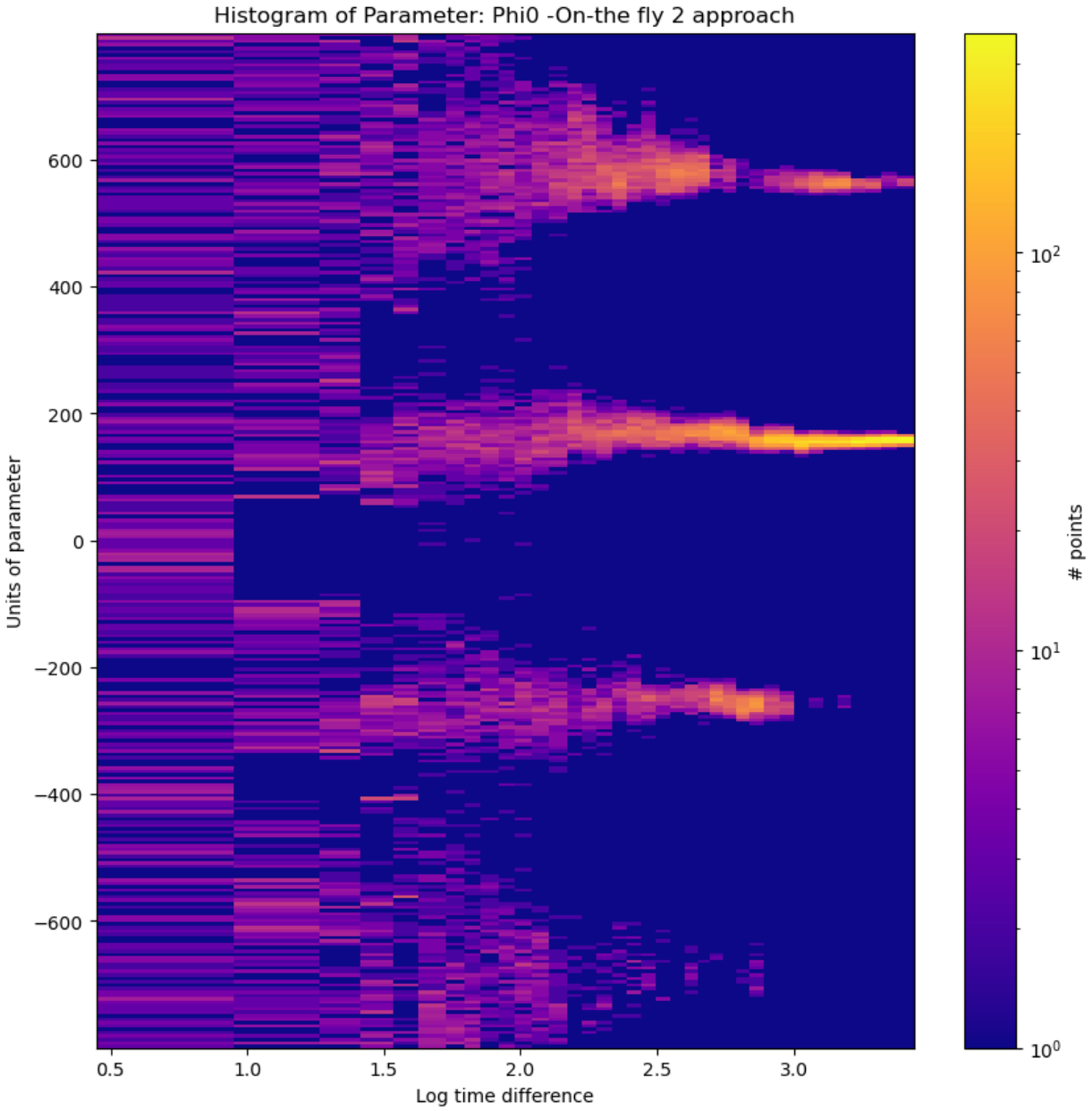

```
my x edges
[0.44639502 0.95154499 1.31774187 1.50557368 1.63498984 1.72044998
 1.78944125 1.86551887 1.93368955 1.99505089 2.06220452 2.12181476
 2.16869847 2.21762037 2.27296752 2.32546545 2.38789077 2.43996251
 2.47011073 2.51051997 2.55720065 2.61467453 2.66339217 2.69702697
 2.74562125 2.80238    2.84492702 2.88532973 2.93216611 2.98475581
 3.0442753  3.1081969  3.16564268 3.20220066 3.27005994 3.34112851
 3.37471937 3.40931831]
```



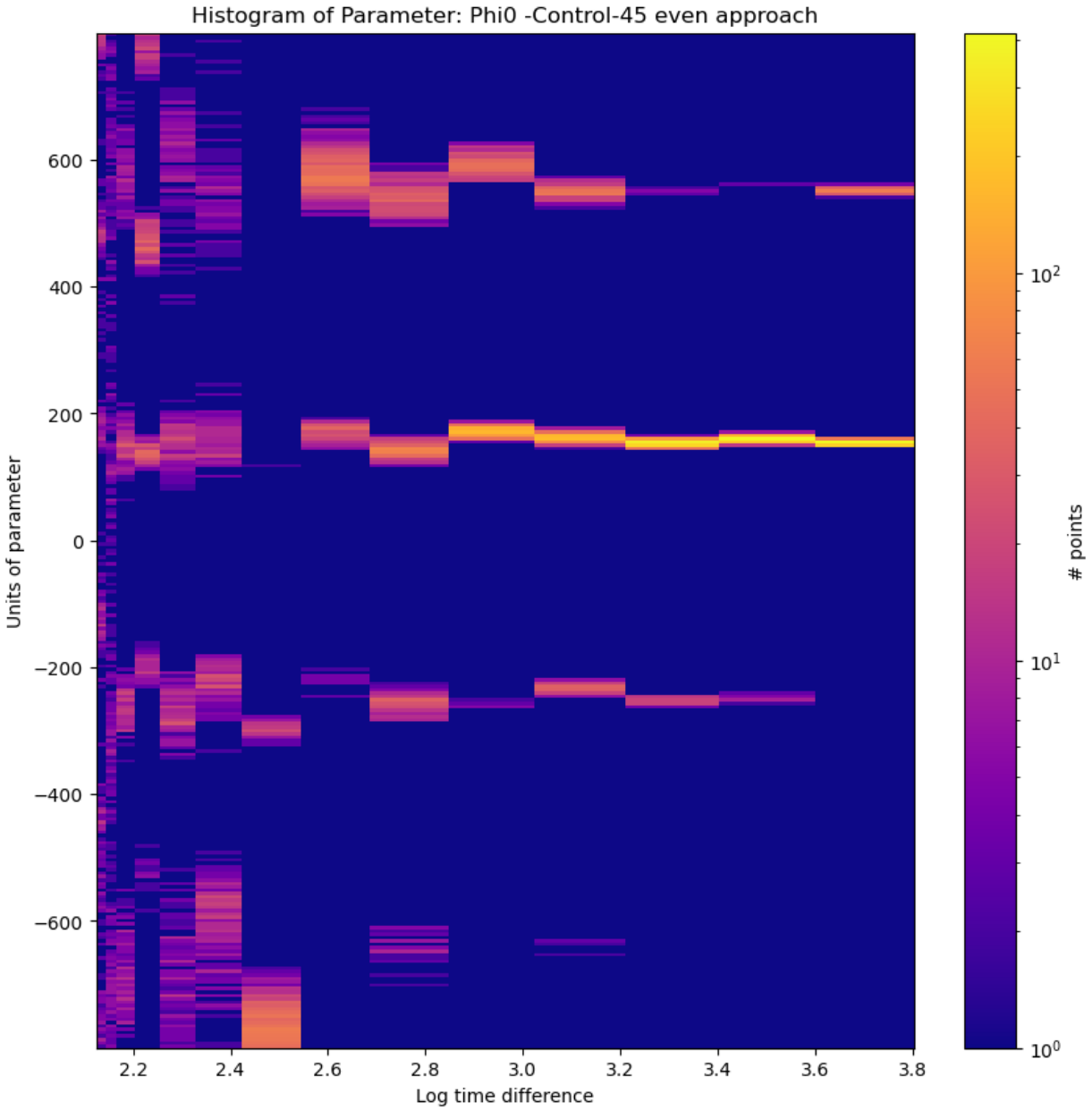

```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.54711242 1.64324682
 1.74073877 1.80318351 1.85558475 1.91122789 1.96316759 2.01948022
 2.07340611 2.12741956 2.18306767 2.24275265 2.29775704 2.34720704
 2.4017414  2.45838616 2.51061901 2.56065071 2.60915022 2.65718061
 2.7047217  2.75214743 2.79919776 2.85347019 2.91548412 2.97237346
 3.02585956 3.07448248 3.12540436 3.18373907 3.24244474 3.30106135
 3.35582976 3.40698161]
```




```
my x edges
[0.44639502 0.95154499 1.26316964 1.41368464 1.53667585 1.62472148
 1.72604662 1.79625765 1.8555356  1.92029574 1.98081054 2.03966319
 2.10436084 2.17107604 2.22637098 2.27846113 2.33570388 2.38956964
 2.4404791  2.49502846 2.54789818 2.60138809 2.65034166 2.69200149
 2.73983251 2.78879424 2.83924197 2.89328811 2.94809892 3.00221855
 3.05284095 3.10758895 3.16302443 3.21012688 3.26139188 3.31927847
 3.37794914 3.43913074]
```



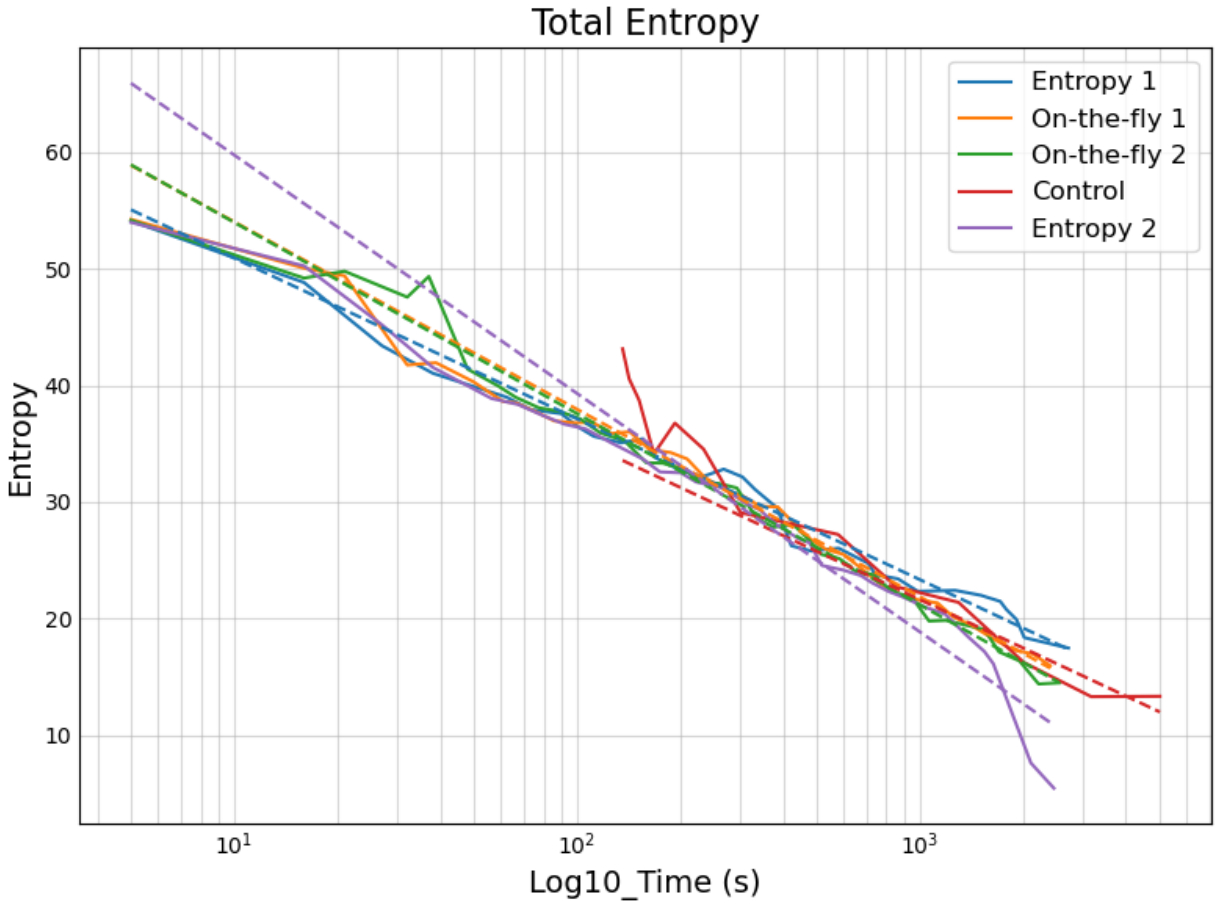

```
my x edges
[2.12400496 2.14307285 2.16713147 2.203179   2.25542118 2.32797081
 2.42377446 2.54362306 2.68585652 2.84696932 3.02270427 3.209021
 3.40261866 3.60105122 3.80139375]
```



10.3 Entropy V.S Time

In [13]:
```
#Notice we could also print the total entropy, instead, of the marginalized entropy.
#On-thefly always deals with the total entropy. You cannot choose a parameter of inter
times = [exp_entropy1.totaltimes(), exp_on_the_fly1.totaltimes(),
         exp_on_the_fly2.totaltimes(),exp_control.totaltimes(), exp_entropy2.totaltime

entropies = [exp_entropy1.entropy(), exp_on_the_fly1.entropy(),
             exp_on_the_fly2.entropy(), exp_control.entropy(), exp_entropy2.entropy()]

list_names = ["Entropy 1 ", "On-the-fly 1", "On-the-fly 2", "Control", "Entropy 2"]

MyPlots.plot_entropy_times(times, entropies,list_names, "Total Entropy")


#C1 blue entrop
#C2 yellow on the
#C3 green on the 2
```

```
#C4 red control
#C5 Purple entropy2

#Total Entropy
```



In [14]:
```
#DELETE LATER THIS WORK ONLY IF YOU HAVE A GMM

#Entropy 1 Comparisson
#Blue fast mvn
#Orange gmm


# MyPlots.plot_entropy_times([exp_entropy1.totaltimes(), exp_entropy1_gmm.totaltimes()
#                             [exp_entropy1.entropy(), exp_entropy1_gmm.entropy()])
# plt.savefig("entropy1 total entropy mvn_blue gmm_orange.png")
```

In [15]:
```
#DELETE LATER THIS WORK ONLY IF YOU HAVE A GMM

#Entropy 2 Comparisson
#Blue fast mvn
#Orange gmm

#COMMENT OUT IF YOU DO NOT HAVE A GMM VERSION

# MyPlots.plot_entropy_times([exp_entropy2.totaltimes(), exp_entropy2_gmm.totaltimes()
#                             [exp_entropy2.entropy(), exp_entropy2_gmm.entropy()])
```

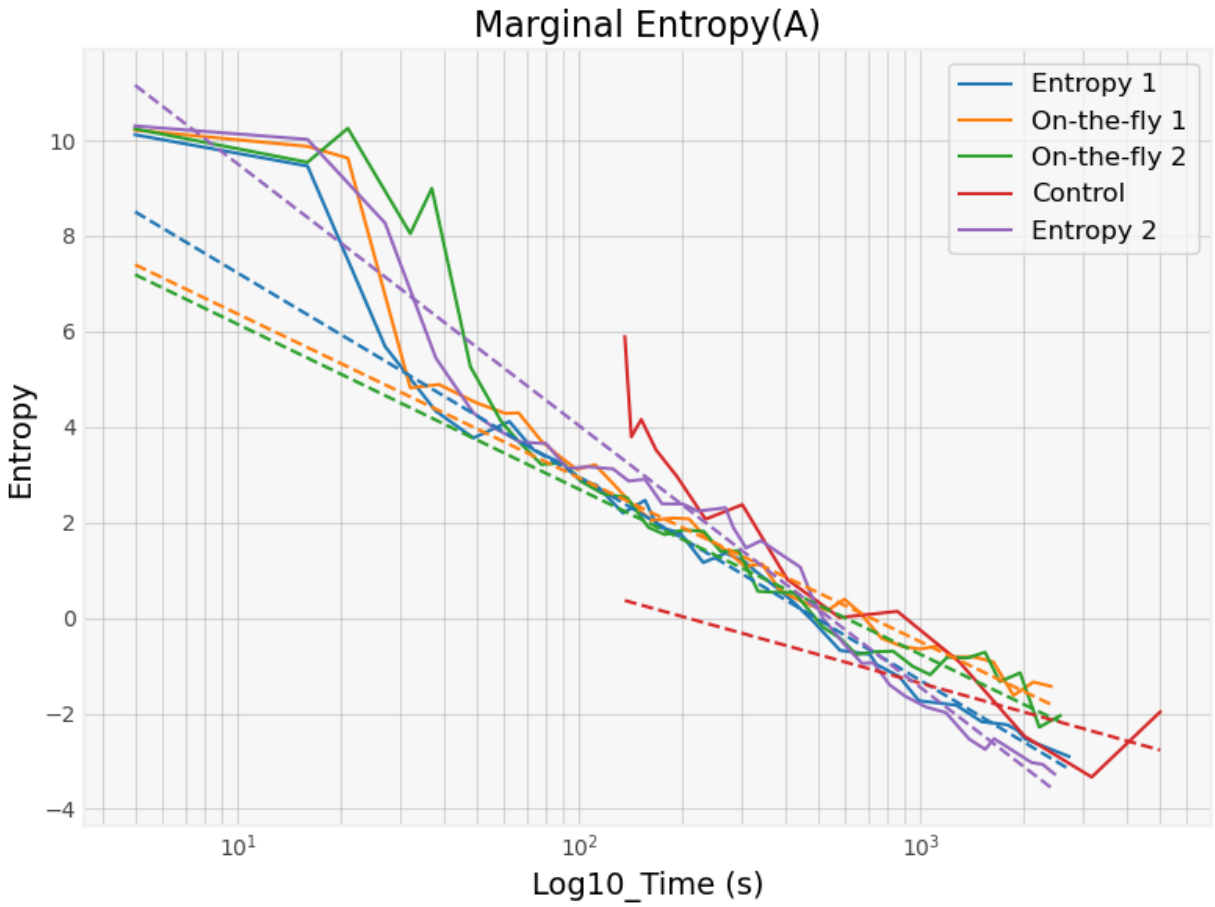
In [16]:
```
#On the fly Comparisson
#Blue fast mvn
#Orange gmm
```

```
# MyPlots.plot_entropy_times([exp_on_the_fly1.totaltimes(), exp_on_the_fly1_gmm.totalt
#                             [exp_on_the_fly1.entropy(), exp_on_the_fly1_gmm.entropy()]
```

In [17]:
```
#On the fly 2- Total Entropy Comparisson
#Blue fast mvn
#Orange gmm


# MyPlots.plot_entropy_times([exp_on_the_fly2.totaltimes(), exp_on_the_fly2_gmm.totalt
#                             [exp_on_the_fly2.entropy(), exp_on_the_fly2_gmm.entropy()]
```

In [ ]:
```
```

In [18]:
```
#Ask REMEMBER THE RETURN OF ENOTROPY_MARG() BC entropy2 does not have a marginal
times = [exp_entropy1.totaltimes(), exp_on_the_fly1.totaltimes(),
         exp_on_the_fly2.totaltimes(),exp_control.totaltimes(), exp_entropy2.totaltime


list_names = ["Entropy 1 ", "On-the-fly 1", "On-the-fly 2", "Control", "Entropy 2"]

#Rememeber that the marginal entropy for entropy2 apporach is the same as total entrop
#is not selecting any parameters. Thus, we calculate here using the select of any of t
#approaches that it must be same.
entro = [calc_entropy(this_pts, select_pars=exp_on_the_fly2.settings.sel,
                options=exp_entropy2.settings.entropy_options)[0] for this_pts in exp_

entropies = [exp_entropy1.entropy_marg(), exp_on_the_fly1.entropy_marg(),
             exp_on_the_fly2.entropy_marg(), exp_control.entropy_marg(), entro]
MyPlots.plot_entropy_times(times, entropies, list_names,"Marginal Entropy(A)")
```



In [19]:
```
#DELETE LATER THIS WORK ONLY IF YOU HAVE A GMM

#Entropy 1 Marginal  Comparisson
#Blue fast mvn
#Orange gmm


# MyPlots.plot_entropy_times([exp_entropy1.totaltimes(), exp_entropy1_gmm.totaltimes()
#                             [exp_entropy1.entropy_marg(), exp_entropy1_gmm.entropy_mar
```

In [20]:
```
#Entropy 2- Marginal  Comparisson

# ###################Comment out unless you have a GMM version
# gmm_setting= {'method': 'gmm', 'n_components': None}
# entro1 = recalculating_entropy(exp_entropy2, exp_on_the_fly2.settings.sel,gmm_settir
# entro2 = recalculating_entropy(exp_entropy2_gmm, exp_on_the_fly2.settings.sel,gmm_se
# #Blue fast mvn
# #Orange gmm
# MyPlots.plot_entropy_times([exp_entropy2.totaltimes(), exp_entropy2_gmm.totaltimes()
#                             [entro1, entro2])
```

In [21]:
```
#DELETE LATER THIS WORK ONLY IF YOU HAVE A GMM

#On the fly 1 Marginal  Comparisson
#Blue fast mvn
#Orange gmm

#Comment out if you do not have GMM version


```

```
# MyPlots.plot_entropy_times([exp_on_the_fly1.totaltimes(), exp_on_the_fly1_gmm.totalt
#                           [exp_on_the_fly1.entropy_marg(), exp_on_the_fly1_gmm.entro
```

In [22]:
```
#DELETE LATER THIS WORK ONLY IF YOU HAVE A GMM

#On the fly 1 Marginal  Comparisson
#Blue fast mvn
#Orange gmm


# MyPlots.plot_entropy_times([exp_on_the_fly2.totaltimes(), exp_on_the_fly2_gmm.totalt
#                           [exp_on_the_fly2.entropy_marg(), exp_on_the_fly2_gmm.entro
```

Helper Functions for Estimator of PDF and Log-likelihoods

These function wll be used in the remaining sections

"""

estimator_avg_at

Note: In my opinion, the estimator_avg_at causes an error in some cases bc at some points of the iteration the values are concentrate around the ground truth. Thus, there are no many points to take on the left or right of the interval. So the checking below alert us!

```
if (left_value_index < 0) or (right_value_index > (NUMBER_SAMPLES -
1)): Alert!
```

""" Note: Notice compute_likeloohs assumes independence of the parameters (columns). It is using David's estimator for pdf. Ask But can we assume that?

""" Notes likelihood_helper_kde:

1. Using KDE to estimate the pdf. Notice that KDE is a non-parametric estimator. However, it assumes independent samples; this could be a problem. Remember each sample is measurememnt point in the main loop is chosen based in the previous results.

2. Ask about the bandwidth for this function. In the next functions, we use a kde in a single feature (a parameter or a y at a given measurement place); so we can use the std as the bandwidth. We use the std bc all the other methods s.a. silverman or scott gave us terrible estimators. Thus, it may be the case that they are terrible estimators since we are using silverman. In this case, I am using "silverman". Since it is a multidimesonal pdf I cannot use just the std. Should I tried to use something smilar to the std?
   """ #likelihood_helper_kde

10.4 Estimator of Log Likelihoods for the Y's

We will use David's estimator and a multidimensional Kde

Using David's Estimator

In [23]:
```
#all_total_likelihoods
#At each iteration, we have a y-profiles. We compute the likelihhood at each x and add
Sum_likelihoods_at_each_iter_entropy1_for_ys = MyPlots.compute_likelihoods(exp_entropy
                                                                           exp_entropy2
Sum_likelihoods_at_each_iter_entropy2_for_ys = MyPlots.compute_likelihoods(exp_entropy
                                                                           exp_entropy2
Sum_likelihoods_at_each_iter_on_the_fly1_for_ys = MyPlots.compute_likelihoods(exp_on_t
                                                                              exp_on_th

Sum_likelihoods_at_each_iter_on_the_fly2_for_ys = MyPlots.compute_likelihoods(exp_on_t
                                                                              exp_on_th

Sum_likelihoods_at_each_iter_control_for_ys = MyPlots.compute_likelihoods(exp_control.
                                                                          exp_contr
#Sum_likelihoods_at_each_iter_control_for_ys = compute_likelihoods(total_yprofs_contro
```

```
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
839
this is rigth index
840
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
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nought samples eitheron the left or right of the ground truth
This is the left index
839
this is rigth index
840
```

```
C:\Users\rober\anaconda3\lib\site-packages\numpy\core\fromnumeric.py:3432: RuntimeWar
ning: Mean of empty slice.
  return _methods._mean(a, axis=axis, dtype=dtype,
C:\Users\rober\anaconda3\lib\site-packages\numpy\core\_methods.py:190: RuntimeWarnin
g: invalid value encountered in double_scalars
  ret = ret.dtype.type(ret / rcount)
```

```
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
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this is rigth index
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This is the left index
839
this is rigth index
840
```

```
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nought samples eitheron the left or right of the ground truth
This is the left index
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this is rigth index
840
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
-1
this is rigth index
0
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
-1
this is rigth index
0
```

```
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
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this is rigth index
0
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
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this is rigth index
0
```

```
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-1
this is rigth index
0
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this is rigth index
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this is rigth index
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this is rigth index
0
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This is the left index
-1
this is rigth index
0
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
-1
this is rigth index
0
```
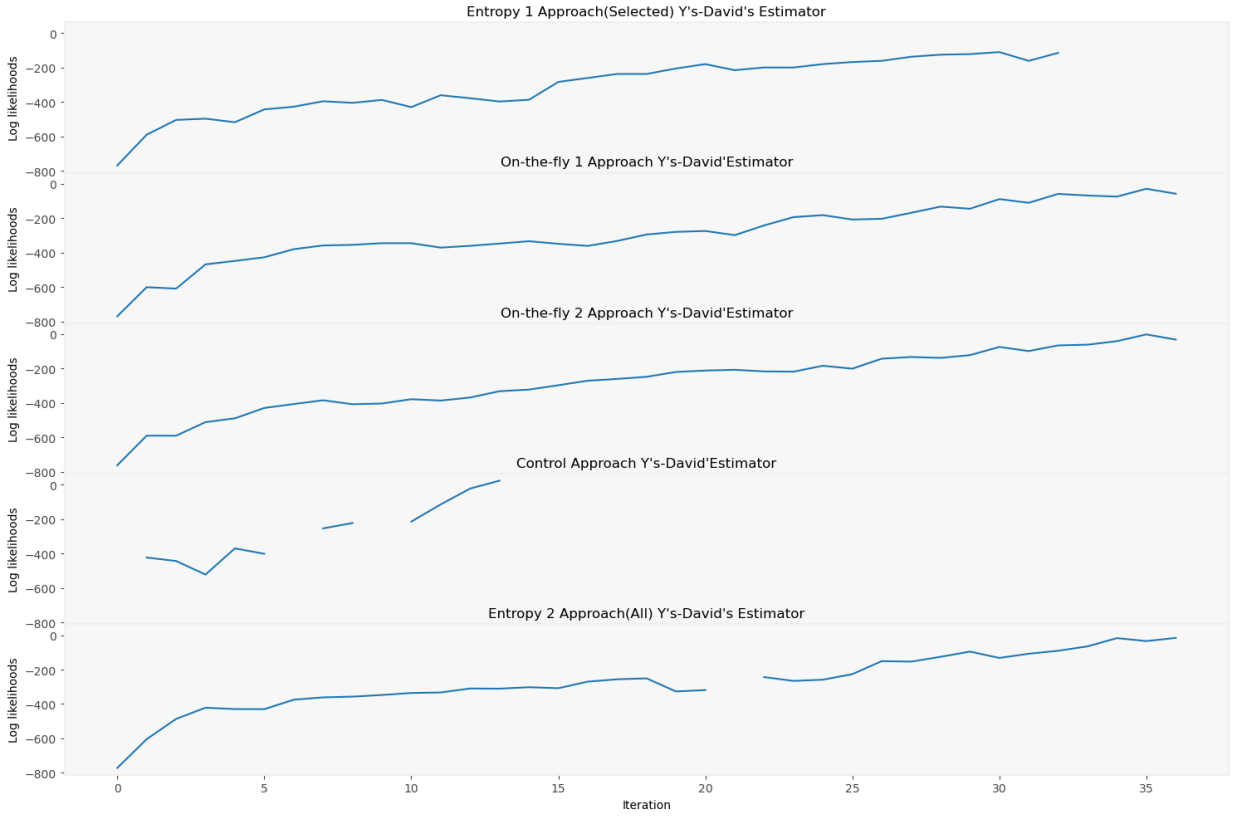
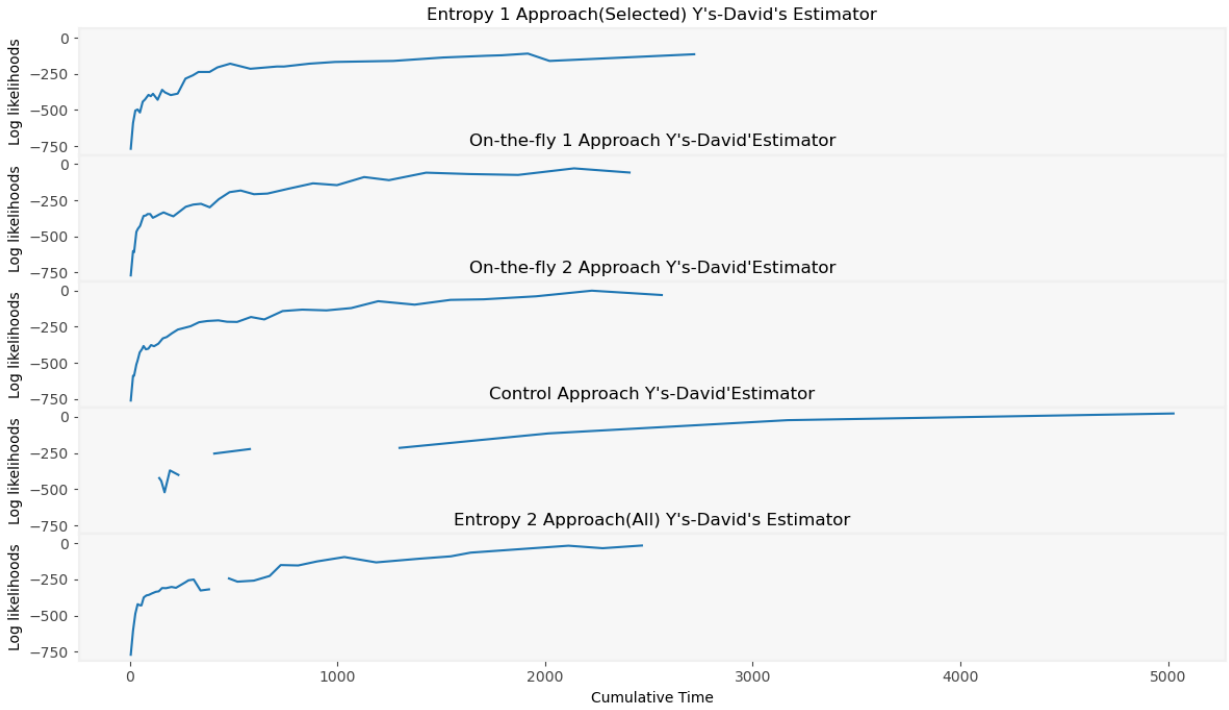

In [24]:

```
MyPlots.plot_likelihood_iterations(5,1, [Sum_likelihoods_at_each_iter_entropy1_for_ys,
                                          Sum_likelihoods_at_each_iter_on_the_fly1_for_
                                          Sum_likelihoods_at_each_iter_on_the_fly2_for_
                                          Sum_likelihoods_at_each_iter_control_for_ys,
                                          Sum_likelihoods_at_each_iter_entropy2_for_ys
```

```
                          ,["Entropy 1 Approach(Selected) Y's-David's Estimator",
                            "On-the-fly 1 Approach Y's-David'Estimator",
                            "On-the-fly 2 Approach Y's-David'Estimator",
                            "Control Approach Y's-David'Estimator",
                           "Entropy 2 Approach(All) Y's-David's Estimator"])

#REMEMBER: CONTROL TAKES A DIFFERENT NUMBER OF POINTS THAN THE OTHER APPORACHES.
```



In [25]:
```
#Add later the other apporaches to this plot
#[exp_entropy.totaltimes()[1:], exp_on_the_fly.totaltimes()[1:], exp_control.totaltime
MyPlots.plot_likelihood_time(5,1, [Sum_likelihoods_at_each_iter_entropy1_for_ys,
                                   Sum_likelihoods_at_each_iter_on_the_fly1_for_
                                   Sum_likelihoods_at_each_iter_on_the_fly2_for_
                                   Sum_likelihoods_at_each_iter_control_for_ys,
                                   Sum_likelihoods_at_each_iter_entropy2_for_ys]
                          ,[exp_entropy1.totaltimes(), exp_on_the_fly1.totaltimes(),
                            exp_on_the_fly2.totaltimes(), exp_control.totaltimes(),
                            exp_entropy2.totaltimes()],
                            ["Entropy 1 Approach(Selected) Y's-David's Estimator",
                            "On-the-fly 1 Approach Y's-David'Estimator",
                            "On-the-fly 2 Approach Y's-David'Estimator",
                            "Control Approach Y's-David'Estimator",
                           "Entropy 2 Approach(All) Y's-David's Estimator"])
```



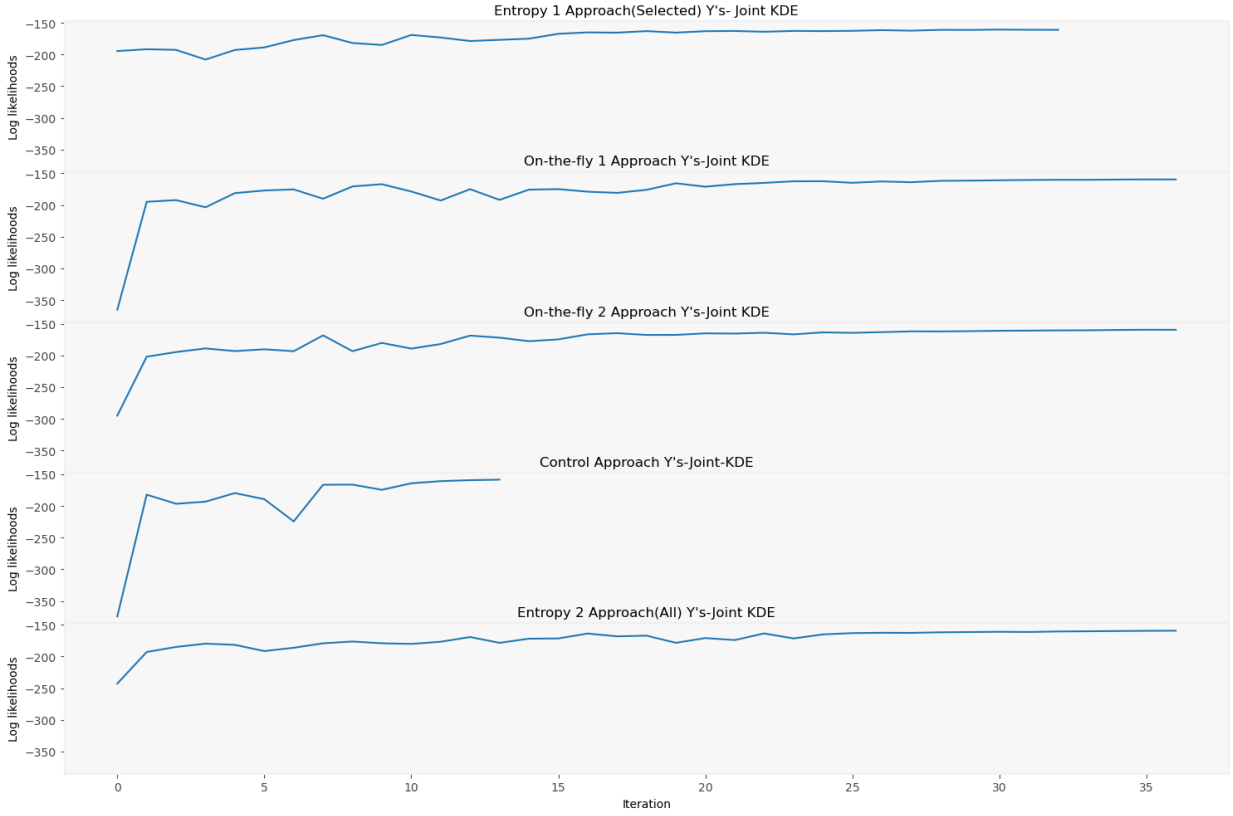
Using Multi-Dimensional KDE

In [26]:
```
#all_total_likelihoods
Sum_likelihoods_at_each_iter_entropy1_for_ys_kde = MyPlots.likelihood_helper_kde(exp_e
                                                                                 exp_er

Sum_likelihoods_at_each_iter_entropy2_for_ys_kde = MyPlots.likelihood_helper_kde(exp_e
                                                                                 exp_er
Sum_likelihoods_at_each_iter_on_the_fly1_for_ys_kde = MyPlots.likelihood_helper_kde(ex
                                                                                   exp
Sum_likelihoods_at_each_iter_on_the_fly2_for_ys_kde = MyPlots.likelihood_helper_kde(ex
                                                                                   exp
Sum_likelihoods_at_each_iter_control_for_ys_kde = MyPlots.likelihood_helper_kde(exp_co
                                                                                   exp
#Sum_likelihoods_at_each_iter_control_for_ys_kde = likelihood_helper_kde(total_yprofs_
```

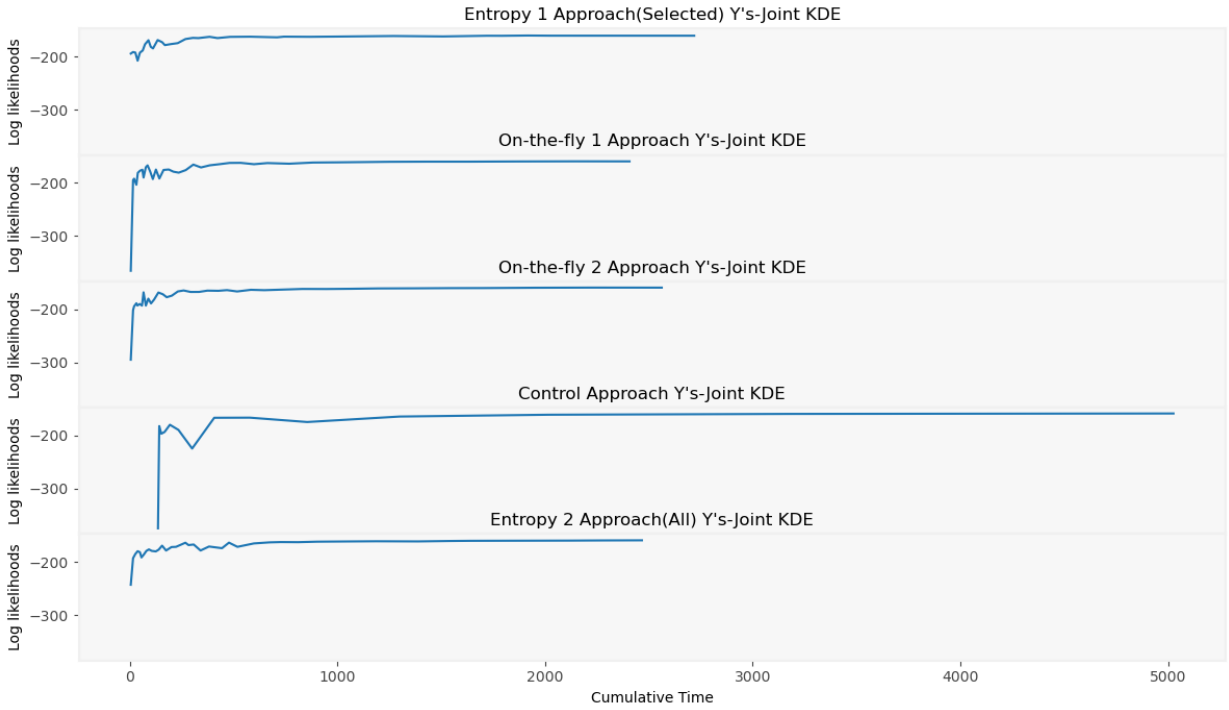
```
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:346: VisibleDeprecationWarning: Creat
ing an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do t
his, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_yprof)
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:346: VisibleDeprecationWarning: Creat
ing an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do t
his, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_yprof)
```

In [27]:
```
#Add later the other apporaches to this plot
MyPlots.plot_likelihood_iterations(5,1
                        ,[Sum_likelihoods_at_each_iter_entropy1_for_ys_kde,
                          Sum_likelihoods_at_each_iter_on_the_fly1_for_ys_kde,
                         Sum_likelihoods_at_each_iter_on_the_fly2_for_ys_kde,
                         Sum_likelihoods_at_each_iter_control_for_ys_kde,
                         Sum_likelihoods_at_each_iter_entropy2_for_ys_kde]
                        , ["Entropy 1 Approach(Selected) Y's- Joint KDE",
```

```
                          "On-the-fly 1 Approach Y's-Joint KDE",
                          "On-the-fly 2 Approach Y's-Joint KDE",
                          "Control Approach Y's-Joint-KDE",
                         "Entropy 2 Approach(All) Y's-Joint KDE"])
```



In [28]:
```
MyPlots.plot_likelihood_time(5,1
                        ,[Sum_likelihoods_at_each_iter_entropy1_for_ys_kde,
                          Sum_likelihoods_at_each_iter_on_the_fly1_for_ys_kde,
                         Sum_likelihoods_at_each_iter_on_the_fly2_for_ys_kde,
                         Sum_likelihoods_at_each_iter_control_for_ys_kde,
                         Sum_likelihoods_at_each_iter_entropy2_for_ys_kde
                         ],
                         [ exp_entropy1.totaltimes(),
                          exp_on_the_fly1.totaltimes(),
                          exp_on_the_fly2.totaltimes(),
                          exp_control.totaltimes(),
                          exp_entropy2.totaltimes()
                         ],

                        ["Entropy 1 Approach(Selected) Y's-Joint KDE",
                            "On-the-fly 1 Approach Y's-Joint KDE",
                            "On-the-fly 2 Approach Y's-Joint KDE",
                            "Control Approach Y's-Joint KDE",
                           "Entropy 2 Approach(All) Y's-Joint KDE"])
```



8.5 Estimator of log-likelihood for the Parameters

The log likelihhods estimator will be computed with two fitting: The loglikelihhods are computed for the ground truth values.

We compute the loglikelihoods in two ways:

-David's estimator for pdf: by default this estimator calculate the pdf for each parameter separatly. It is equivalent to the second fitting in Kde

-Kde estimator for pdf: For the kde we use two apporaches The first fitting will use all the samples for all the parameters at a given iteration
The second fitting will use only the data for one parameter to estimate a pdf of each parameter at a given iteration

David's Estimator for Parameters

In [29]:
```
#all_total_likelihoods
Sum_likelihoods_at_each_iter_entropy1_for_pars = MyPlots.compute_likelihoods(exp_entro
                                                                             exp_entrop
                                                                             3)
Sum_likelihoods_at_each_iter_entropy2_for_pars = MyPlots.compute_likelihoods(exp_entro
                                                                             exp_entrop
                                                                             3)

Sum_likelihoods_at_each_iter_on_the_fly1_for_pars = MyPlots.compute_likelihoods(exp_or
                                                                                exp_on_
                                                                                 3)

Sum_likelihoods_at_each_iter_on_the_fly2_for_pars = MyPlots.compute_likelihoods(exp_or
                                                                                exp_on_
```

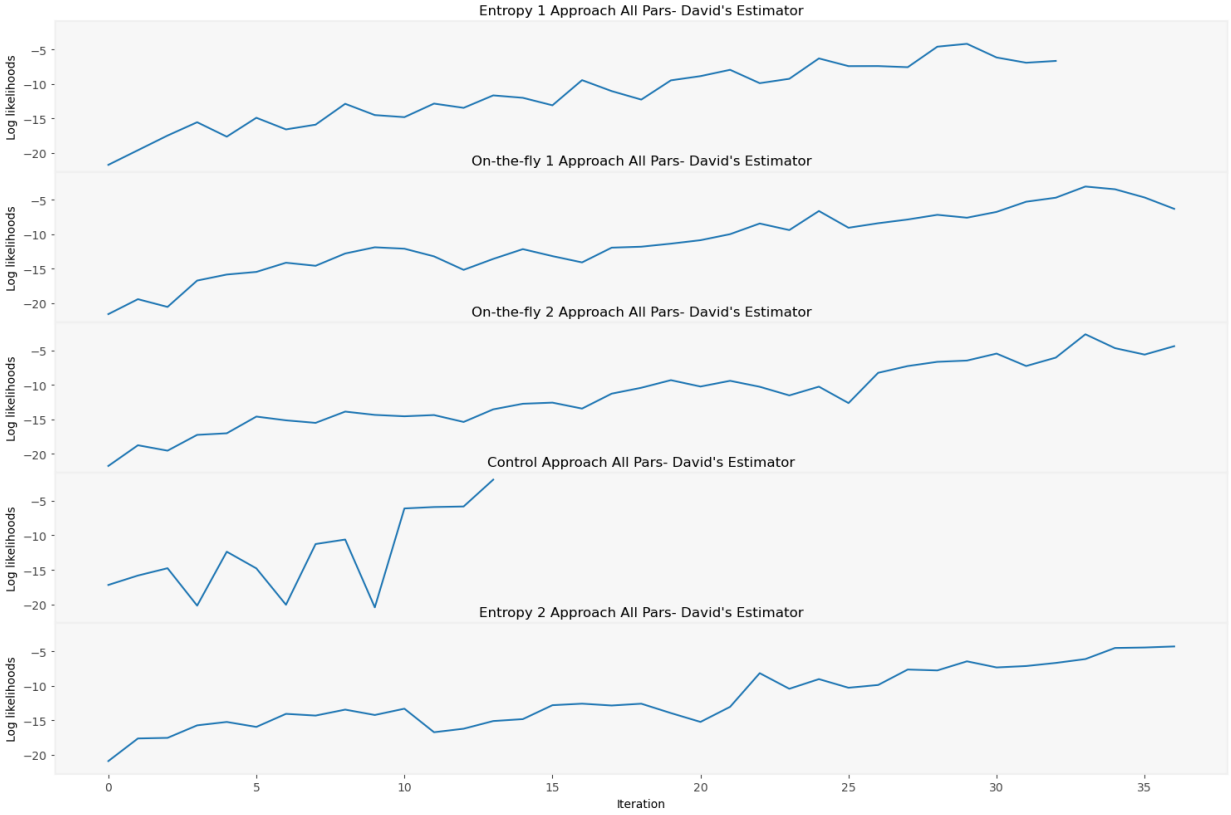
```
                                                                                3)

Sum_likelihoods_at_each_iter_control_for_pars = MyPlots.compute_likelihoods(exp_contro
                                                                              exp_cor
                                                                                3)
#Sum_likelihoods_at_each_iter_control_for_pars = compute_likelihoods(total_pts_control
```

```
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
836
this is rigth index
841
ERROR: the ground truth to estimate is too close to one extreme. So, we do not have e
nought samples eitheron the left or right of the ground truth
This is the left index
835
this is rigth index
840
```

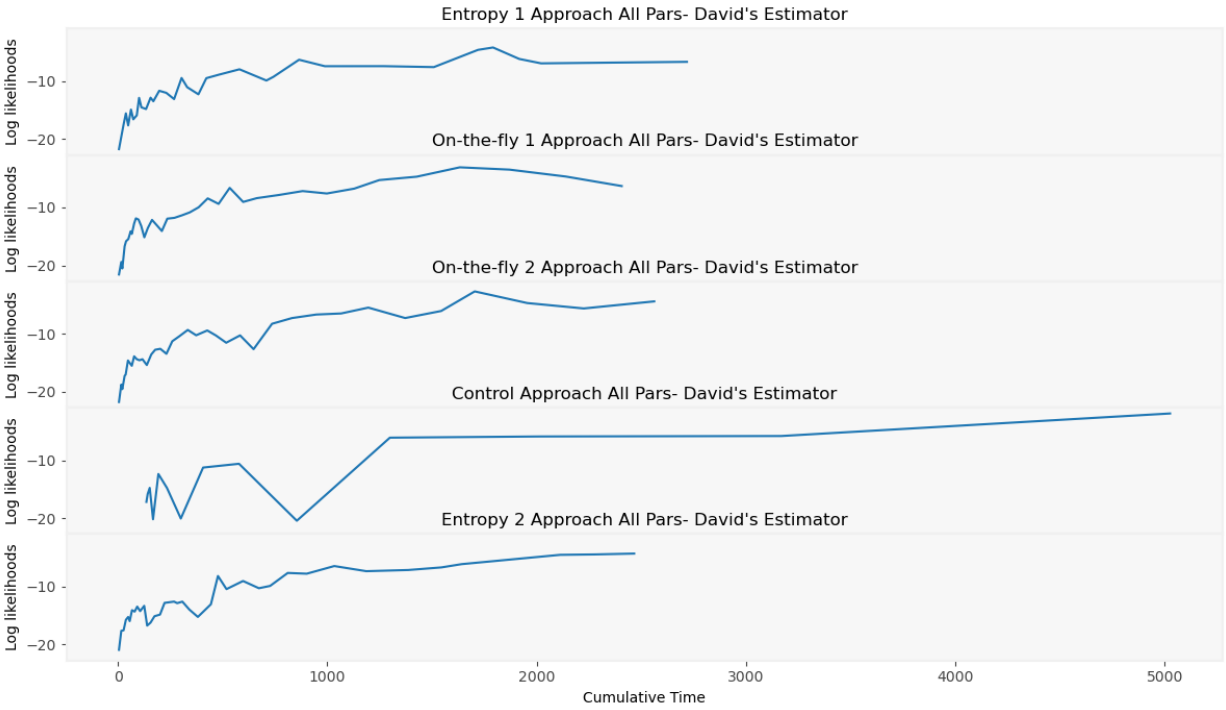
```
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:353: VisibleDeprecationWarning: Creat
ing an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do t
his, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_pts)
```

In [30]:

```
MyPlots.plot_likelihood_iterations(5,1,
                            [Sum_likelihoods_at_each_iter_entropy1_for_pars,
                             Sum_likelihoods_at_each_iter_on_the_fly1_for_pars,
                             Sum_likelihoods_at_each_iter_on_the_fly2_for_pars,
                             Sum_likelihoods_at_each_iter_control_for_pars,
                             Sum_likelihoods_at_each_iter_entropy2_for_pars,
                            ],
                           ["Entropy 1 Approach All Pars- David's Estimator",
                            "On-the-fly 1 Approach All Pars- David's Estimator",
                            "On-the-fly 2 Approach All Pars- David's Estimator",
                            "Control Approach All Pars- David's Estimator",
                            "Entropy 2 Approach All Pars- David's Estimator"
                           ])
#help(plot_likelihood_iterations)
```



In [31]:
```
MyPlots.plot_likelihood_time(5,1,
                             [Sum_likelihoods_at_each_iter_entropy1_for_pars,
                              Sum_likelihoods_at_each_iter_on_the_fly1_for_pars,
                              Sum_likelihoods_at_each_iter_on_the_fly2_for_pars,
                              Sum_likelihoods_at_each_iter_control_for_pars,
                              Sum_likelihoods_at_each_iter_entropy2_for_pars
                             ],
                            [ exp_entropy1.totaltimes(),
                              exp_on_the_fly1.totaltimes(),
                              exp_on_the_fly2.totaltimes(),
                              exp_control.totaltimes(),
                             exp_entropy2.totaltimes()
                            ],
                             ["Entropy 1 Approach All Pars- David's Estimator",
                              "On-the-fly 1 Approach All Pars- David's Estimator",
                              "On-the-fly 2 Approach All Pars- David's Estimator",
                              "Control Approach All Pars- David's Estimator",
                              "Entropy 2 Approach All Pars- David's Estimator"
                             ])
```



Multidimentional KDE Estimator for Parameters

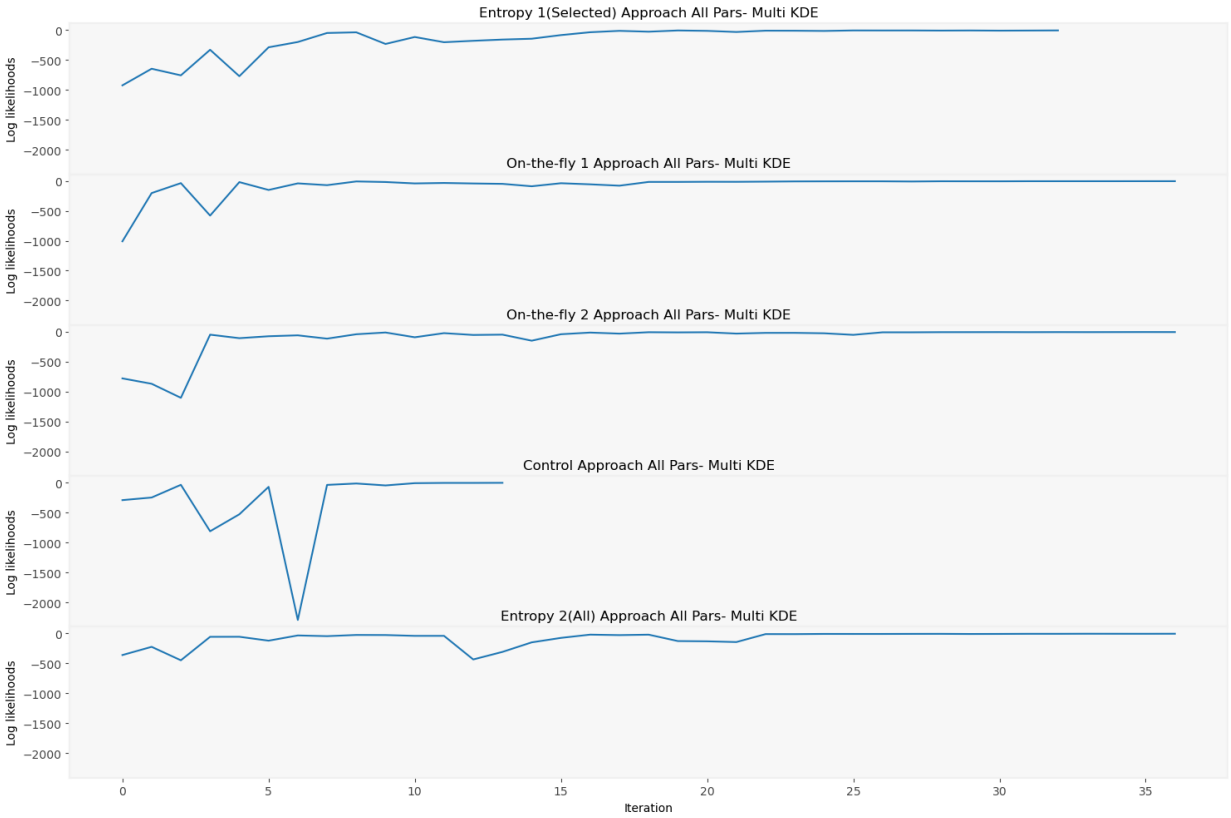
Combined Parameters

In [32]:
```
#all_total_likelihoods
Sum_likelihoods_at_each_iter_entropy1_for_pars_kde = MyPlots.likelihood_helper_kde(exp
                                                                                   exp_entropy1.get_t
Sum_likelihoods_at_each_iter_entropy2_for_pars_kde = MyPlots.likelihood_helper_kde(exp
                                                                                   exp_

Sum_likelihoods_at_each_iter_on_the_fly1_for_pars_kde = MyPlots.likelihood_helper_kde(
                                                                                   exp_on_the

Sum_likelihoods_at_each_iter_on_the_fly2_for_pars_kde = MyPlots.likelihood_helper_kde(
                                                                                   exp_on_the

Sum_likelihoods_at_each_iter_control_for_pars_kde = MyPlots.likelihood_helper_kde(exp_
                                                                                   exp_on_the
```

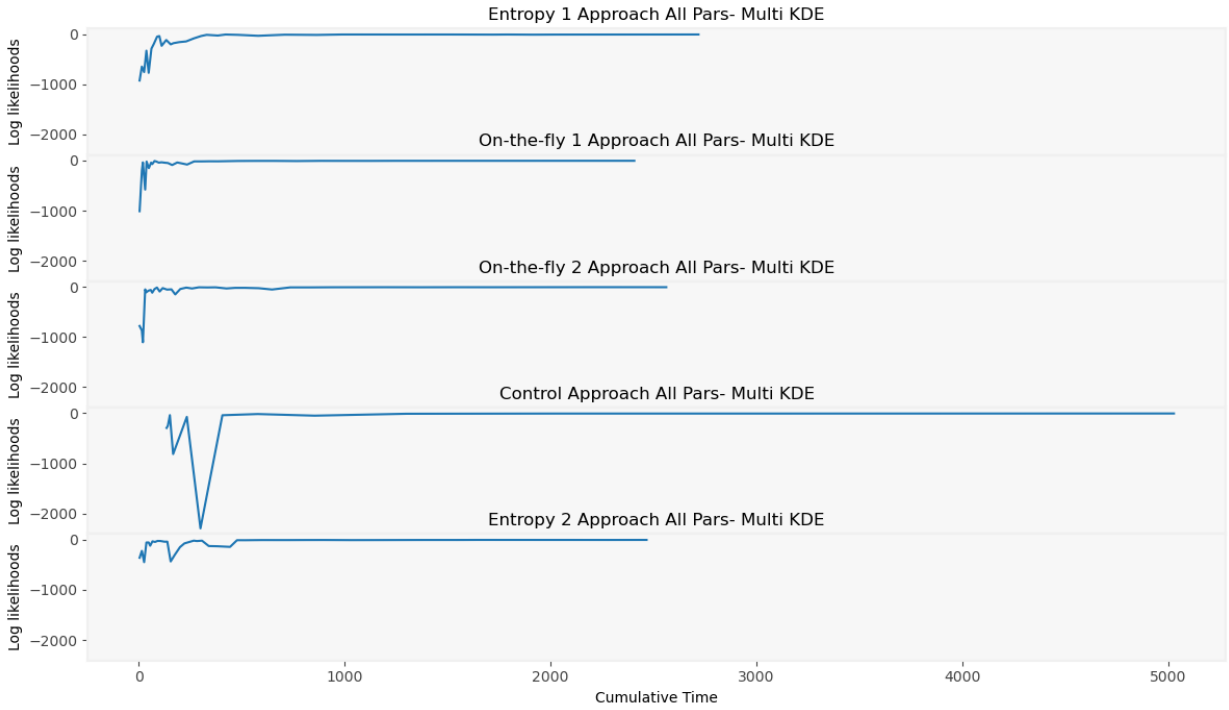
```
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:353: VisibleDeprecationWarning: Creat
ing an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do t
his, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_pts)
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:353: VisibleDeprecationWarning: Creat
ing an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tup
les-or ndarrays with different lengths or shapes) is deprecated. If you meant to do t
his, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_pts)
```

In [33]:
```
MyPlots.plot_likelihood_iterations(5,1,
                           [Sum_likelihoods_at_each_iter_entropy1_for_pars_kde,
                            Sum_likelihoods_at_each_iter_on_the_fly1_for_pars_kde,
                            Sum_likelihoods_at_each_iter_on_the_fly2_for_pars_kde,
```

```
                          Sum_likelihoods_at_each_iter_control_for_pars_kde,
                          Sum_likelihoods_at_each_iter_entropy2_for_pars_kde
                         ]
                        ,["Entropy 1(Selected) Approach All Pars- Multi KDE",
                          "On-the-fly 1 Approach All Pars- Multi KDE",
                          "On-the-fly 2 Approach All Pars- Multi KDE",
                          "Control Approach All Pars- Multi KDE",
                          "Entropy 2(All) Approach All Pars- Multi KDE"
                         ])
```



In [34]:
```
MyPlots.plot_likelihood_time(5,1,
                         [Sum_likelihoods_at_each_iter_entropy1_for_pars_kde,
                          Sum_likelihoods_at_each_iter_on_the_fly1_for_pars_kde,
                          Sum_likelihoods_at_each_iter_on_the_fly2_for_pars_kde,
                          Sum_likelihoods_at_each_iter_control_for_pars_kde,
                          Sum_likelihoods_at_each_iter_entropy2_for_pars_kde
                         ],
                        [exp_entropy1.totaltimes(),
                         exp_on_the_fly1.totaltimes(),
                         exp_on_the_fly2.totaltimes(),
                         exp_control.totaltimes(),
                         exp_entropy2.totaltimes()
                        ],
                       ["Entropy 1 Approach All Pars- Multi KDE",
                         "On-the-fly 1 Approach All Pars- Multi KDE",
                         "On-the-fly 2 Approach All Pars- Multi KDE",
                         "Control Approach All Pars- Multi KDE",
                         "Entropy 2 Approach All Pars- Multi KDE"
                        ])
```



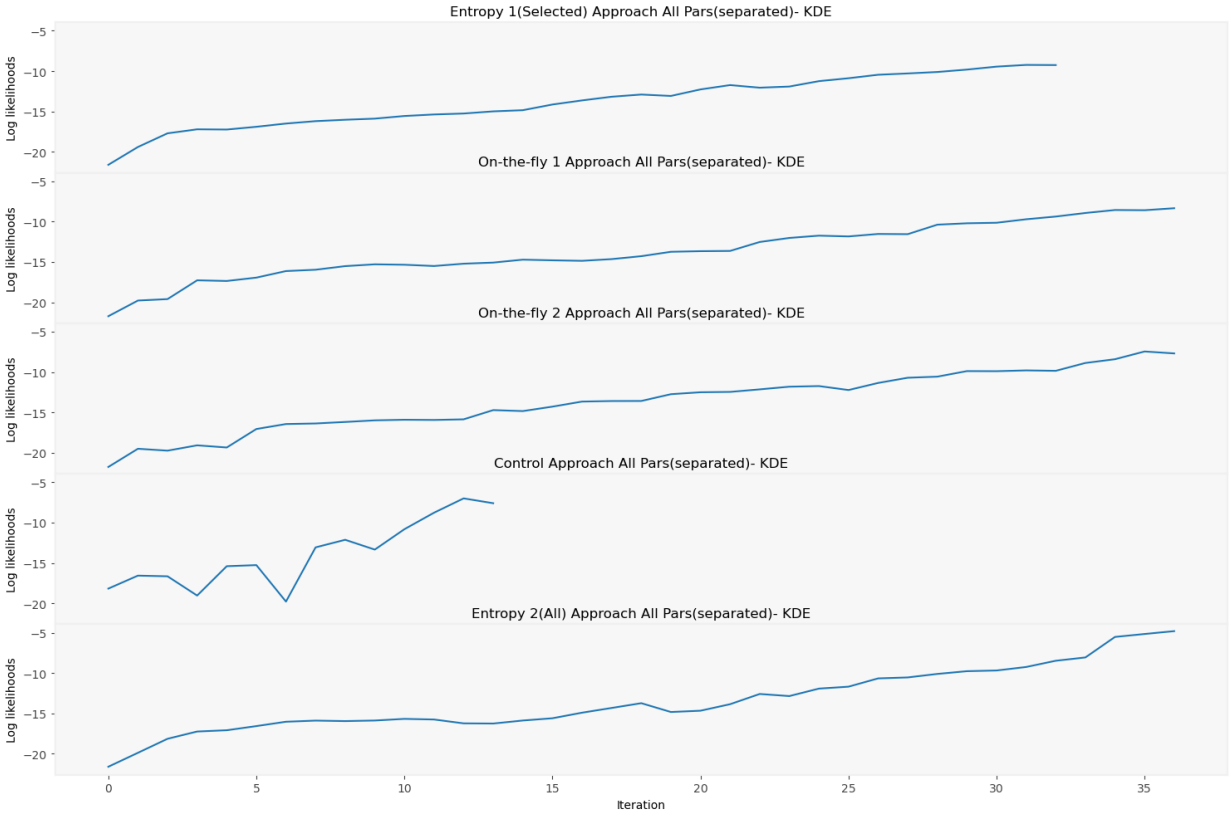
Separated for each parameter. We will use the kde in the data for each parameter to build independent pdf's for each parameter

In [35]:
```
#Example with entropy approach
kdes_entropy1, log_pars_entropy1 = MyPlots.kdes_and_loglikelihoods_for_pars(exp_entrop
                                                                            exp_entropy1.get_tru

kdes_entropy2, log_pars_entropy2 = MyPlots.kdes_and_loglikelihoods_for_pars(exp_entrop
                                                                            exp_entropy2.get_tru
#Example with on-the-fly apporach
kdes_on_the_fly1, log_pars_on_the_fly1 = MyPlots.kdes_and_loglikelihoods_for_pars(exp_
                                                                                exp_on_the_fly1.
kdes_on_the_fly2, log_pars_on_the_fly2 = MyPlots.kdes_and_loglikelihoods_for_pars(exp_
                                                                                exp_on_the_fly2.

kdes_control, log_pars_control = MyPlots.kdes_and_loglikelihoods_for_pars(exp_control.
                                                                          exp_control.get_true

##############################################################################
#Comment out the section below. It makes sense only if you have a GMM version
##############################################################################

# #Example with entropy approach
# kdes_entropy1_gmm, log_pars_entropy1_gmm = MyPlots.kdes_and_loglikelihoods_for_pars(
#                                                                               exp_entropy1_gmm.g

# kdes_entropy2_gmm, log_pars_entropy2_gmm = MyPlots.kdes_and_loglikelihoods_for_pars(
#                                                                               exp_entropy2_gmm.g
# #Example with on-the-fly apporach
# kdes_on_the_fly1_gmm, log_pars_on_the_fly1_gmm = MyPlots.kdes_and_loglikelihoods_for
#                                                                                   exp_on_the_fly
# kdes_on_the_fly2_gmm, log_pars_on_the_fly2_gmm = MyPlots.kdes_and_loglikelihoods_for
#                                                                               exp_on_the_fly

# kdes_control_gmm, log_pars_control_gmm = MyPlots.kdes_and_loglikelihoods_for_pars(ex
#                                                                               exp_control_gmm.ge
```

```
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:353: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_pts)
C:\Users\rober\FINAL NIST PROJECT\datastruct.py:353: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the ndarray.
  return np.array(all_pts)
```

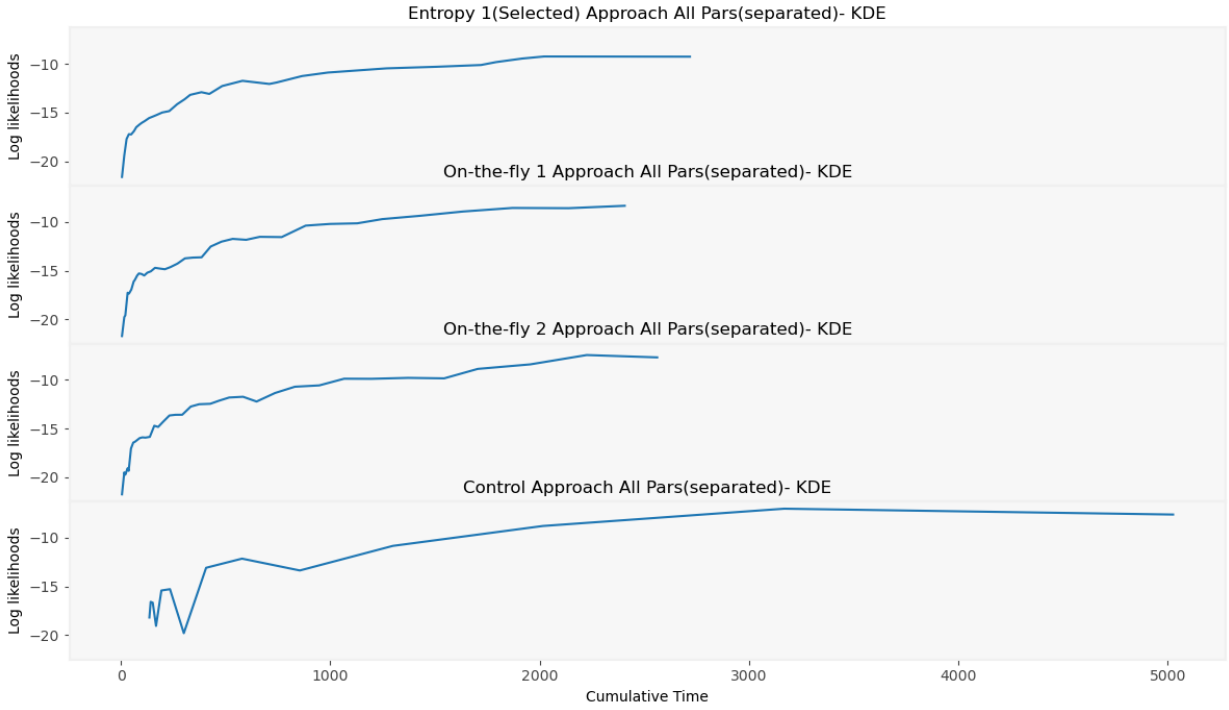
In [36]:
```
#Adding the loglikelihhods of the parameters at a given iteration
log_sums_kde_separated_iters_entropy1 = np.sum(log_pars_entropy1,axis= 1)
log_sums_kde_separated_iters_entropy2 = np.sum(log_pars_entropy2,axis= 1)
log_sums_kde_sepataed_iters_on_the_fly1 = np.sum(log_pars_on_the_fly1,axis= 1)
log_sums_kde_sepataed_iters_on_the_fly2 = np.sum(log_pars_on_the_fly2,axis= 1)
log_sums_kde_separated_iters_control = np.sum(log_pars_control,axis= 1)
```

In [37]:
```
MyPlots.plot_likelihood_iterations(5,1,
                          [log_sums_kde_separated_iters_entropy1,
                           log_sums_kde_sepataed_iters_on_the_fly1,
                          log_sums_kde_sepataed_iters_on_the_fly2 ,
                          log_sums_kde_separated_iters_control,
                          log_sums_kde_separated_iters_entropy2],
                          ["Entropy 1(Selected) Approach All Pars(separated)- KDE",
                           "On-the-fly 1 Approach All Pars(separated)- KDE",
                          "On-the-fly 2 Approach All Pars(separated)- KDE",
                          "Control Approach All Pars(separated)- KDE",
                          "Entropy 2(All) Approach All Pars(separated)- KDE"])
```



In [38]:
```
MyPlots.plot_likelihood_time(4,1,
                          [log_sums_kde_separated_iters_entropy1,
```

```
                          log_sums_kde_sepataed_iters_on_the_fly1,
                         log_sums_kde_sepataed_iters_on_the_fly2,
                         log_sums_kde_separated_iters_control,
                         log_sums_kde_separated_iters_entropy2],
                          [exp_entropy1.totaltimes(),
                           exp_on_the_fly1.totaltimes(),
                          exp_on_the_fly2.totaltimes(),
                          exp_control.totaltimes(),
                          exp_entropy2.totaltimes()],
                         ["Entropy 1(Selected) Approach All Pars(separated)- KDE",
                          "On-the-fly 1 Approach All Pars(separated)- KDE",
                          "On-the-fly 2 Approach All Pars(separated)- KDE",
                          "Control Approach All Pars(separated)- KDE",
                          "Entropy 2(All) Approach All Pars(separated)- KDE"
                         ])
```



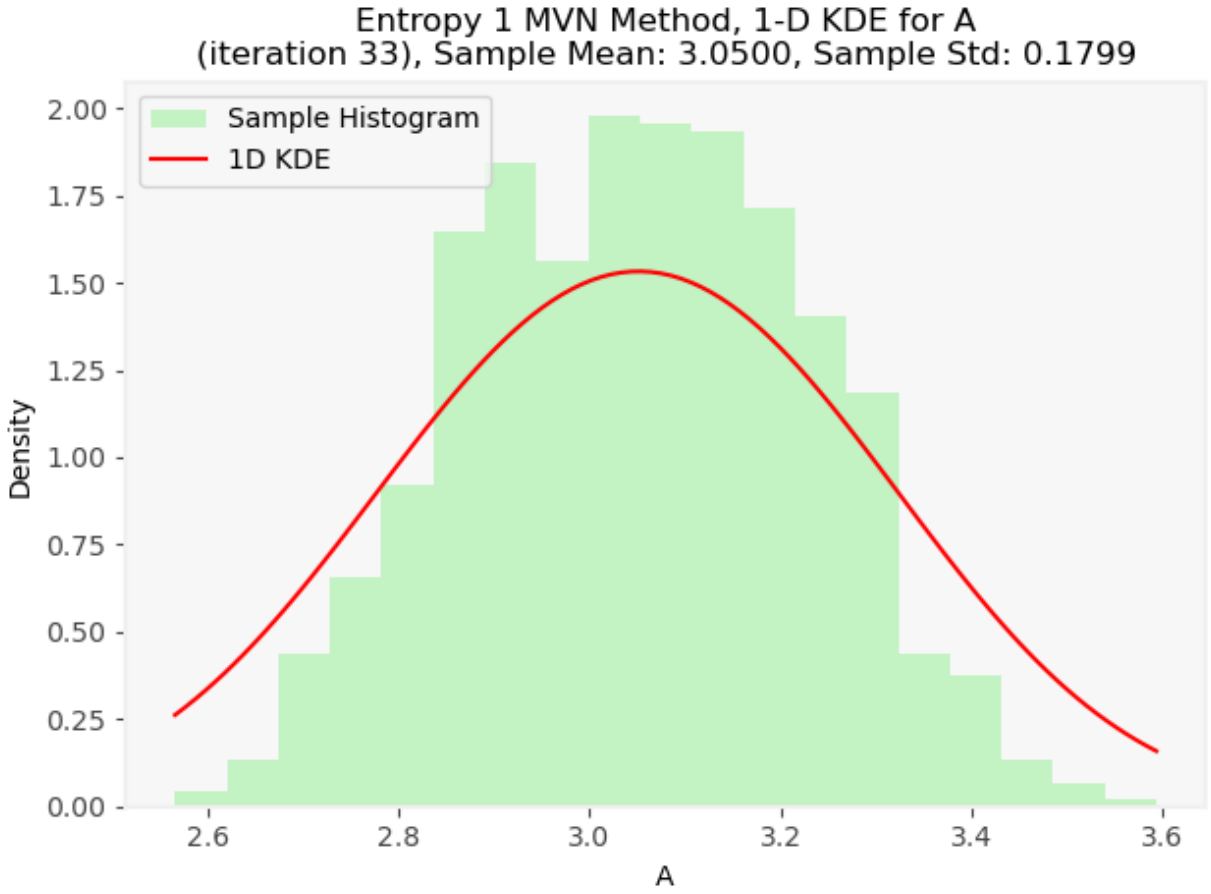
Histogram for Paramter Samples

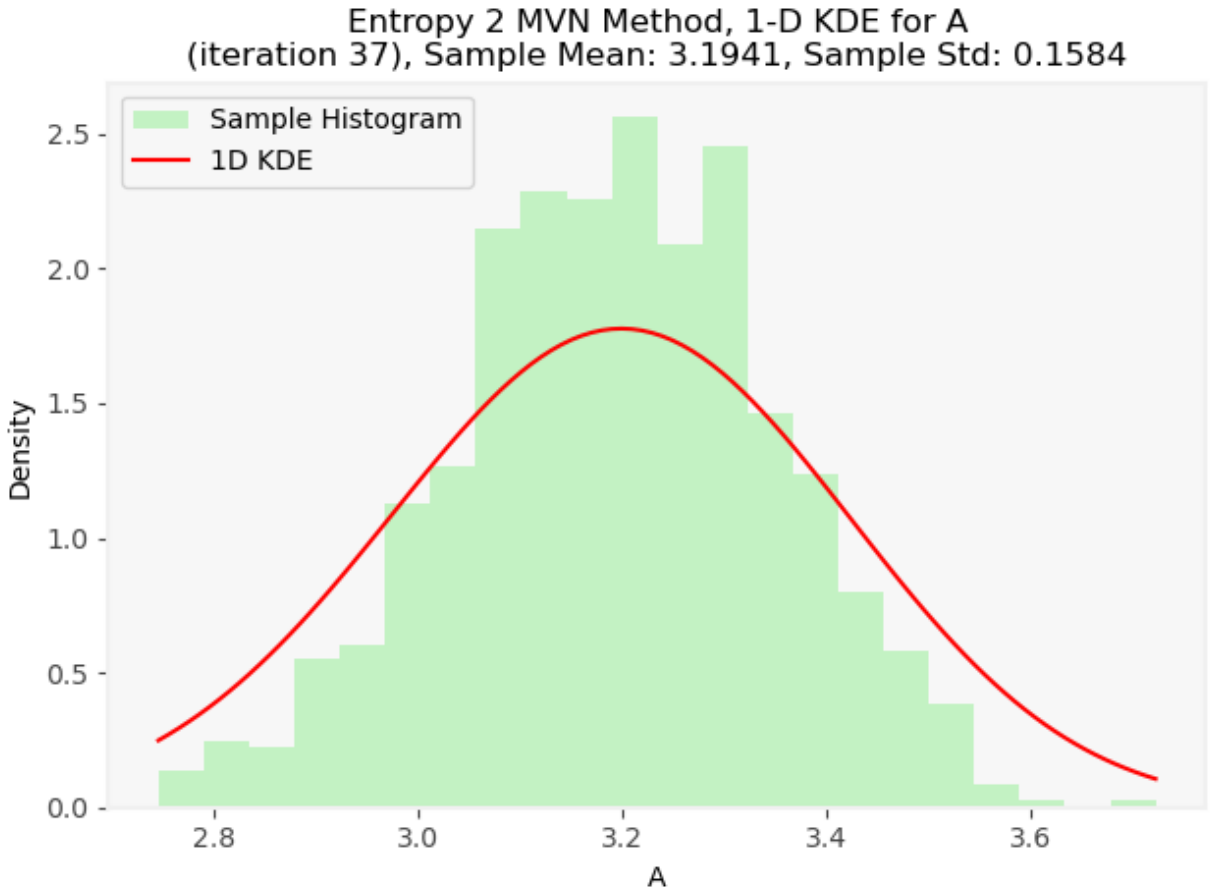
A

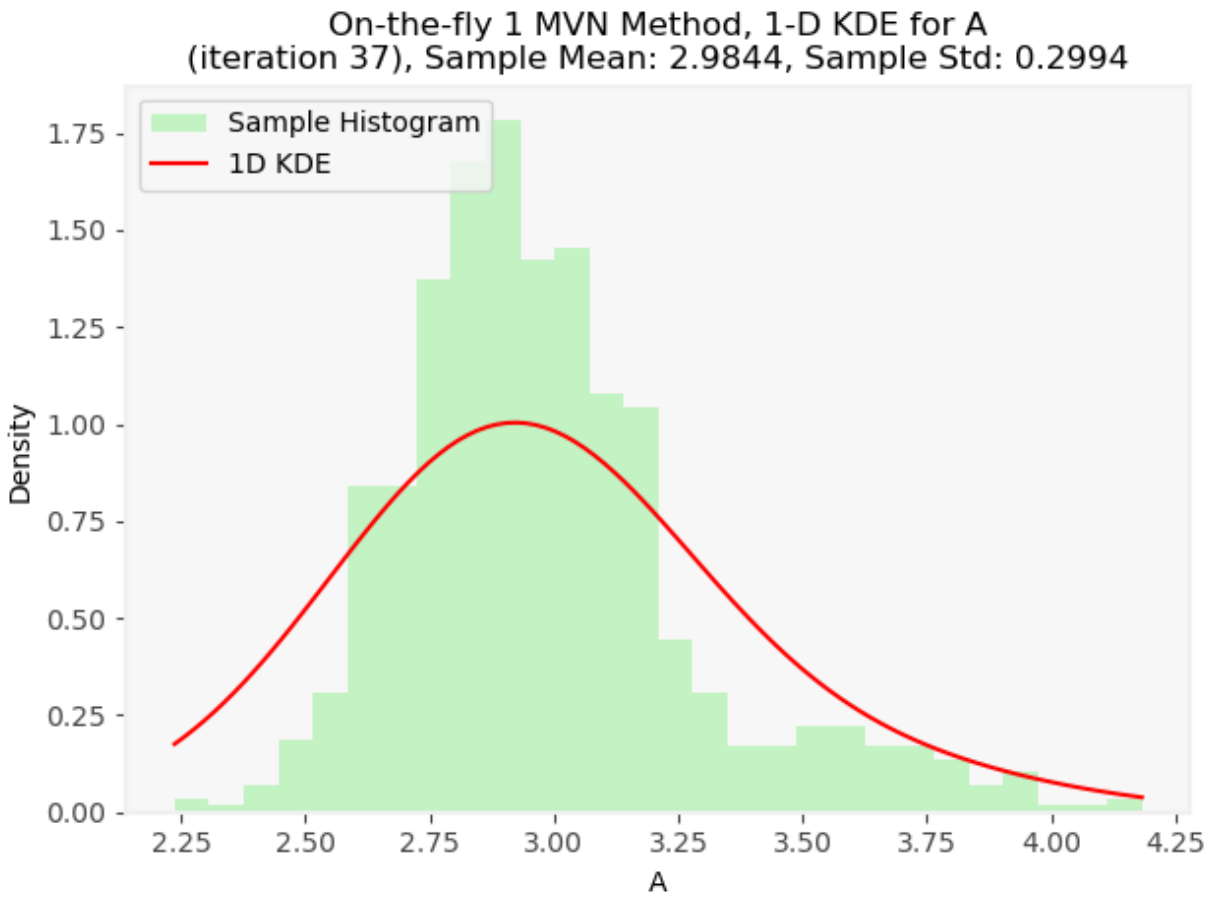
1.First we look at the last sample for all the autonomous approaches. 2.Second, we look at the result using GMM

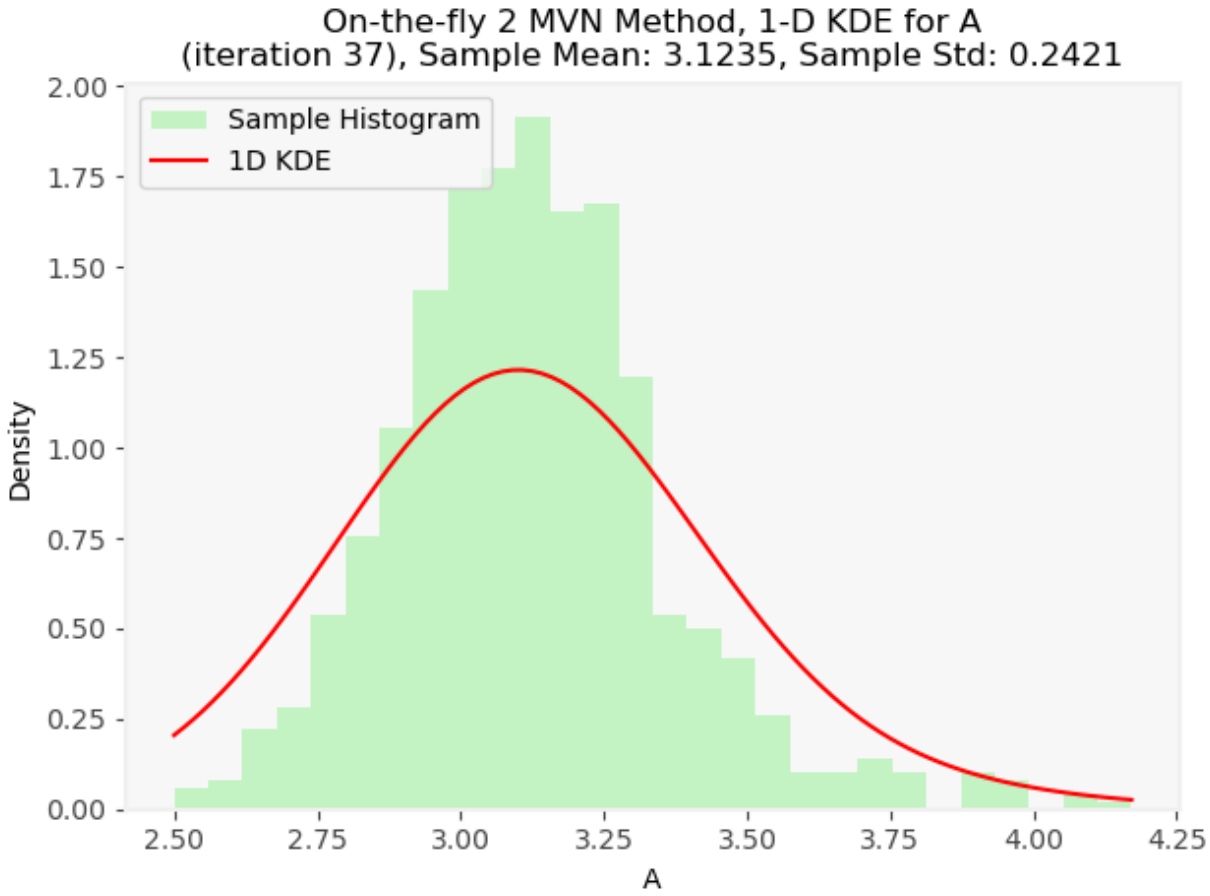
In [39]:
```
MyPlots.plot_hist_1d_kde(list_par_separated_e1[0][-1], kdes_entropy1[-1,0],"Entropy 1
plt.show()

MyPlots.plot_hist_1d_kde(list_par_separated_e2[0][-1], kdes_entropy2[-1,0],"Entropy 2
                         len(exp_entropy2.totaltimes()))
plt.show()

MyPlots.plot_hist_1d_kde(list_par_separated_o1[0][-1], kdes_on_the_fly1[-1,0],"On-the-
                          len(exp_on_the_fly1.totaltimes()))
plt.show()
```

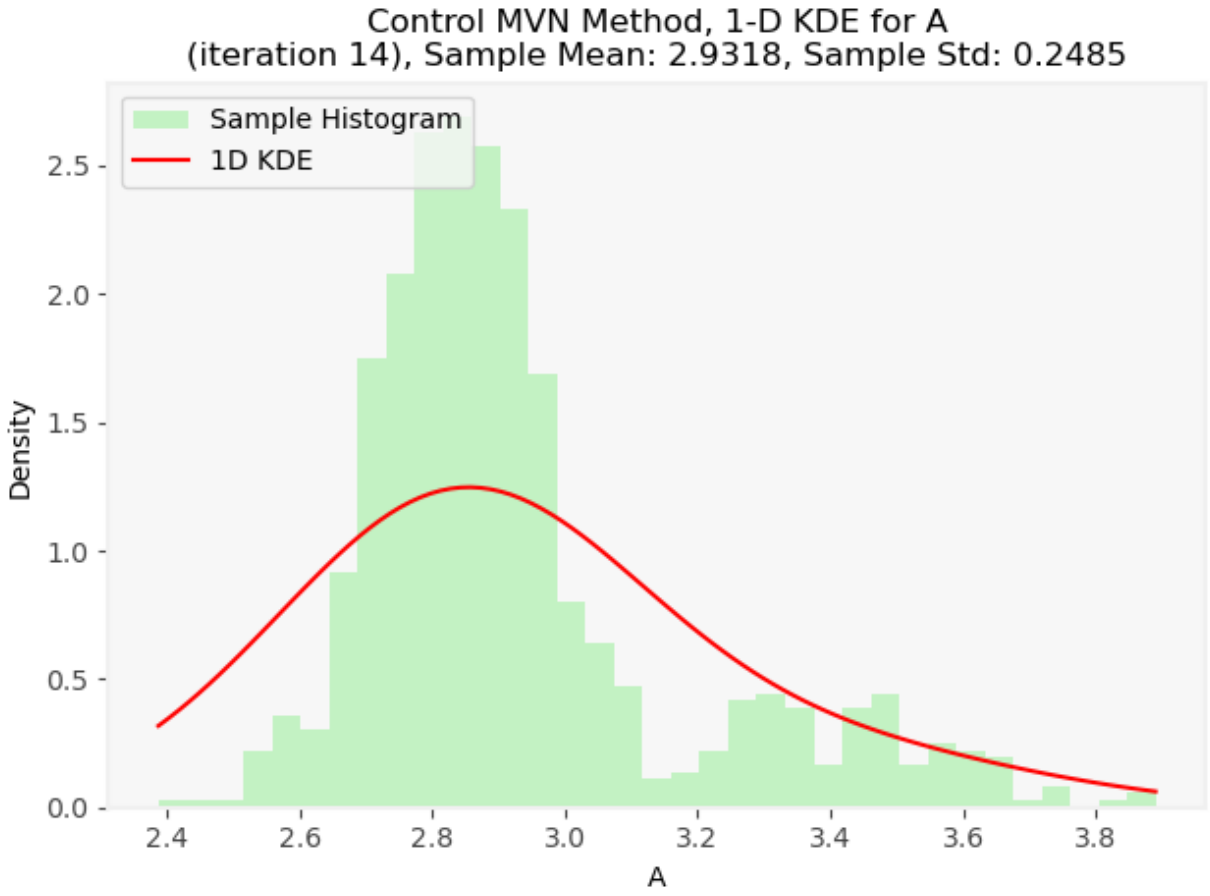
```
MyPlots.plot_hist_1d_kde(list_par_separated_o2[0][-1], kdes_on_the_fly2[-1,0],"On-the-
                         len(exp_on_the_fly2.totaltimes()))
plt.show()

MyPlots.plot_hist_1d_kde(list_par_separated_c[0][-1], kdes_control[-1,0],"Control MVN"
                         len(exp_control.totaltimes()))
plt.show()
```




Entropy 2 MVN Method, 1-D KDE for A
(iteration 37), Sample Mean: 3.1941, Sample Std: 0.1584
Sample Histogram
1D KDE
Density
A
0.0
0.5
1.0
1.5
2.0
2.5
2.8
3.0
3.2
3.4
3.6


On-the-fly 1 MVN Method, 1-D KDE for A
(iteration 37), Sample Mean: 2.9844, Sample Std: 0.2994
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25





In [40]:
```
#DELETE THIS LATER THIS MAKES SENSE ONLY IF YOU HAVE ALSO A GMM VERSION ##############
```

```
# MyPlots.plot_hist_1d_kde(list_par_separated_e1_gmm[0][-1],
#                          kdes_entropy1_gmm[-1,0],"Entropy 1 GMM", "A", len(exp_entro
# plt.show()


# MyPlots.plot_hist_1d_kde(list_par_separated_e2_gmm[0][-1], kdes_entropy2_gmm[-1,0],'
#                         len(exp_entropy2_gmm.totaltimes()))
# plt.show()


# MyPlots.plot_hist_1d_kde(list_par_separated_o1_gmm[0][-1], kdes_on_the_fly1_gmm[-1,0
#                          len(exp_on_the_fly1_gmm.totaltimes()))
# plt.show()


# MyPlots.plot_hist_1d_kde(list_par_separated_o2_gmm[0][-1], kdes_on_the_fly2_gmm[-1,0
#                         len(exp_on_the_fly2_gmm.totaltimes()))
# plt.show()

# MyPlots.plot_hist_1d_kde(list_par_separated_c_gmm[0][-1], kdes_control_gmm[-1,0],"Co
#                         len(exp_control_gmm.totaltimes()))









##############################################################################################
```

Recalculating Entropies for the cases using the GMM

In [41]:
```
# entropy1_H_total_gmm = recalculating_entropy(exp_entropy1, None, gmm_setting)
# entropy1_H_marg_gmm = recalculating_entropy(exp_entropy1, exp_entropy1.settings.sel,

# entropy2_H_total_gmm = recalculating_entropy(exp_entropy2, None,gmm_setting)
# entropy2_H_marg_gmm = recalculating_entropy(exp_entropy2, exp_on_the_fly1.settings.s
#

# on_the_fly1_H_total_gmm = recalculating_entropy(exp_on_the_fly1, None, gmm_setting)
# on_the_fly1_H_marg_gmm = recalculating_entropy(exp_on_the_fly1, exp_on_the_fly1.sett

# on_the_fly2_H_total_gmm = recalculating_entropy(exp_on_the_fly2, None,gmm_setting)
# on_the_fly2_H_marg_gmm = recalculating_entropy(exp_on_the_fly2, exp_on_the_fly2.sett

# control_H_total_gmm = recalculating_entropy(exp_control, None, gmm_setting)
# control_H_marg_gmm = recalculating_entropy(exp_control, exp_control.settings.sel, gm
```

In [42]:
```
#Notice we could also print the total entropy, instead, of the marginalized entropy.
#On-thefly always deals with the total entropy. You cannot choose a parameter of inter

#Using the recalcualed entropies using GMM
```

```
# times = [exp_entropy1.totaltimes(), exp_on_the_fly1.totaltimes(),
#          exp_on_the_fly2.totaltimes(),exp_control.totaltimes(), exp_entropy2.totalti
# entropies = [entropy1_H_total_gmm, on_the_fly1_H_total_gmm,
#              on_the_fly2_H_total_gmm, control_H_total_gmm, entropy2_H_total_gmm]
# MyPlots.plot_entropy_times(times, entropies)



#C1 blue entrop
#C2 yellow on the
#C3 green on the 2
#C4 red control
#C5 Purple entropy2

#Total Entropy
```

In [43]:
```
##########This works only if you have a GMM version

# MyPlots.plot_entropy_times([exp_entropy1.totaltimes(),exp_entropy1.totaltimes()],
#                            [exp_entropy1.entropy(), entropy1_H_total_gmm])

#Blue MVN
#Orange GMM
```

In [44]:
```
# MyPlots.plot_entropy_times([exp_entropy2.totaltimes(),exp_entropy2.totaltimes()],
#                            [exp_entropy2.entropy(), entropy2_H_total_gmm])



#Again undistingishable
```

In [45]:
```
# MyPlots.plot_entropy_times([exp_on_the_fly1.totaltimes(),exp_on_the_fly1.totaltimes(
#                            [exp_on_the_fly1.entropy(), on_the_fly1_H_total_gmm])


#Again undistingishable
```

In [46]:
```
# MyPlots.plot_entropy_times([exp_on_the_fly2.totaltimes(),exp_on_the_fly2.totaltimes(
#                            [exp_on_the_fly2.entropy(), on_the_fly2_H_total_gmm])


#Again undistingishable
```

In [47]:
```
#Notice we could also print the total entropy, instead, of the marginalized entropy.
#On-thefly always deals with the total entropy. You cannot choose a parameter of inter


# times = [exp_entropy1.totaltimes(), exp_on_the_fly1.totaltimes(),
#          exp_on_the_fly2.totaltimes(),exp_control.totaltimes(), exp_entropy2.totalti
# entropies = [entropy1_H_marg_gmm, on_the_fly1_H_marg_gmm,
#              on_the_fly2_H_marg_gmm, control_H_marg_gmm, entropy2_H_marg_gmm]
# MyPlots.plot_entropy_times(times, entropies)
```

In [48]:
```
# MyPlots.plot_entropy_times([exp_entropy1.totaltimes(),exp_entropy1.totaltimes()],
#                            [exp_entropy1.entropy_marg(),entropy1_H_marg_gmm ])
```

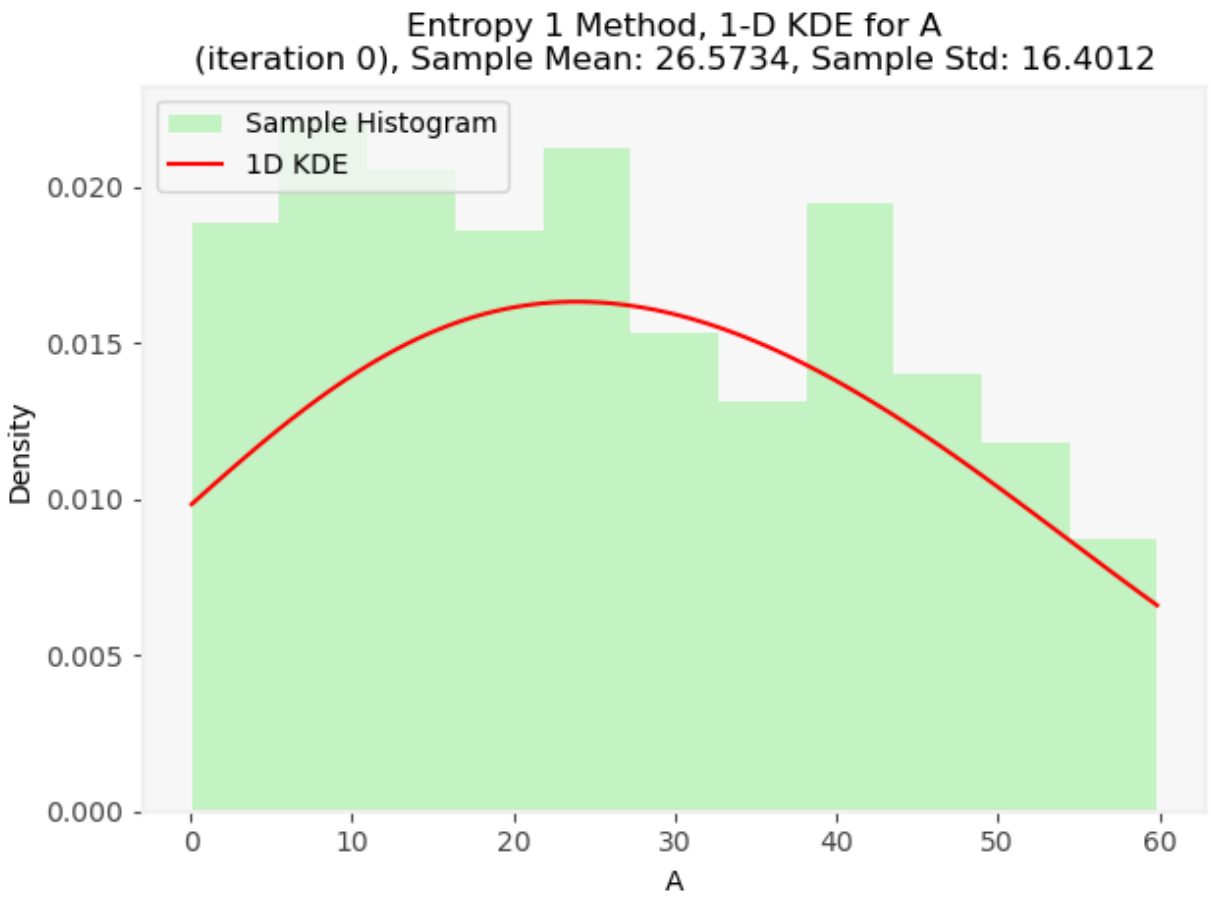
In [49]:
```
# MyPlots.plot_entropy_times([exp_entropy2.totaltimes(),exp_entropy2.totaltimes()],
#                            [exp_entropy2.entropy_marg(),entropy2_H_marg_gmm ])
```

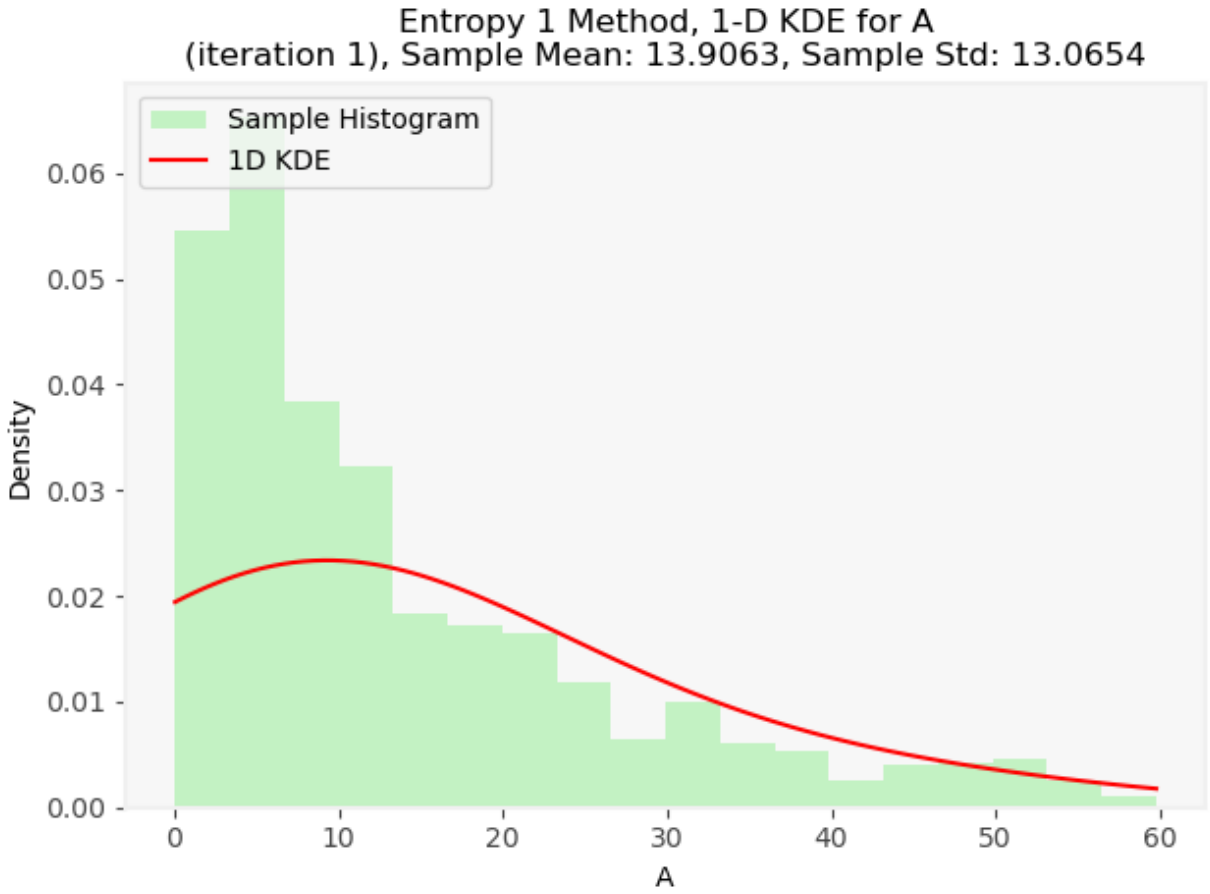
In [50]:
```
# MyPlots.plot_entropy_times([exp_on_the_fly1.totaltimes(),exp_on_the_fly1.totaltimes(
#                            [exp_on_the_fly1.entropy_marg(),on_the_fly1_H_marg_gmm])
```

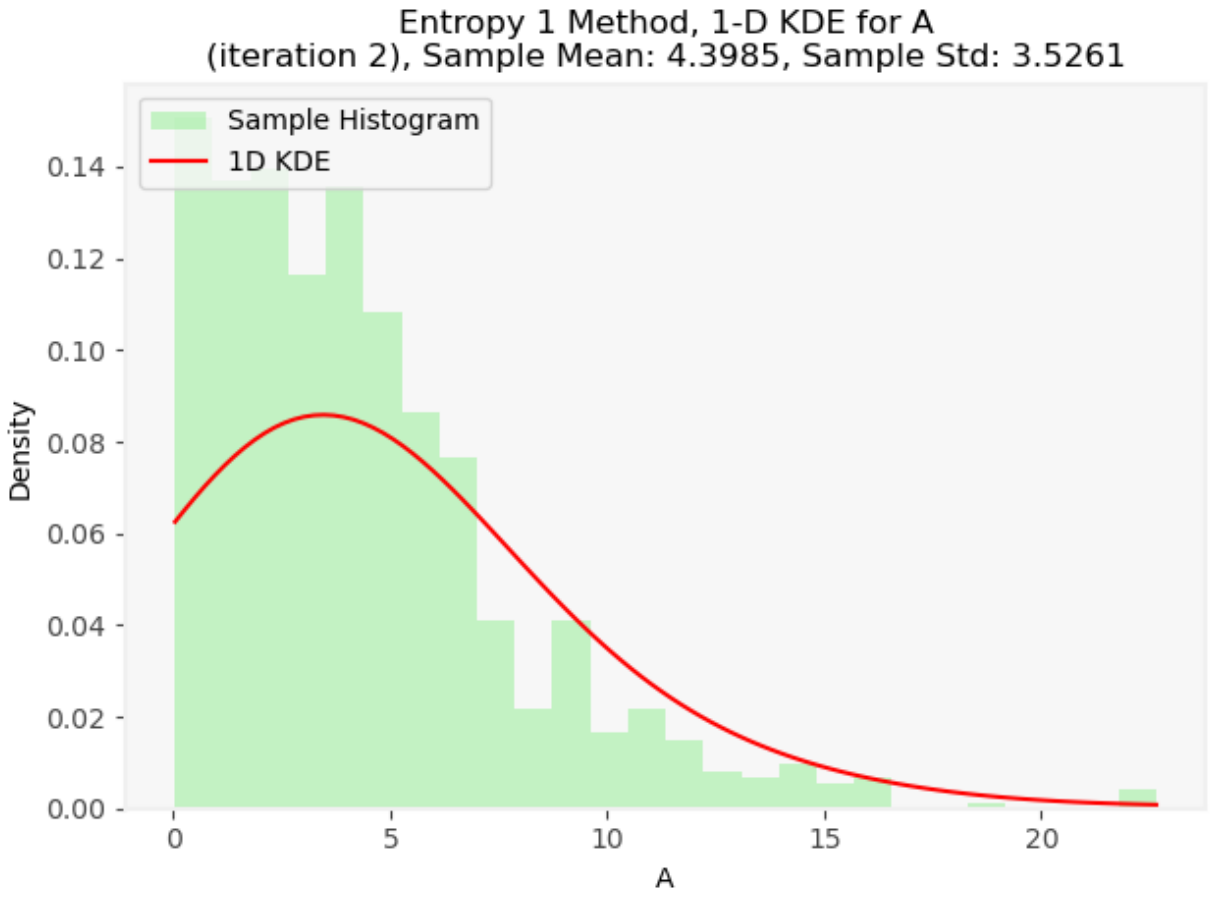
In [51]:
```
# MyPlots.plot_entropy_times([exp_on_the_fly2.totaltimes(),exp_on_the_fly2.totaltimes(
#                            [exp_on_the_fly2.entropy_marg(),on_the_fly2_H_marg_gmm])
```

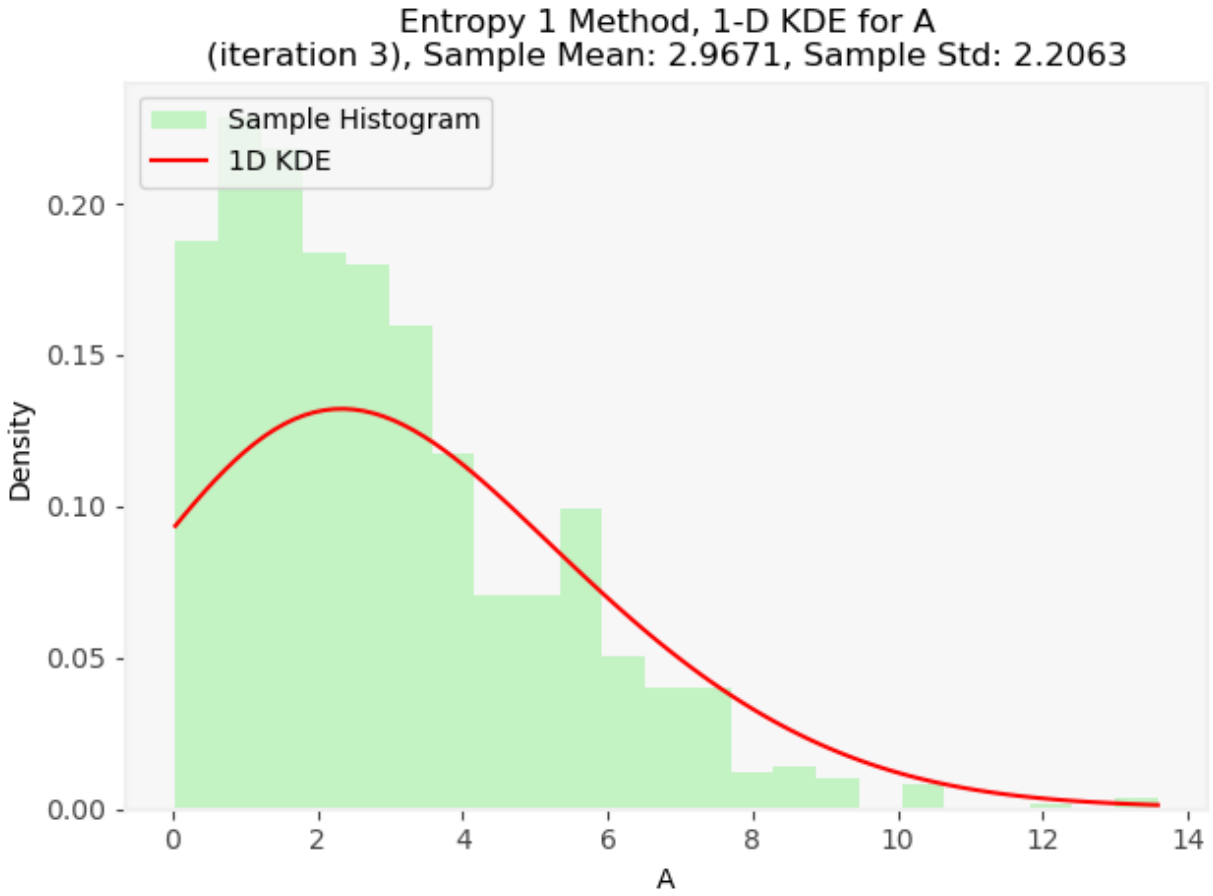
Enf of the Recalculation section

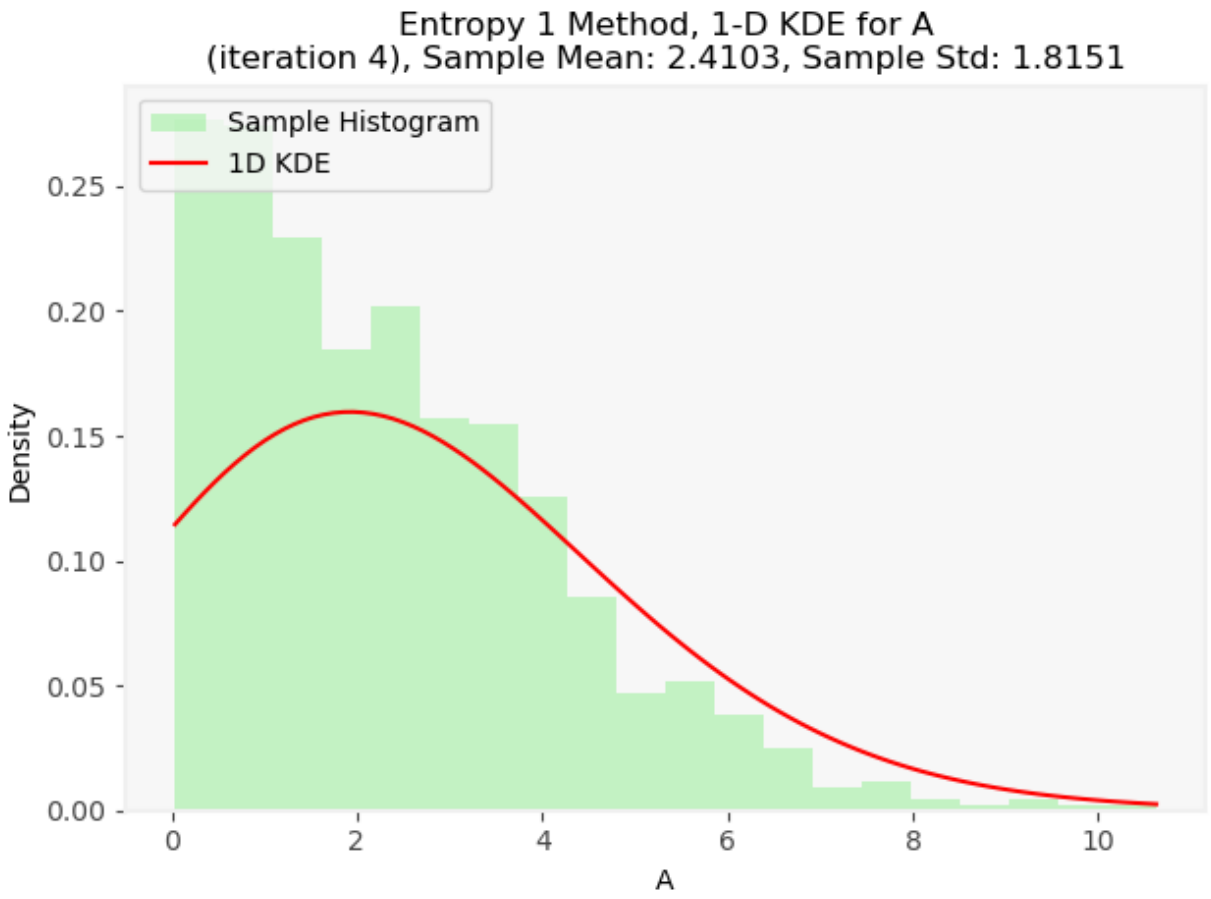
In [52]:
```
#Printing the evolution of parameter I for Entropy
#later do the same for parameter A since that was the parameter selected by entropy


for i in range(len(exp_entropy1.totaltimes())):
    MyPlots.plot_hist_1d_kde(list_par_separated_e1[0][i], kdes_entropy1[i,0],"Entropy
```

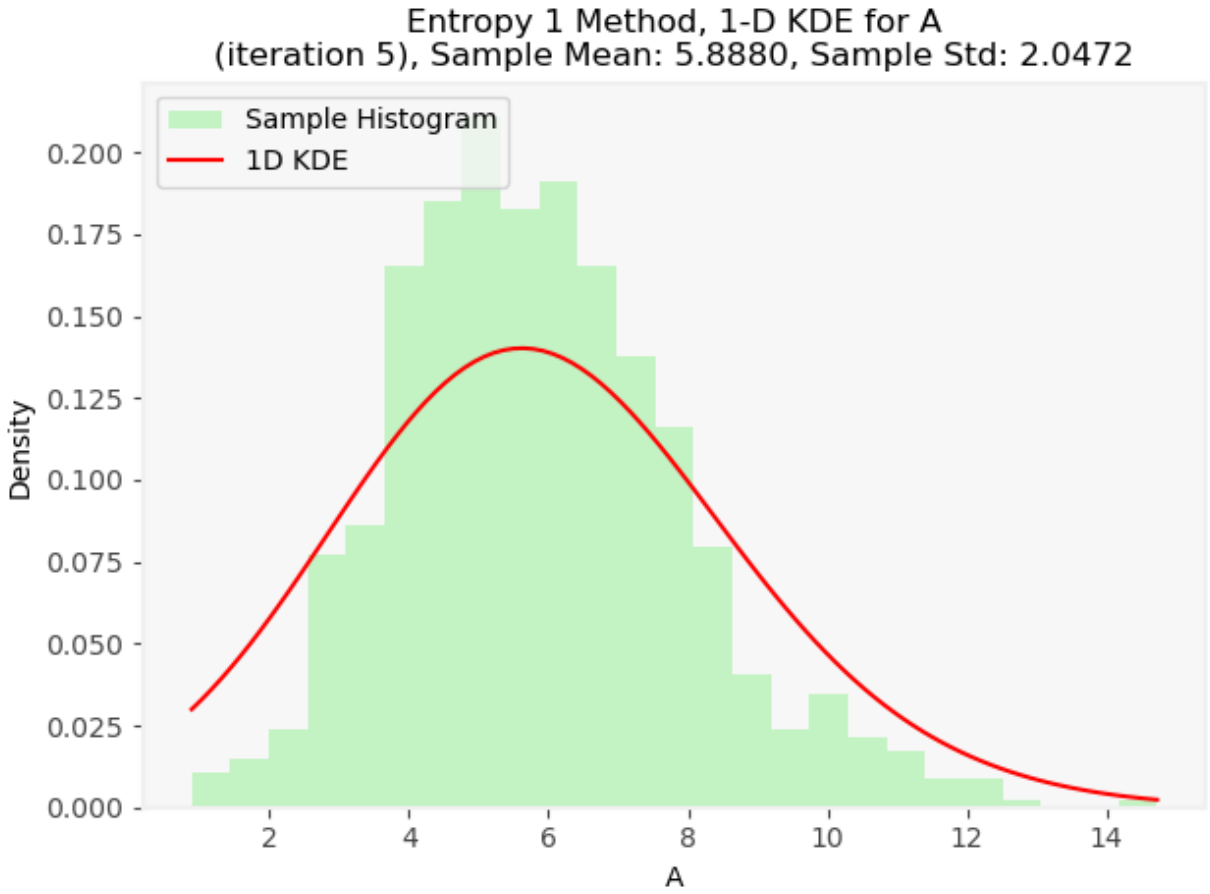


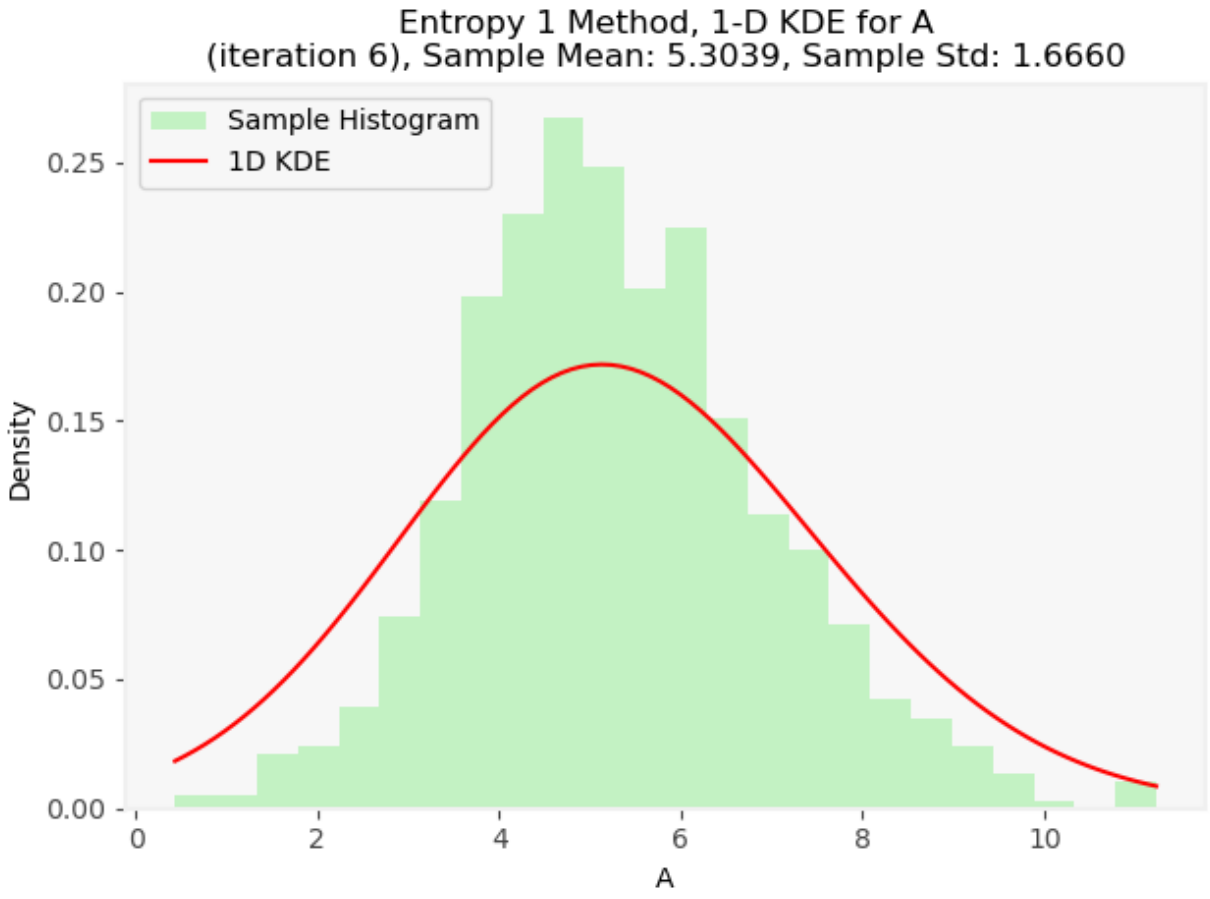

Entropy 1 Method, 1-D KDE for A
(iteration 1), Sample Mean: 13.9063, Sample Std: 13.0654
Sample Histogram
1D KDE
Density
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
10
20
30
40
50
60
A

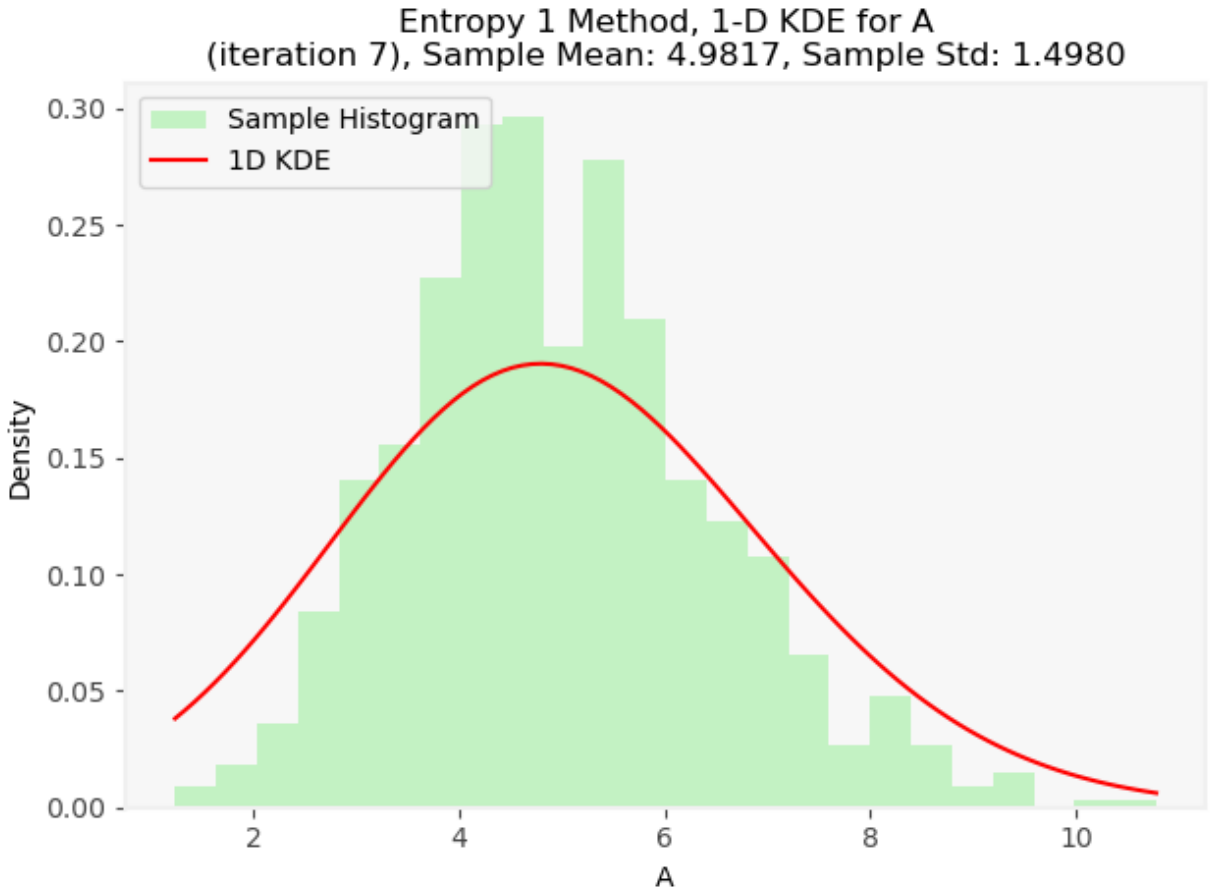

Entropy 1 Method, 1-D KDE for A
(iteration 2), Sample Mean: 4.3985, Sample Std: 3.5261
Sample Histogram
1D KDE
Density
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0
5
10
15
20
A

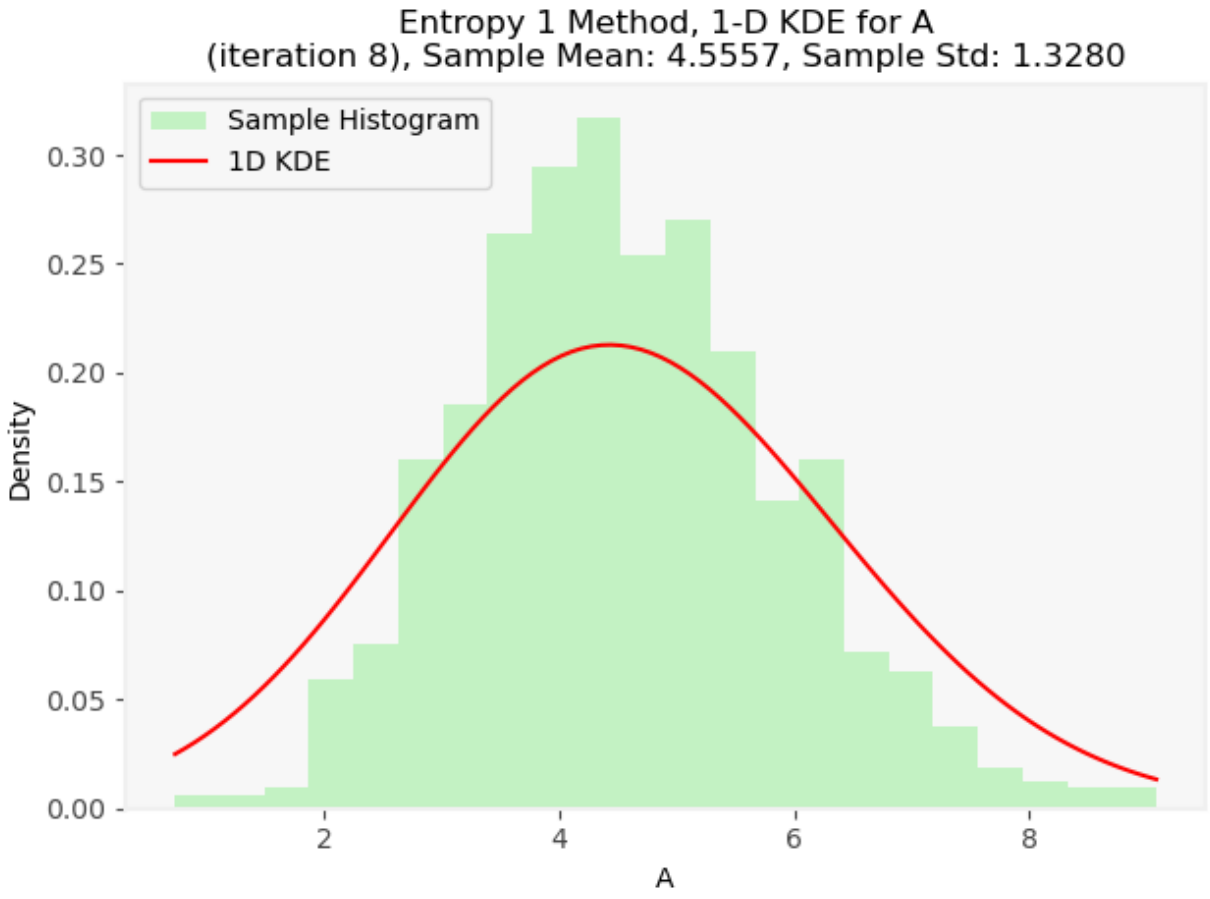

Entropy 1 Method, 1-D KDE for A
(iteration 3), Sample Mean: 2.9671, Sample Std: 2.2063
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0
2
4
6
8
10
12
14
A

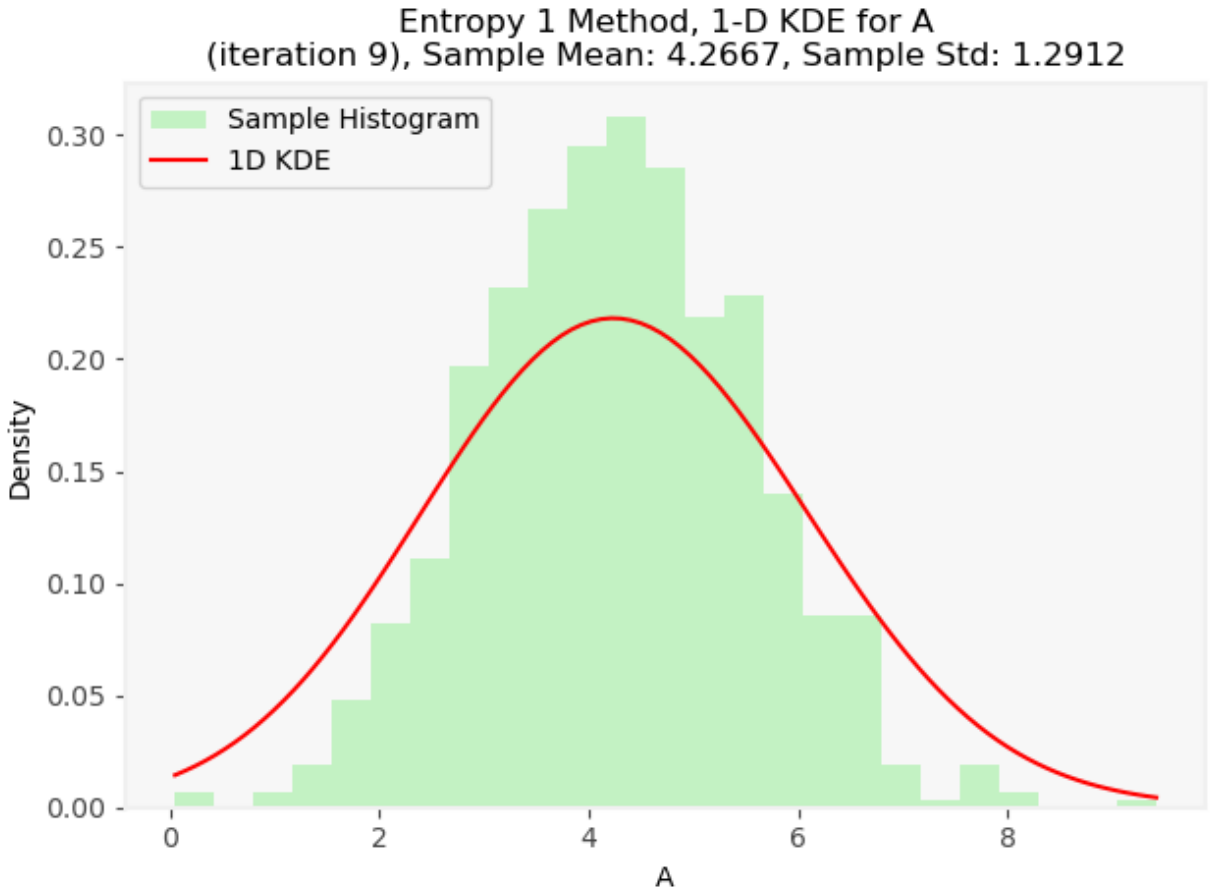

Entropy 1 Method, 1-D KDE for A
(iteration 4), Sample Mean: 2.4103, Sample Std: 1.8151
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
2
4
6
8
10
A

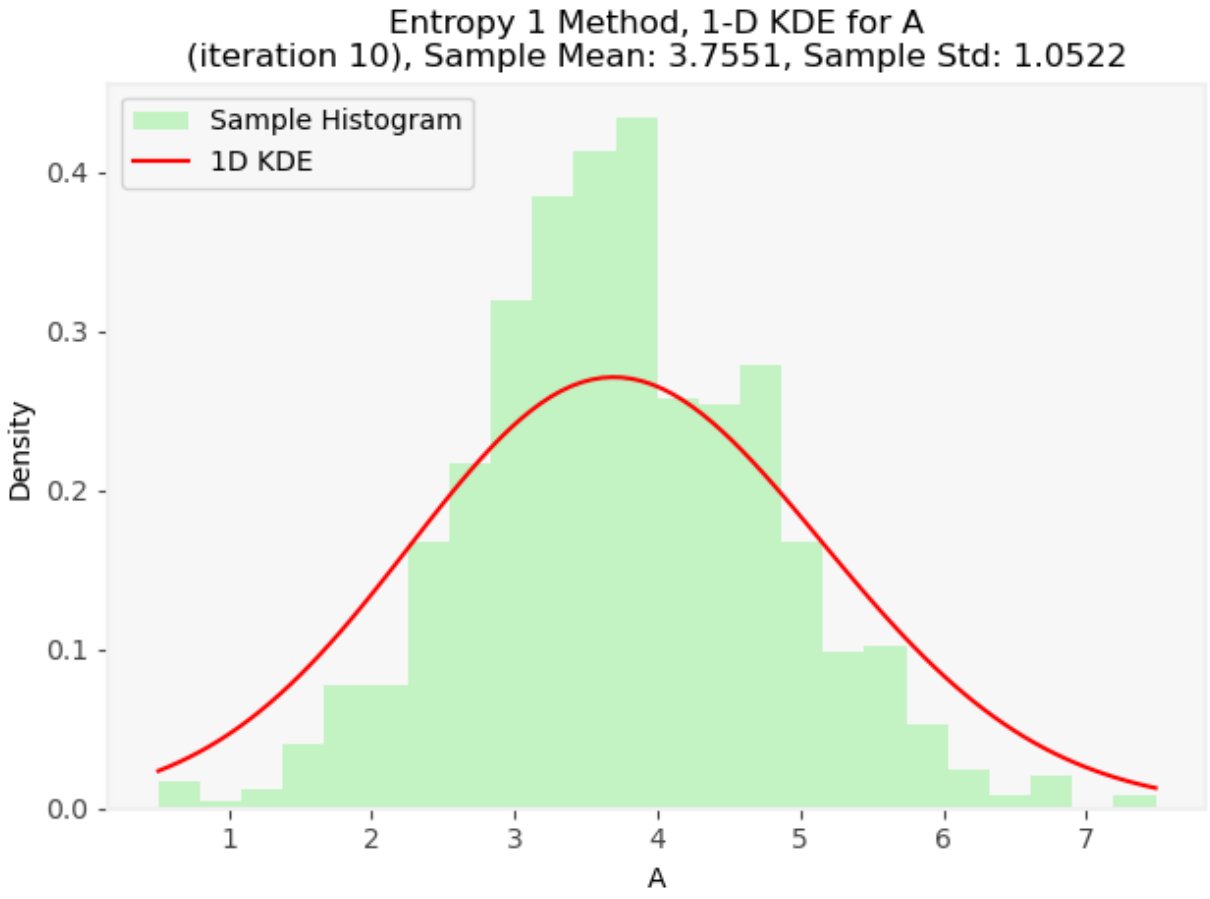

Entropy 1 Method, 1-D KDE for A
(iteration 5), Sample Mean: 5.8880, Sample Std: 2.0472
Sample Histogram
1D KDE
Density
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
2
4
6
8
10
12
14
A

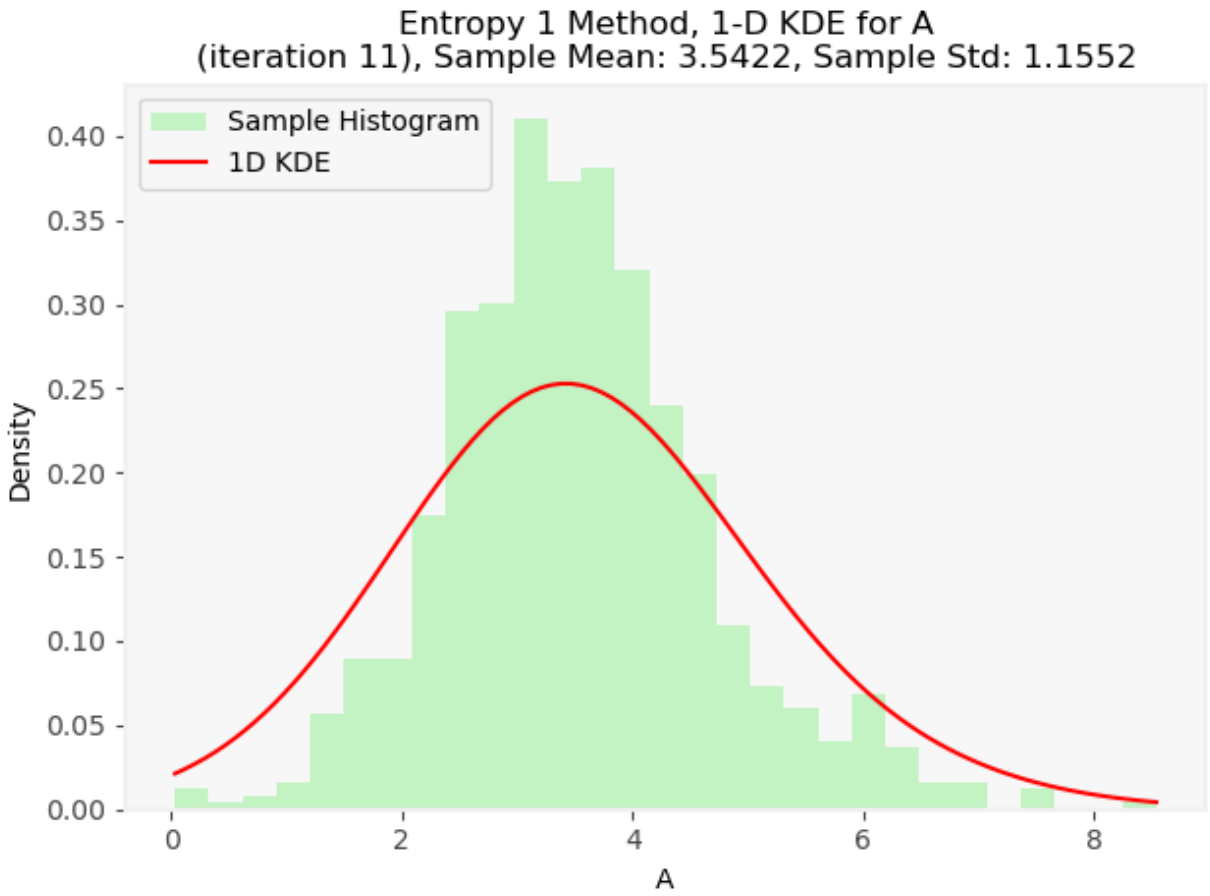

Entropy 1 Method, 1-D KDE for A
(iteration 6), Sample Mean: 5.3039, Sample Std: 1.6660
Sample Histogram
1D KDE
Density
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
10
A

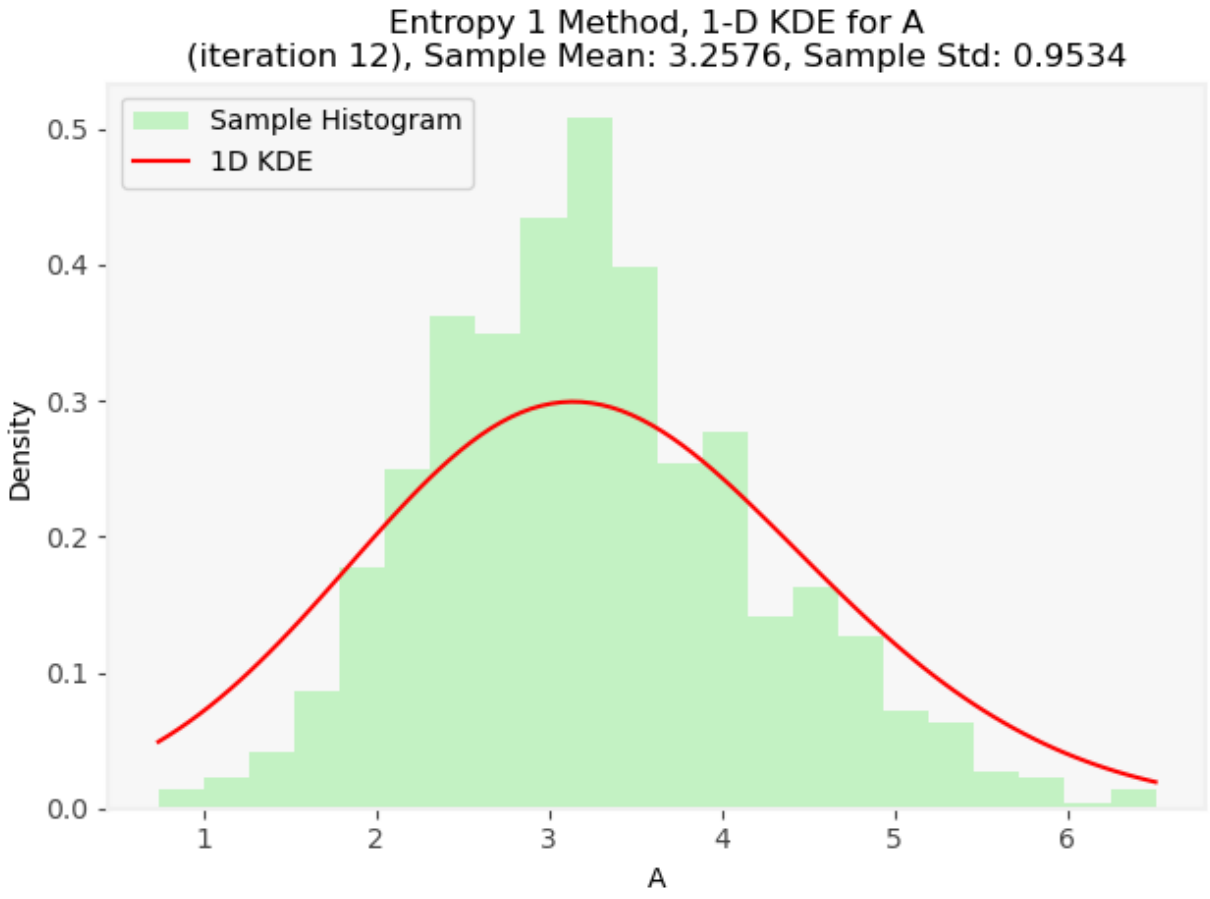

Entropy 1 Method, 1-D KDE for A
(iteration 7), Sample Mean: 4.9817, Sample Std: 1.4980
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
2
4
6
8
10

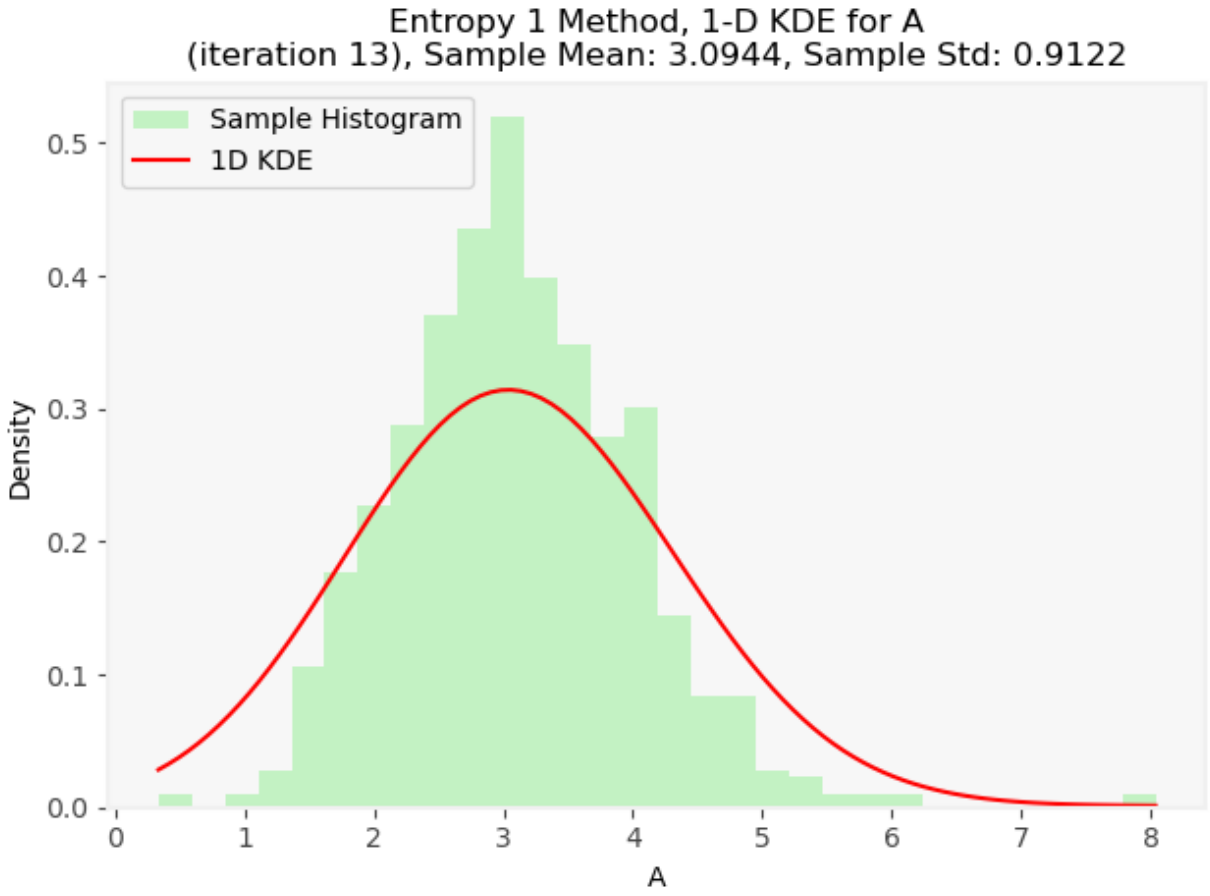

Entropy 1 Method, 1-D KDE for A
(iteration 8), Sample Mean: 4.5557, Sample Std: 1.3280
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
2
4
6
8

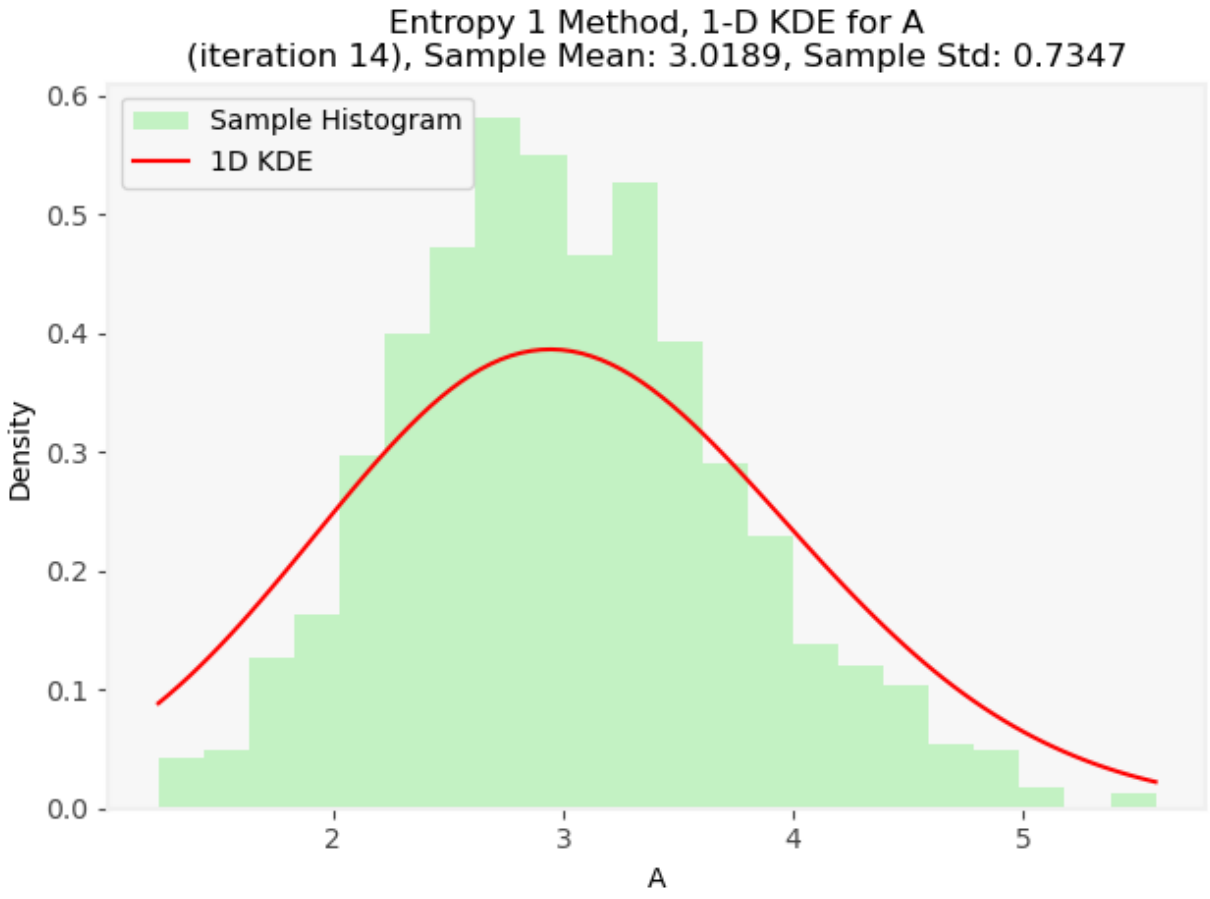

Entropy 1 Method, 1-D KDE for A
(iteration 9), Sample Mean: 4.2667, Sample Std: 1.2912
Sample Histogram
1D KDE
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
A

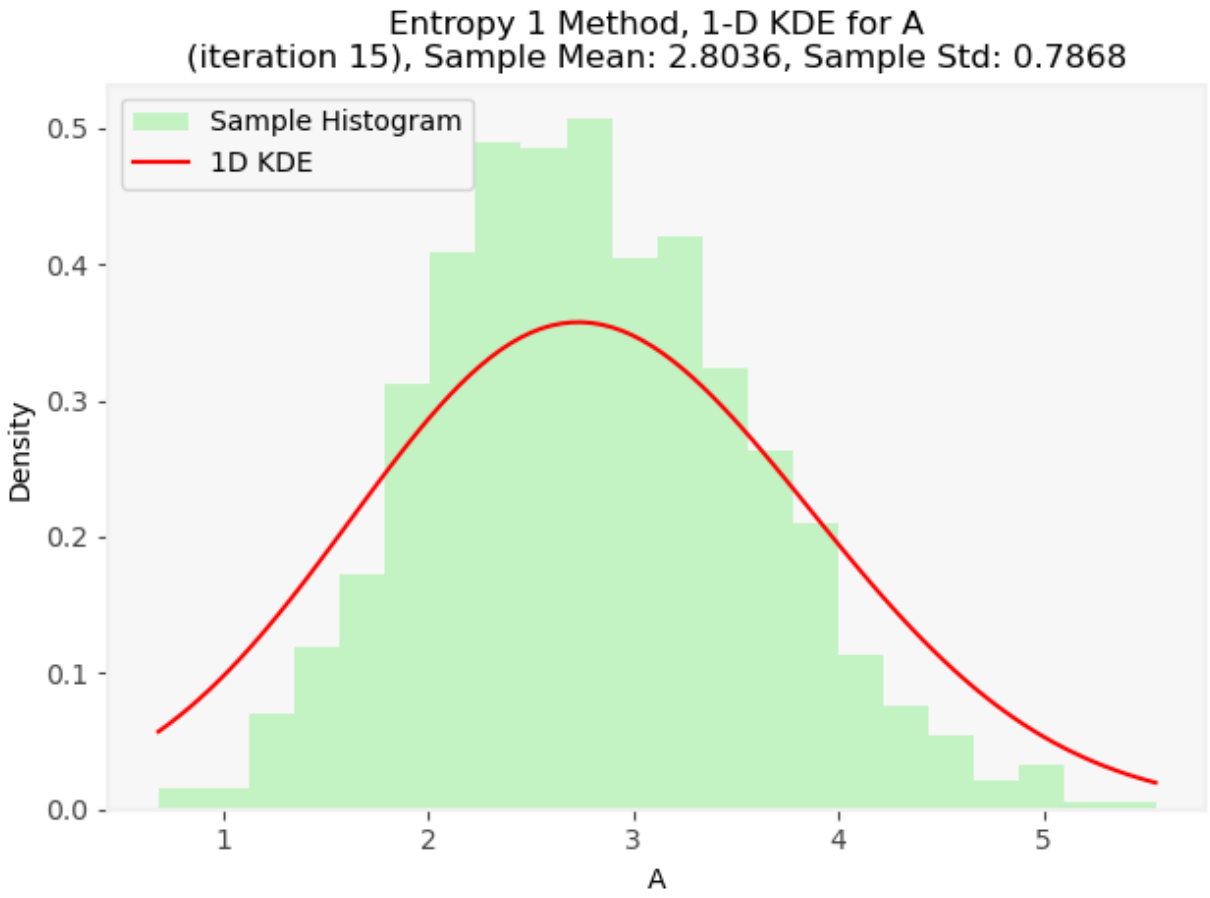

Entropy 1 Method, 1-D KDE for A
(iteration 10), Sample Mean: 3.7551, Sample Std: 1.0522
Sample Histogram
1D KDE
Density
0.4
0.3
0.2
0.1
0.0
1
2
3
4
5
6
7
A

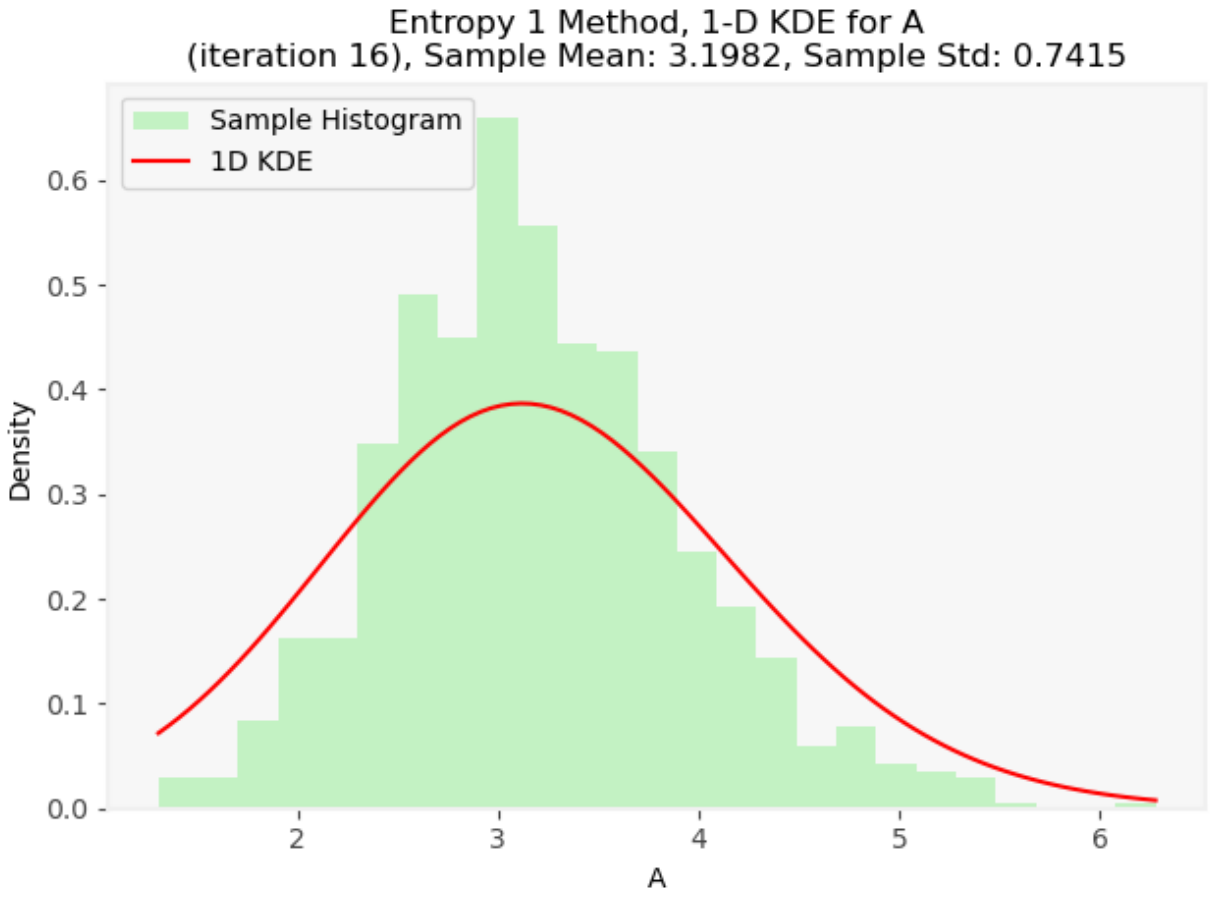

Entropy 1 Method, 1-D KDE for A
(iteration 11), Sample Mean: 3.5422, Sample Std: 1.1552
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0
2
4
6
8

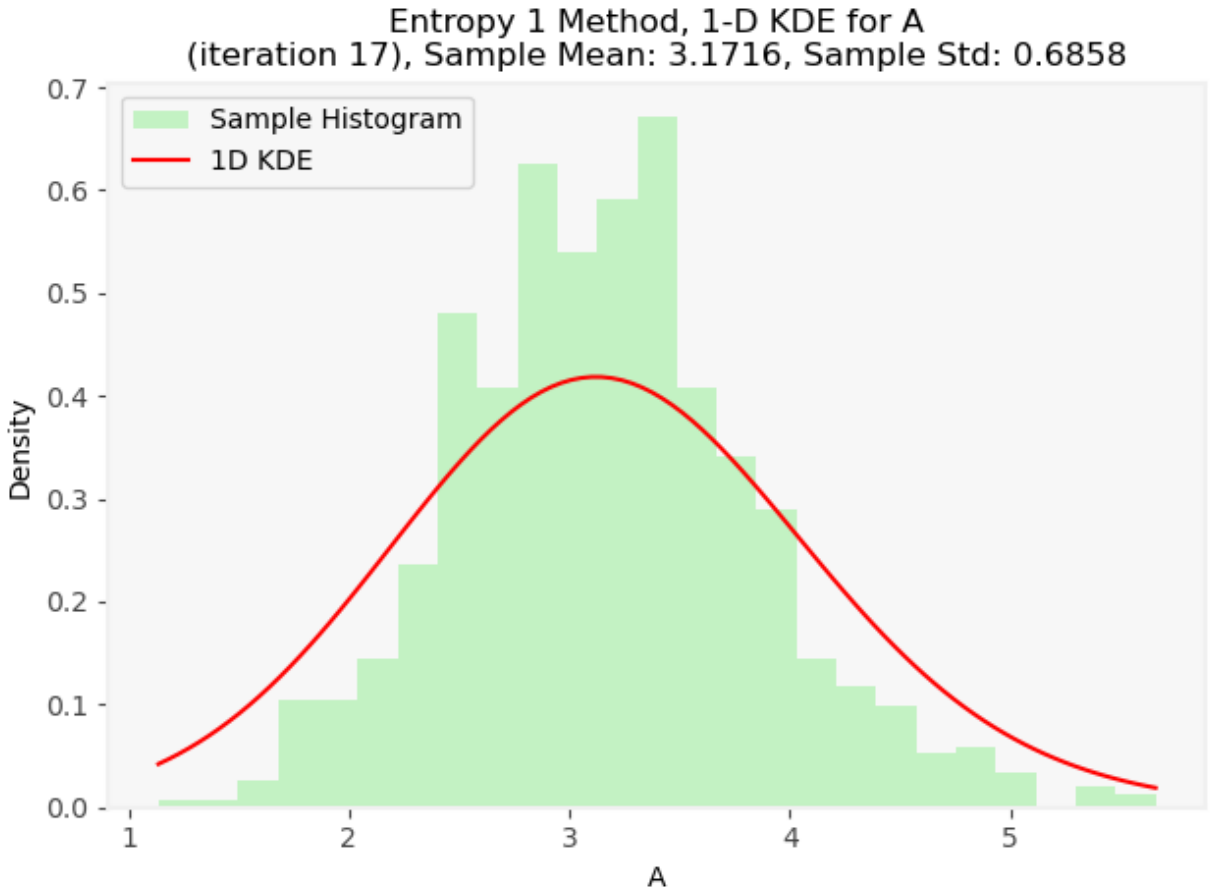

Entropy 1 Method, 1-D KDE for A
(iteration 12), Sample Mean: 3.2576, Sample Std: 0.9534
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6

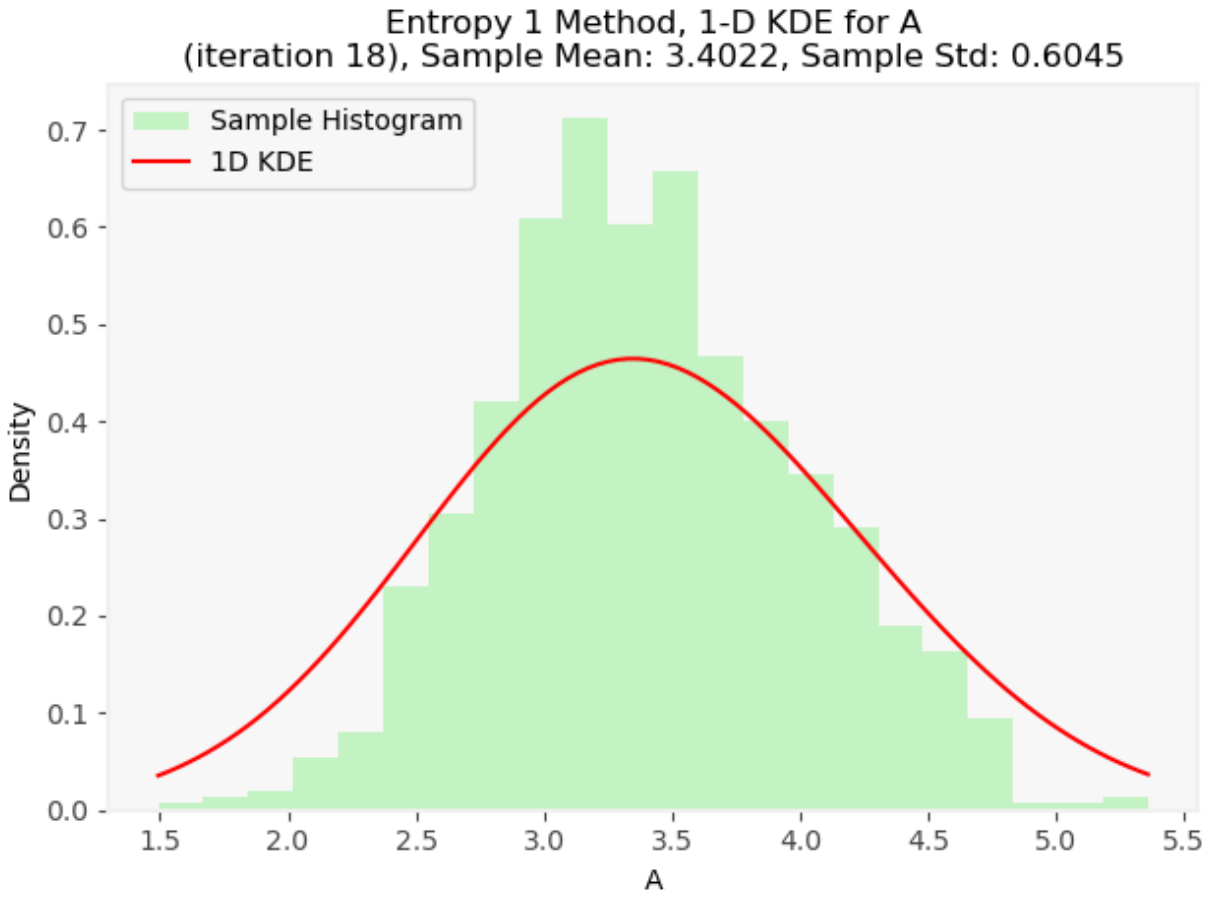

Entropy 1 Method, 1-D KDE for A
(iteration 13), Sample Mean: 3.0944, Sample Std: 0.9122
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0
1
2
3
4
5
6
7
8

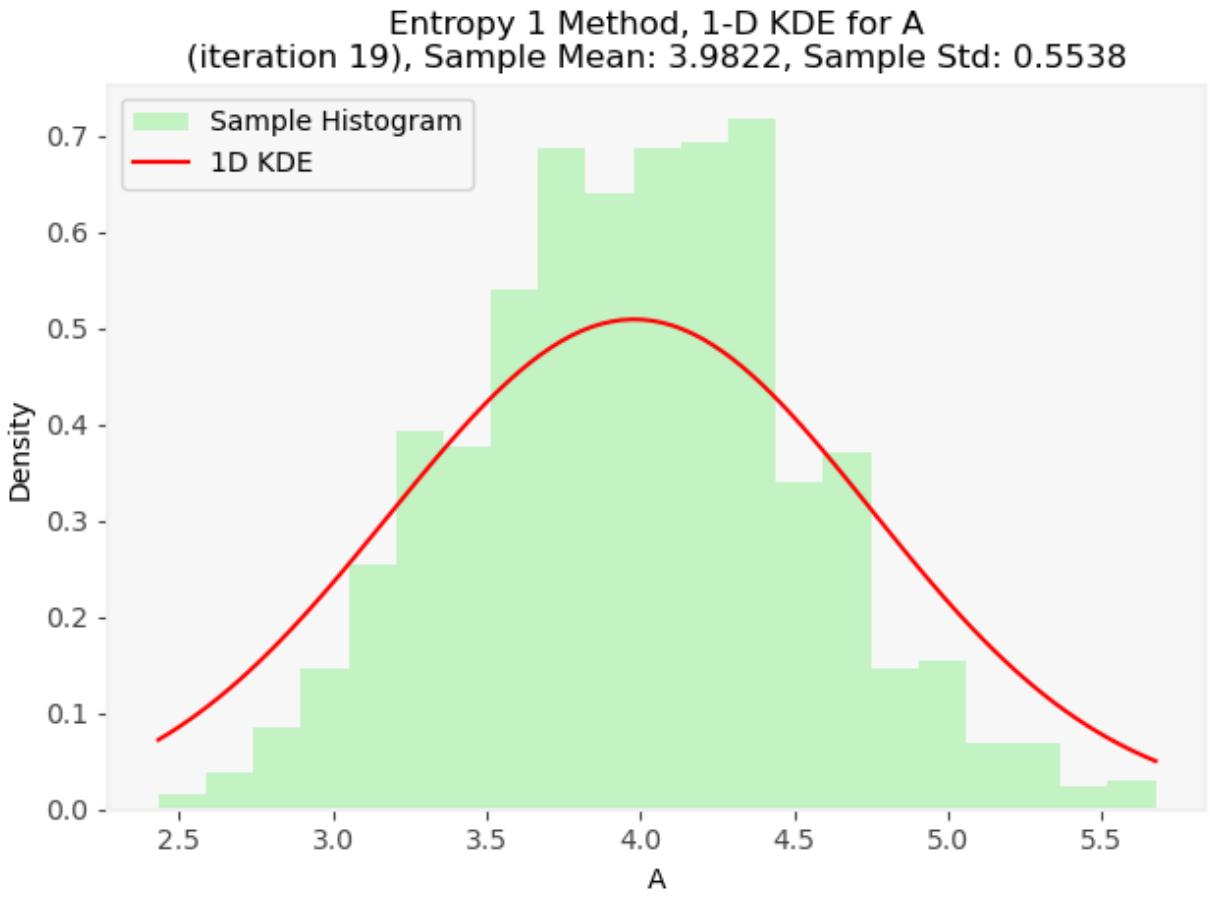

Entropy 1 Method, 1-D KDE for A
(iteration 14), Sample Mean: 3.0189, Sample Std: 0.7347
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2
3
4
5

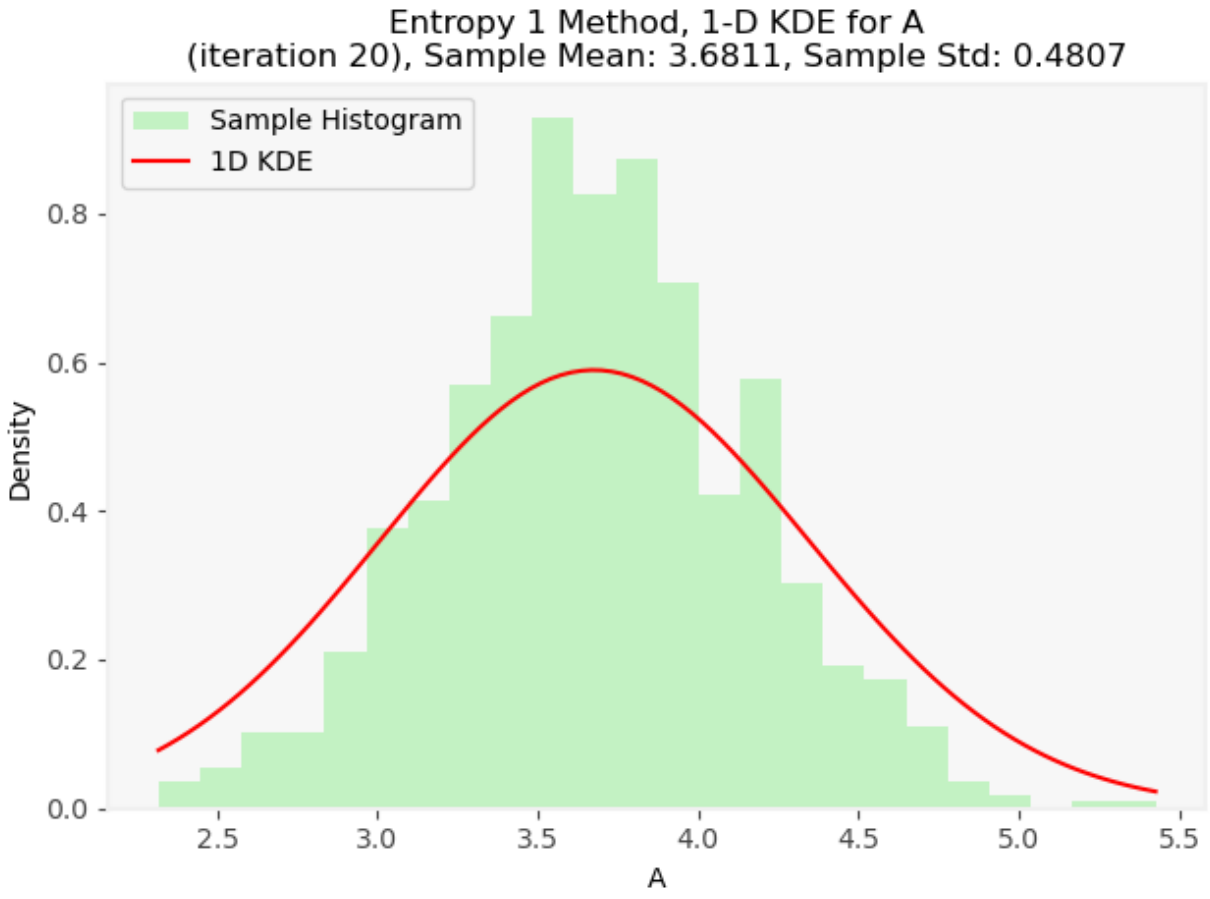

Entropy 1 Method, 1-D KDE for A
(iteration 15), Sample Mean: 2.8036, Sample Std: 0.7868
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5

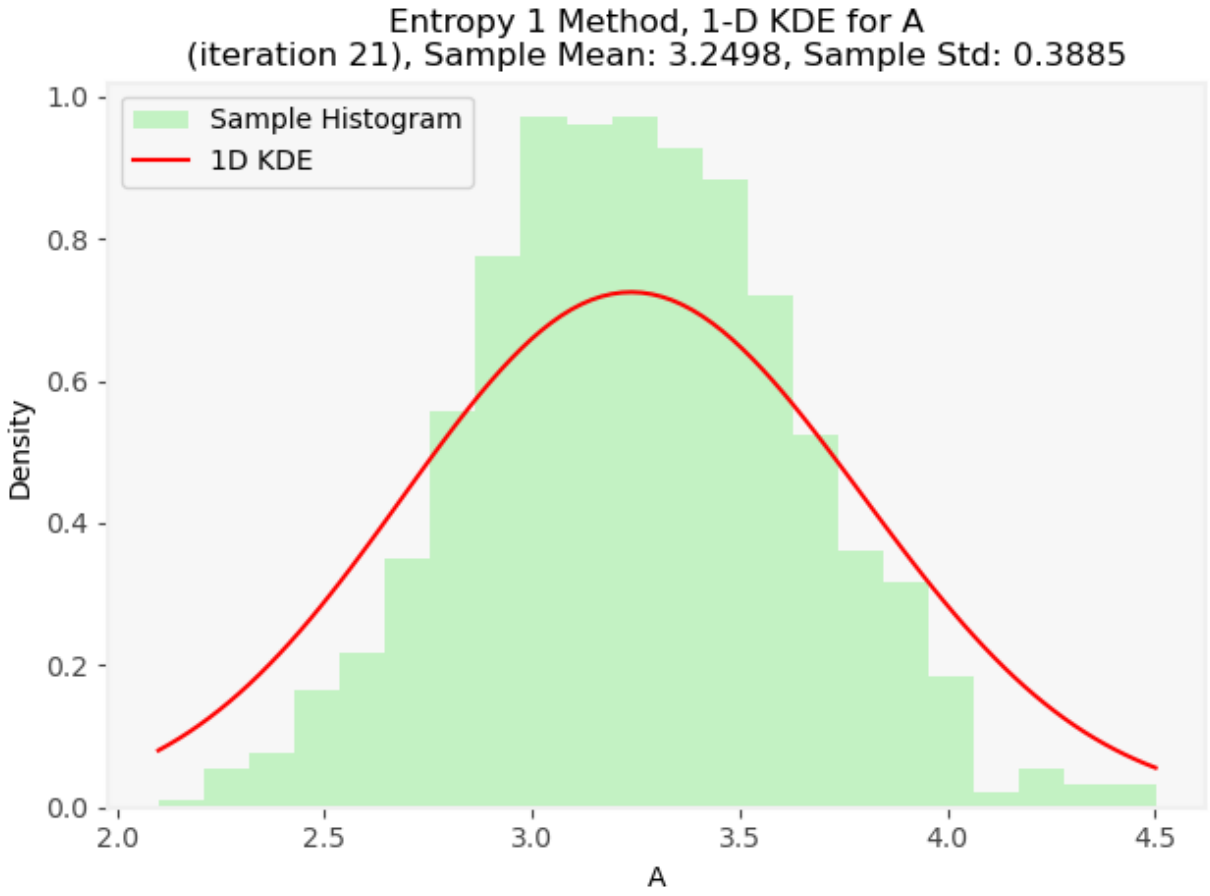

Entropy 1 Method, 1-D KDE for A
(iteration 16), Sample Mean: 3.1982, Sample Std: 0.7415
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2
3
4
5
6

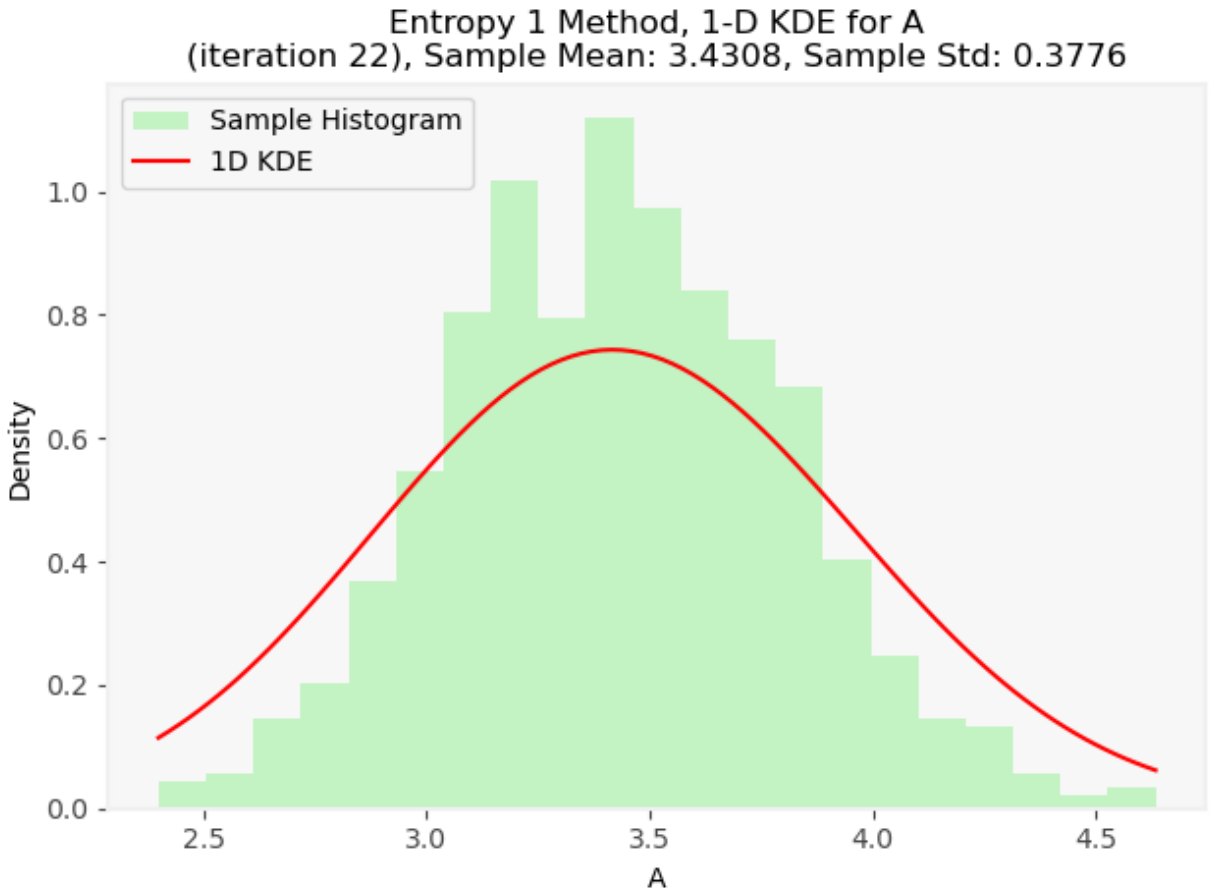

Entropy 1 Method, 1-D KDE for A
(iteration 17), Sample Mean: 3.1716, Sample Std: 0.6858
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1
2
3
4
5

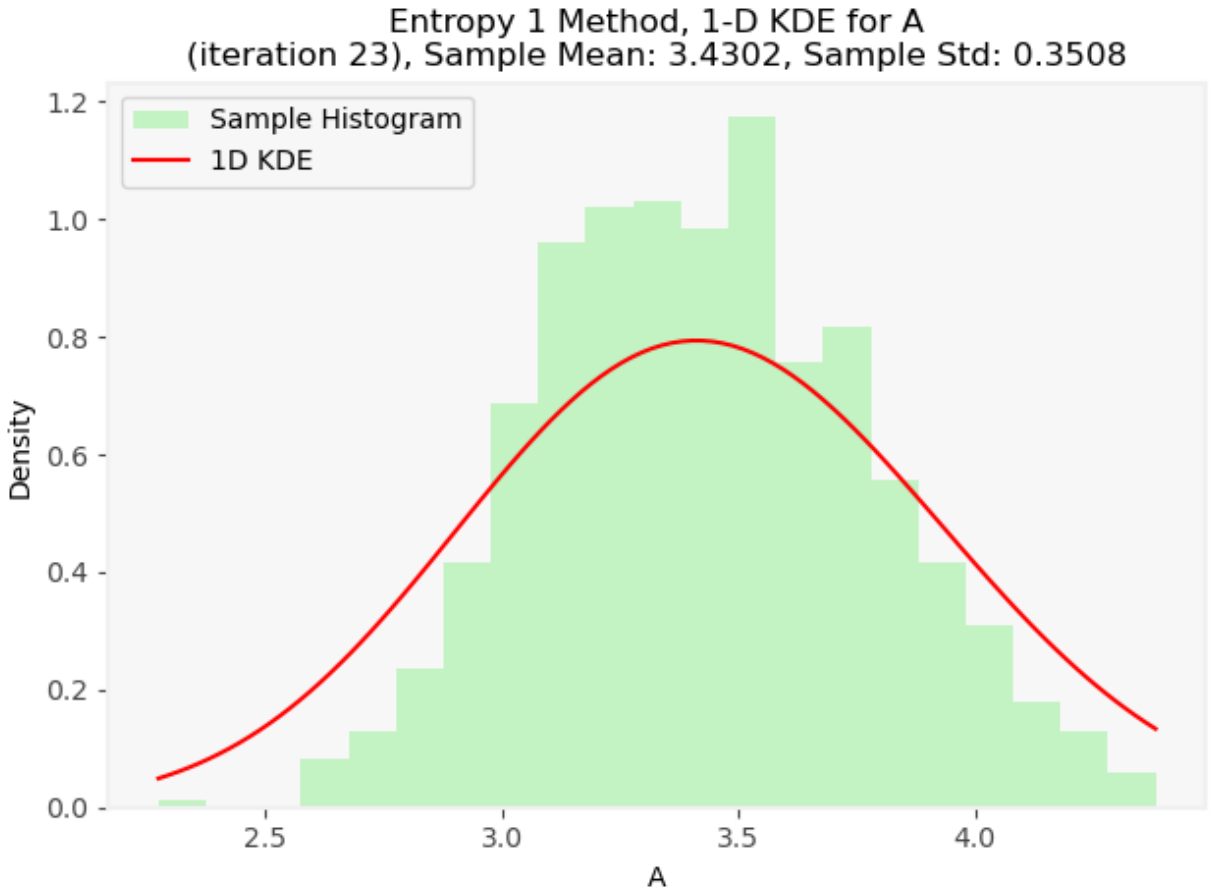

Entropy 1 Method, 1-D KDE for A
(iteration 18), Sample Mean: 3.4022, Sample Std: 0.6045
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5

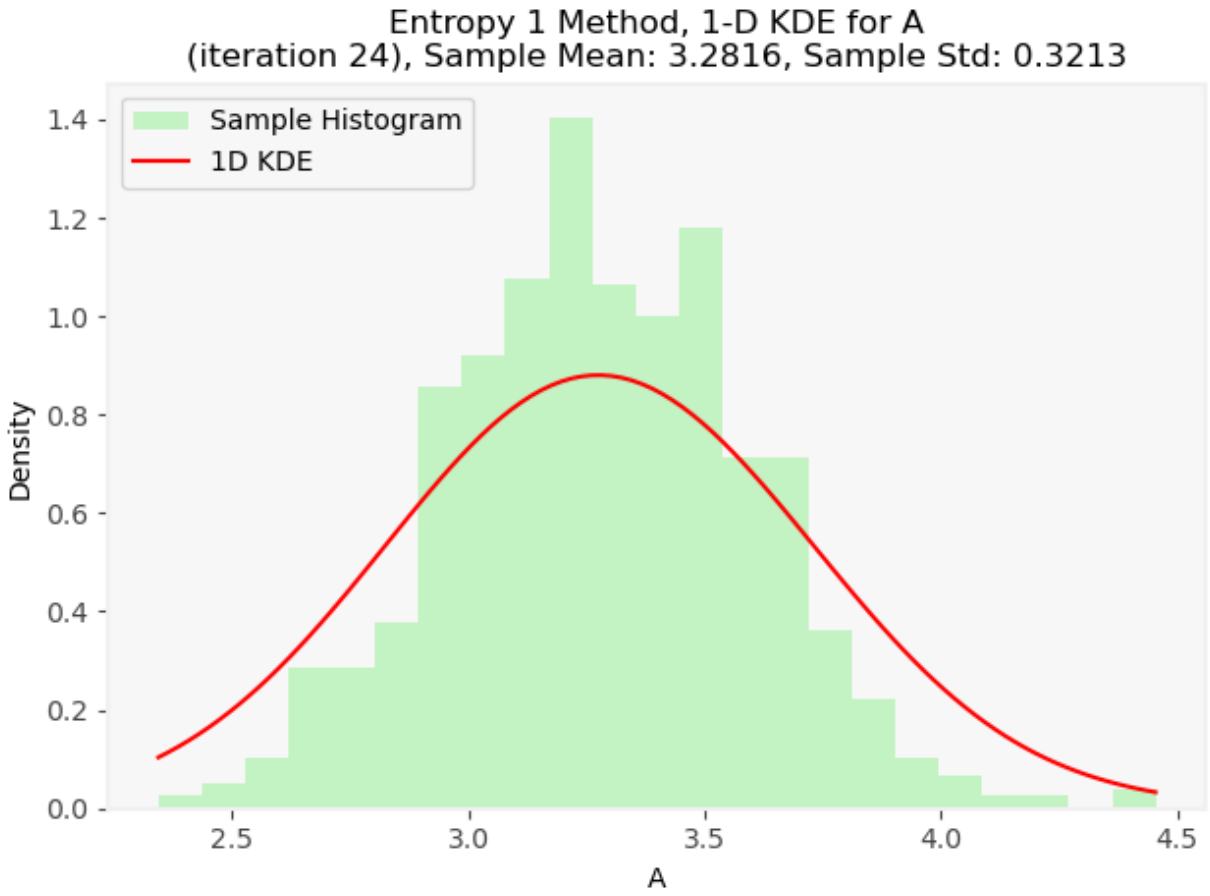

Entropy 1 Method, 1-D KDE for A
(iteration 19), Sample Mean: 3.9822, Sample Std: 0.5538
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
2.5
3.0
3.5
4.0
4.5
5.0
5.5

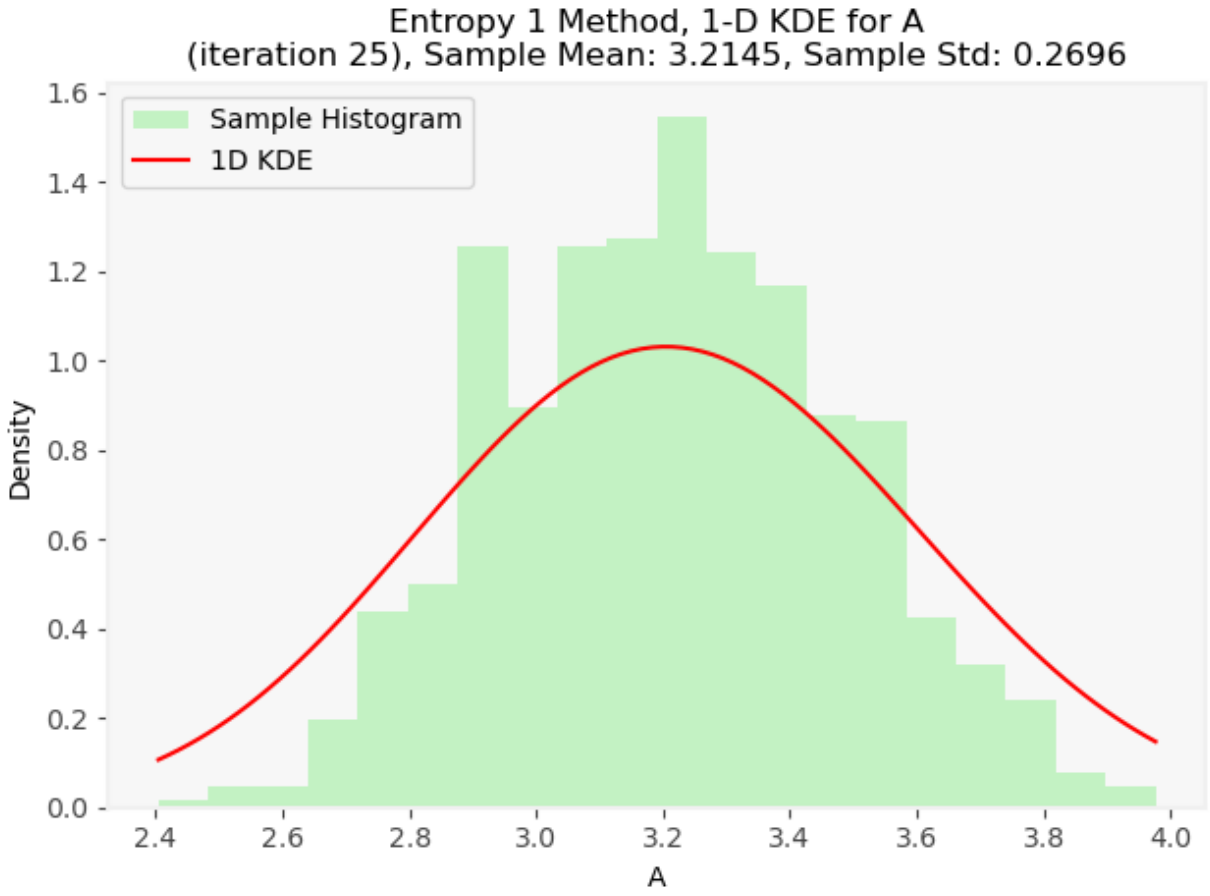

Entropy 1 Method, 1-D KDE for A
(iteration 20), Sample Mean: 3.6811, Sample Std: 0.4807
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
2.5
3.0
3.5
4.0
4.5
5.0
5.5

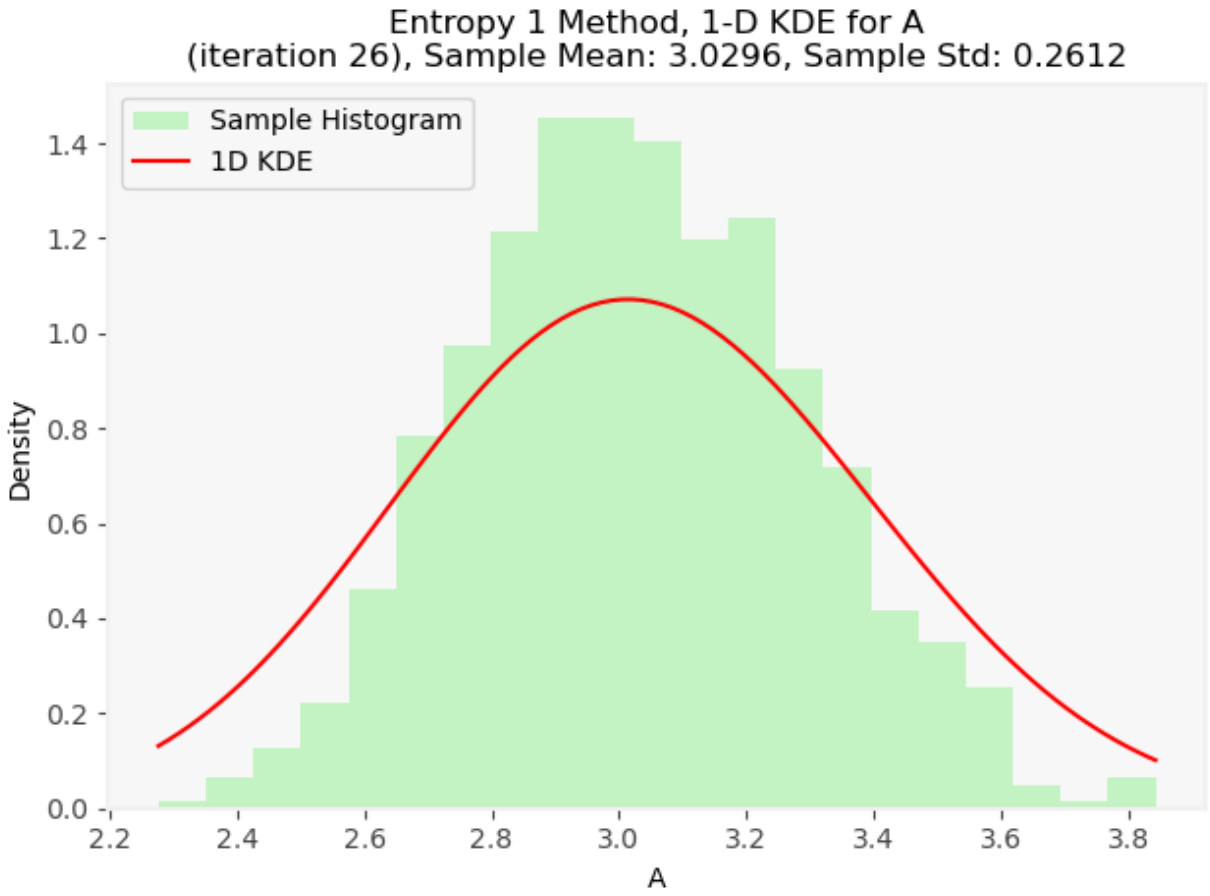

Entropy 1 Method, 1-D KDE for A
(iteration 21), Sample Mean: 3.2498, Sample Std: 0.3885
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
2.0
2.5
3.0
3.5
4.0
4.5

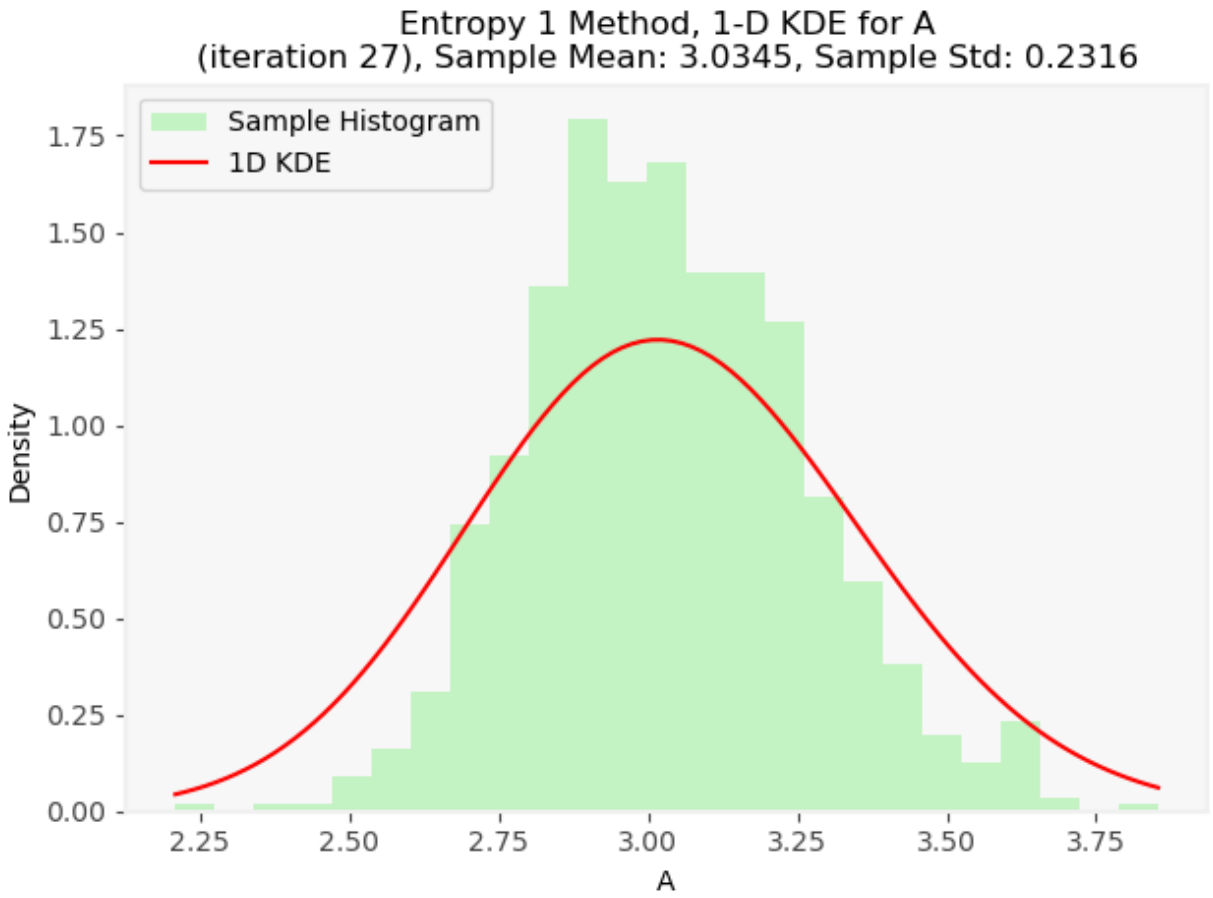

Entropy 1 Method, 1-D KDE for A
(iteration 22), Sample Mean: 3.4308, Sample Std: 0.3776
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
2.5
3.0
3.5
4.0
4.5

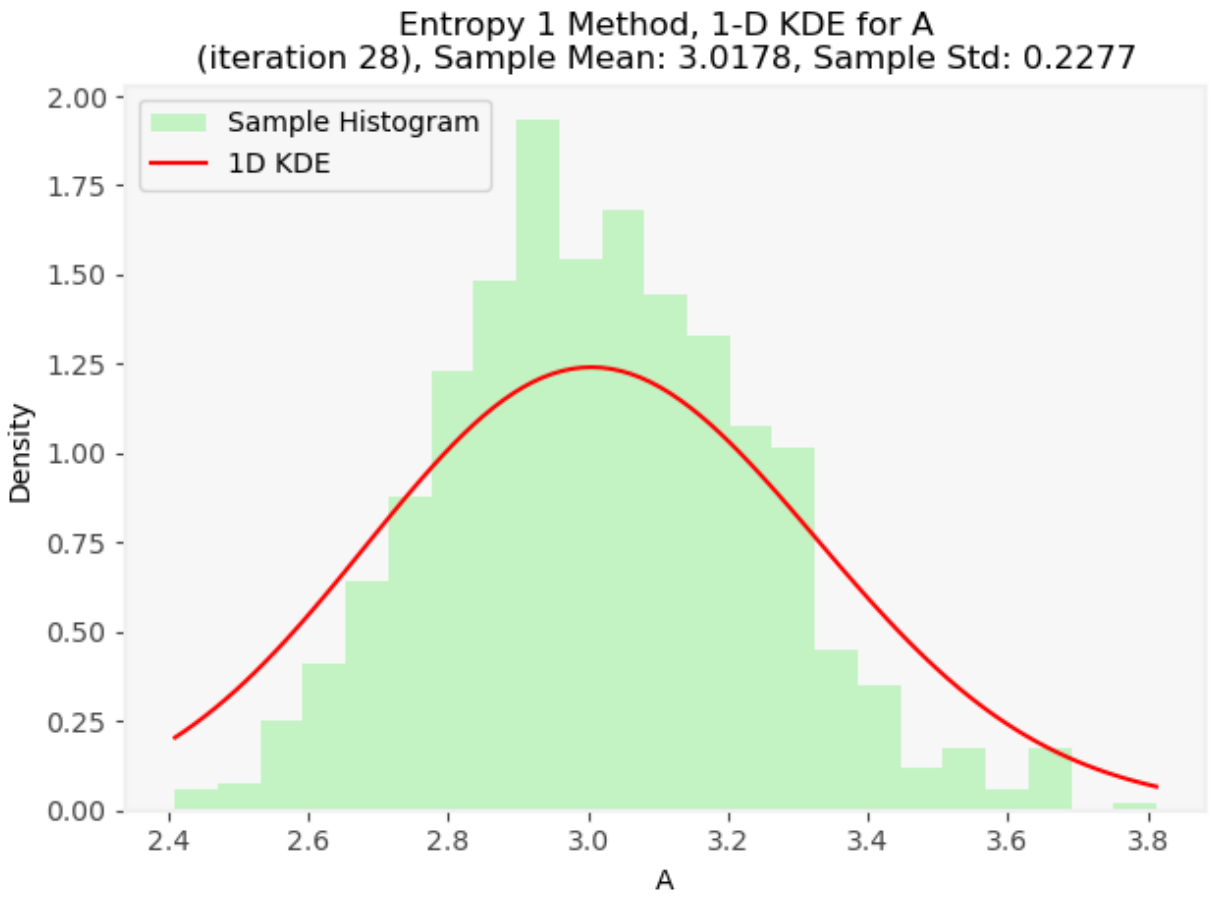

Entropy 1 Method, 1-D KDE for A
(iteration 23), Sample Mean: 3.4302, Sample Std: 0.3508
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0

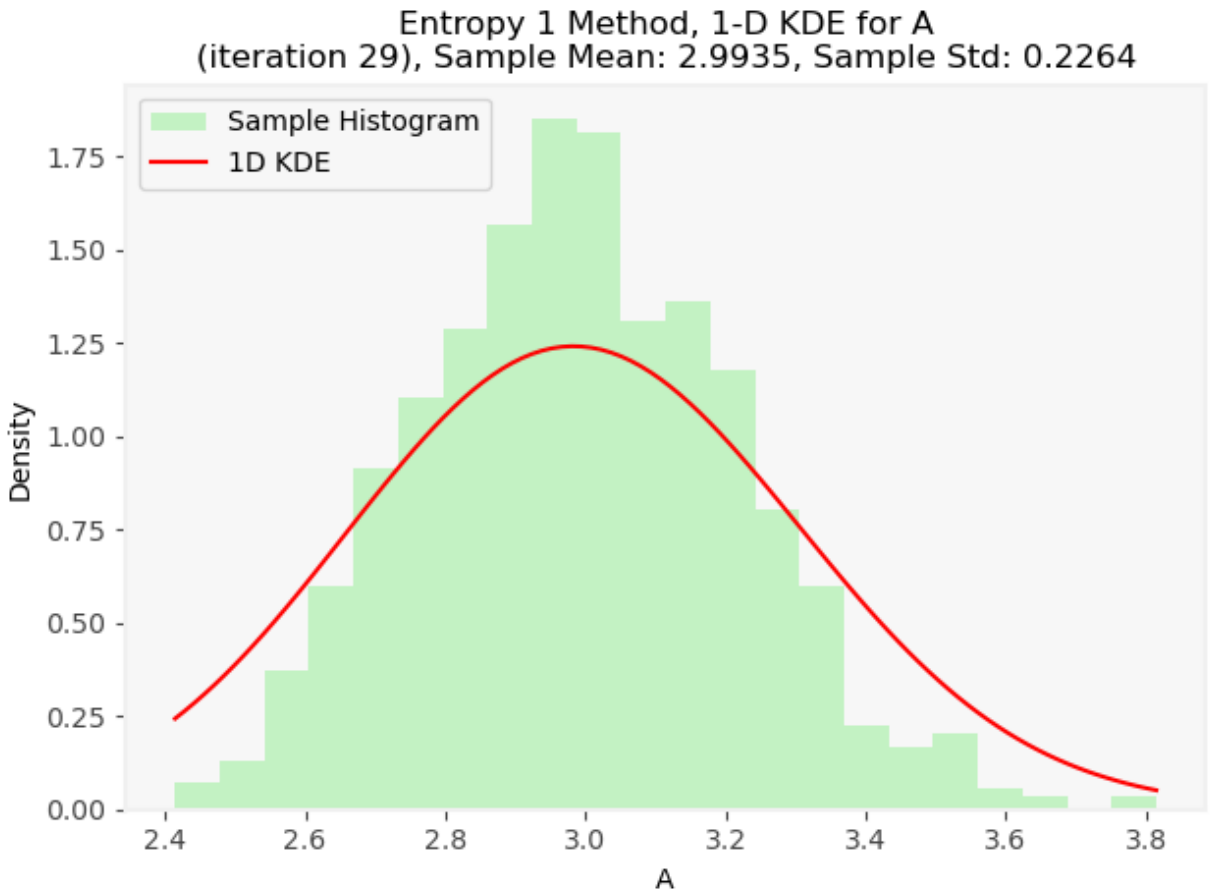

Entropy 1 Method, 1-D KDE for A
(iteration 24), Sample Mean: 3.2816, Sample Std: 0.3213
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.5
3.0
3.5
4.0
4.5

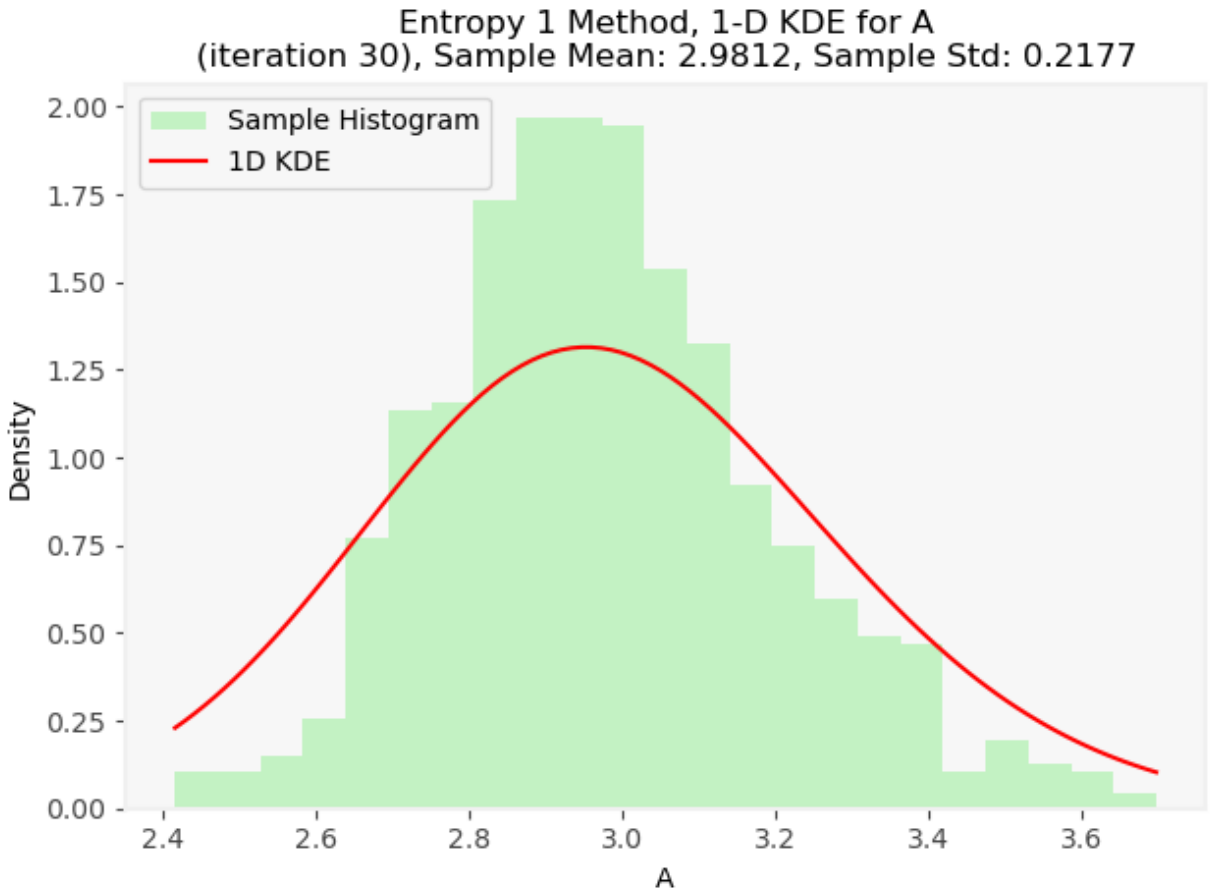

Entropy 1 Method, 1-D KDE for A
(iteration 25), Sample Mean: 3.2145, Sample Std: 0.2696
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0

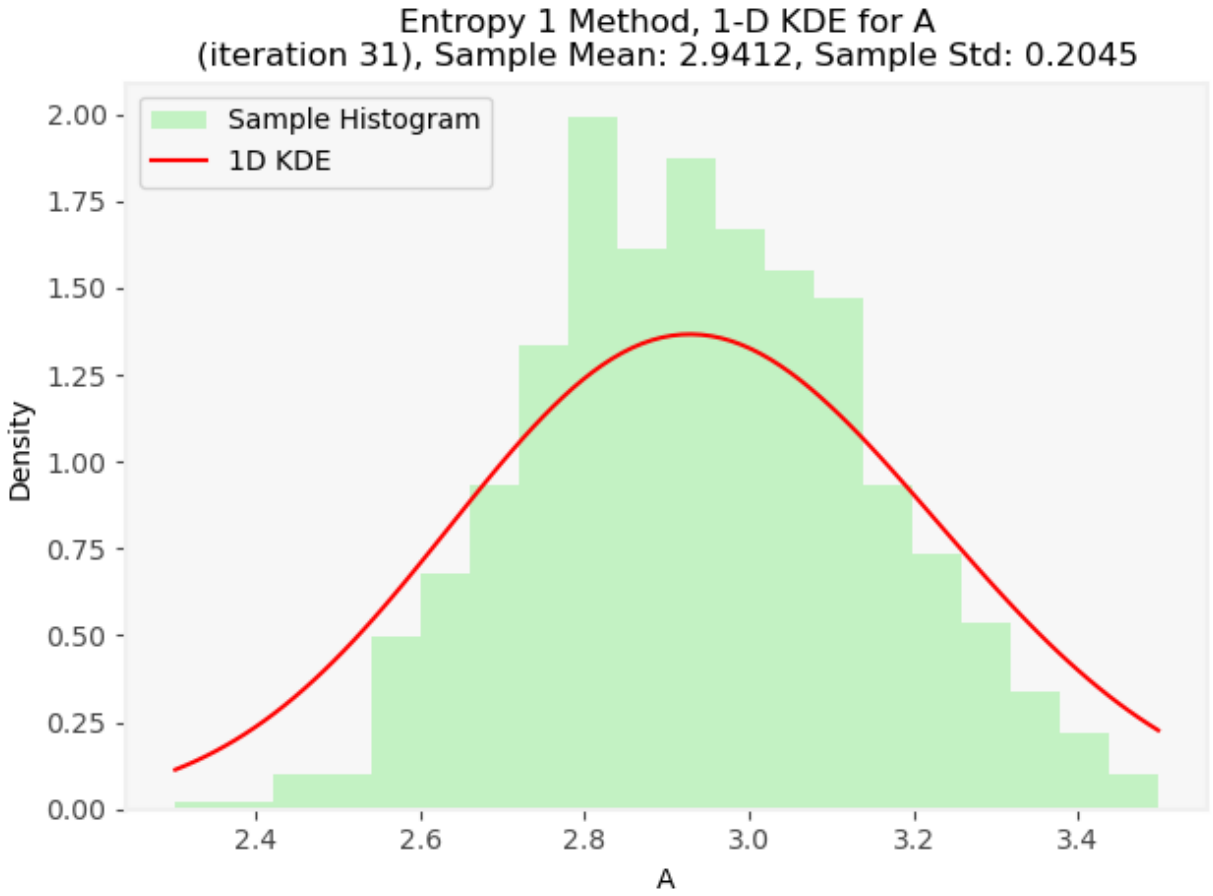

Entropy 1 Method, 1-D KDE for A
(iteration 26), Sample Mean: 3.0296, Sample Std: 0.2612
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.2
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8

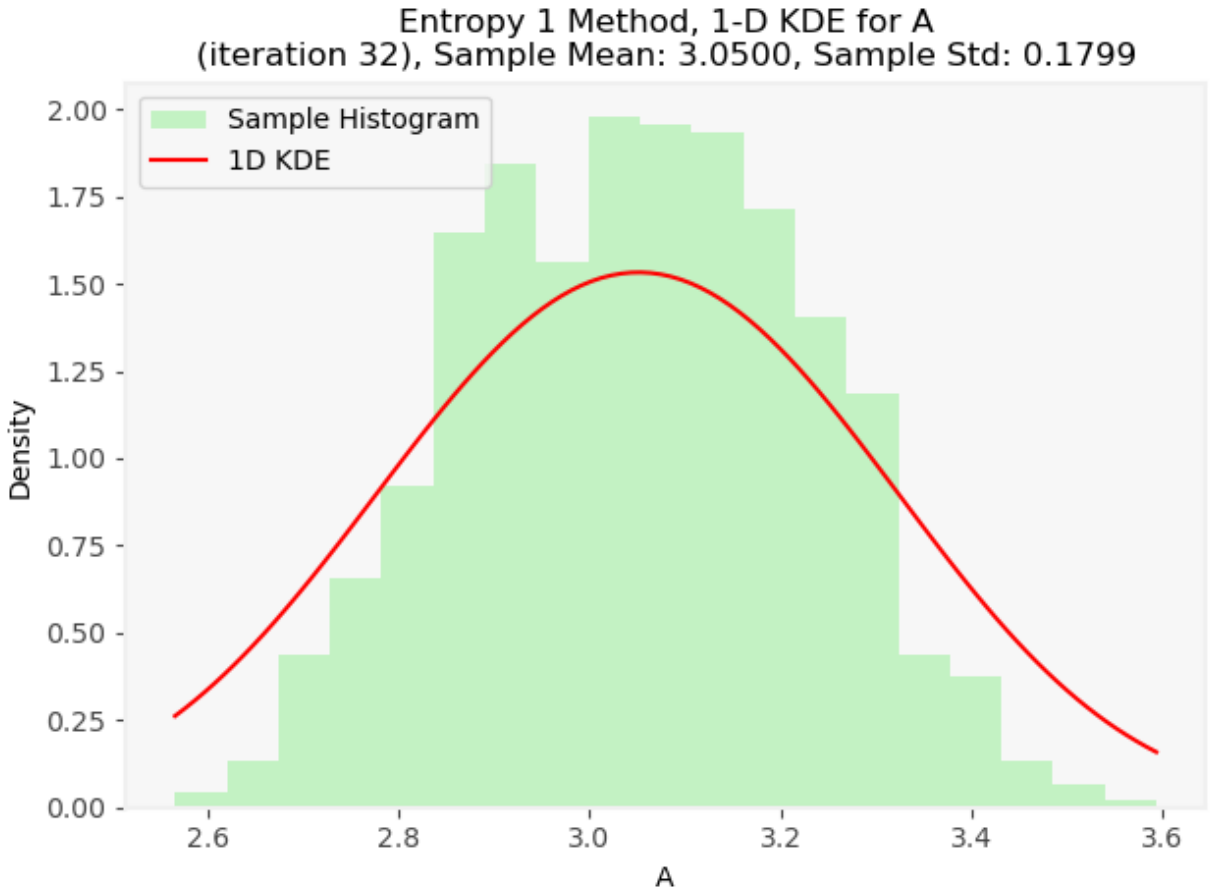

Entropy 1 Method, 1-D KDE for A
(iteration 27), Sample Mean: 3.0345, Sample Std: 0.2316
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.25
2.50
2.75
3.00
3.25
3.50
3.75


Entropy 1 Method, 1-D KDE for A
(iteration 28), Sample Mean: 3.0178, Sample Std: 0.2277
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8


Entropy 1 Method, 1-D KDE for A
(iteration 29), Sample Mean: 2.9935, Sample Std: 0.2264
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8

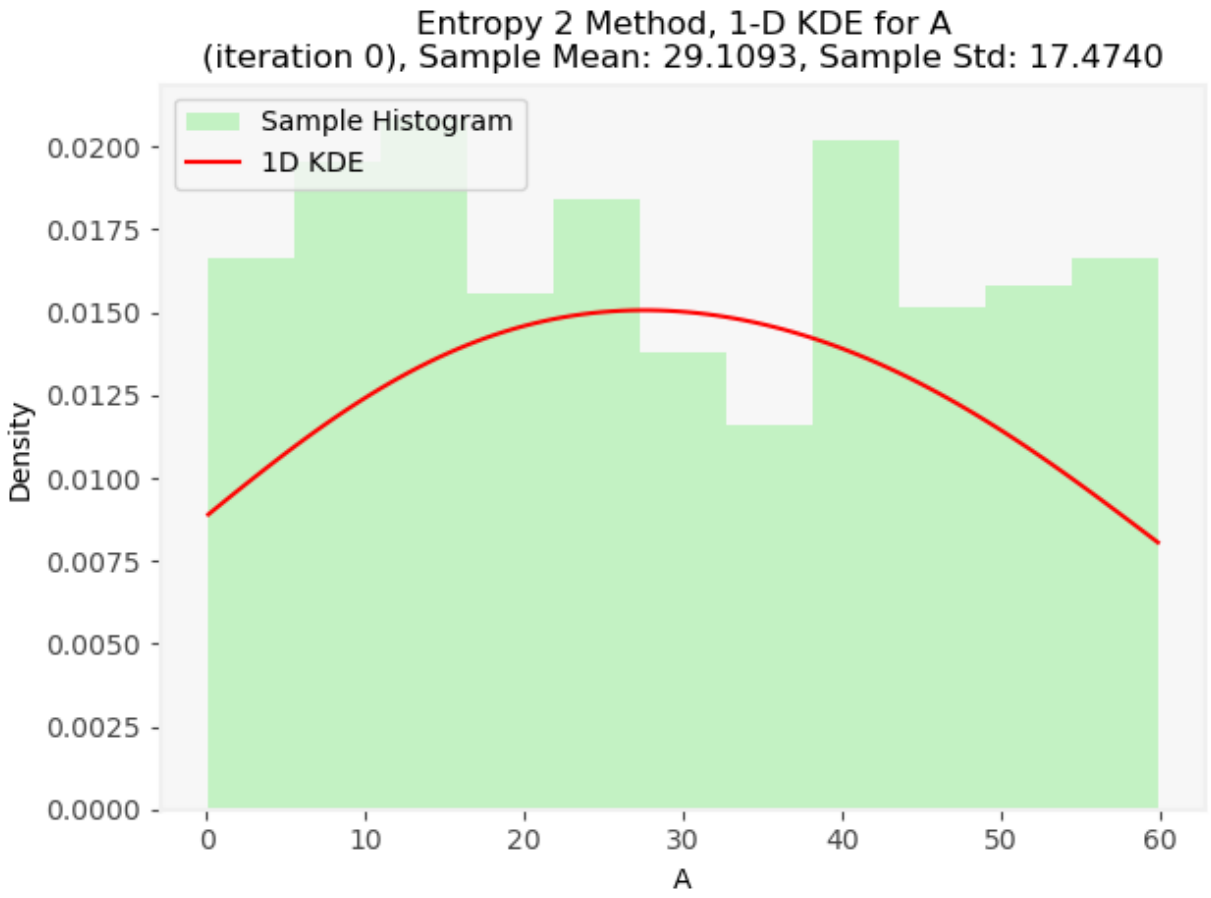

Entropy 1 Method, 1-D KDE for A
(iteration 30), Sample Mean: 2.9812, Sample Std: 0.2177
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.4
2.6
2.8
3.0
3.2
3.4
3.6

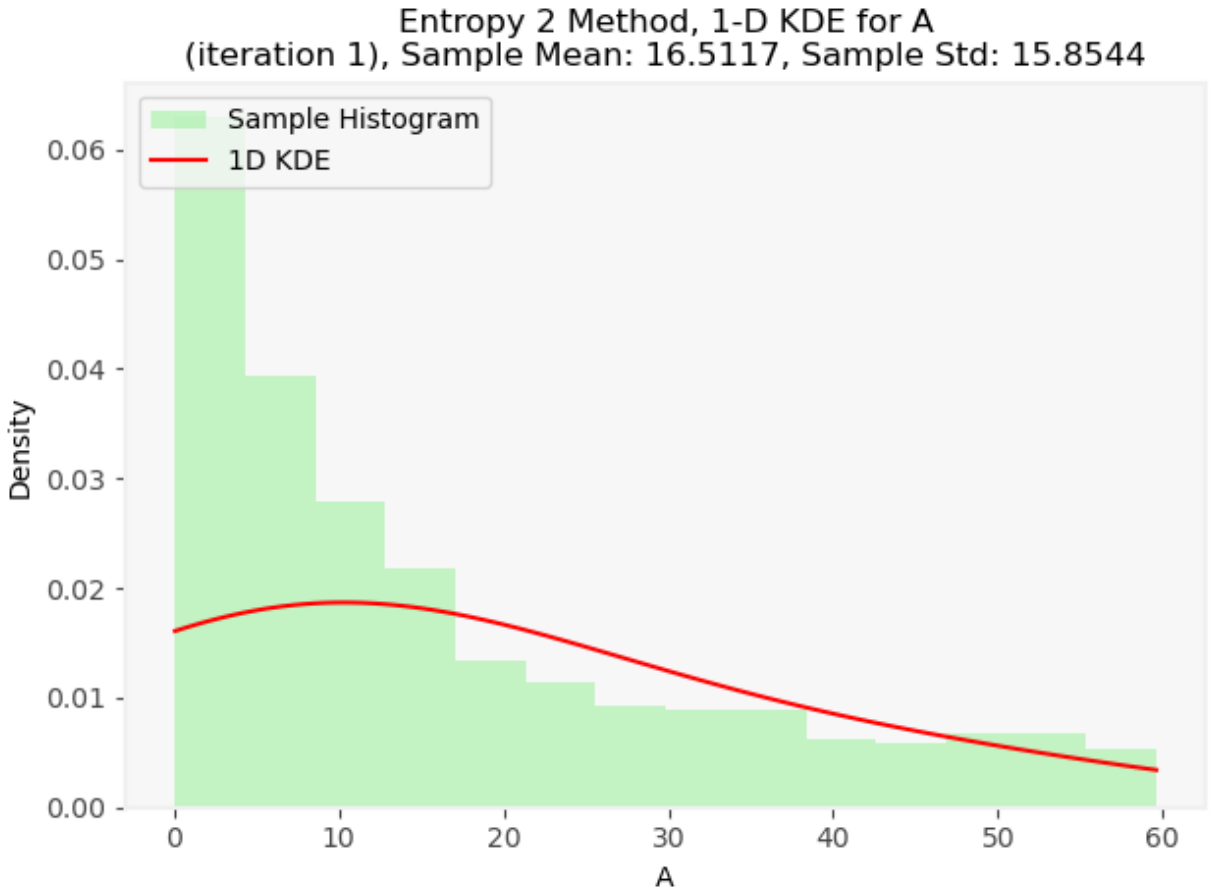

Entropy 1 Method, 1-D KDE for A
(iteration 31), Sample Mean: 2.9412, Sample Std: 0.2045
Sample Histogram
1D KDE
Density
A
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
2.4
2.6
2.8
3.0
3.2
3.4

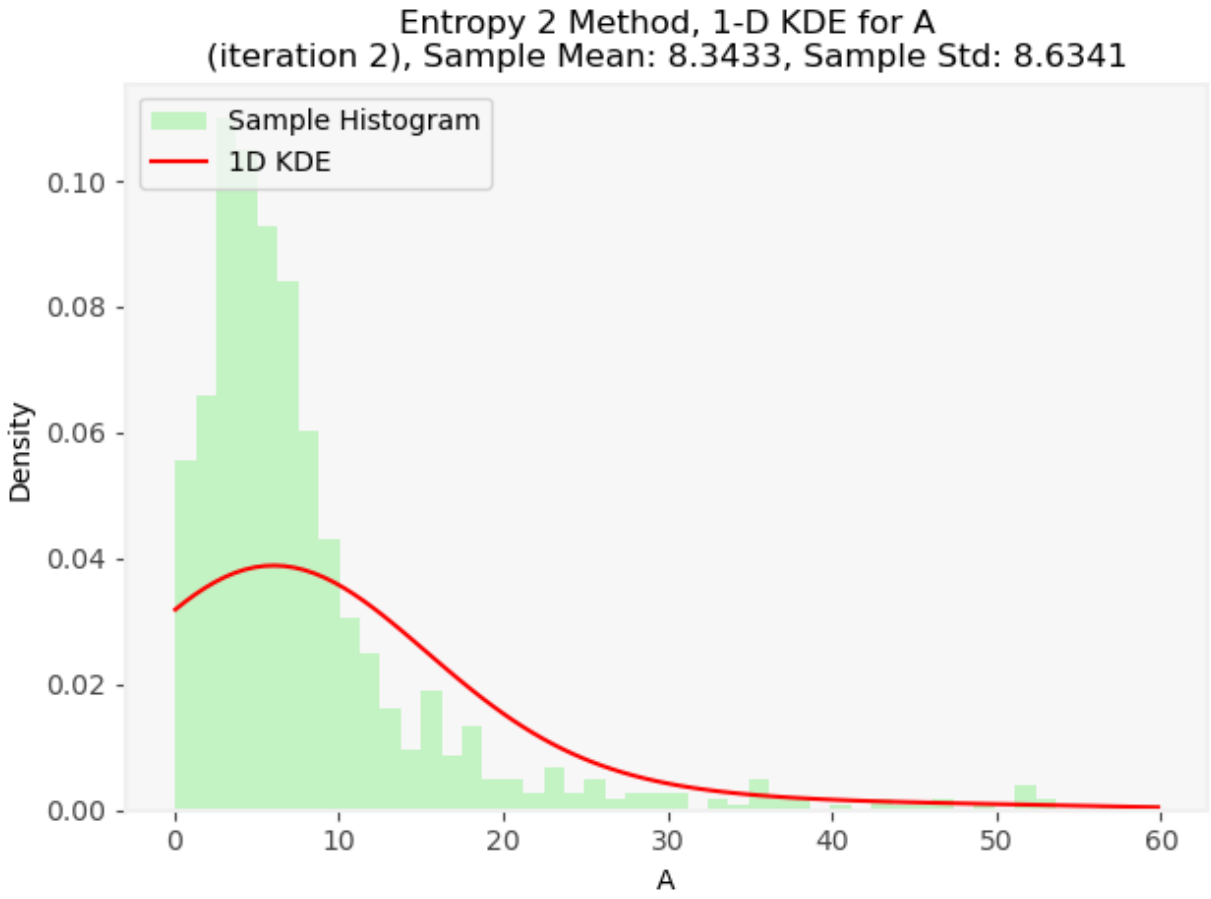

Entropy 1 Method, 1-D KDE for A
(iteration 32), Sample Mean: 3.0500, Sample Std: 0.1799
Sample Histogram
1D KDE
Density
A
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
2.6
2.8
3.0
3.2
3.4
3.6

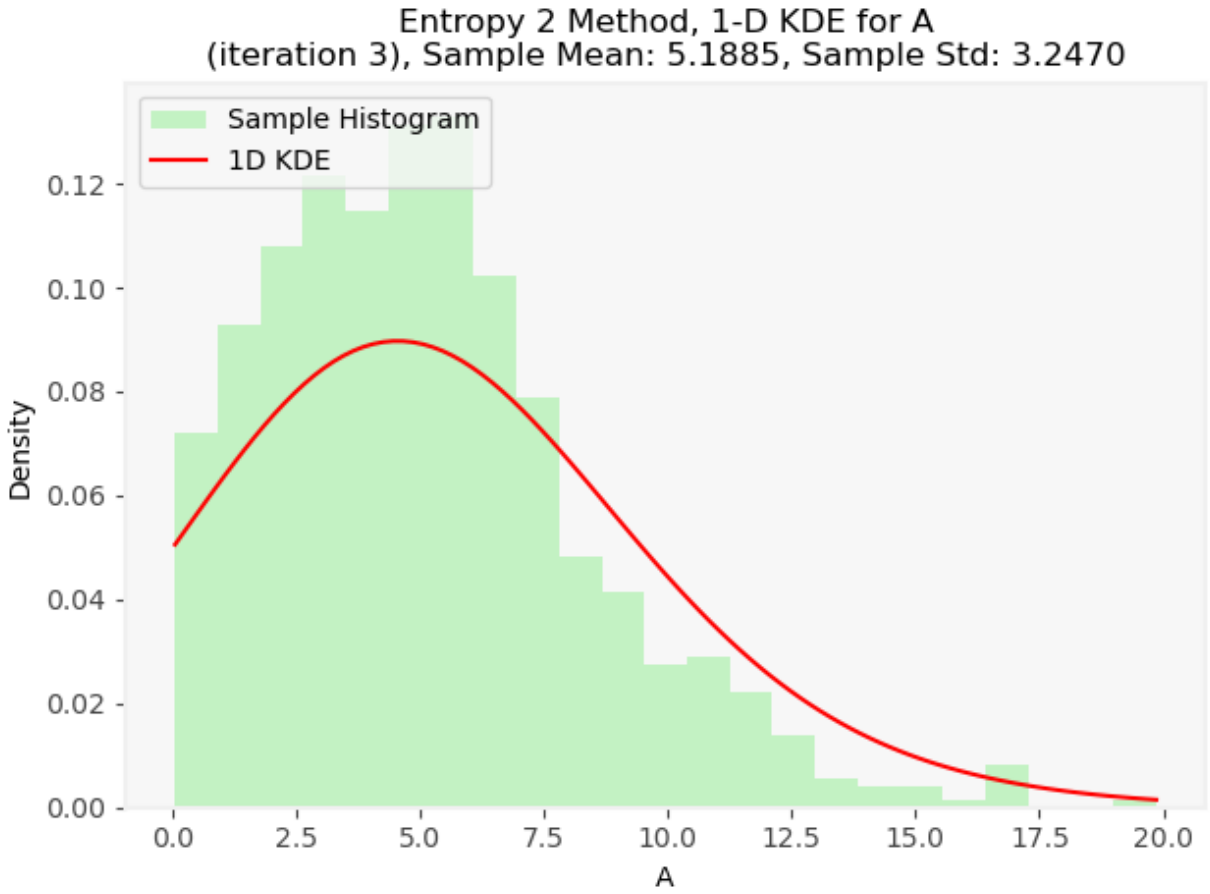
In [ ]:

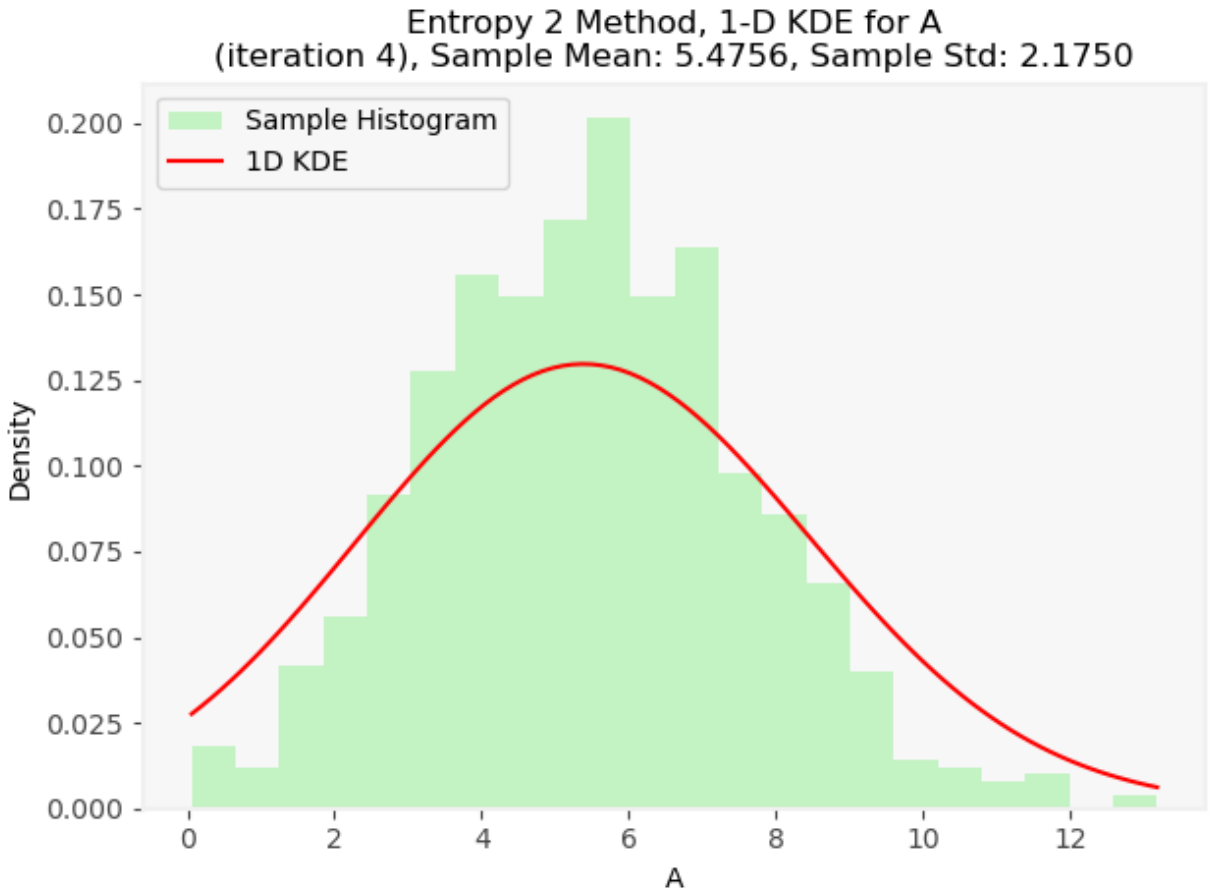
In [53]:
```
for i in range(len(exp_entropy2.totaltimes())):
    MyPlots.plot_hist_1d_kde(list_par_separated_e2[0][i], kdes_entropy2[i,0],"Entropy
```

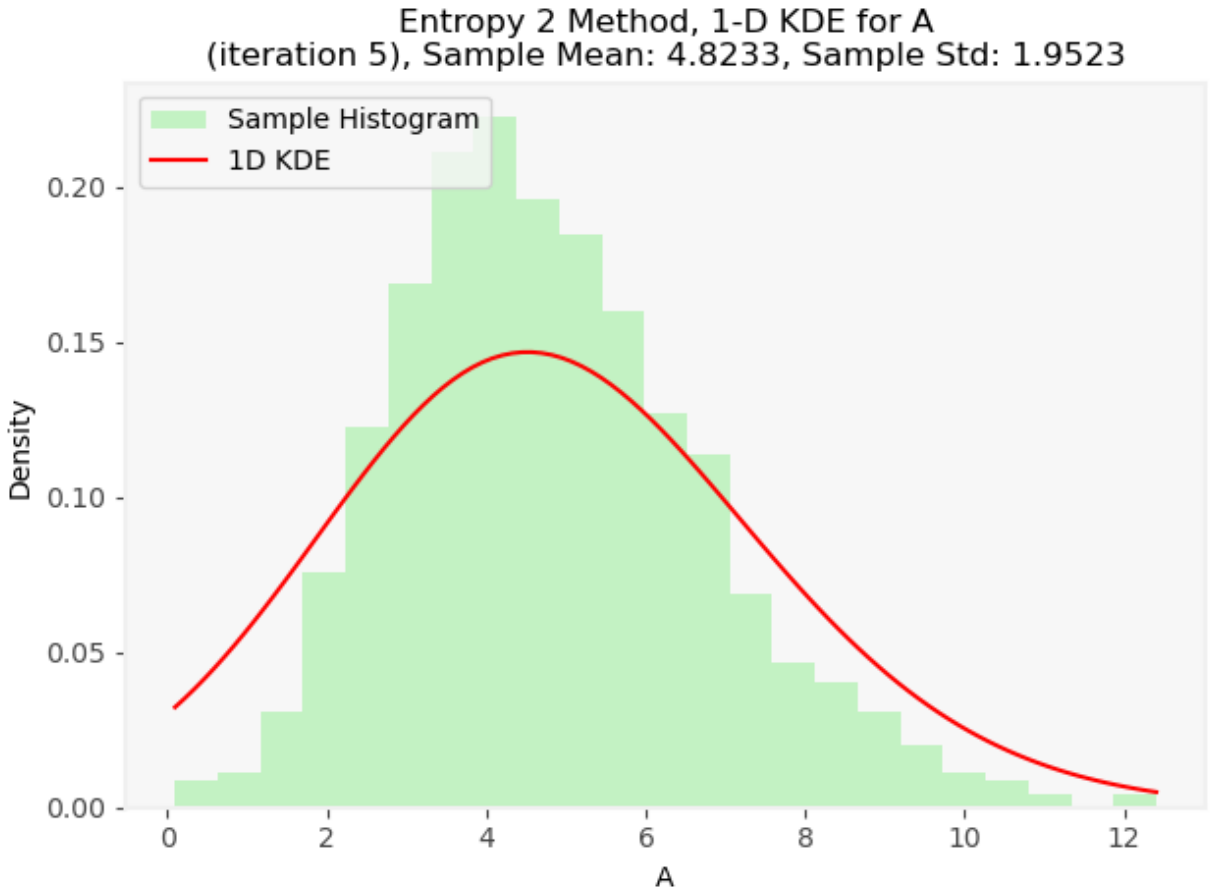


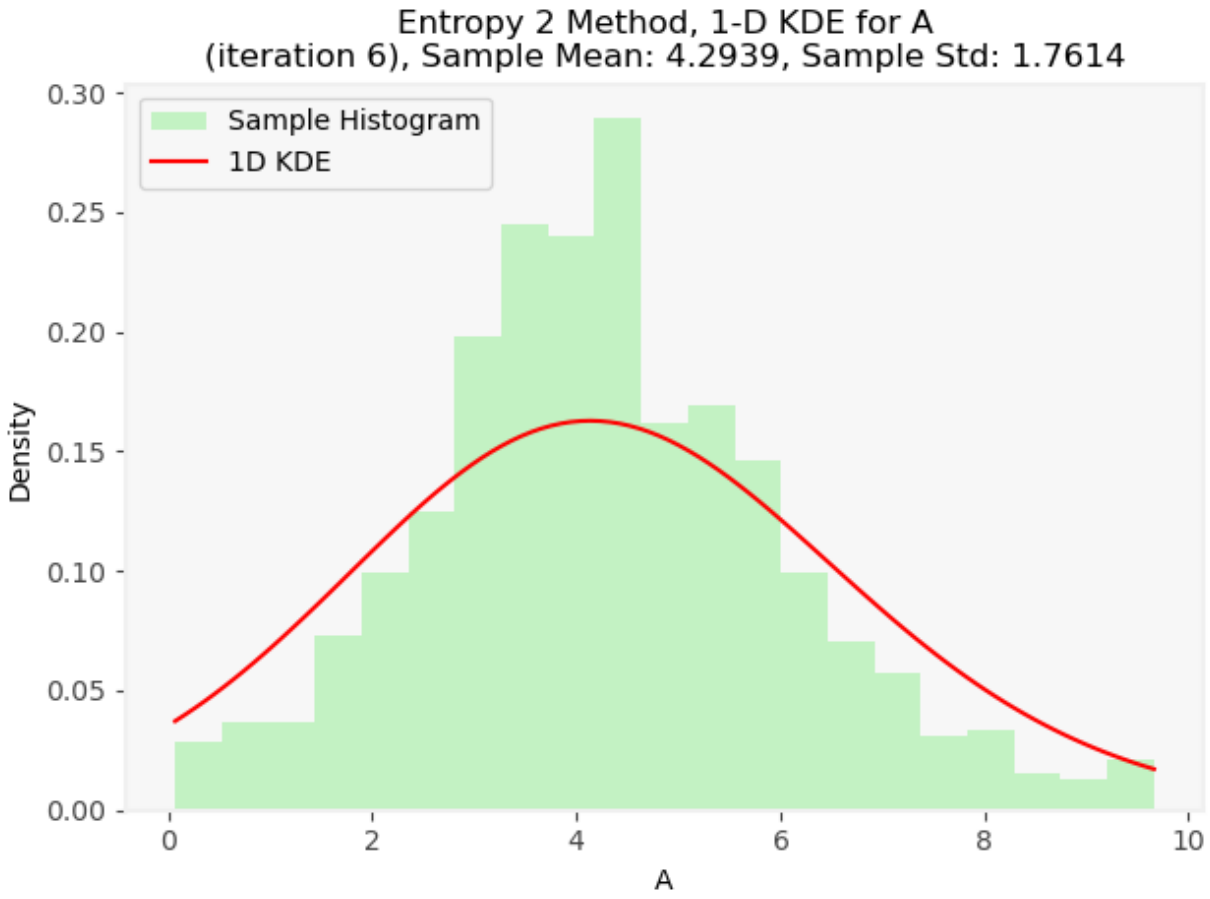

Entropy 2 Method, 1-D KDE for A
(iteration 1), Sample Mean: 16.5117, Sample Std: 15.8544
Sample Histogram
1D KDE
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0
10
20
30
40
50
60
A


Entropy 2 Method, 1-D KDE for A
(iteration 2), Sample Mean: 8.3433, Sample Std: 8.6341
Sample Histogram
1D KDE
Density
0.00
0.02
0.04
0.06
0.08
0.10
0
10
20
30
40
50
60
A


Entropy 2 Method, 1-D KDE for A
(iteration 3), Sample Mean: 5.1885, Sample Std: 3.2470
Sample Histogram
1D KDE
Density
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
A


Entropy 2 Method, 1-D KDE for A
(iteration 4), Sample Mean: 5.4756, Sample Std: 2.1750
Sample Histogram
1D KDE
Density
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
2
4
6
8
10
12
A


Entropy 2 Method, 1-D KDE for A
(iteration 5), Sample Mean: 4.8233, Sample Std: 1.9523
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0
2
4
6
8
10
12
A


Entropy 2 Method, 1-D KDE for A
(iteration 6), Sample Mean: 4.2939, Sample Std: 1.7614
Sample Histogram
1D KDE
Density
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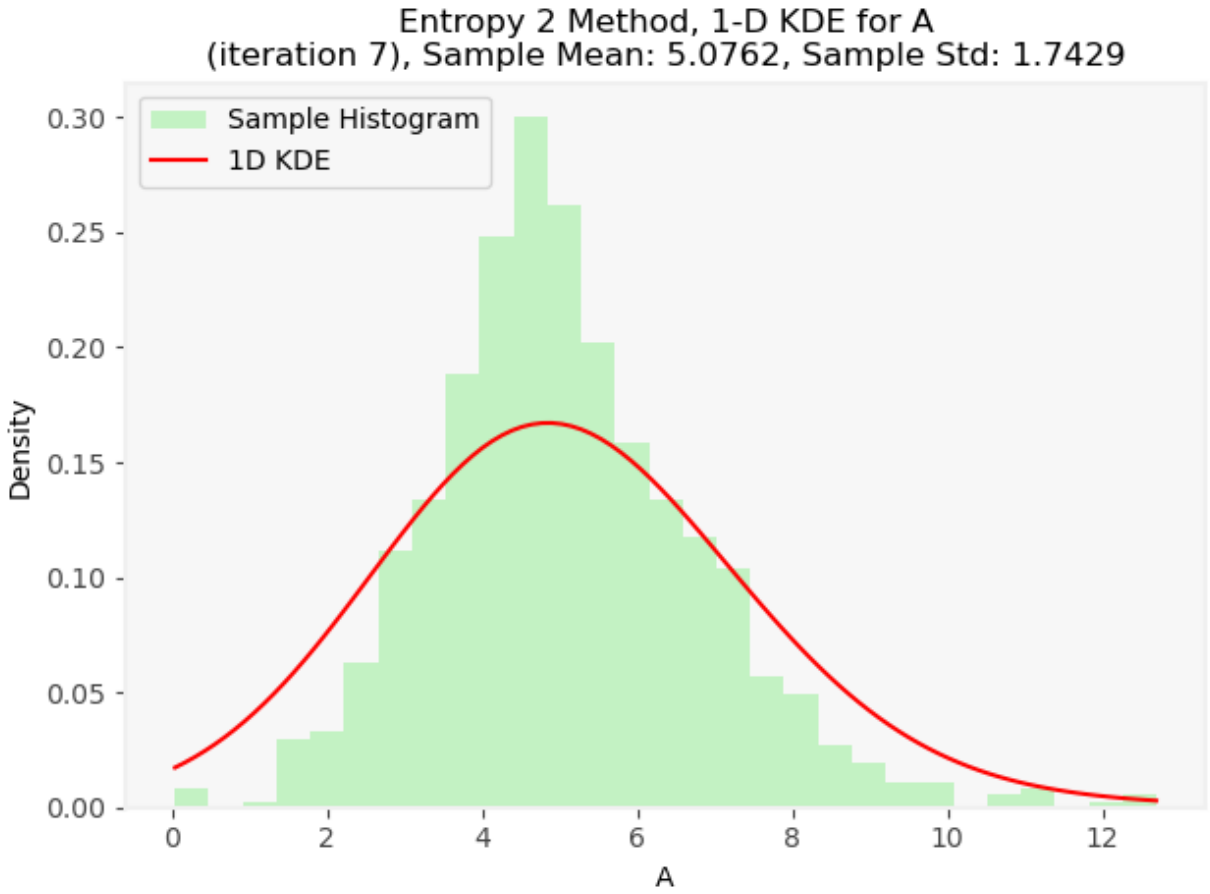
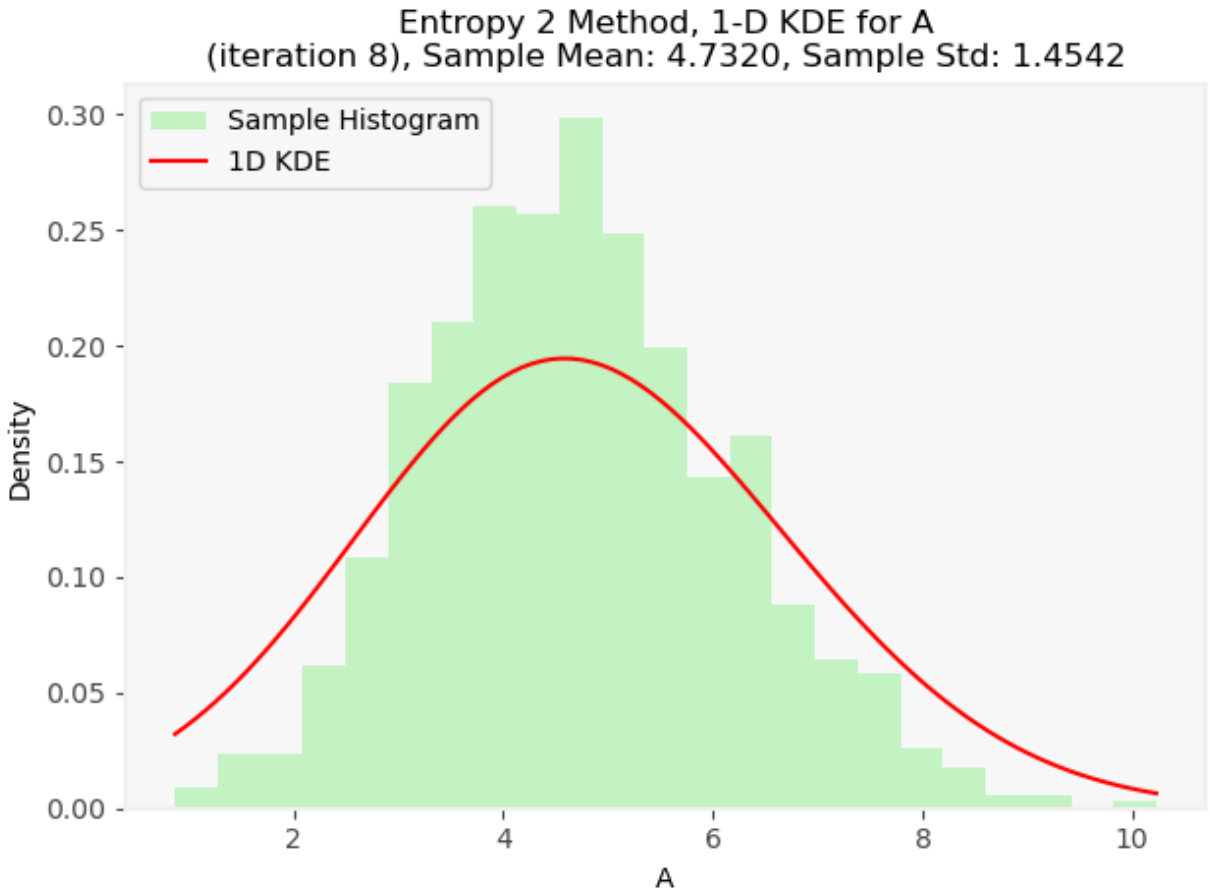
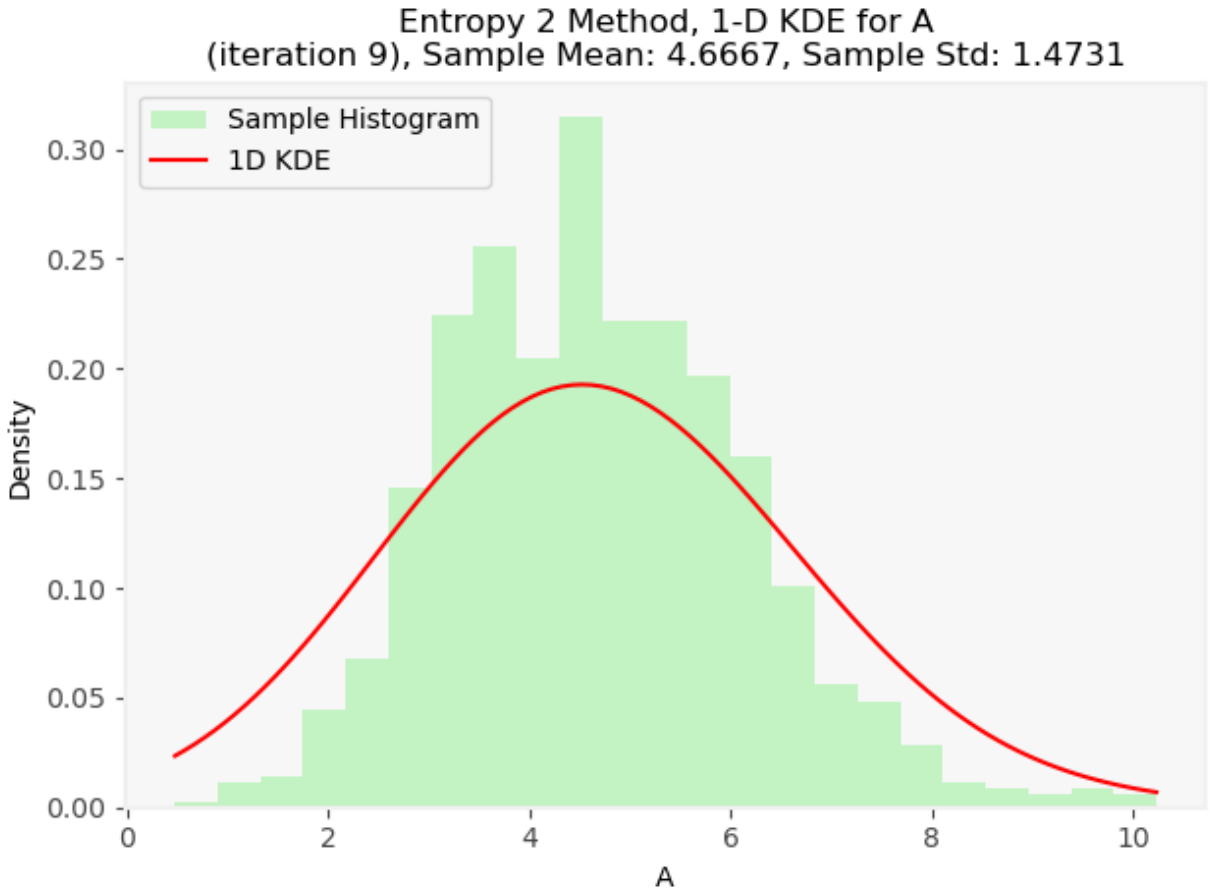
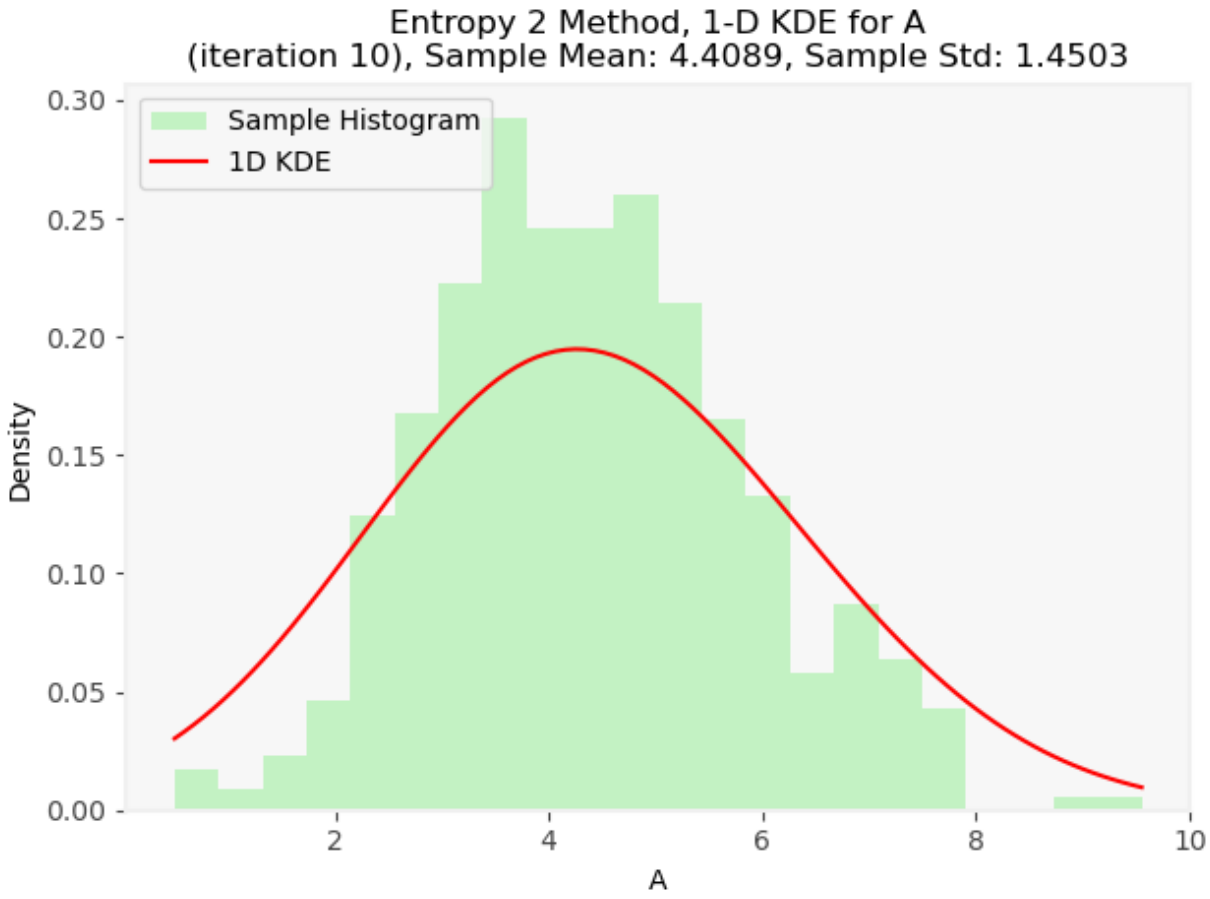
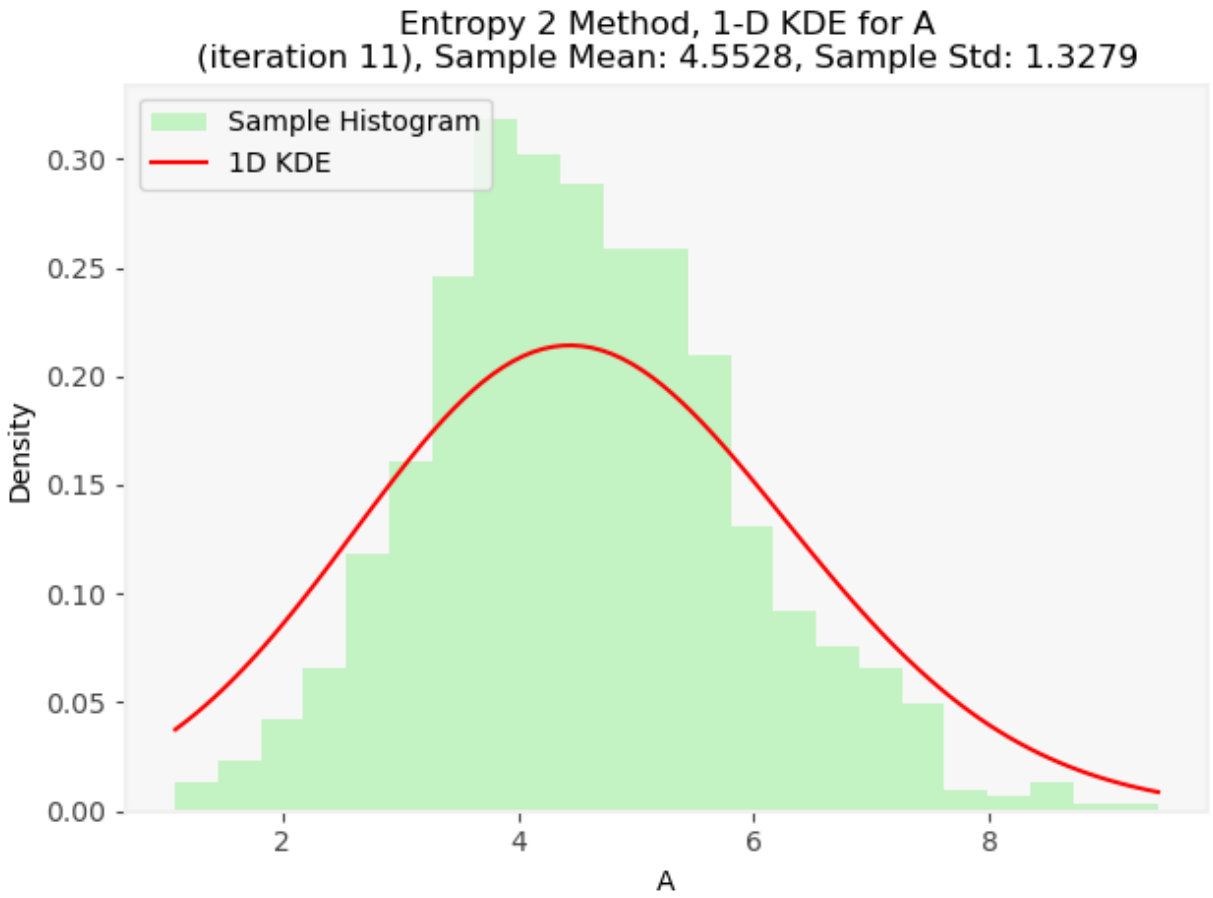
0.05
0.10
0.15
0.20
0.25
0.30
0
2
4
6
8
10
A

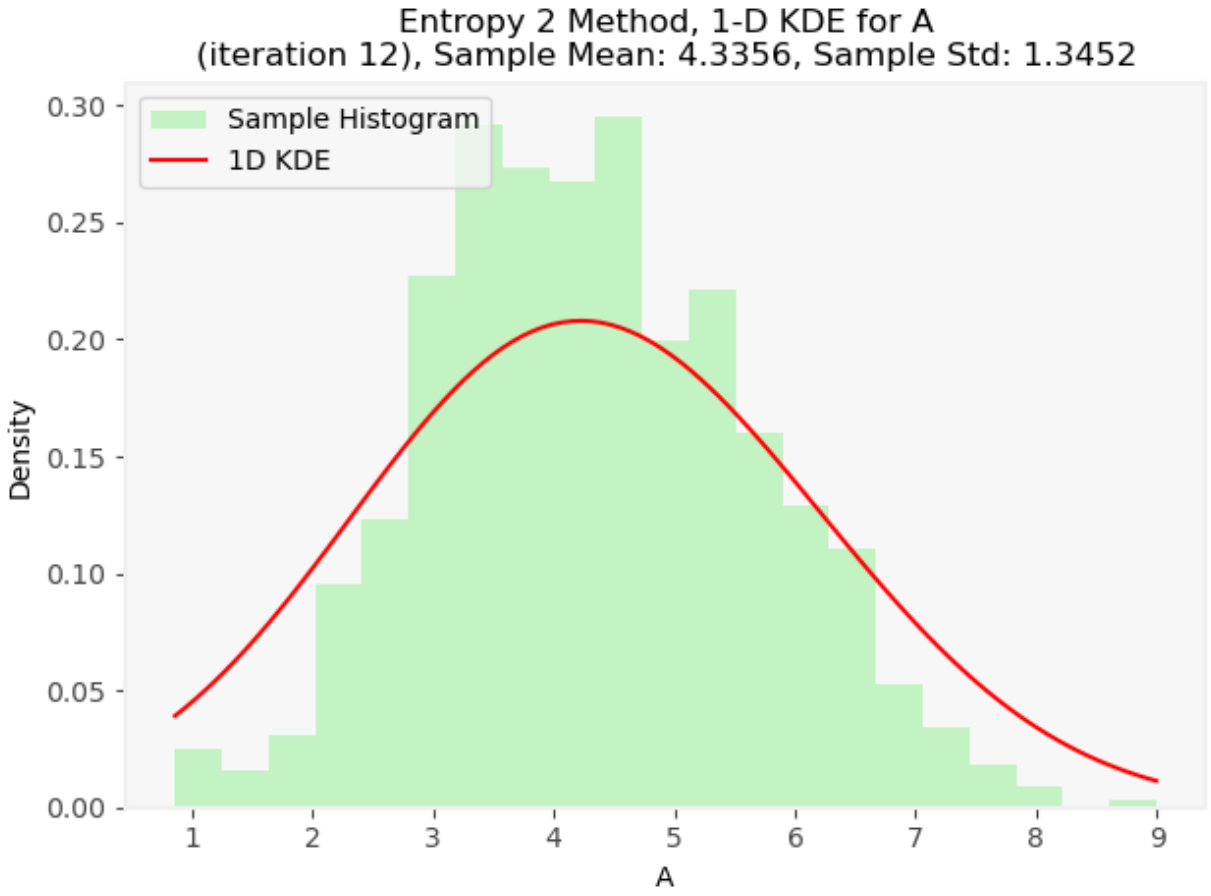

Entropy 2 Method, 1-D KDE for A
(iteration 7), Sample Mean: 5.0762, Sample Std: 1.7429
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
2
4
6
8
10
12

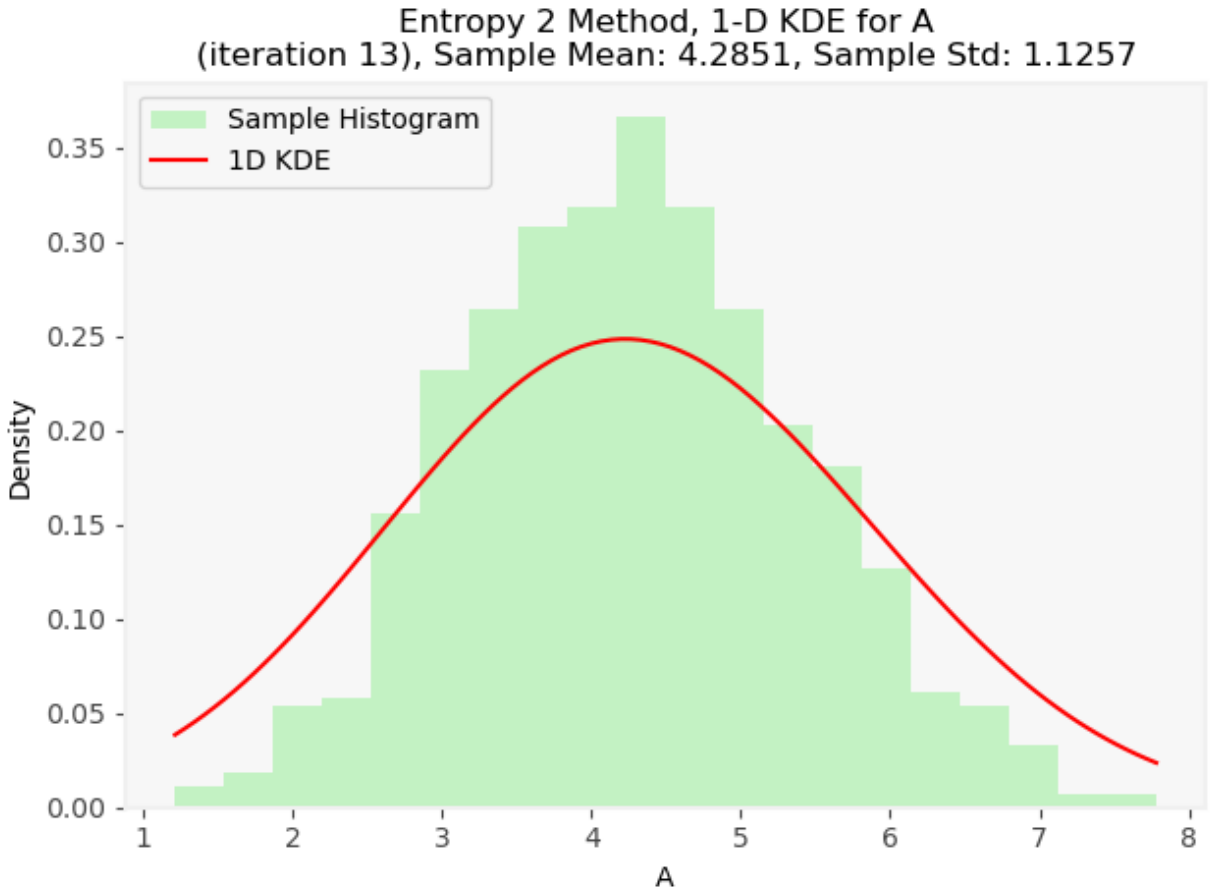

Entropy 2 Method, 1-D KDE for A
(iteration 8), Sample Mean: 4.7320, Sample Std: 1.4542
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
2
4
6
8
10

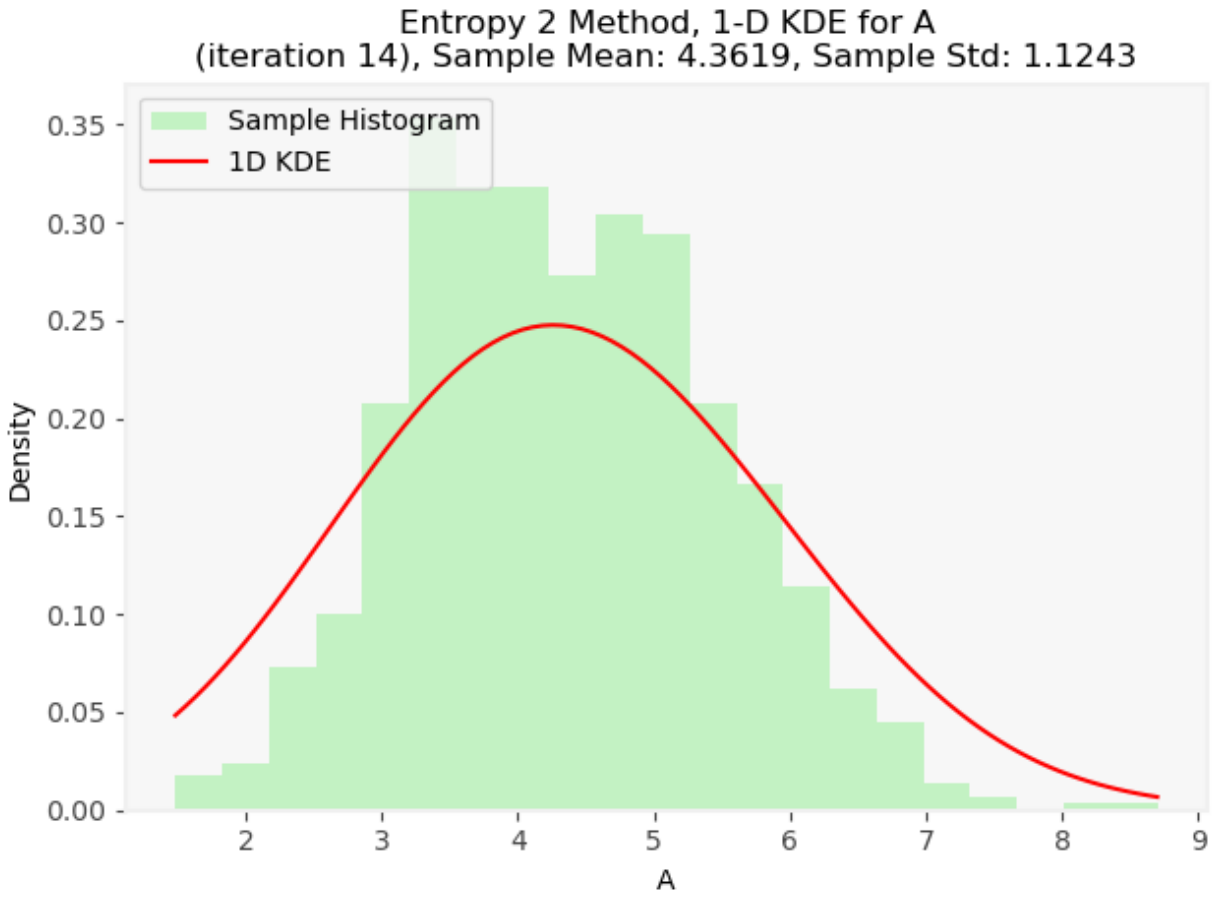

Entropy 2 Method, 1-D KDE for A
(iteration 9), Sample Mean: 4.6667, Sample Std: 1.4731
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
2
4
6
8
10
A

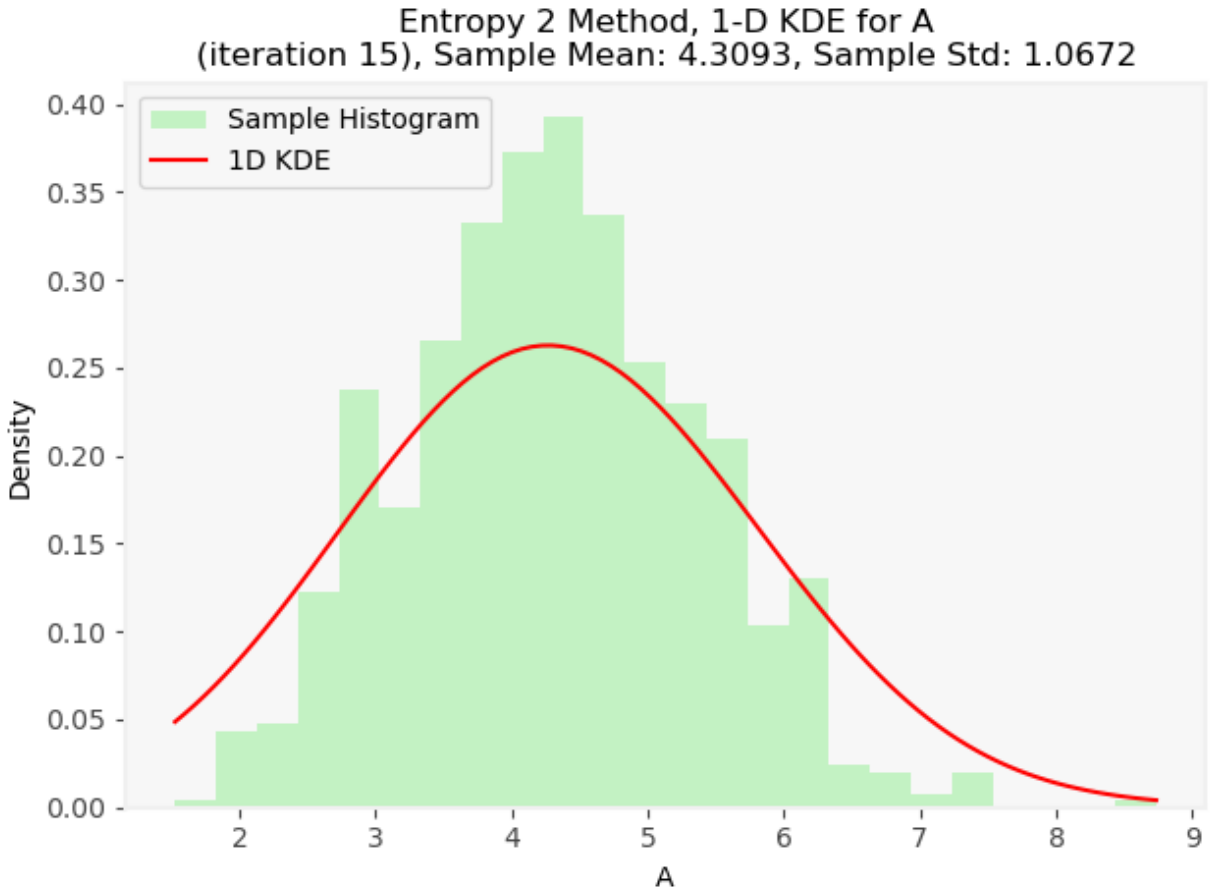

Entropy 2 Method, 1-D KDE for A
(iteration 10), Sample Mean: 4.4089, Sample Std: 1.4503
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
2
4
6
8
10
A

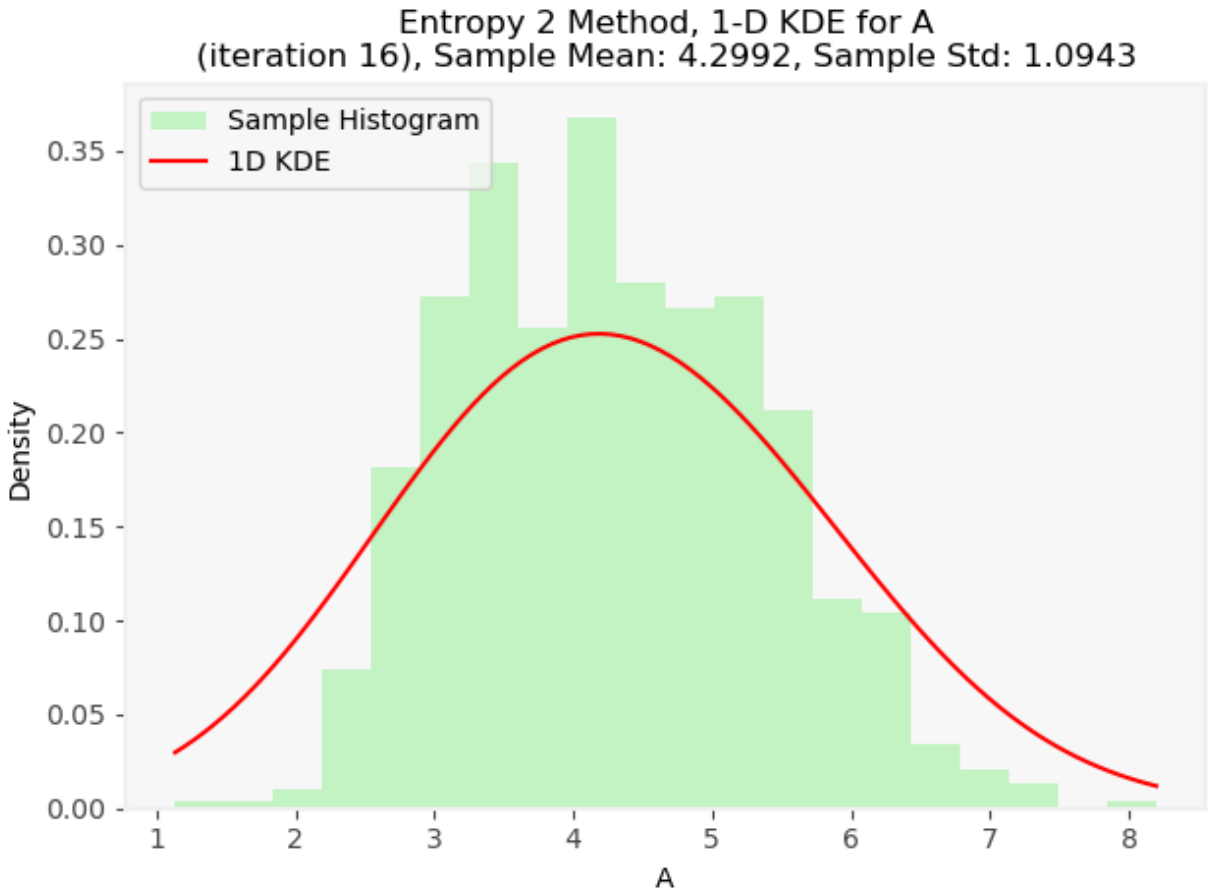

Entropy 2 Method, 1-D KDE for A
(iteration 11), Sample Mean: 4.5528, Sample Std: 1.3279
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
2
4
6
8
A

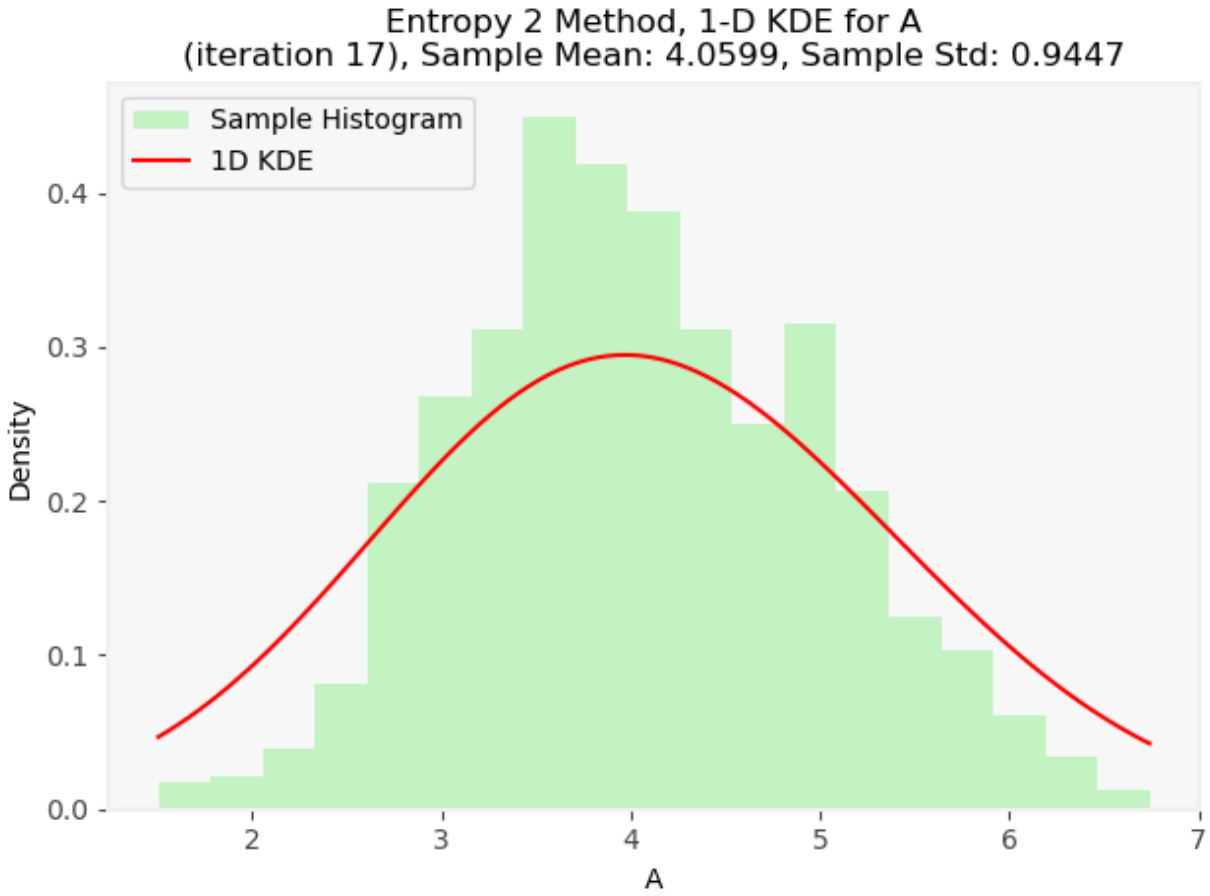

Entropy 2 Method, 1-D KDE for A
(iteration 12), Sample Mean: 4.3356, Sample Std: 1.3452
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
1
2
3
4
5
6
7
8
9
A

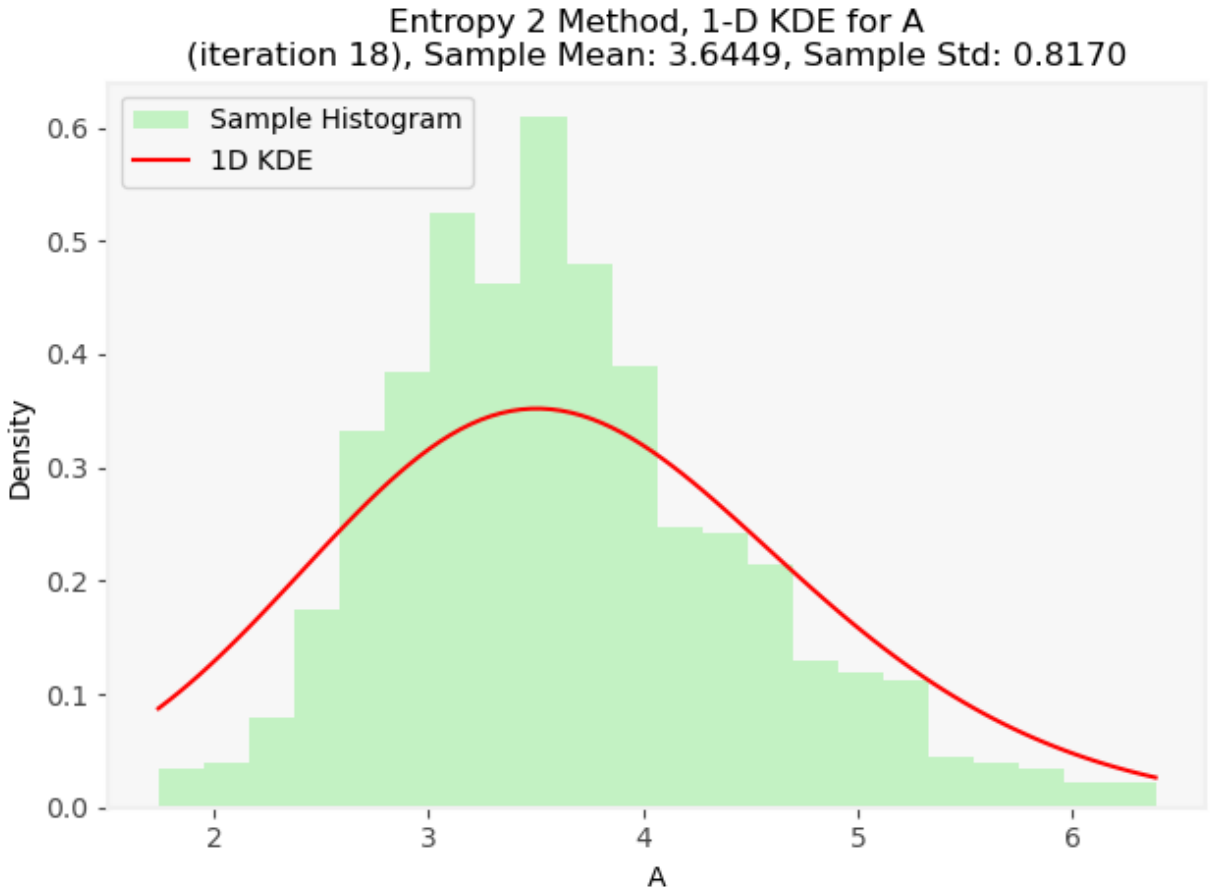

Entropy 2 Method, 1-D KDE for A
(iteration 13), Sample Mean: 4.2851, Sample Std: 1.1257
Sample Histogram
1D KDE
Density
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
1
2
3
4
5
6
7
8
A

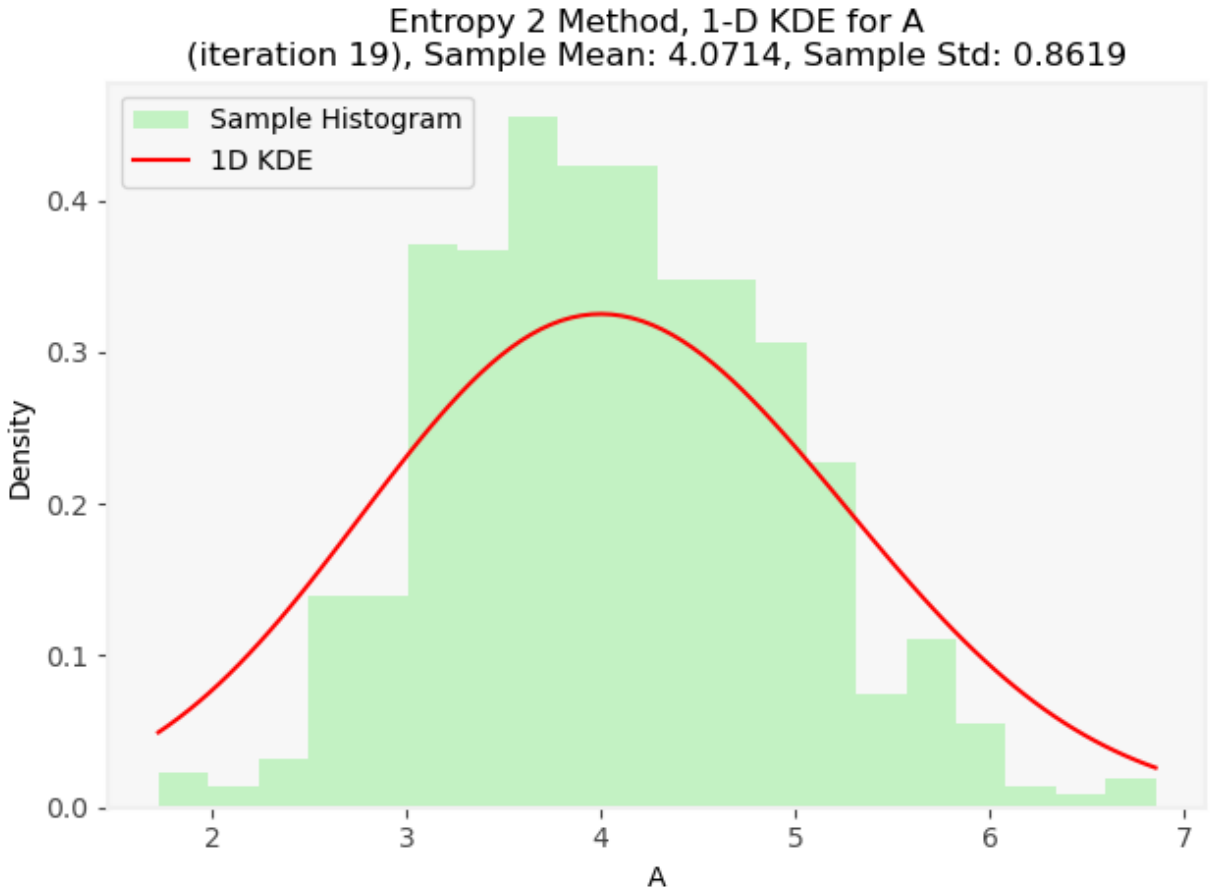

Entropy 2 Method, 1-D KDE for A
(iteration 14), Sample Mean: 4.3619, Sample Std: 1.1243
Sample Histogram
1D KDE
Density
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
2
3
4
5
6
7
8
9
A

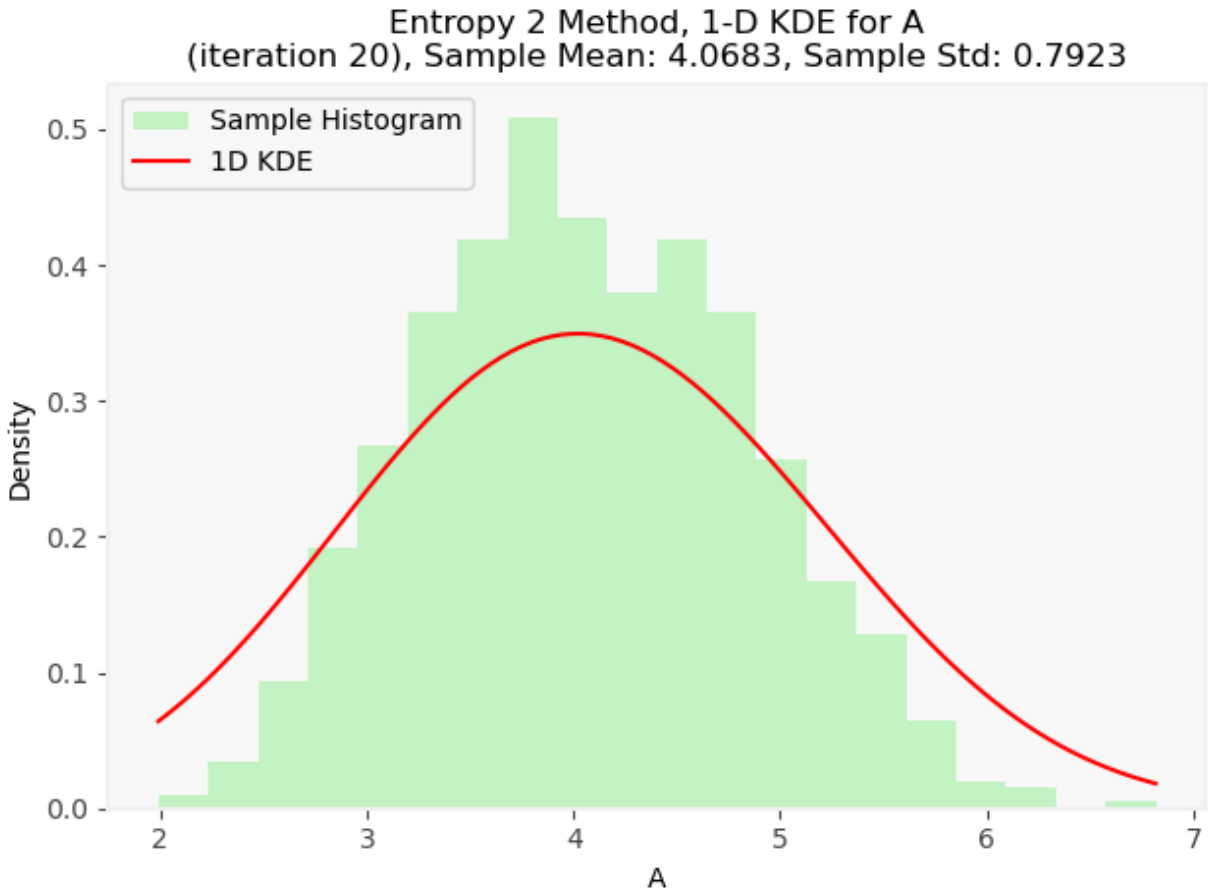

Entropy 2 Method, 1-D KDE for A
(iteration 15), Sample Mean: 4.3093, Sample Std: 1.0672
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
2
3
4
5
6
7
8
9

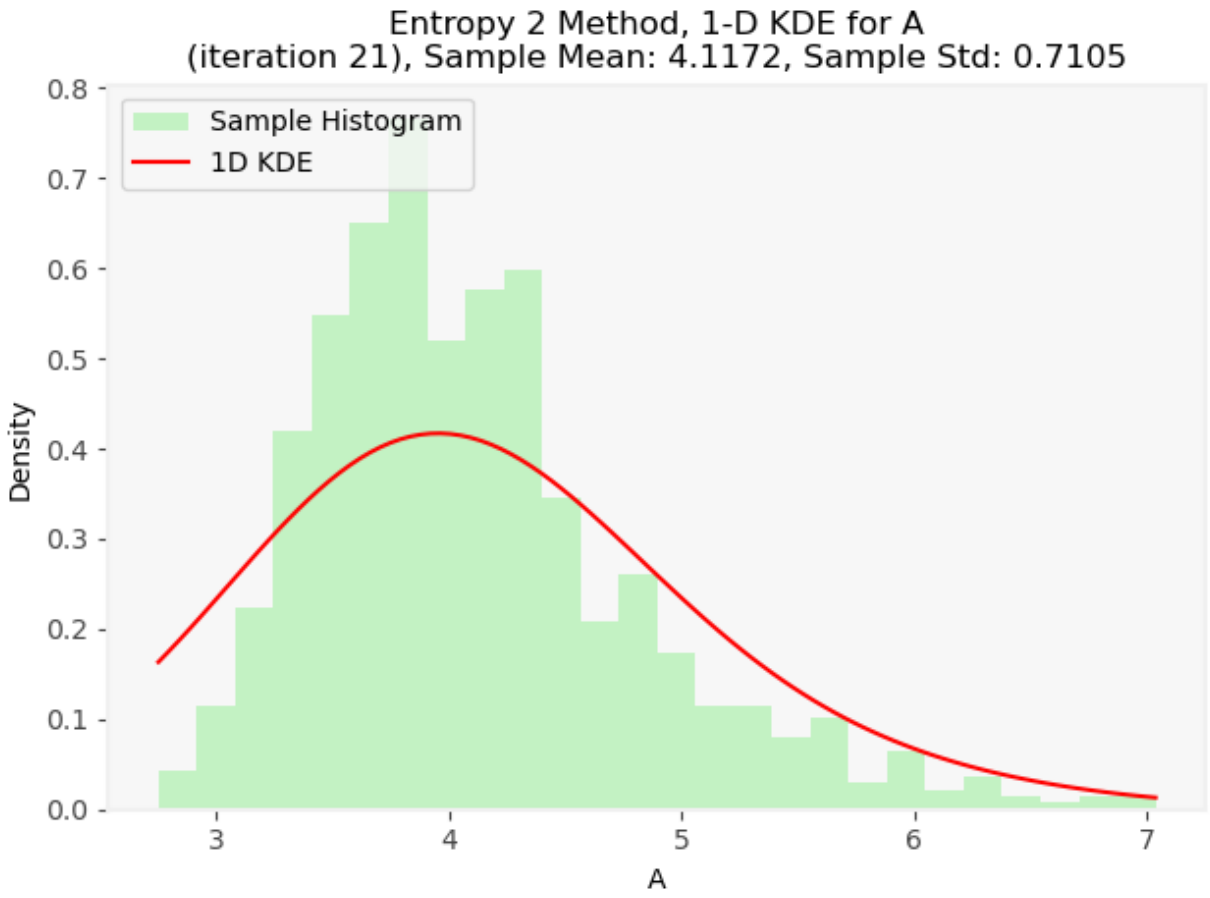

Entropy 2 Method, 1-D KDE for A
(iteration 16), Sample Mean: 4.2992, Sample Std: 1.0943
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
1
2
3
4
5
6
7
8

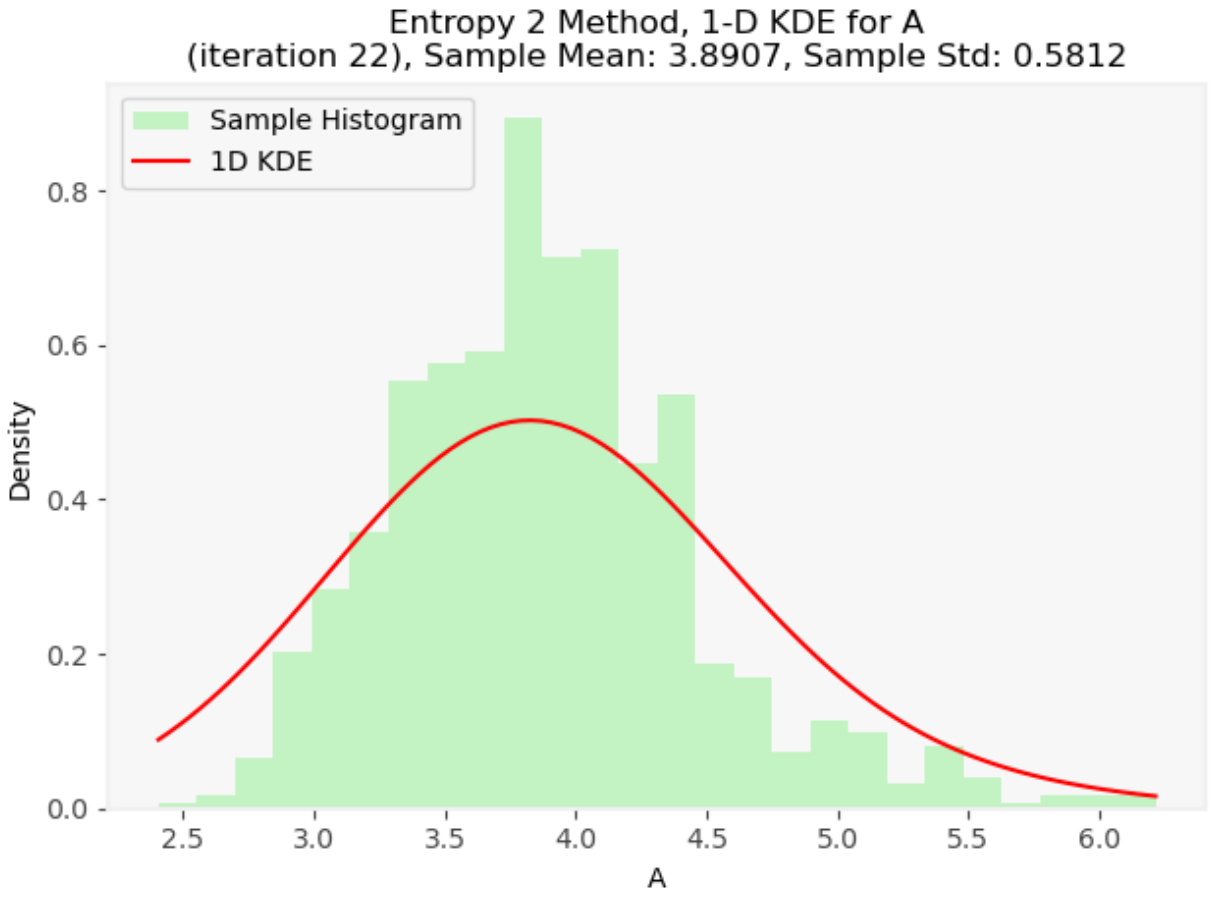

Entropy 2 Method, 1-D KDE for A
(iteration 17), Sample Mean: 4.0599, Sample Std: 0.9447
Sample Histogram
1D KDE
Density
0.0
0.1
0.2
0.3
0.4
2
3
4
5
6
7
A

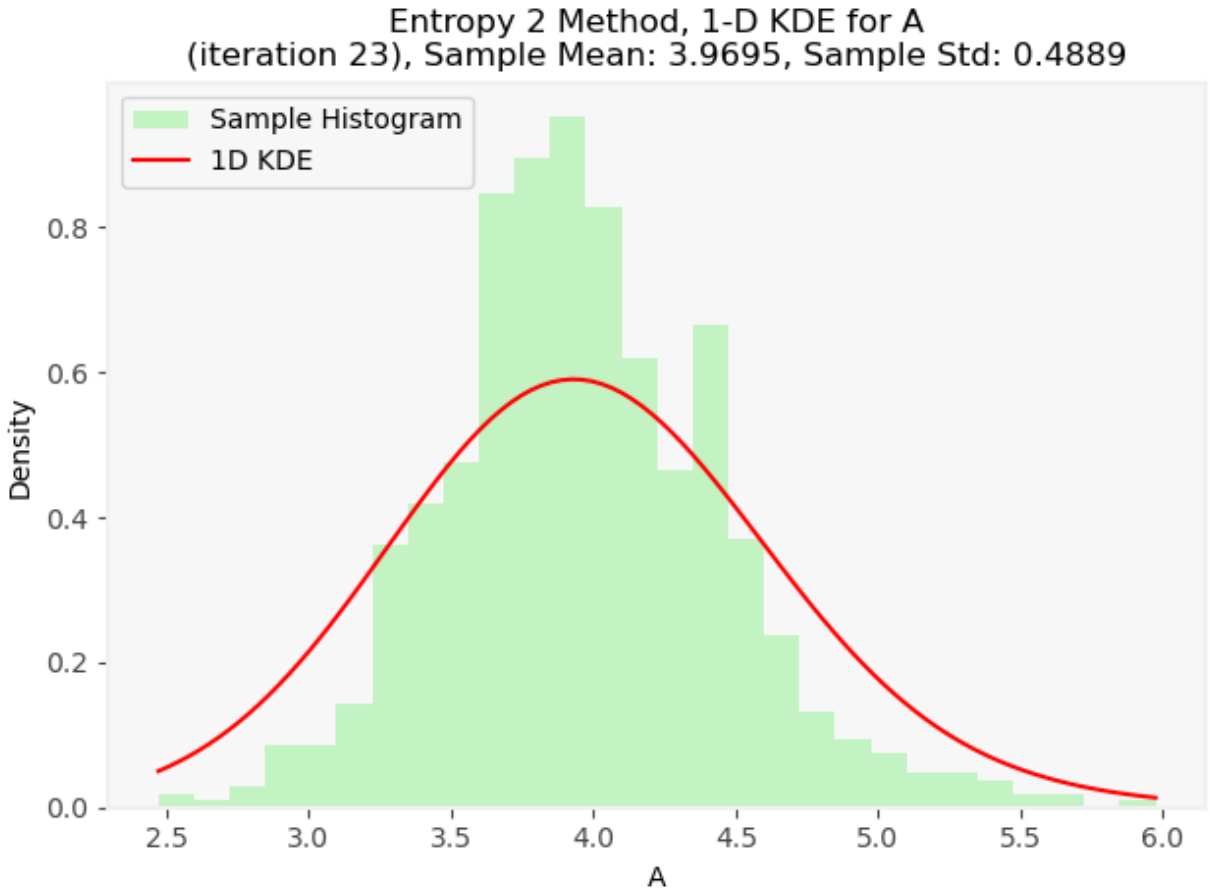

Entropy 2 Method, 1-D KDE for A
(iteration 18), Sample Mean: 3.6449, Sample Std: 0.8170
Sample Histogram
1D KDE
Density
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2
3
4
5
6
A

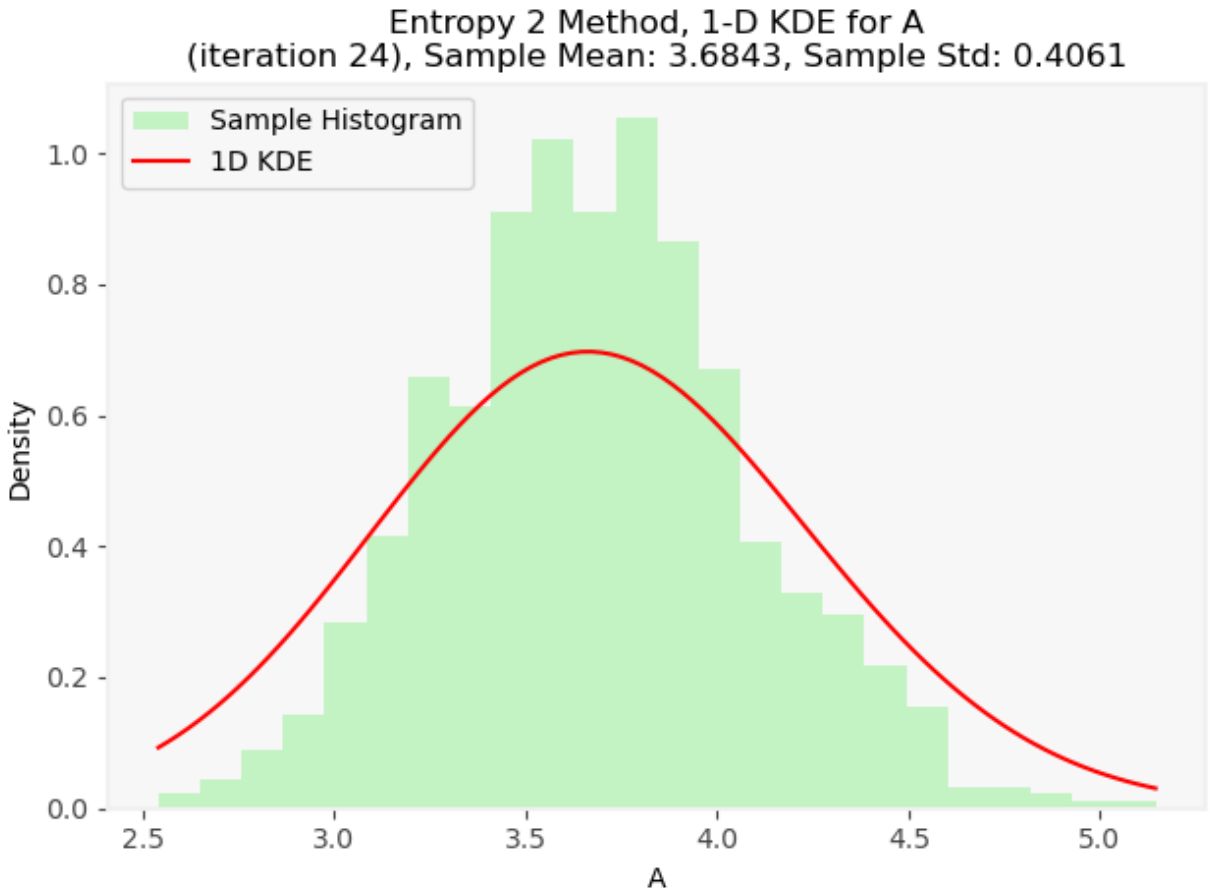

Entropy 2 Method, 1-D KDE for A
(iteration 19), Sample Mean: 4.0714, Sample Std: 0.8619
Sample Histogram
1D KDE
Density
0.0
0.1
0.2
0.3
0.4
2
3
4
5
6
7
A

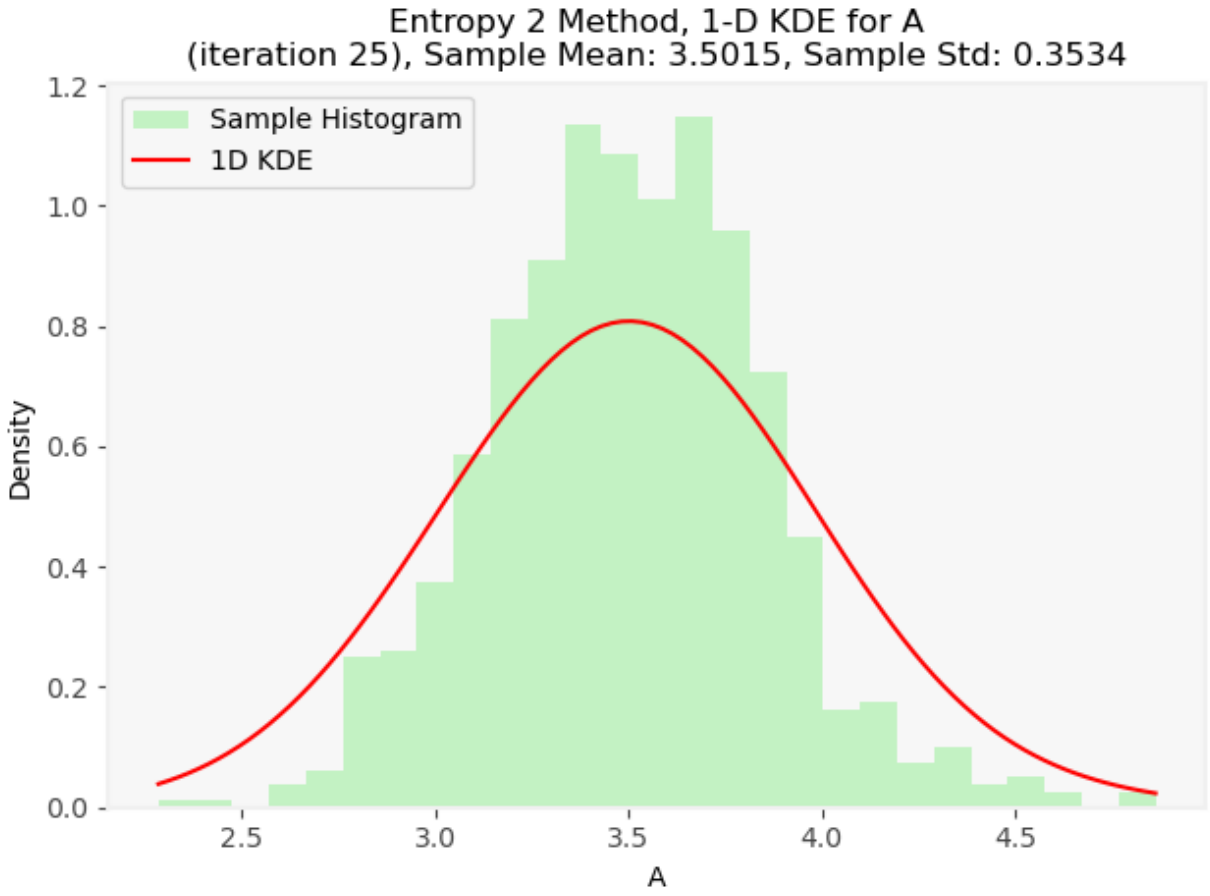

Entropy 2 Method, 1-D KDE for A
(iteration 20), Sample Mean: 4.0683, Sample Std: 0.7923
Sample Histogram
1D KDE
Density
0.0
0.1
0.2
0.3
0.4
0.5
2
3
4
5
6
7
A

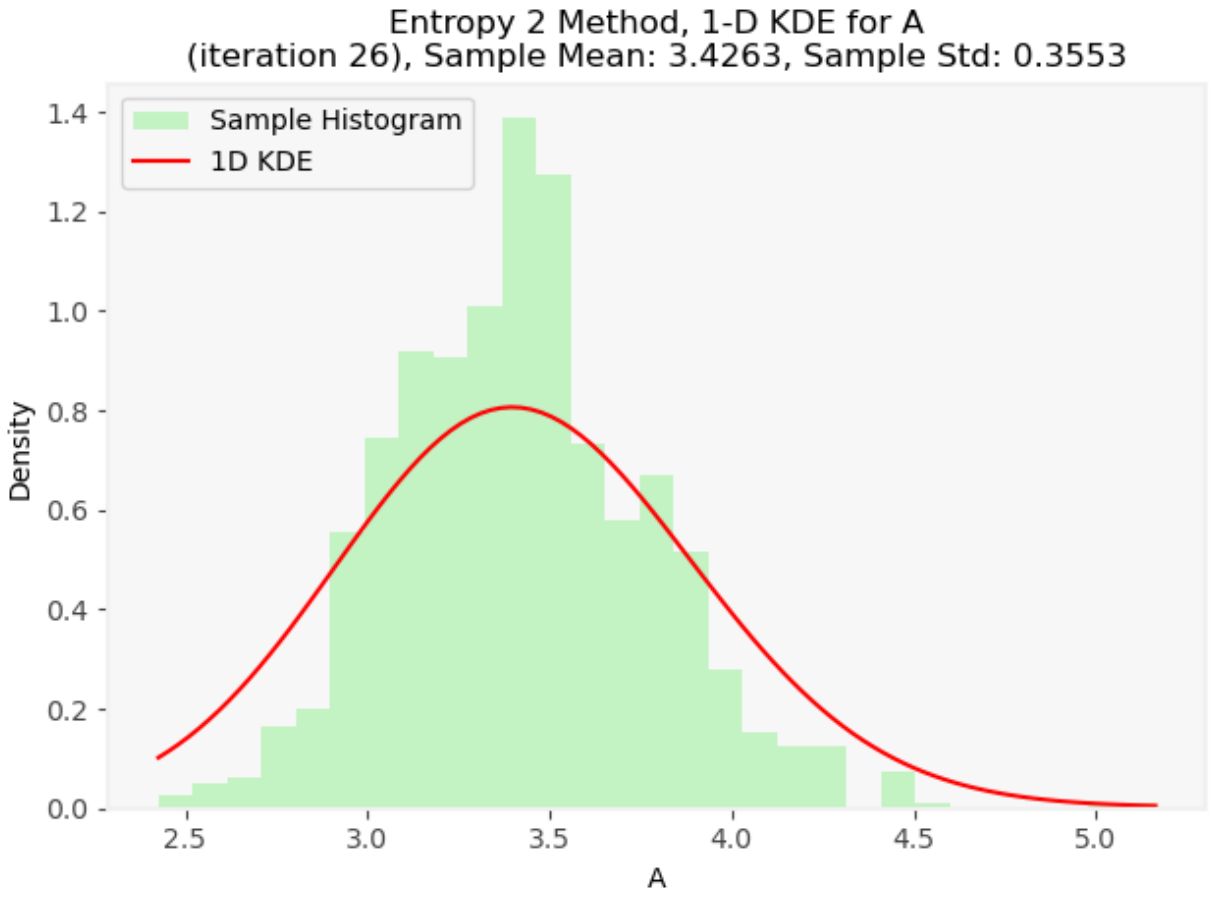

Entropy 2 Method, 1-D KDE for A
(iteration 21), Sample Mean: 4.1172, Sample Std: 0.7105
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
3
4
5
6
7

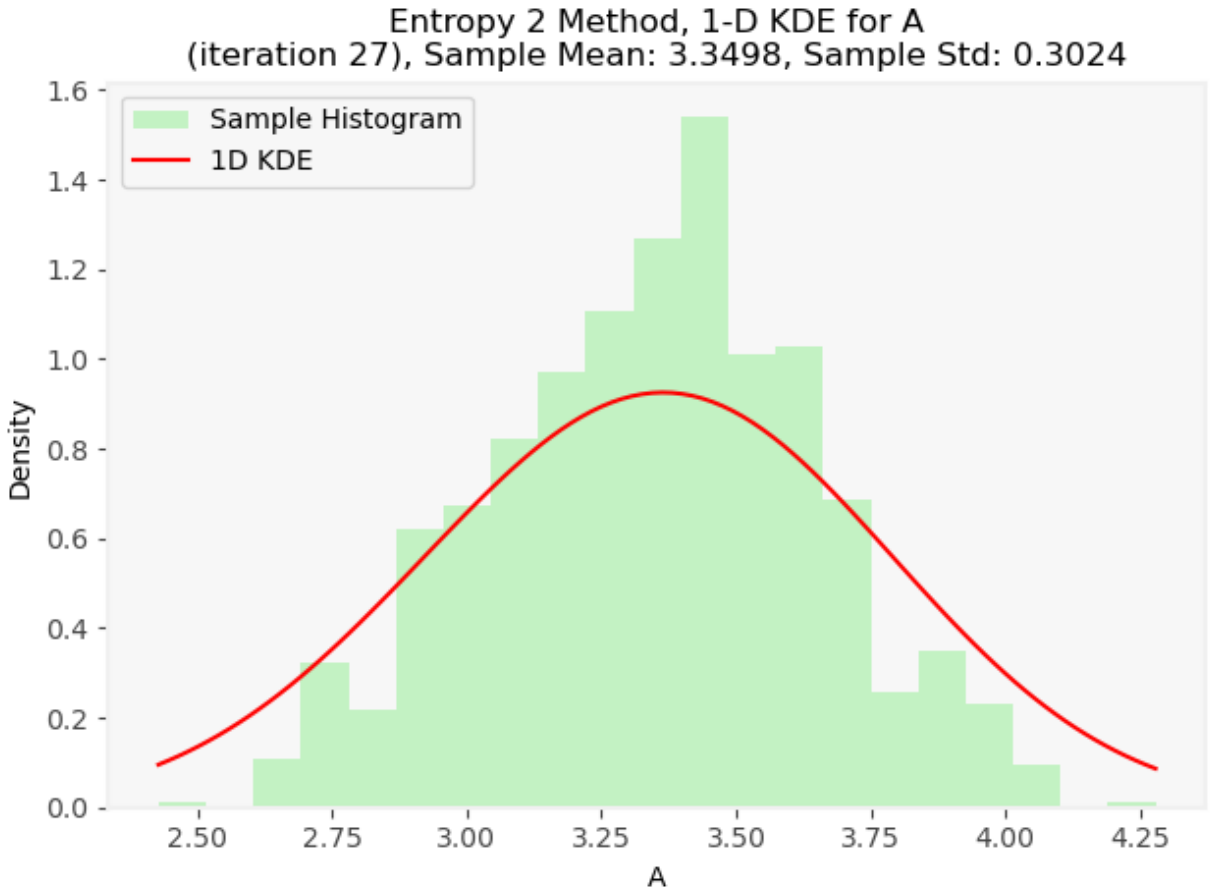

Entropy 2 Method, 1-D KDE for A
(iteration 22), Sample Mean: 3.8907, Sample Std: 0.5812
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
2.5
3.0
3.5
4.0
4.5
5.0
5.5
6.0

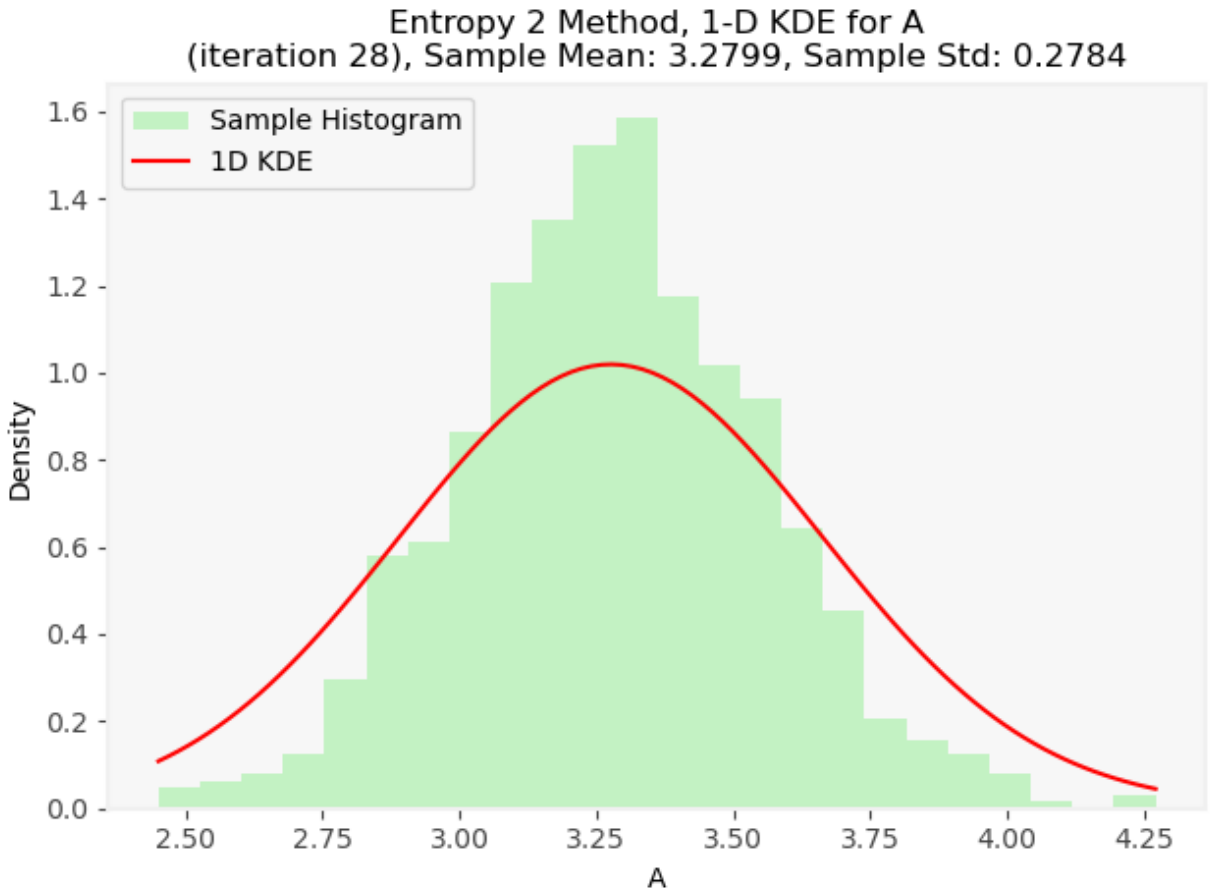

Entropy 2 Method, 1-D KDE for A
(iteration 23), Sample Mean: 3.9695, Sample Std: 0.4889
Sample Histogram
1D KDE
Density
0.0
0.2
0.4
0.6
0.8
2.5
3.0
3.5
4.0
4.5
5.0
5.5
6.0
A

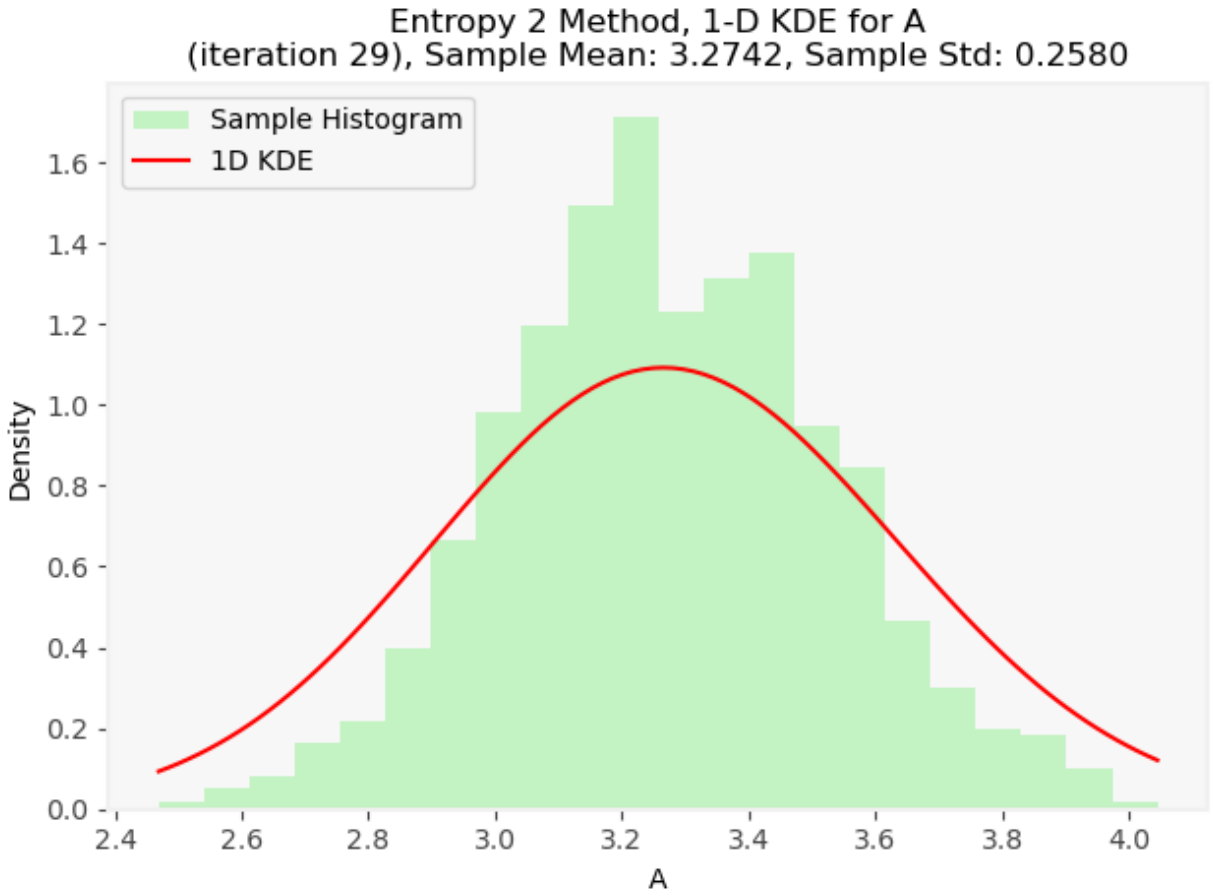

Entropy 2 Method, 1-D KDE for A
(iteration 24), Sample Mean: 3.6843, Sample Std: 0.4061
Sample Histogram
1D KDE
Density
0.0
0.2
0.4
0.6
0.8
1.0
2.5
3.0
3.5
4.0
4.5
5.0
A

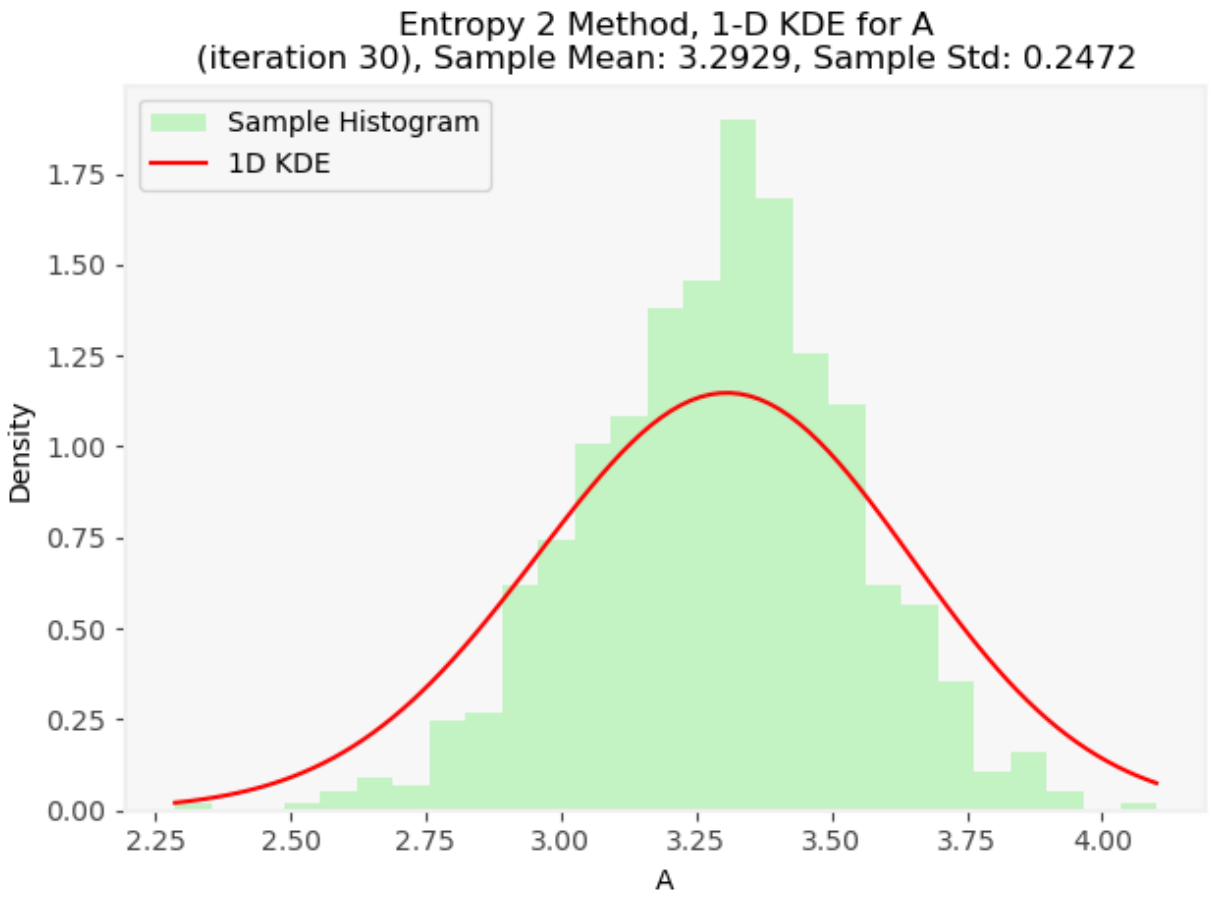

Entropy 2 Method, 1-D KDE for A
(iteration 25), Sample Mean: 3.5015, Sample Std: 0.3534
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0
4.5

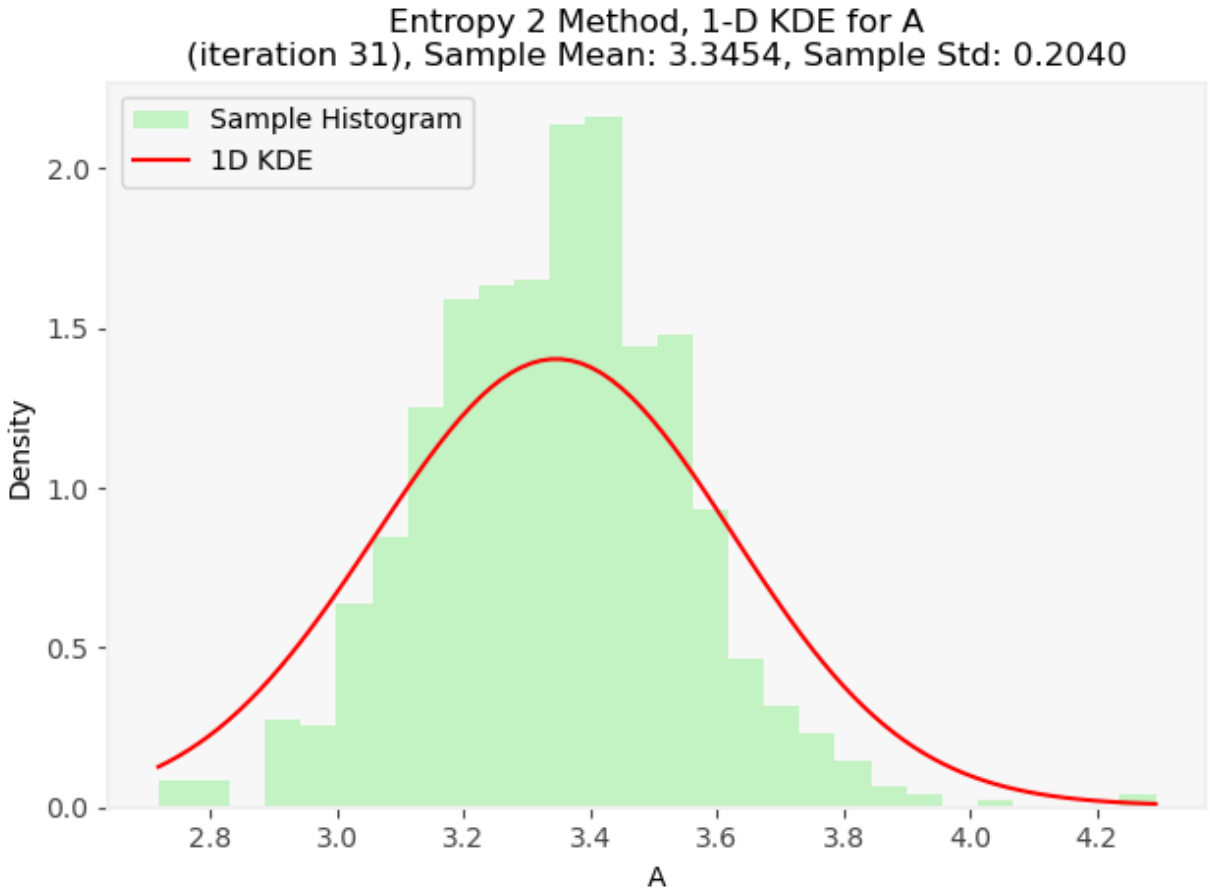

Entropy 2 Method, 1-D KDE for A
(iteration 26), Sample Mean: 3.4263, Sample Std: 0.3553
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.5
3.0
3.5
4.0
4.5
5.0

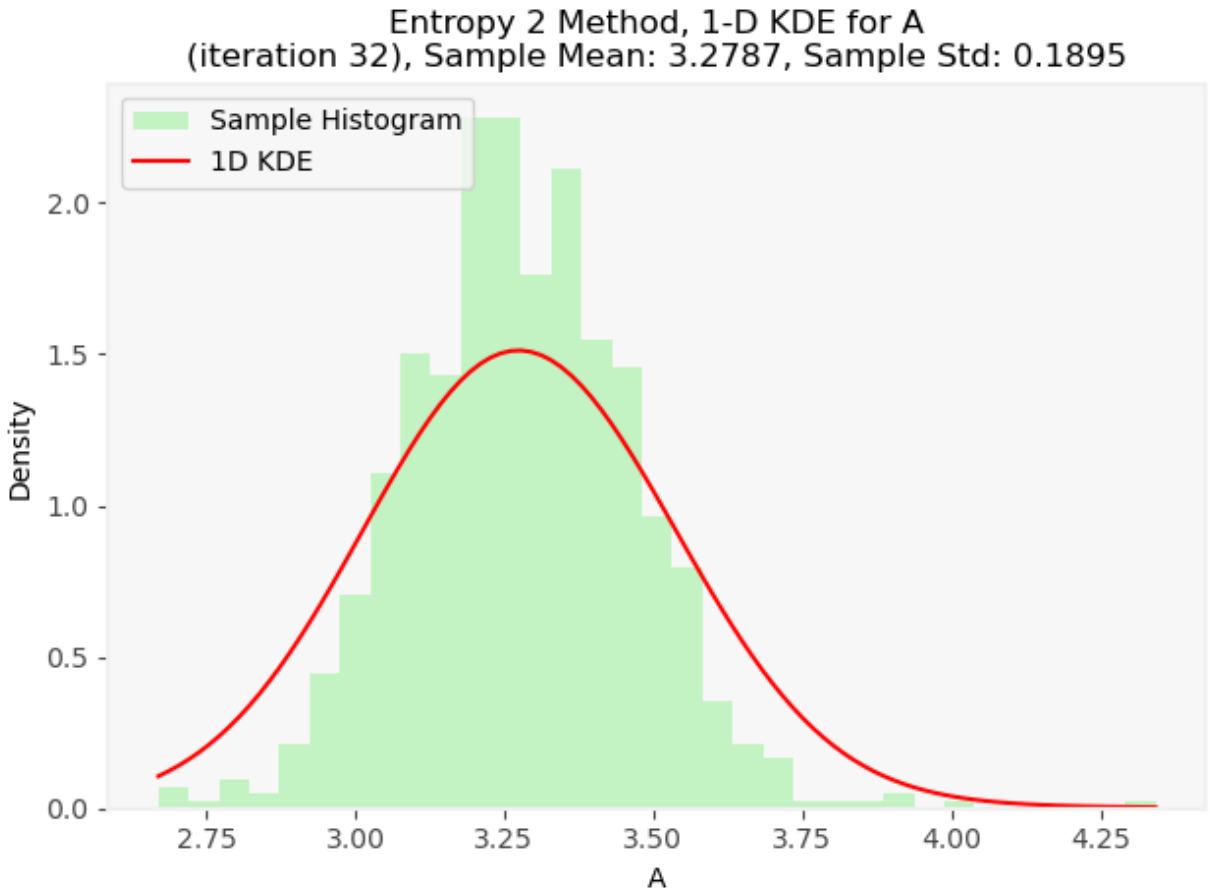

Entropy 2 Method, 1-D KDE for A
(iteration 27), Sample Mean: 3.3498, Sample Std: 0.3024
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25

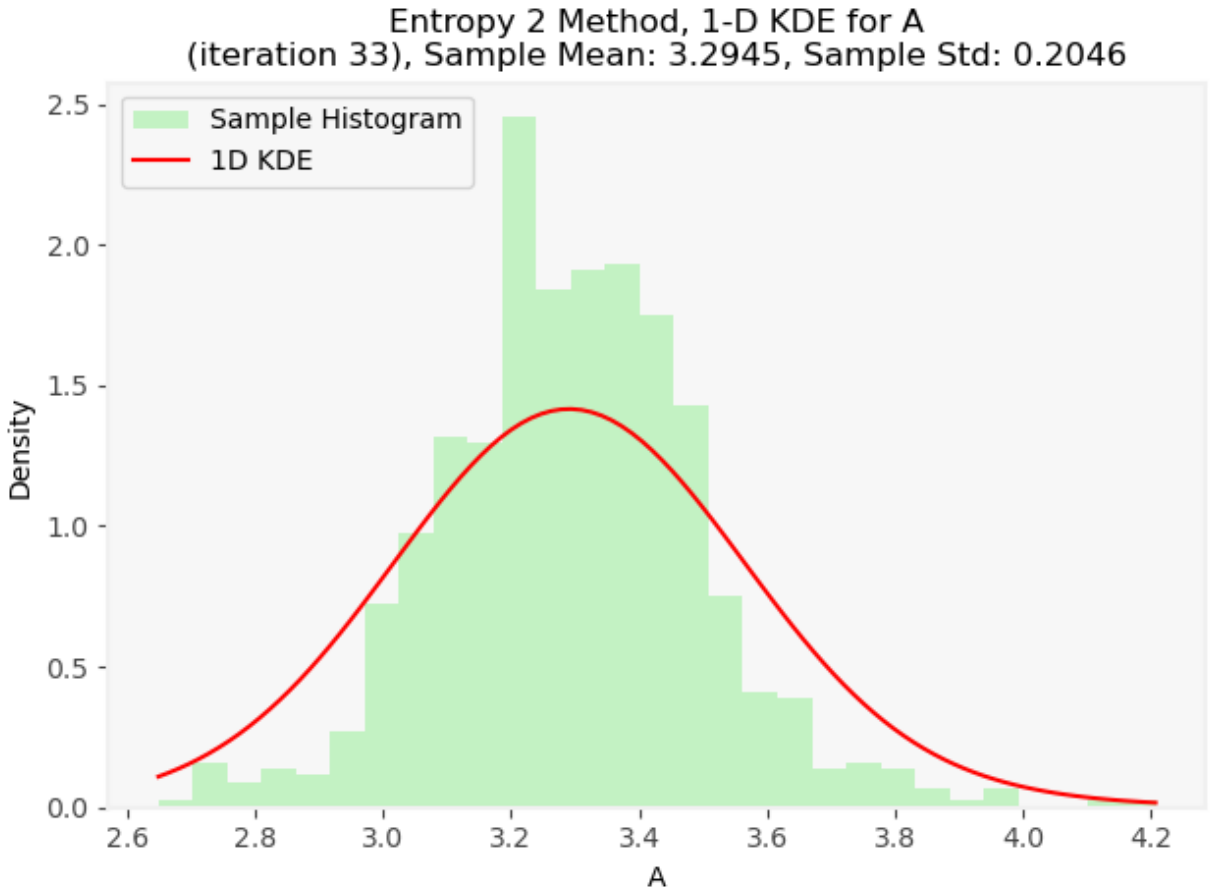

Entropy 2 Method, 1-D KDE for A
(iteration 28), Sample Mean: 3.2799, Sample Std: 0.2784
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25

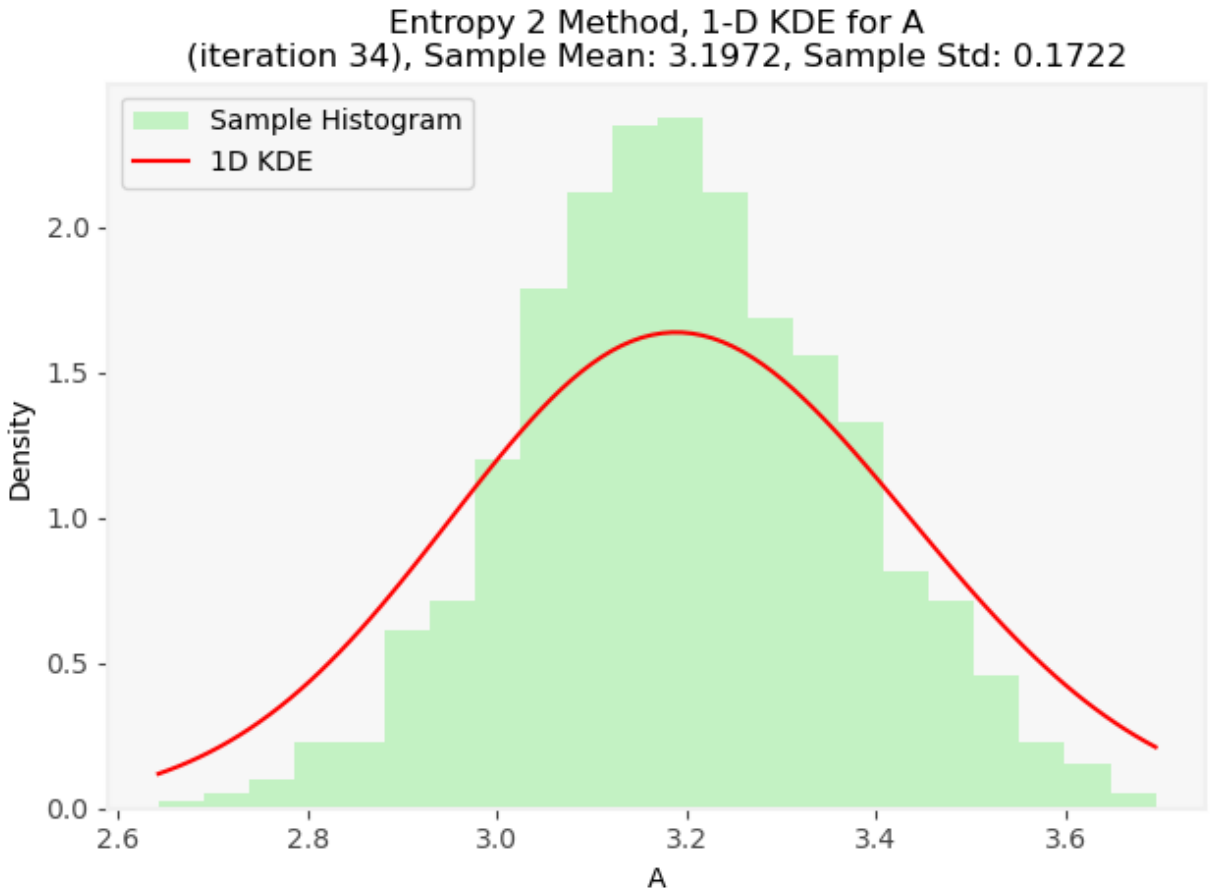

Entropy 2 Method, 1-D KDE for A
(iteration 29), Sample Mean: 3.2742, Sample Std: 0.2580
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0


Entropy 2 Method, 1-D KDE for A
(iteration 30), Sample Mean: 3.2929, Sample Std: 0.2472
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00


Entropy 2 Method, 1-D KDE for A
(iteration 31), Sample Mean: 3.3454, Sample Std: 0.2040
Sample Histogram
1D KDE
Density
A
0.0
0.5
1.0
1.5
2.0
2.8
3.0
3.2
3.4
3.6
3.8
4.0
4.2


Entropy 2 Method, 1-D KDE for A
(iteration 32), Sample Mean: 3.2787, Sample Std: 0.1895
Sample Histogram
1D KDE
Density
A
0.0
0.5
1.0
1.5
2.0
2.75
3.00
3.25
3.50
3.75
4.00
4.25


Entropy 2 Method, 1-D KDE for A
(iteration 33), Sample Mean: 3.2945, Sample Std: 0.2046
Sample Histogram
1D KDE
Density
A
0.0
0.5
1.0
1.5
2.0
2.5
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
4.2


Entropy 2 Method, 1-D KDE for A
(iteration 34), Sample Mean: 3.1972, Sample Std: 0.1722
Sample Histogram
1D KDE
Density
A
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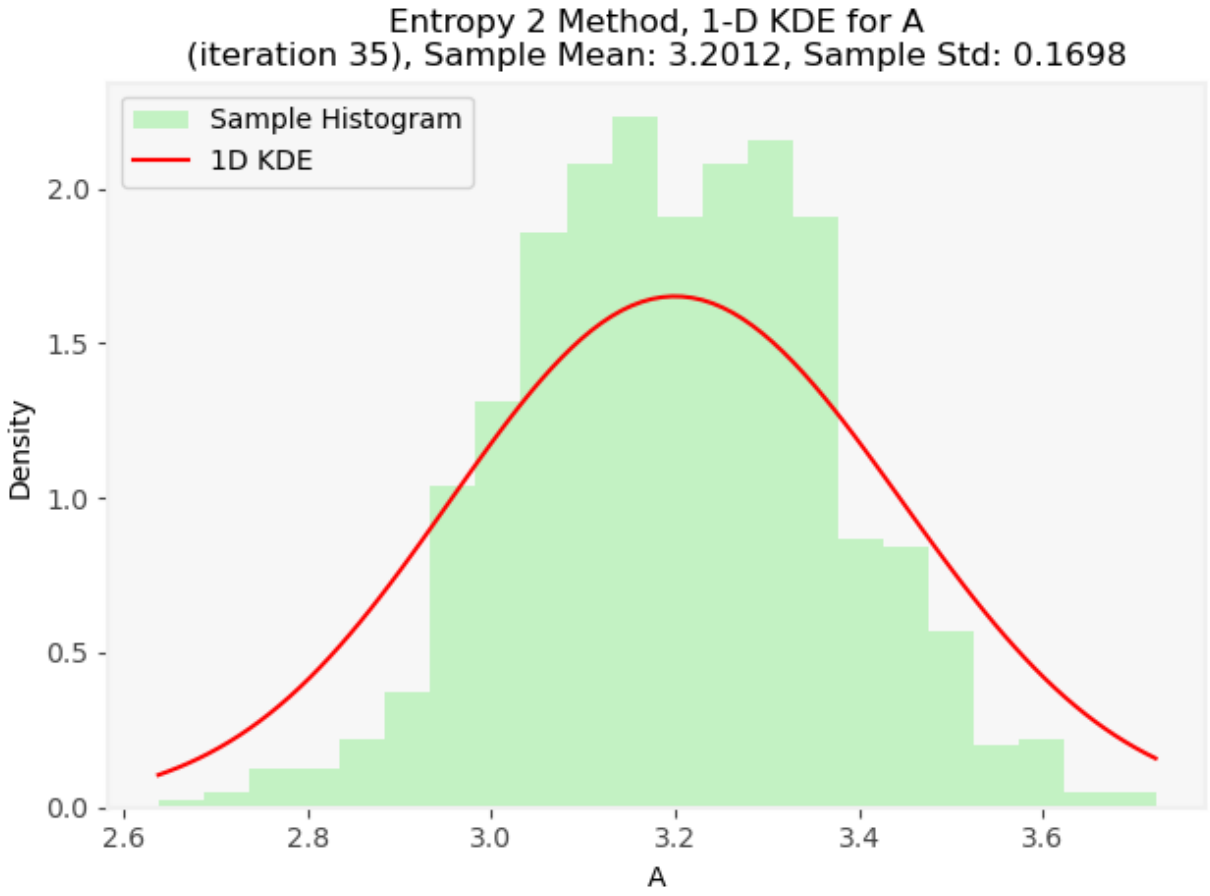
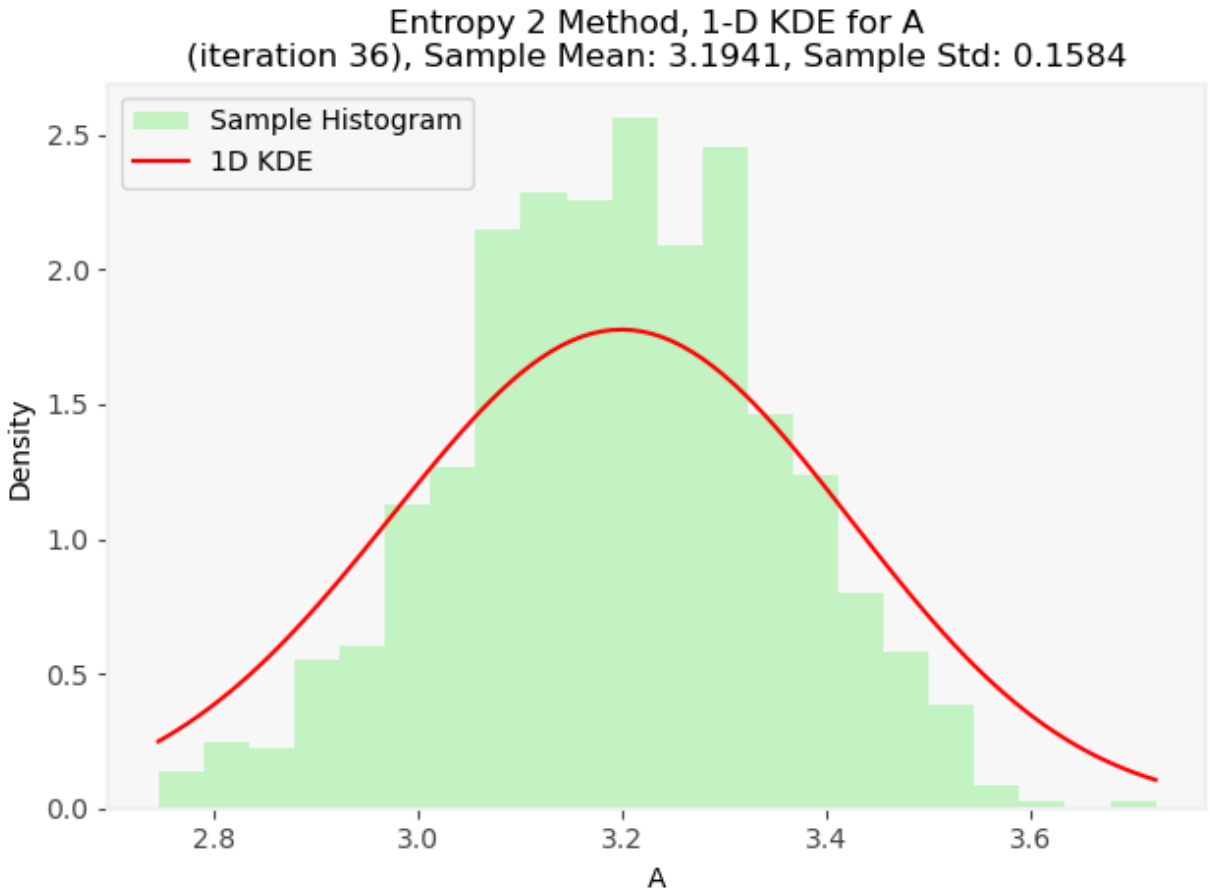
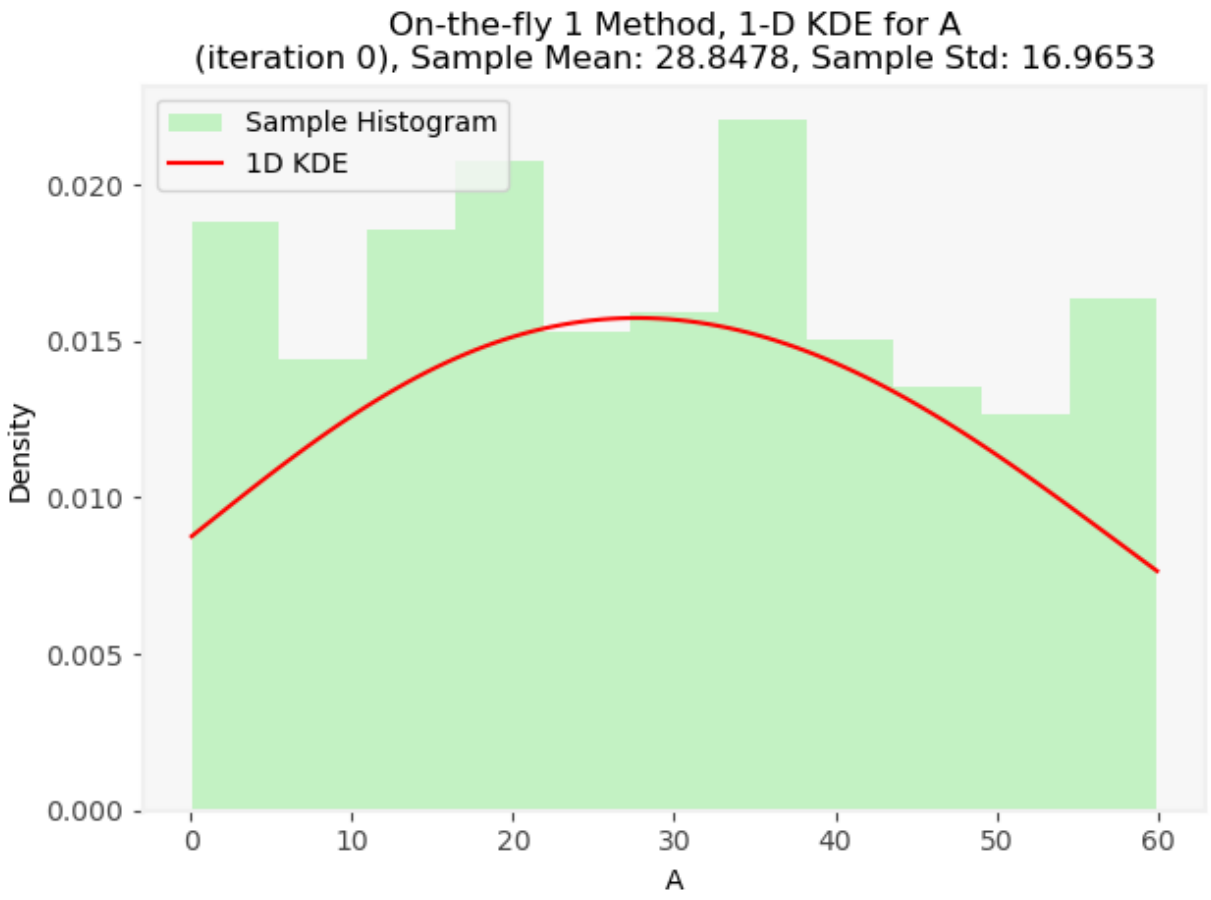
0.5
1.0
1.5
2.0
2.6
2.8
3.0
3.2
3.4
3.6

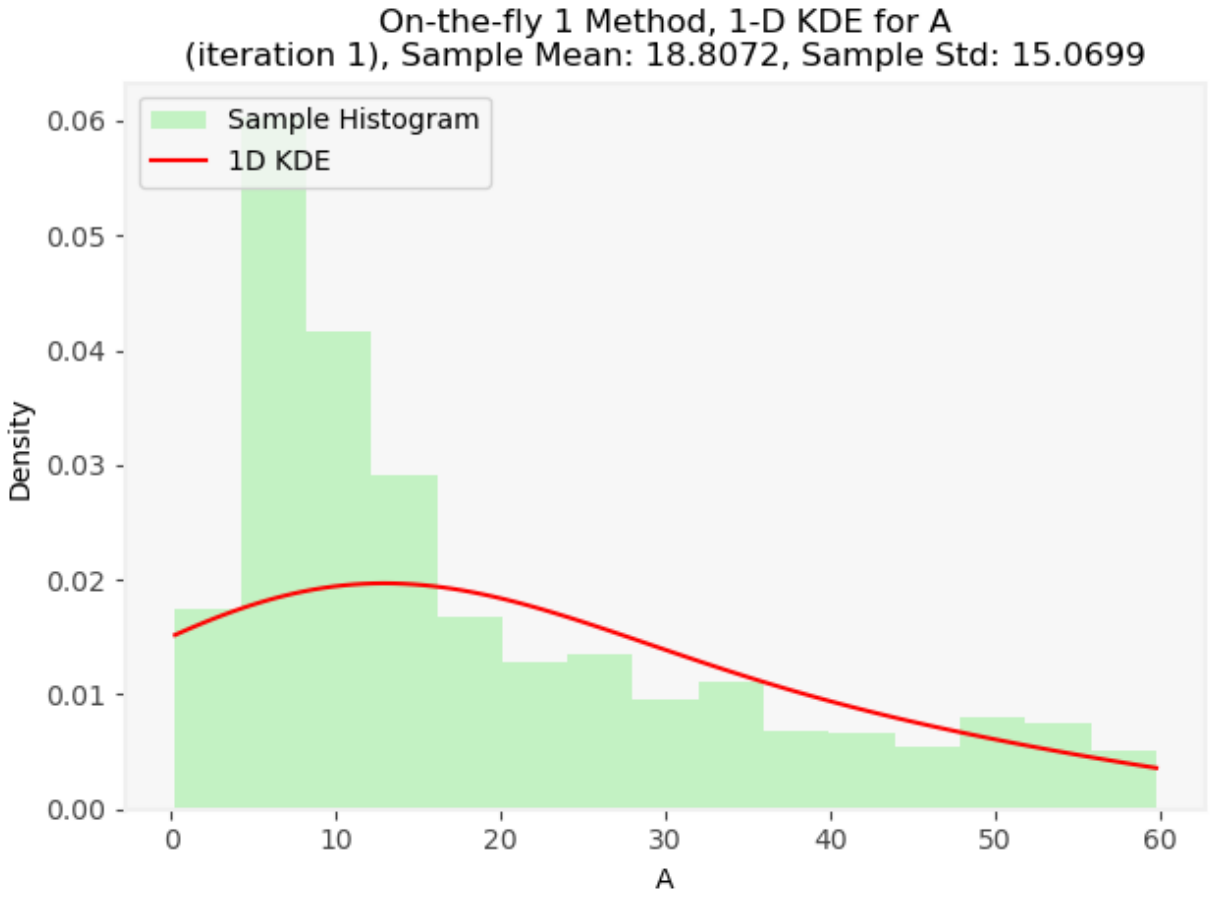


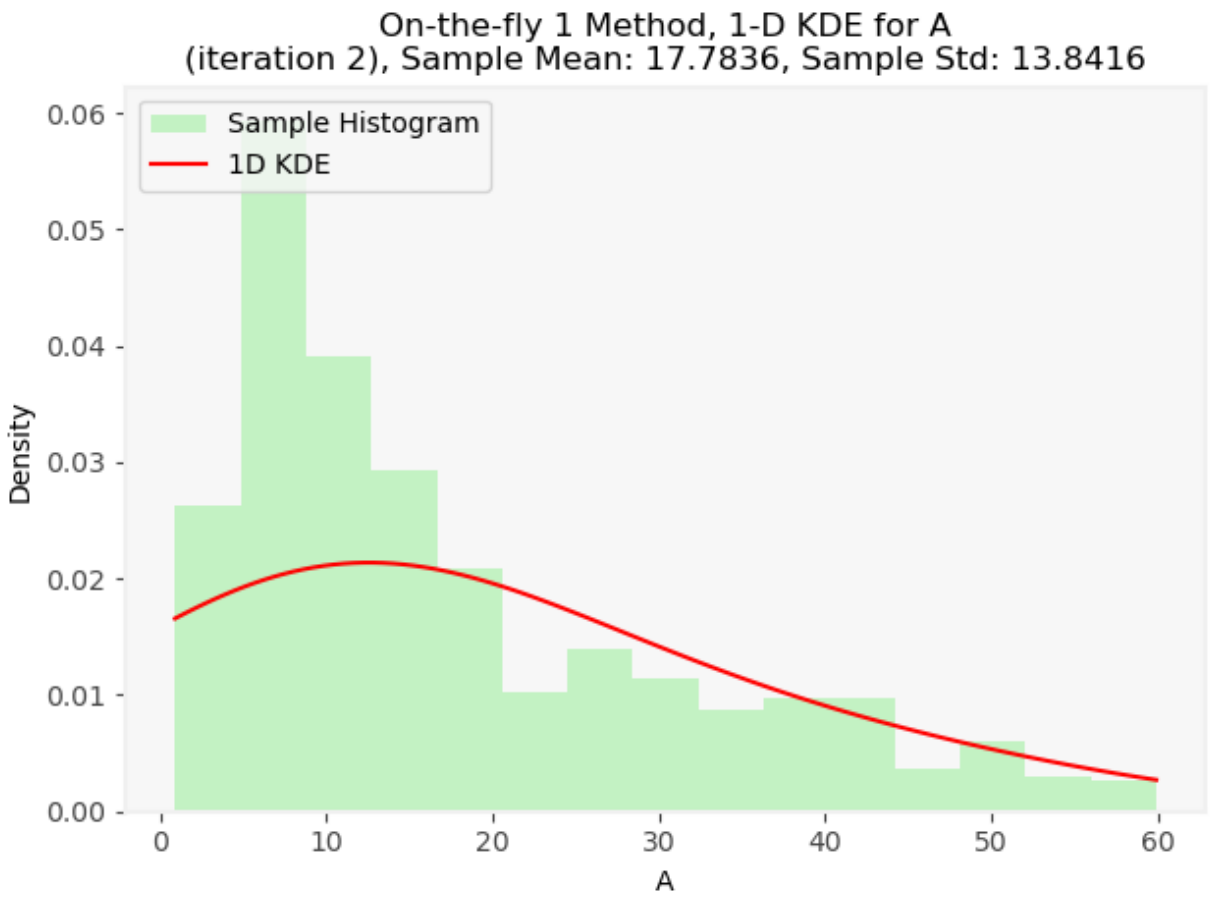


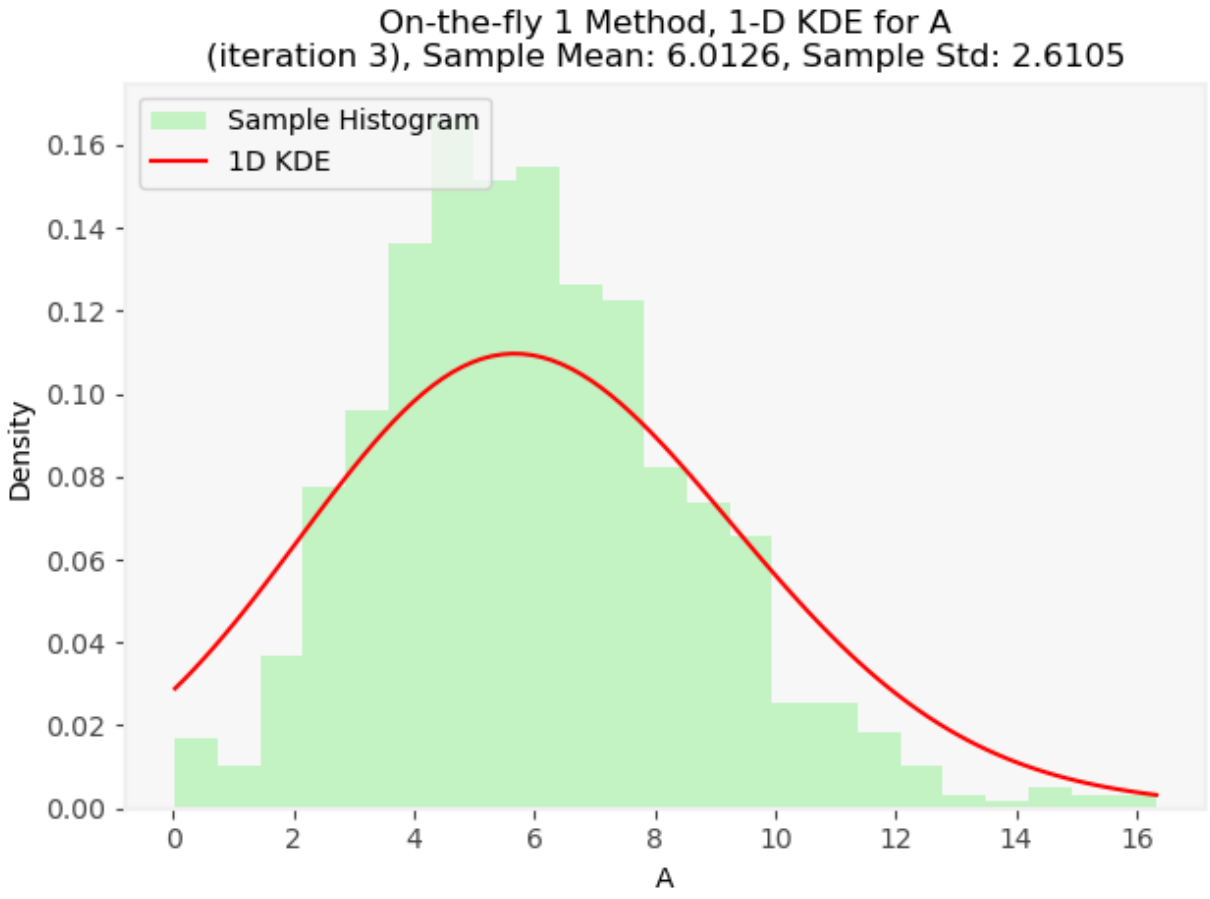
In [54]:
```
#Printing the evolution of parameter A for On-the-fly  1
for i in range(len(exp_on_the_fly1.totaltimes())):
```

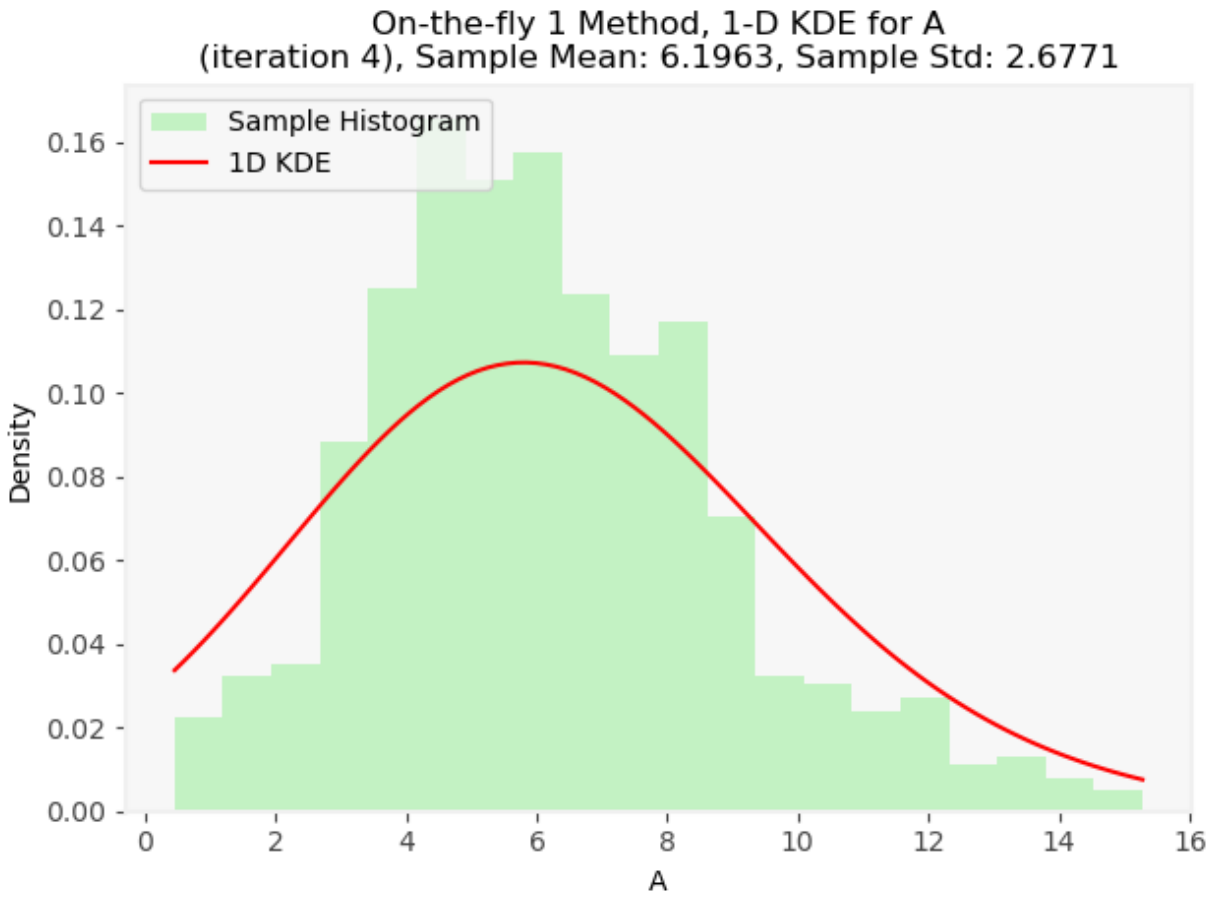
```
MyPlots.plot_hist_1d_kde(list_par_separated_o1[0][i], kdes_on_the_fly1[i,0],"On-th
```

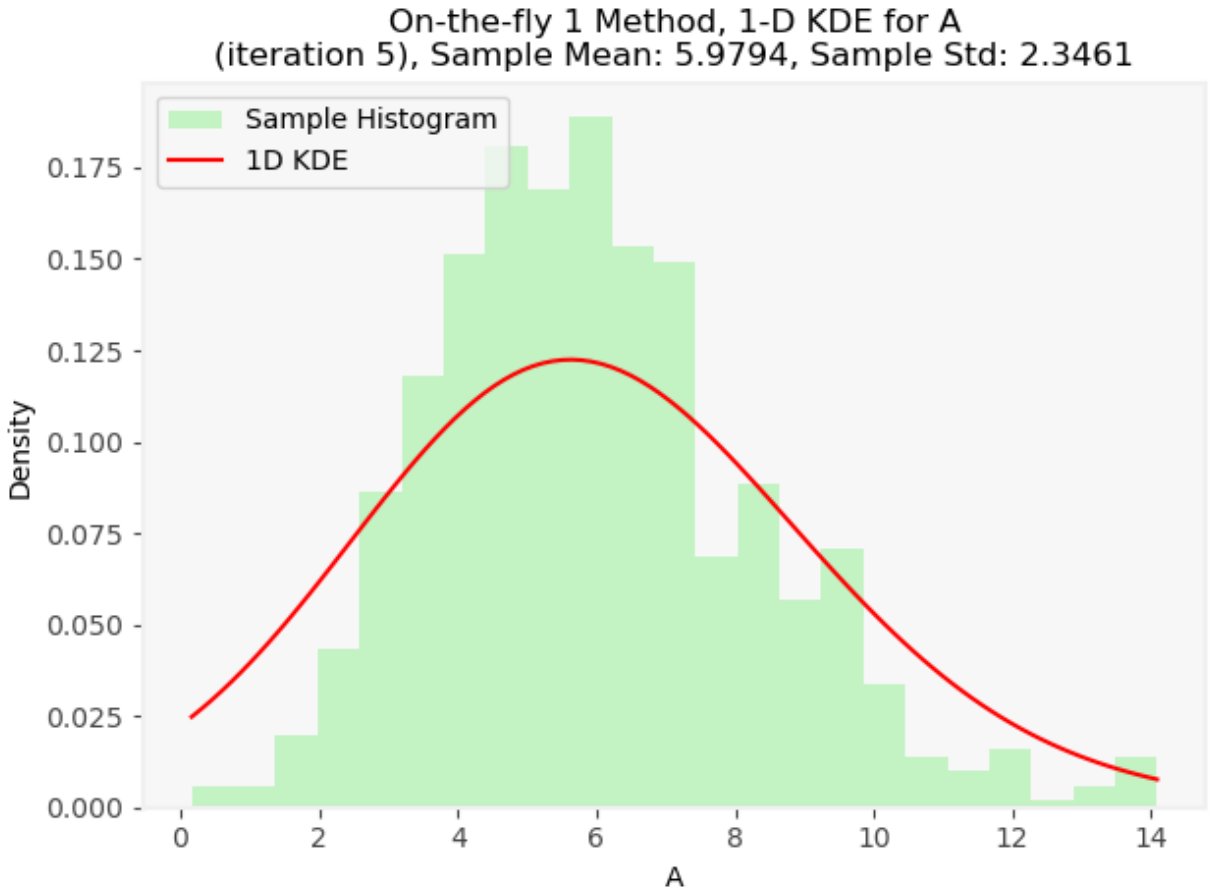


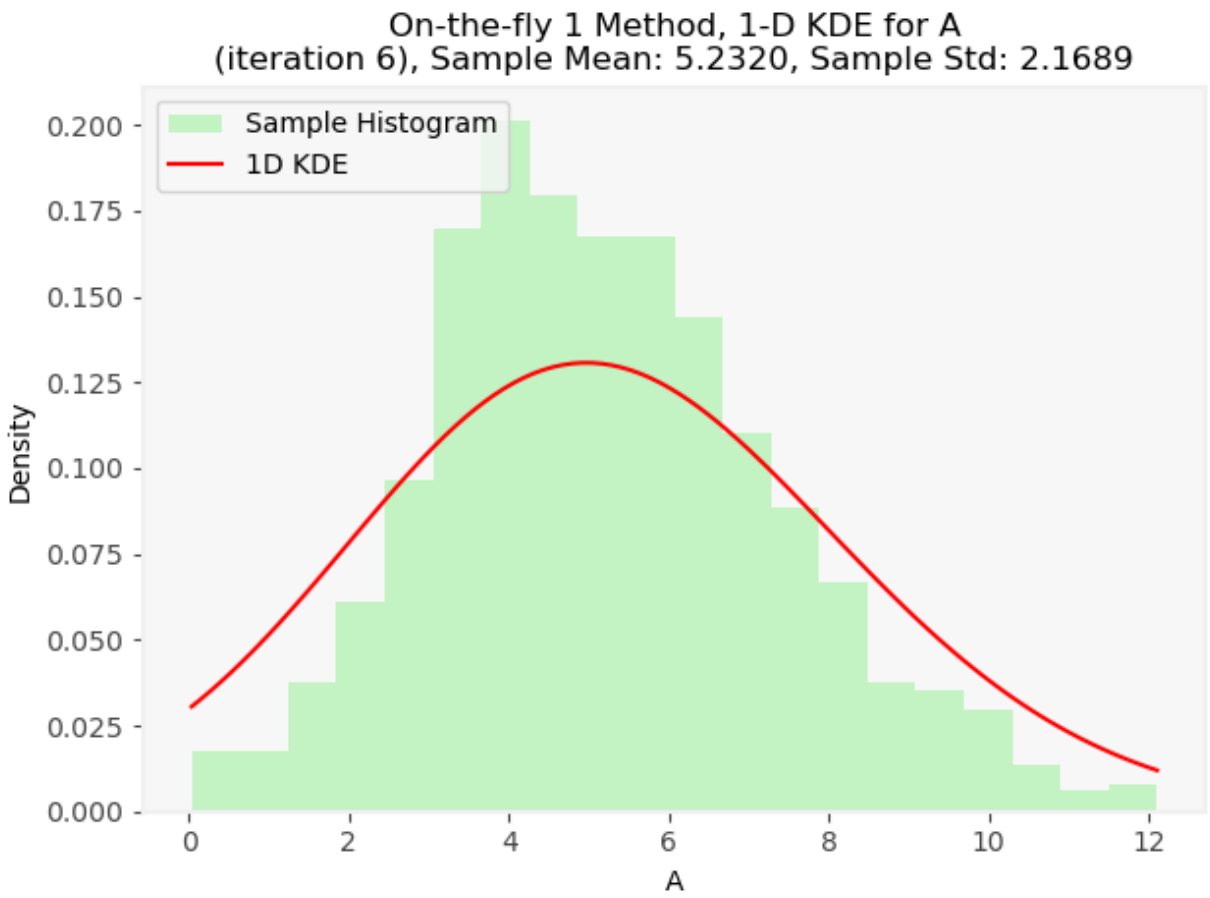


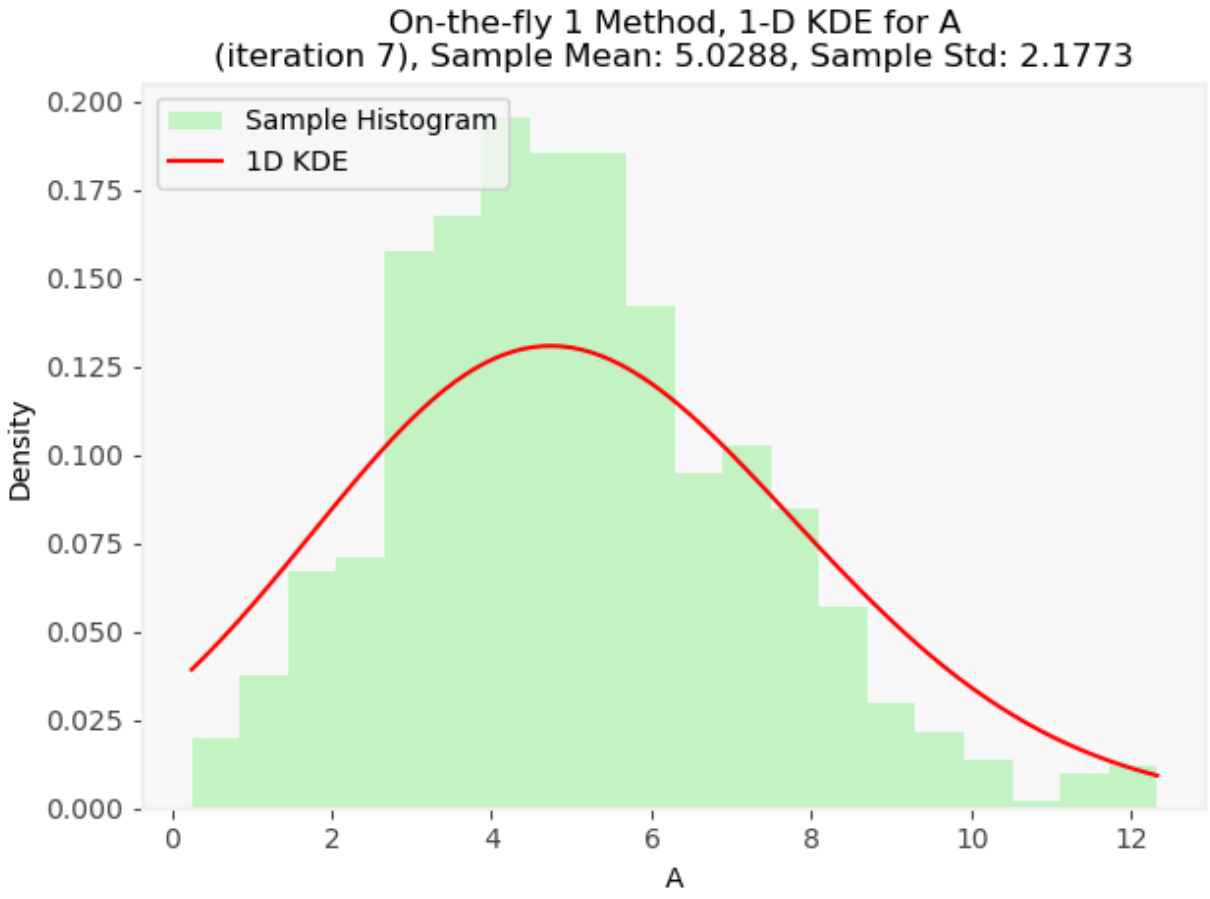

On-the-fly 1 Method, 1-D KDE for A
(iteration 2), Sample Mean: 17.7836, Sample Std: 13.8416
Sample Histogram
1D KDE
Density
A
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0
10
20
30
40
50
60

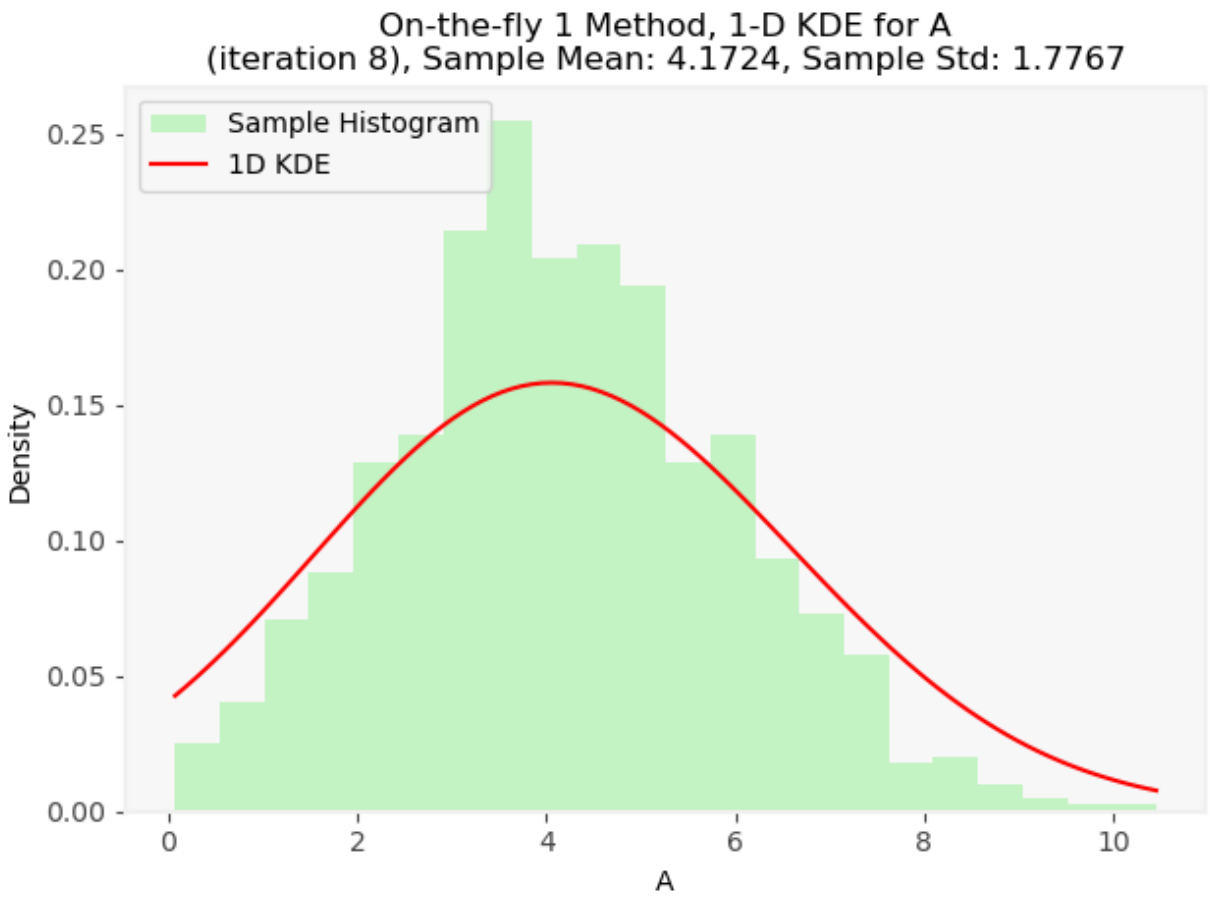

On-the-fly 1 Method, 1-D KDE for A
(iteration 3), Sample Mean: 6.0126, Sample Std: 2.6105
Sample Histogram
1D KDE
Density
A
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0
2
4
6
8
10
12
14
16

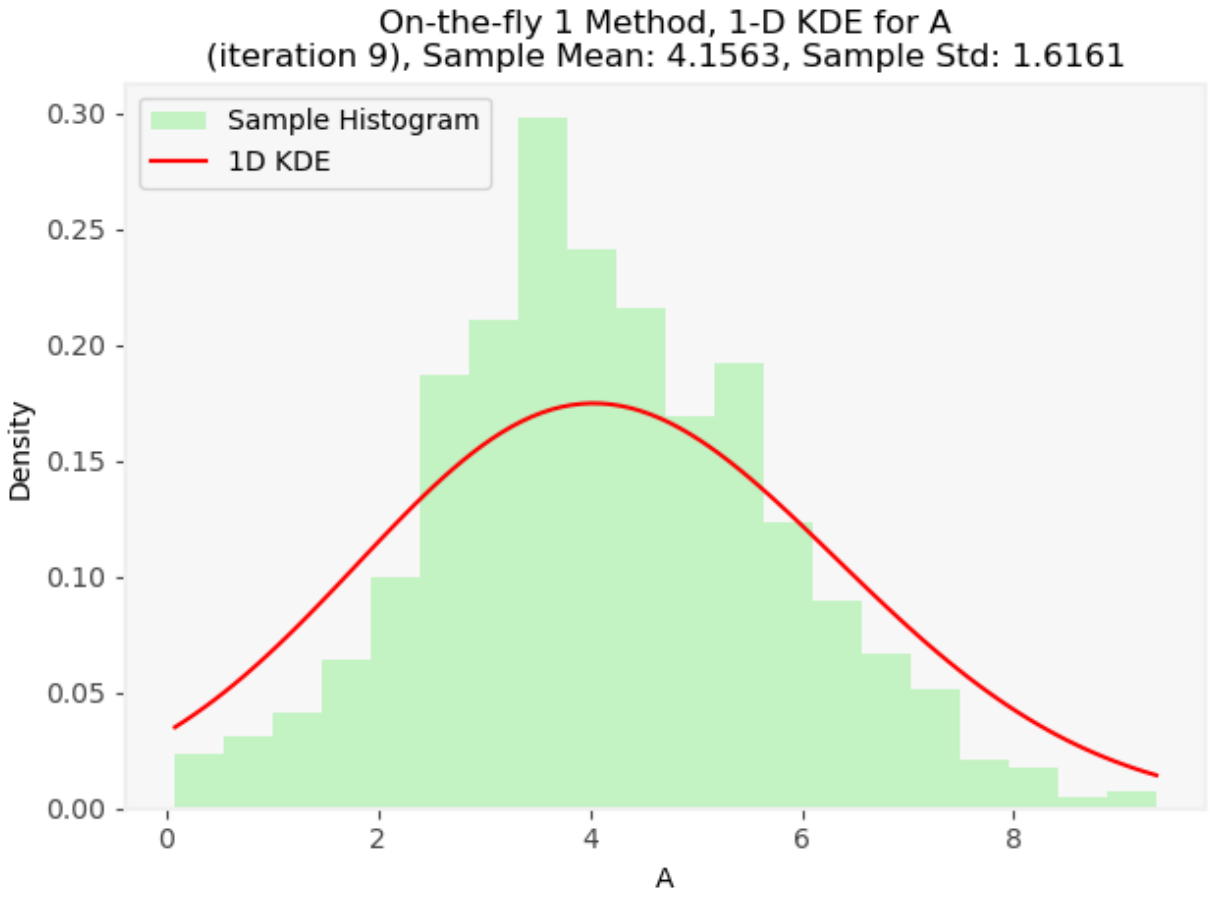

On-the-fly 1 Method, 1-D KDE for A
(iteration 4), Sample Mean: 6.1963, Sample Std: 2.6771
Sample Histogram
1D KDE
Density
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0
2
4
6
8
10
12
14
16
A

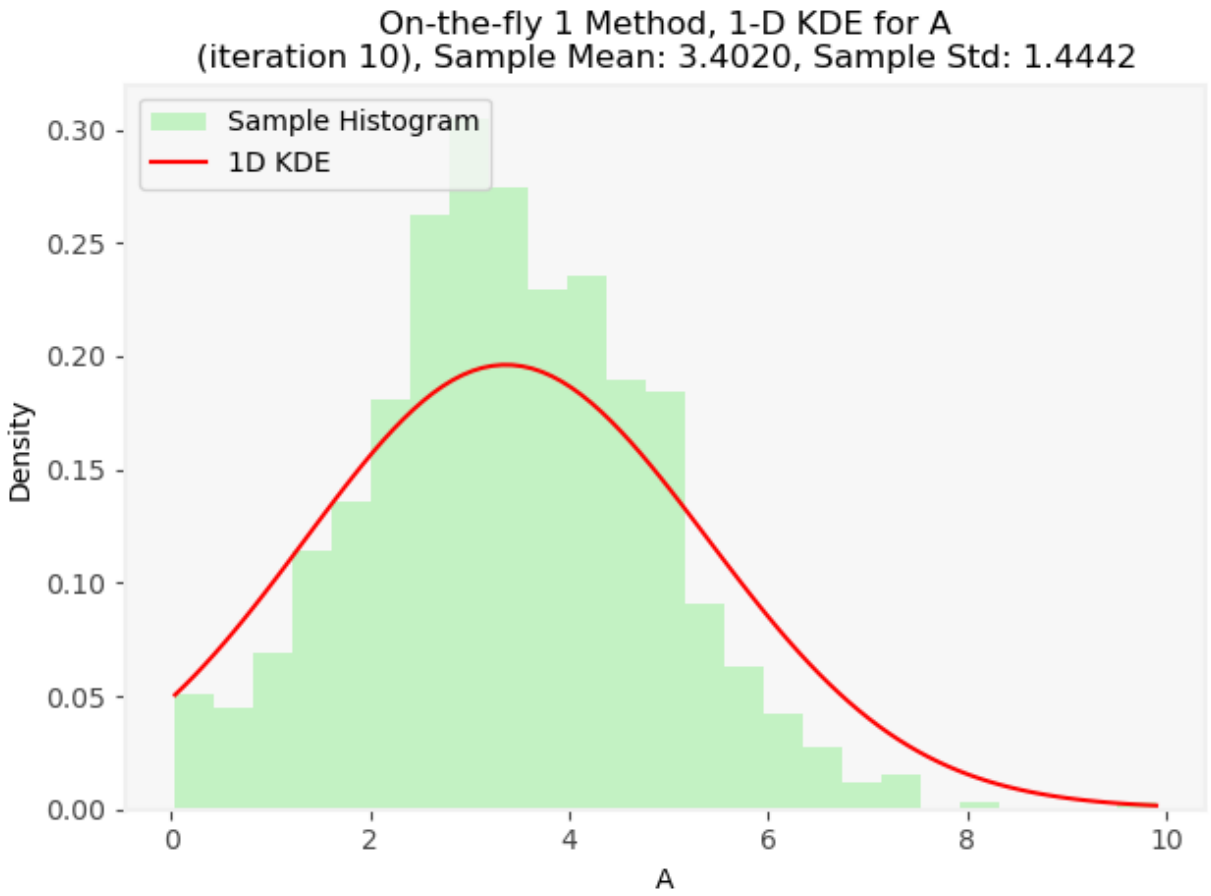

On-the-fly 1 Method, 1-D KDE for A
(iteration 5), Sample Mean: 5.9794, Sample Std: 2.3461
Sample Histogram
1D KDE
Density
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
2
4
6
8
10
12
14
A

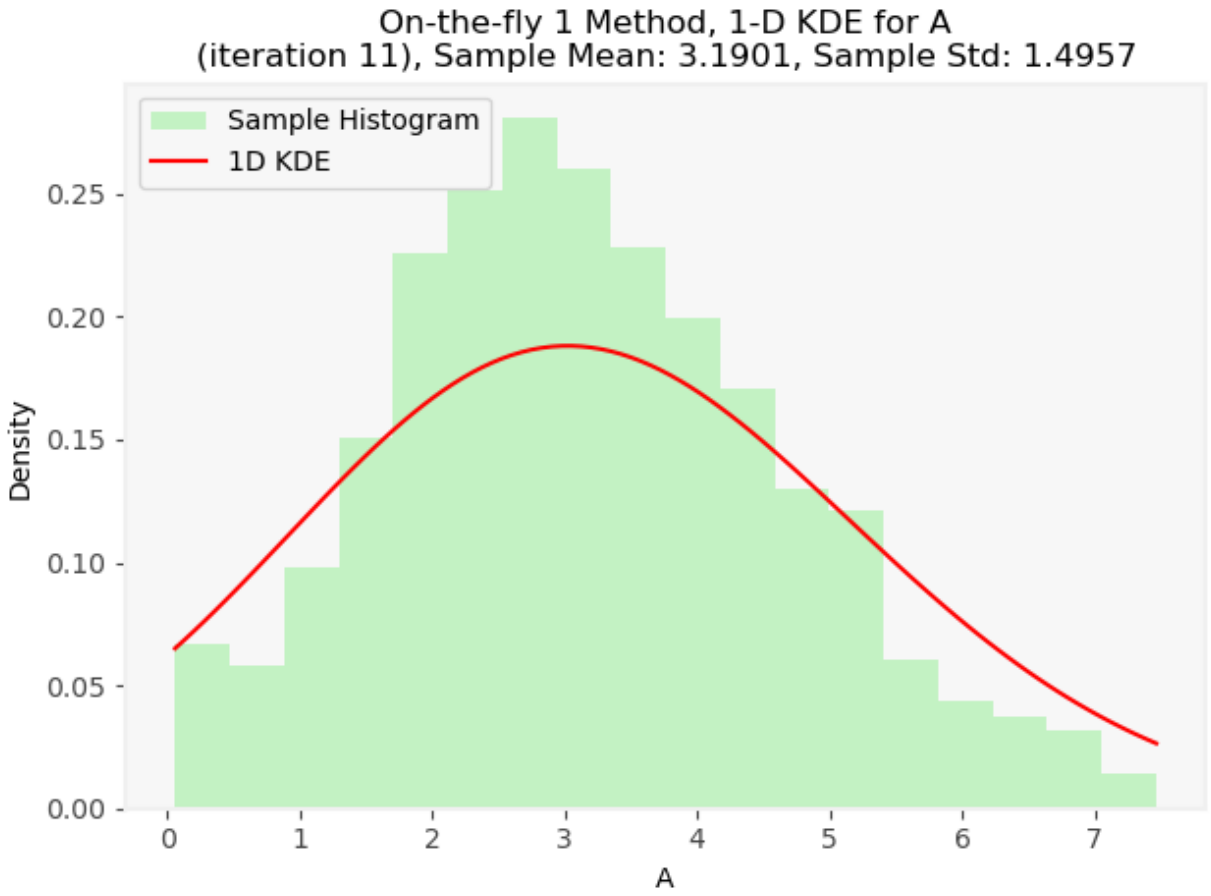

On-the-fly 1 Method, 1-D KDE for A
(iteration 6), Sample Mean: 5.2320, Sample Std: 2.1689
Sample Histogram
1D KDE
Density
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
2
4
6
8
10
12
A

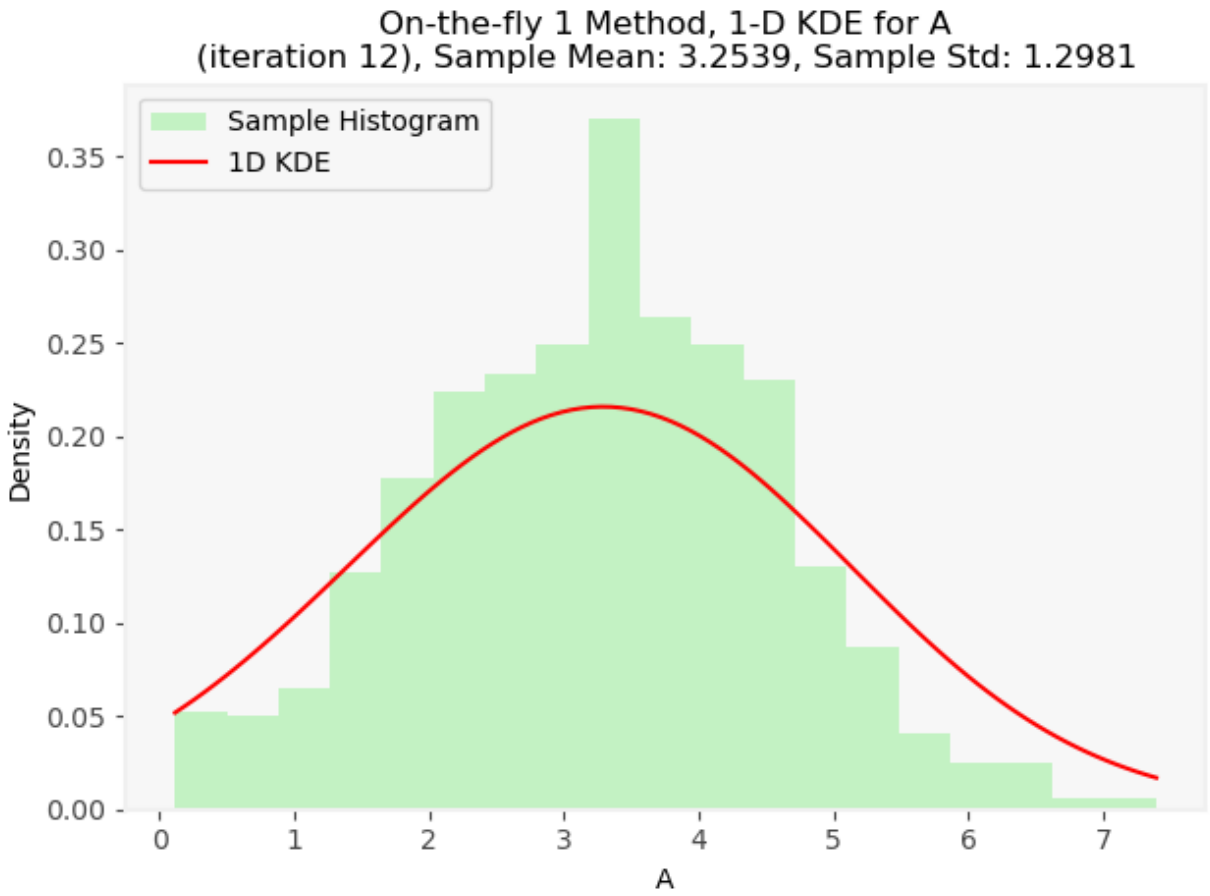

On-the-fly 1 Method, 1-D KDE for A
(iteration 7), Sample Mean: 5.0288, Sample Std: 2.1773
Sample Histogram
1D KDE
Density
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0
2
4
6
8
10
12
A

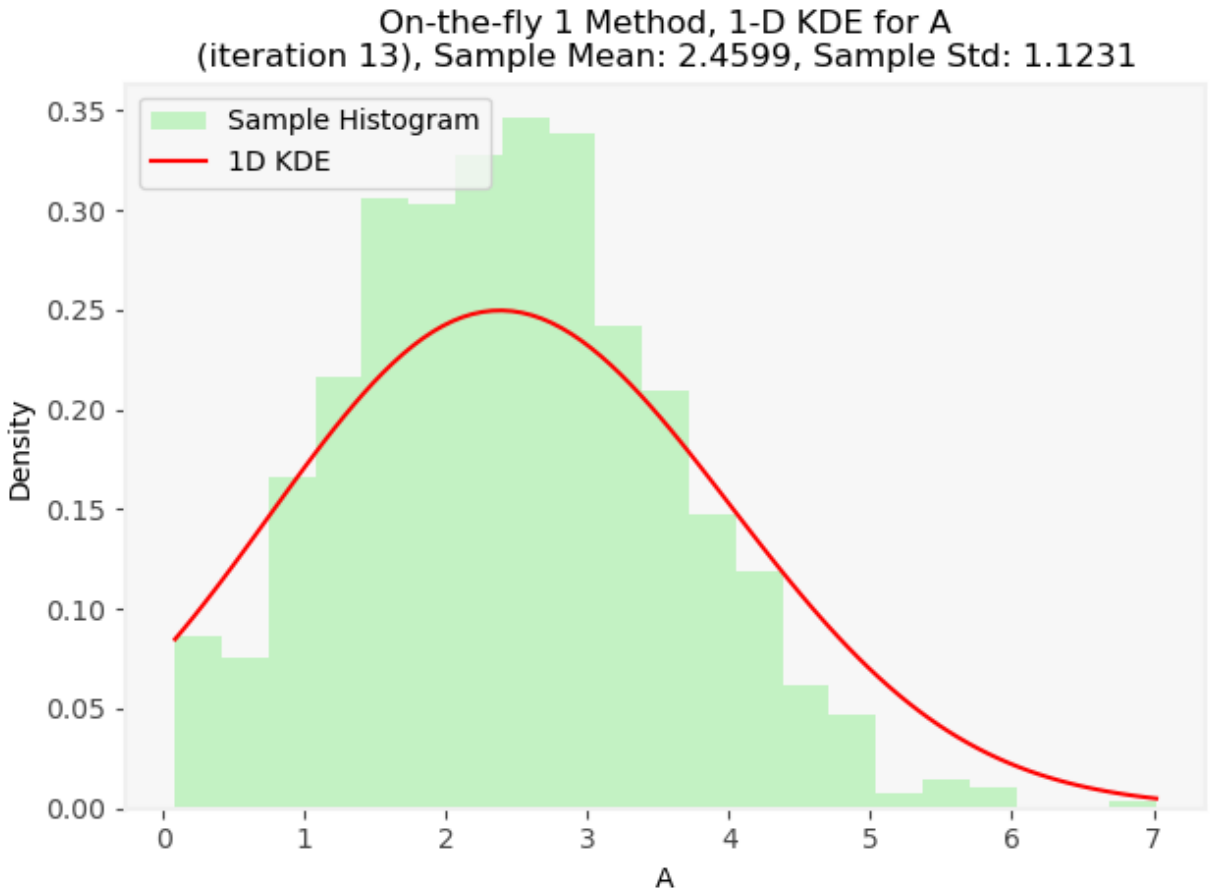

On-the-fly 1 Method, 1-D KDE for A
(iteration 8), Sample Mean: 4.1724, Sample Std: 1.7767
Sample Histogram
1D KDE
Density
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
10
A

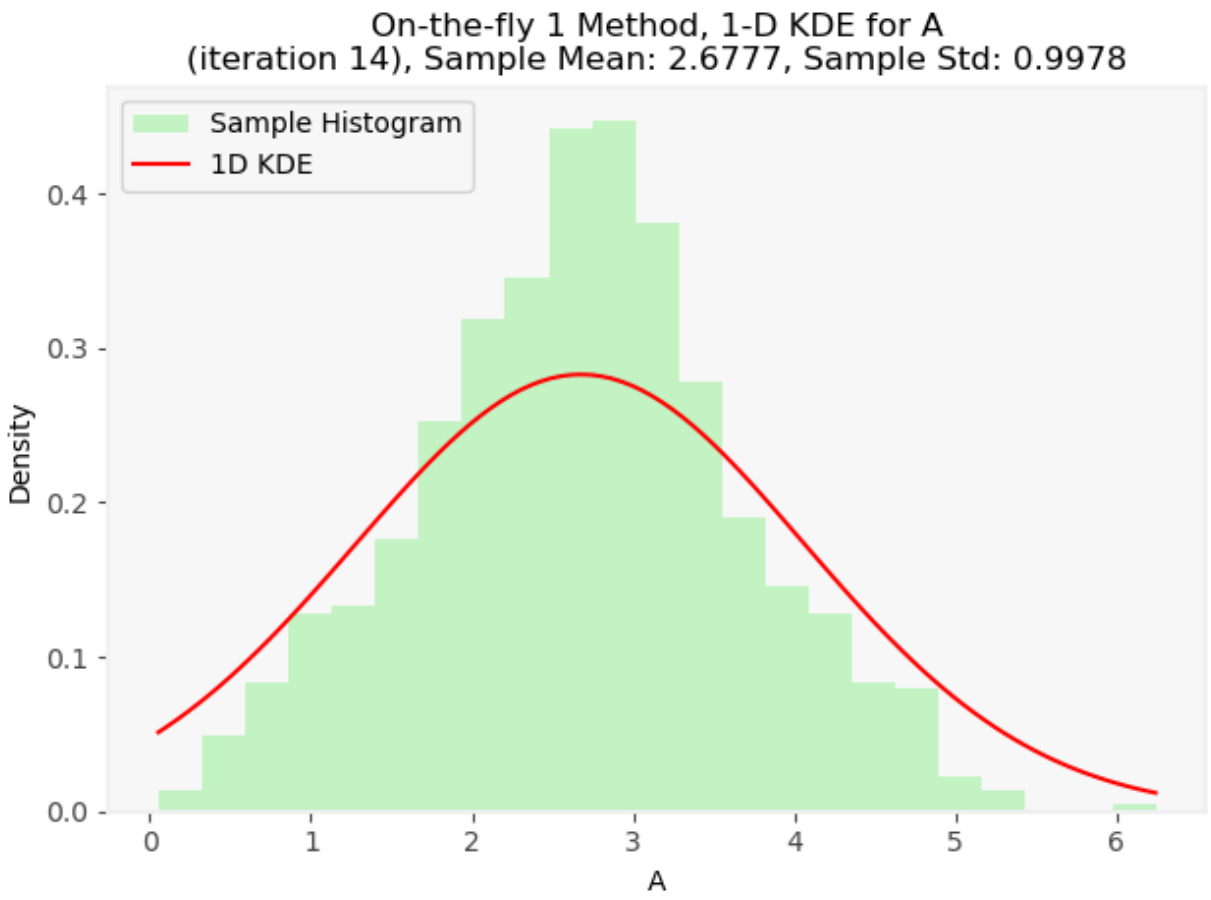

On-the-fly 1 Method, 1-D KDE for A
(iteration 9), Sample Mean: 4.1563, Sample Std: 1.6161
Sample Histogram
1D KDE
Density
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
A

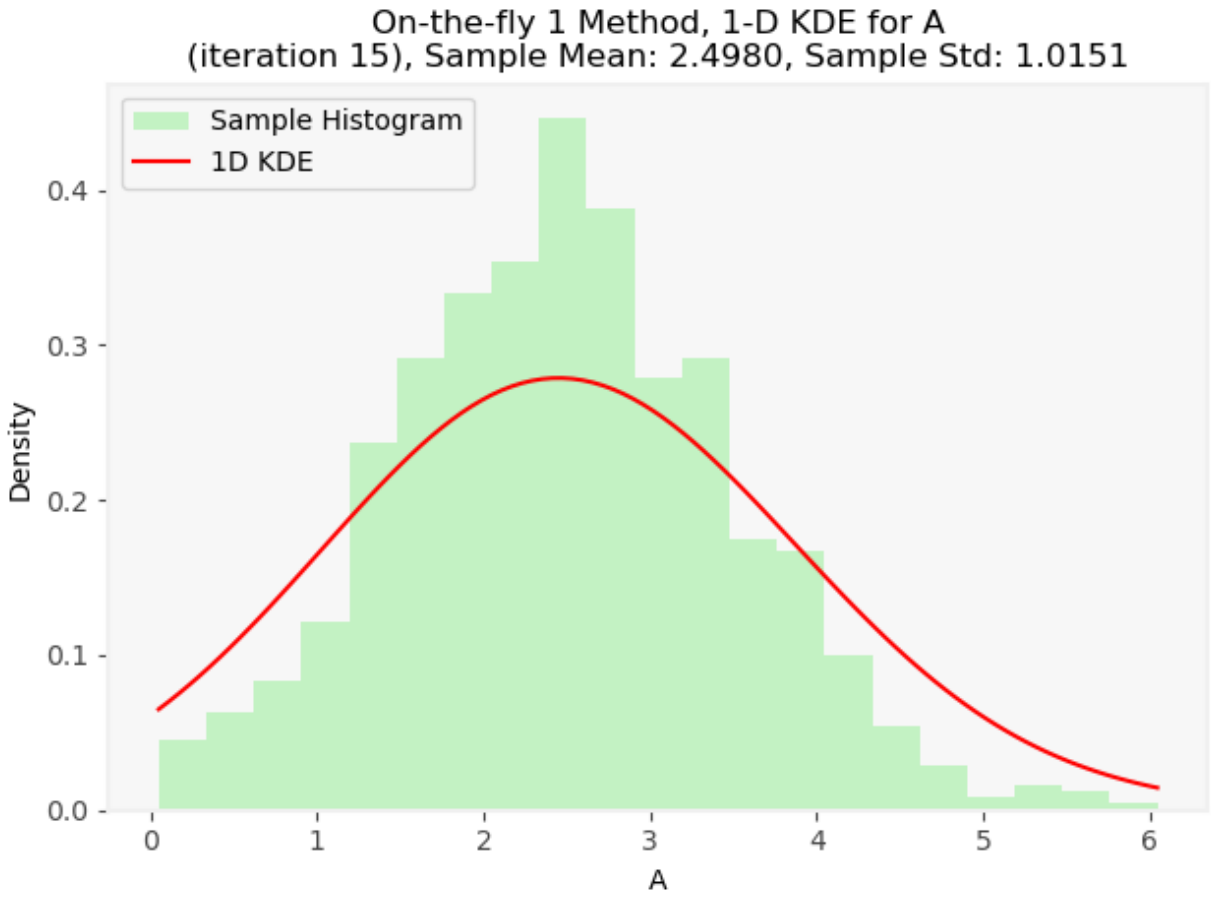

On-the-fly 1 Method, 1-D KDE for A
(iteration 10), Sample Mean: 3.4020, Sample Std: 1.4442
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
2
4
6
8
10

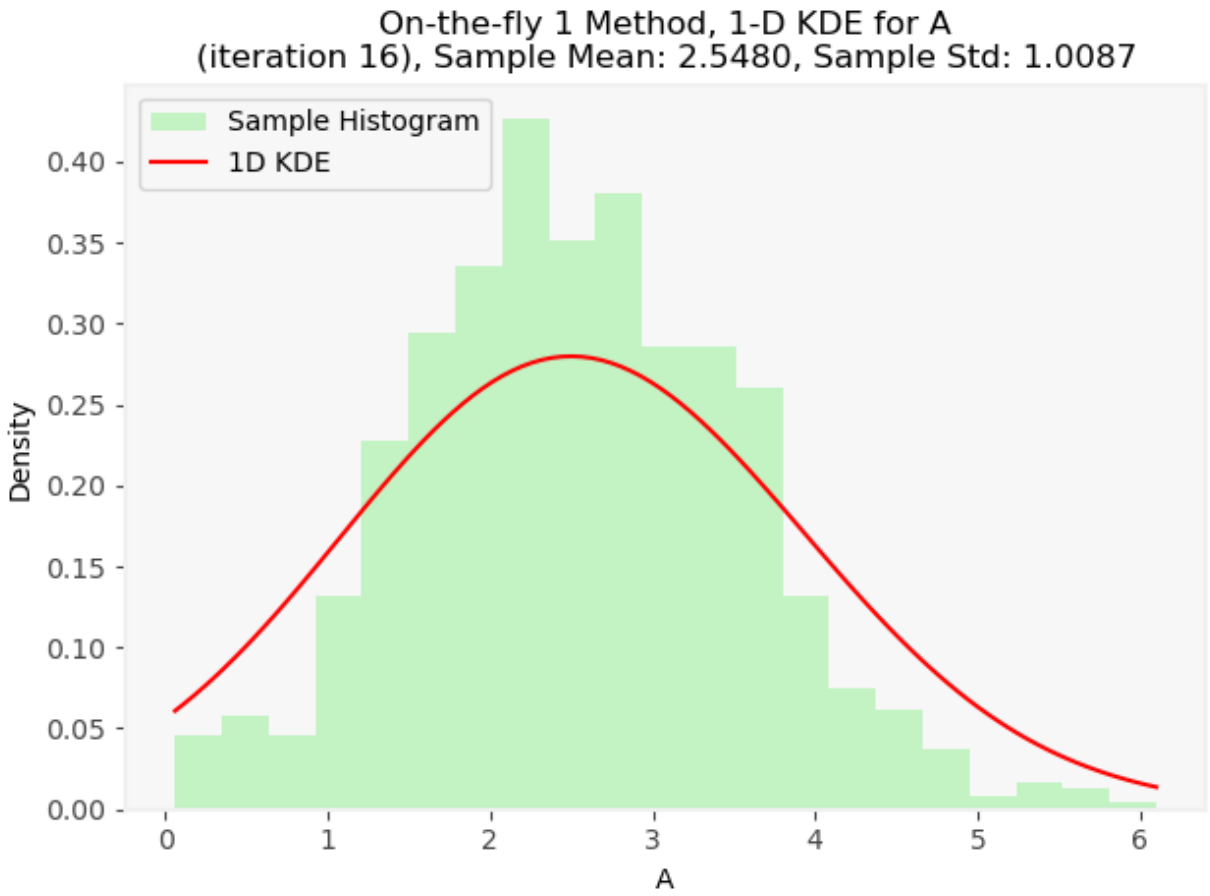

On-the-fly 1 Method, 1-D KDE for A
(iteration 11), Sample Mean: 3.1901, Sample Std: 1.4957
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0
1
2
3
4
5
6
7

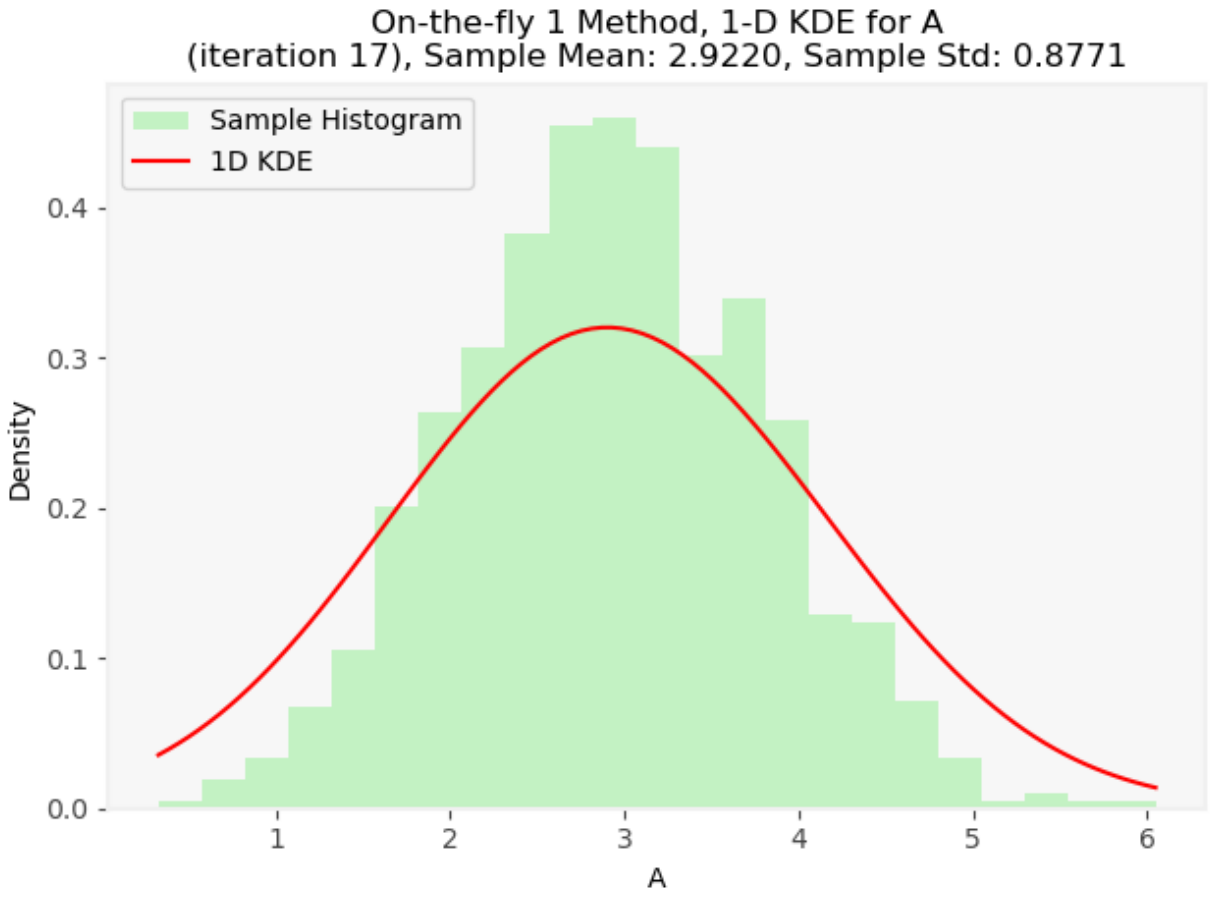

On-the-fly 1 Method, 1-D KDE for A
(iteration 12), Sample Mean: 3.2539, Sample Std: 1.2981
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0
1
2
3
4
5
6
7

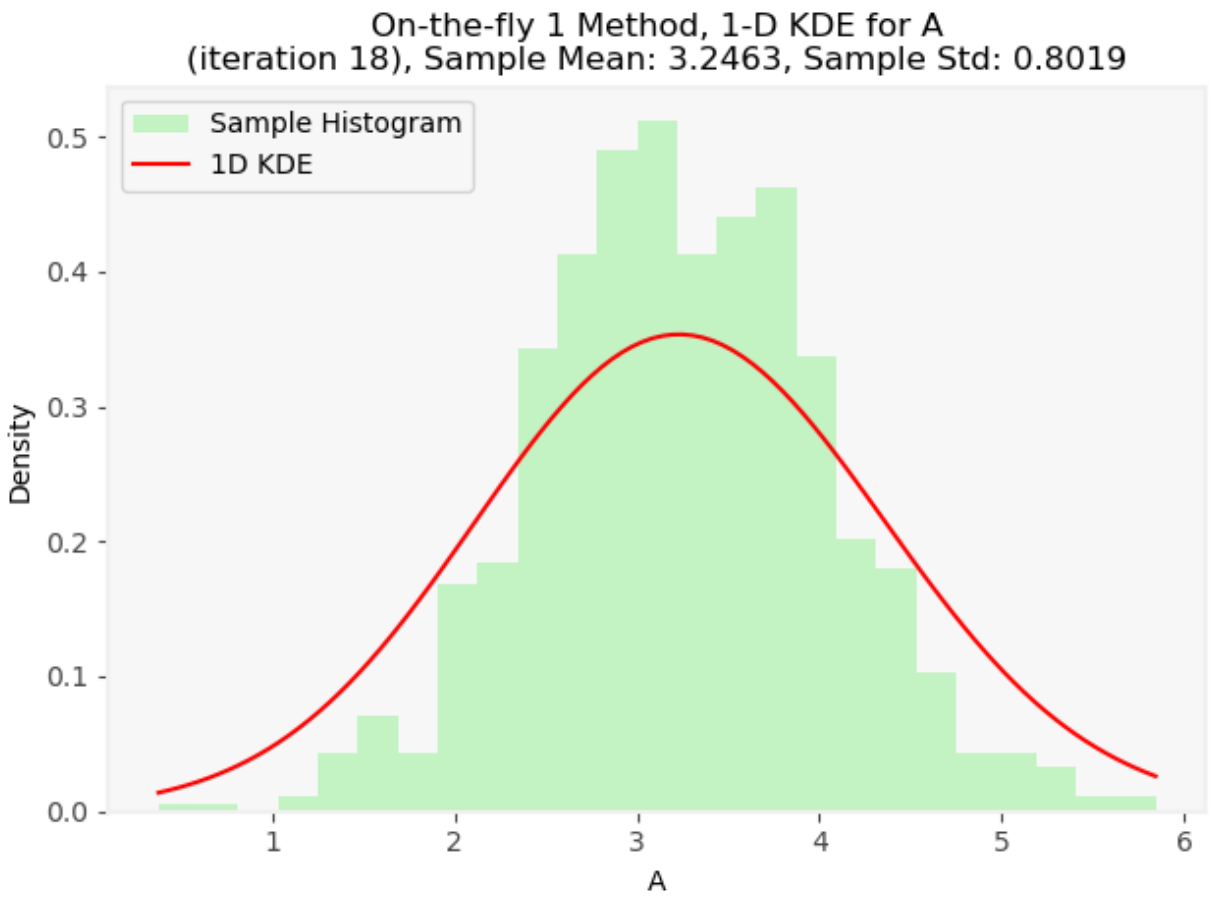

On-the-fly 1 Method, 1-D KDE for A
(iteration 13), Sample Mean: 2.4599, Sample Std: 1.1231
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0
1
2
3
4
5
6
7

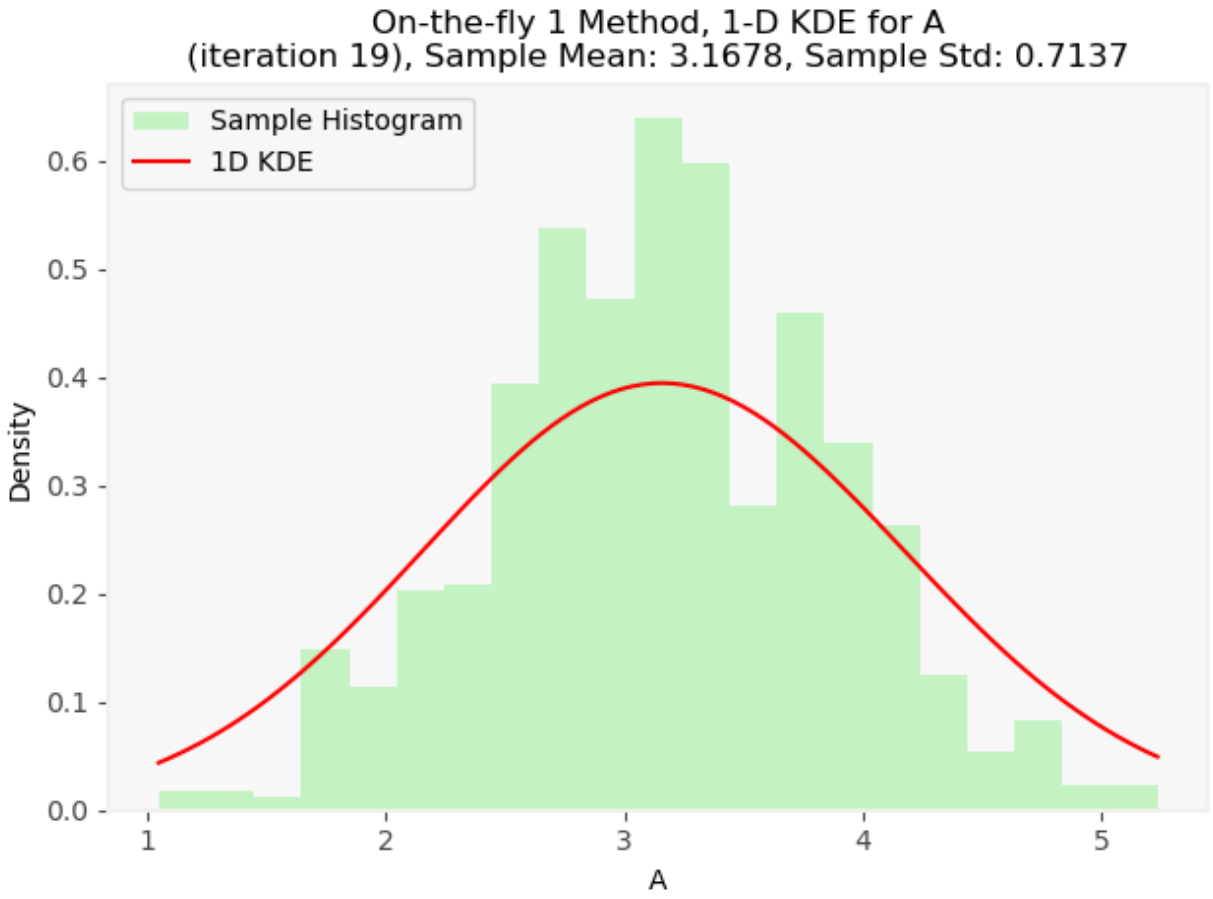

On-the-fly 1 Method, 1-D KDE for A
(iteration 14), Sample Mean: 2.6777, Sample Std: 0.9978
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0
1
2
3
4
5
6

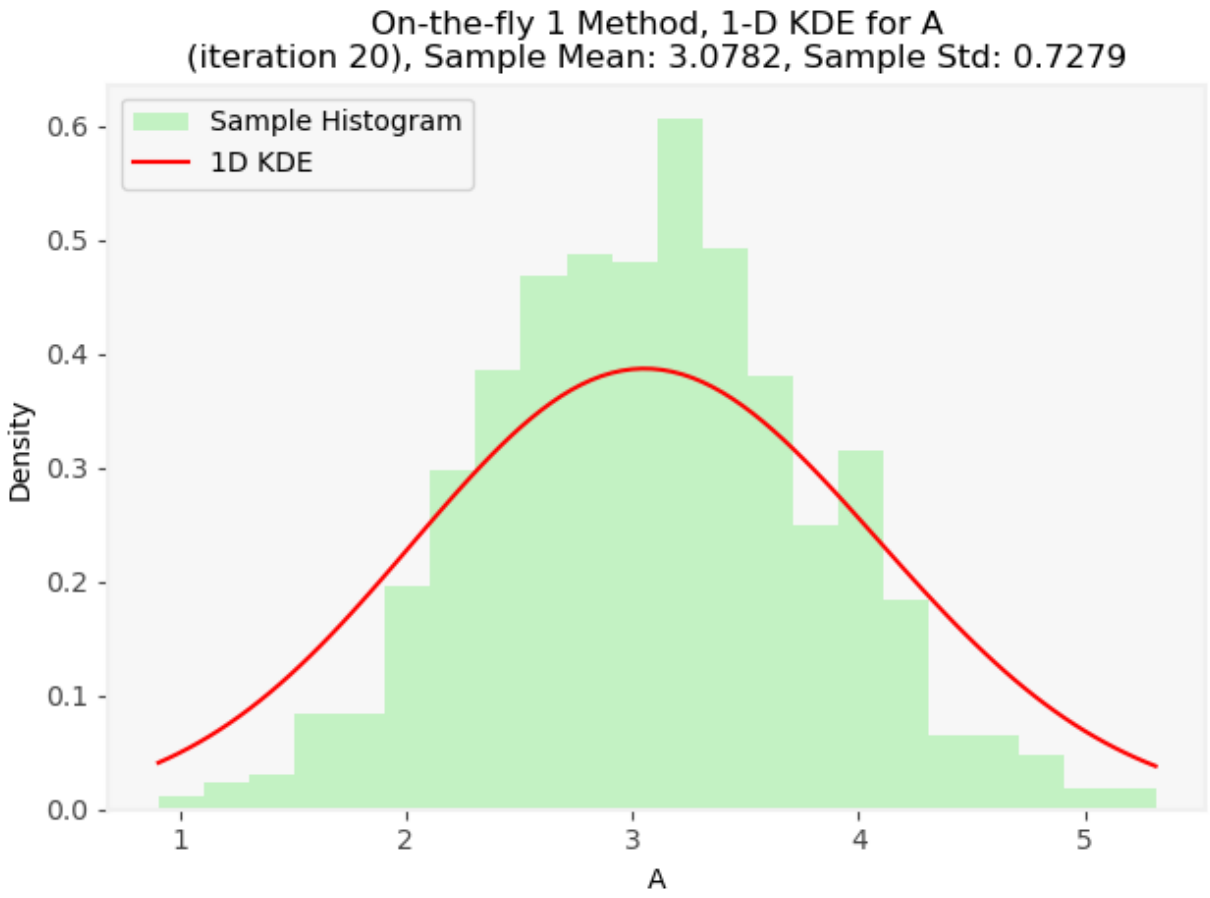

On-the-fly 1 Method, 1-D KDE for A
(iteration 15), Sample Mean: 2.4980, Sample Std: 1.0151
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0
1
2
3
4
5
6

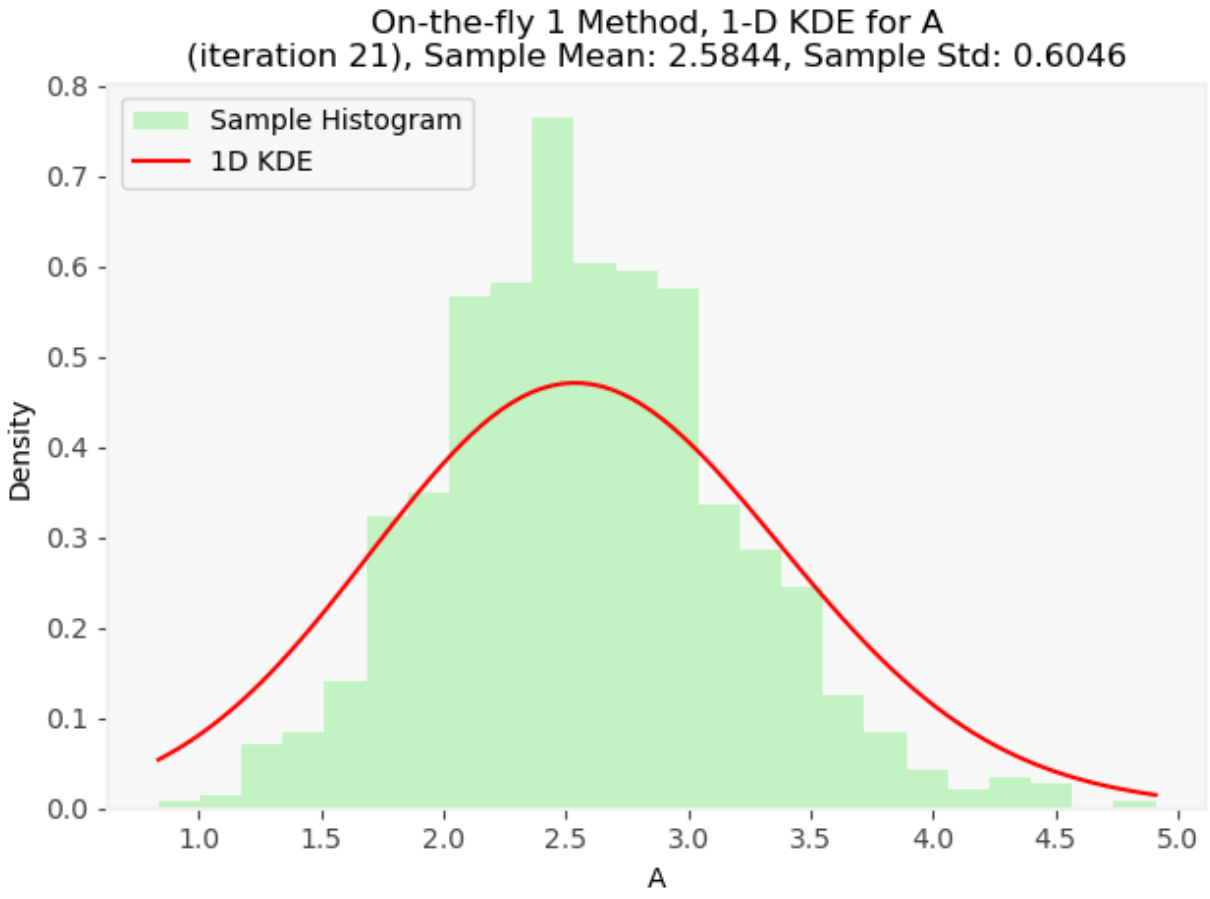

On-the-fly 1 Method, 1-D KDE for A
(iteration 16), Sample Mean: 2.5480, Sample Std: 1.0087
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0
1
2
3
4
5
6

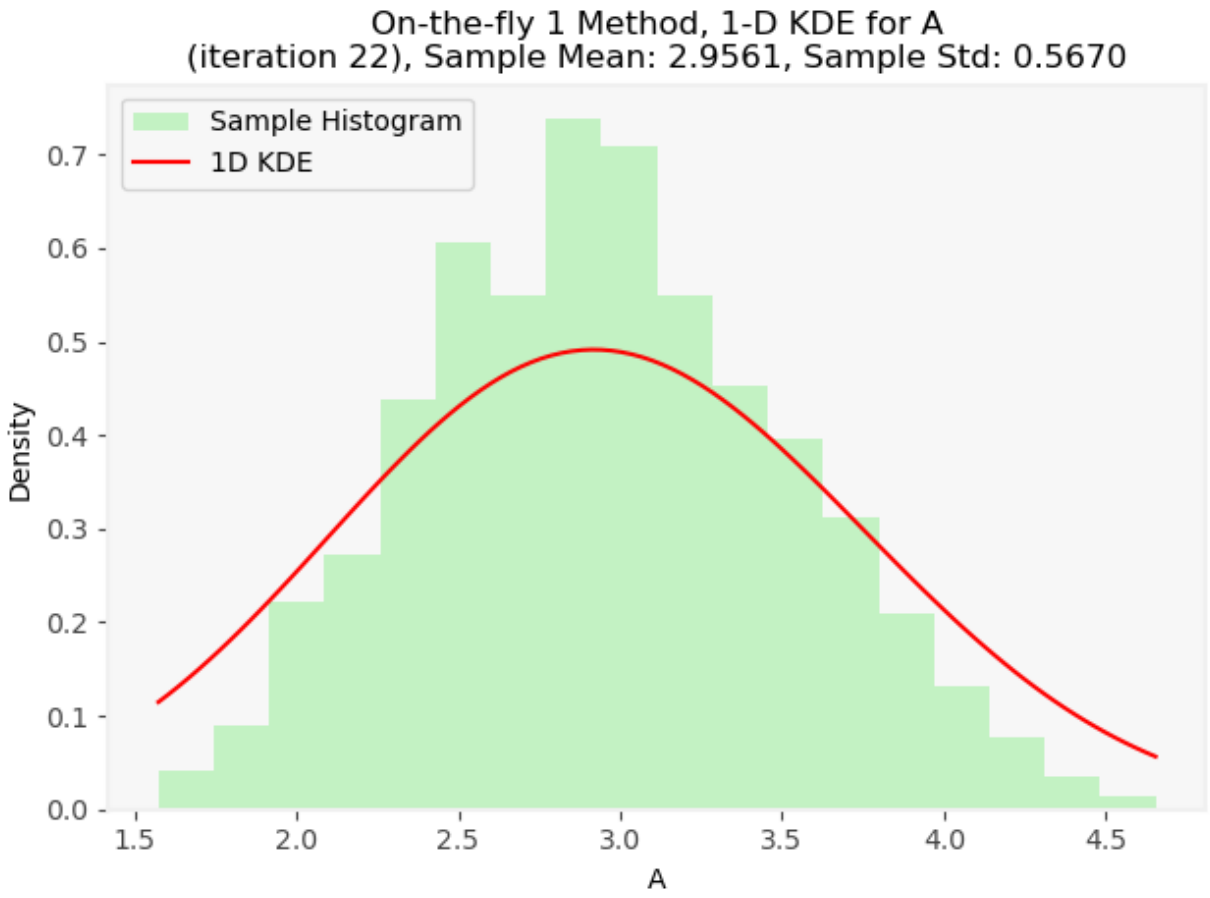

On-the-fly 1 Method, 1-D KDE for A
(iteration 17), Sample Mean: 2.9220, Sample Std: 0.8771
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6

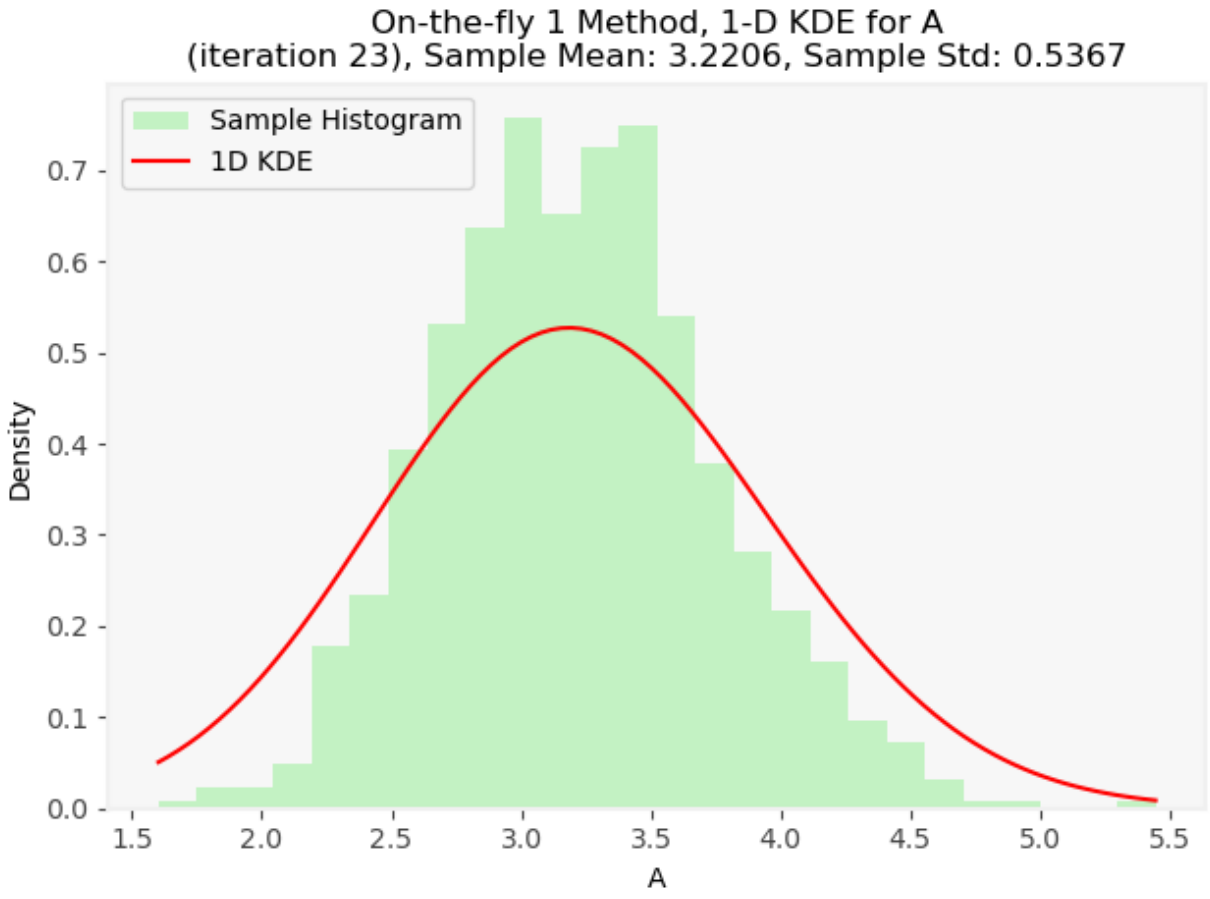

On-the-fly 1 Method, 1-D KDE for A
(iteration 18), Sample Mean: 3.2463, Sample Std: 0.8019
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6

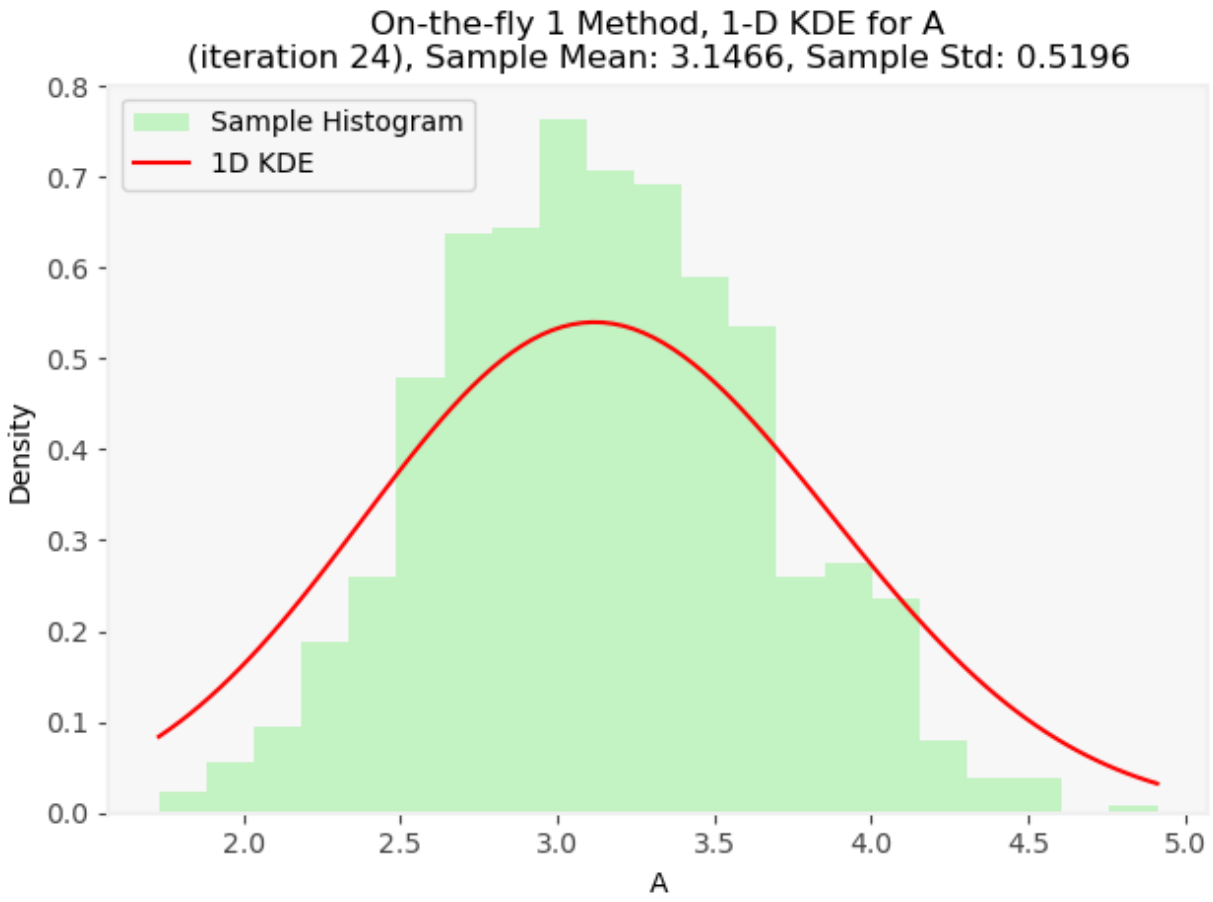

On-the-fly 1 Method, 1-D KDE for A
(iteration 19), Sample Mean: 3.1678, Sample Std: 0.7137
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1
2
3
4
5

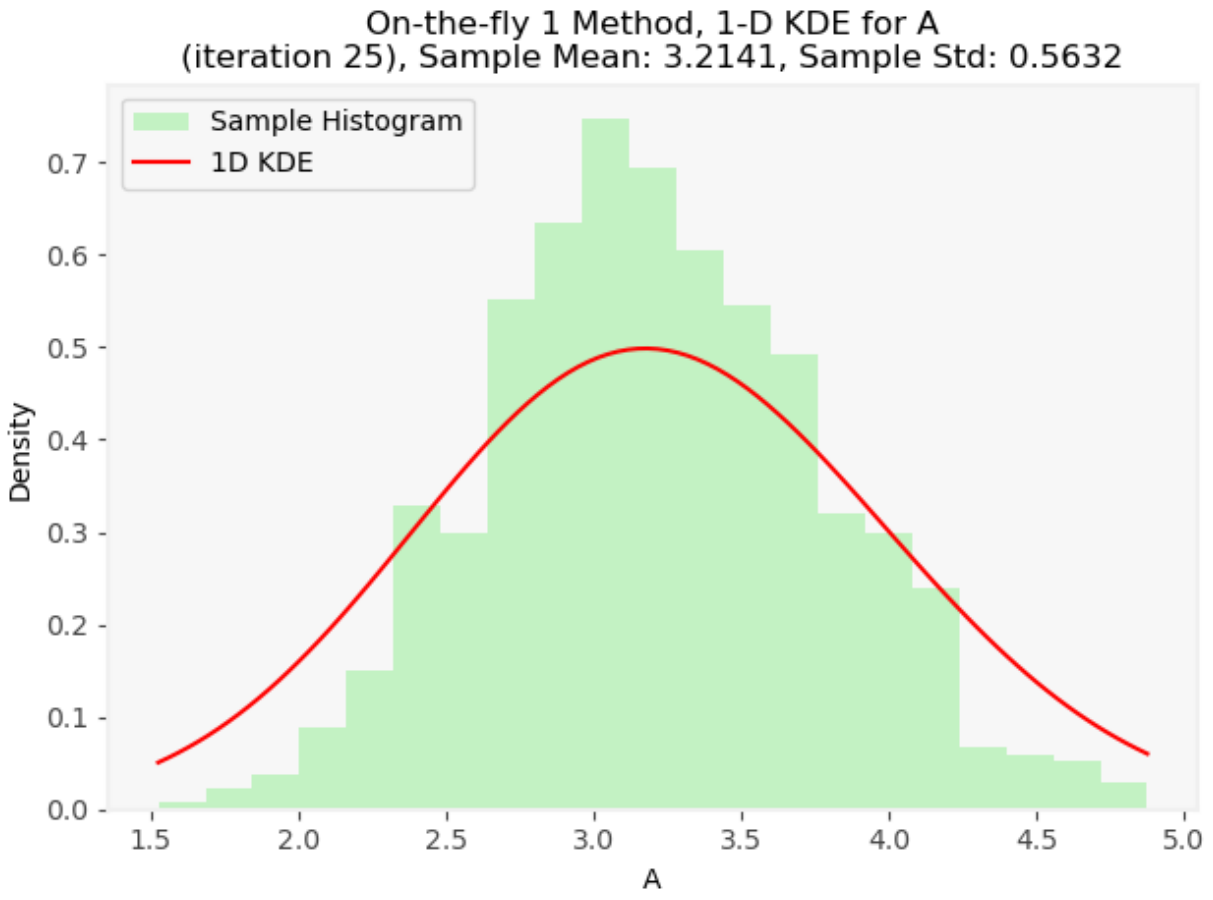

On-the-fly 1 Method, 1-D KDE for A
(iteration 20), Sample Mean: 3.0782, Sample Std: 0.7279
Sample Histogram
1D KDE
Density
A

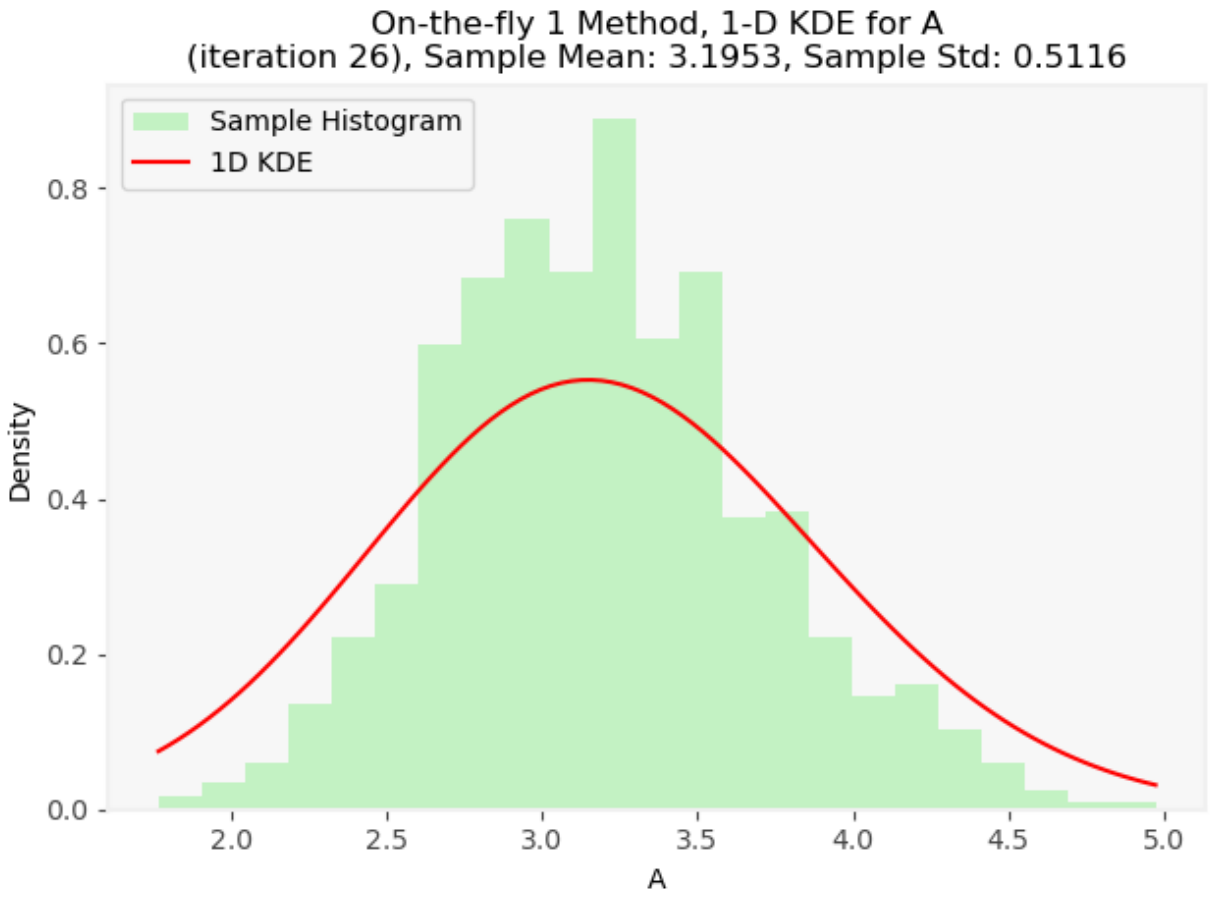

On-the-fly 1 Method, 1-D KDE for A
(iteration 21), Sample Mean: 2.5844, Sample Std: 0.6046
Sample Histogram
1D KDE
Density
A

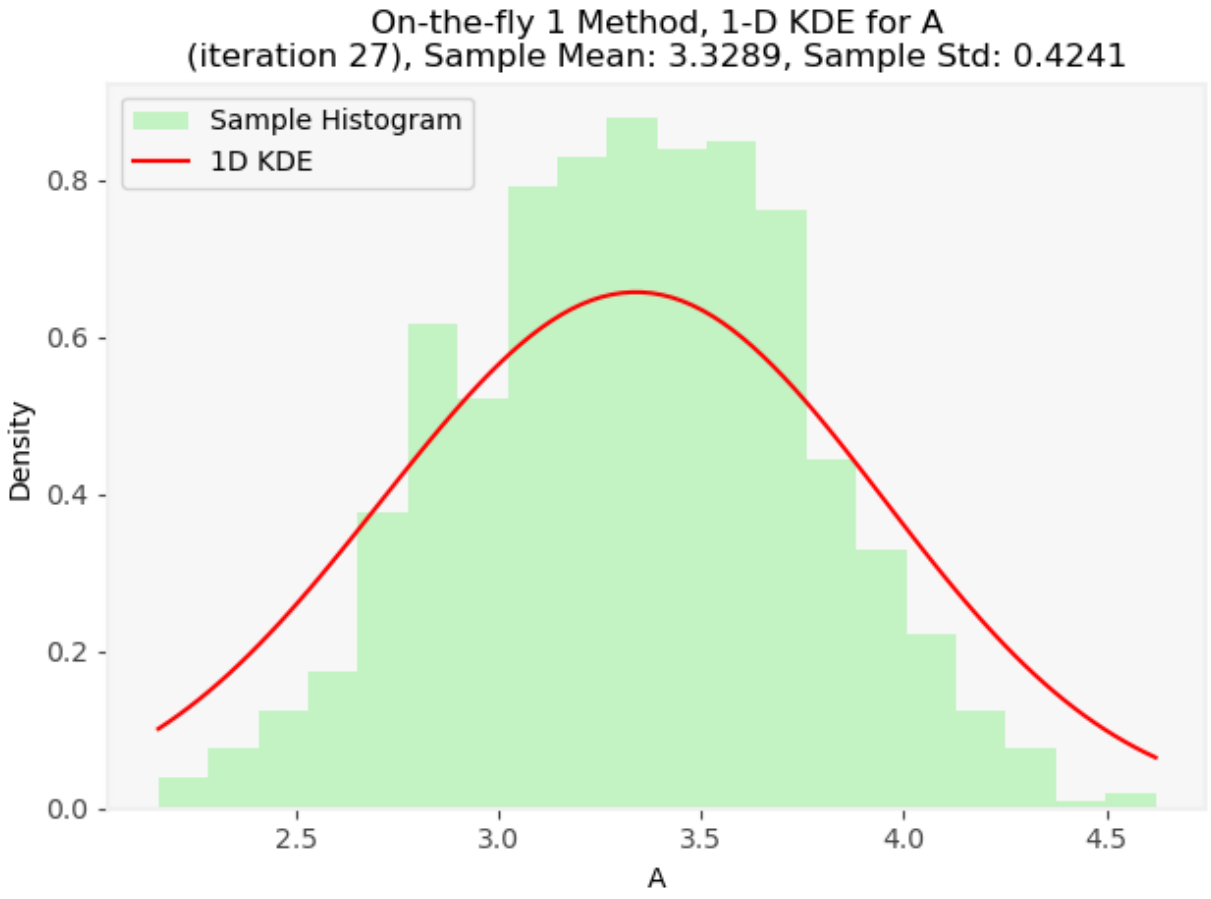

On-the-fly 1 Method, 1-D KDE for A
(iteration 22), Sample Mean: 2.9561, Sample Std: 0.5670
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1.5
2.0
2.5
3.0
3.5
4.0
4.5

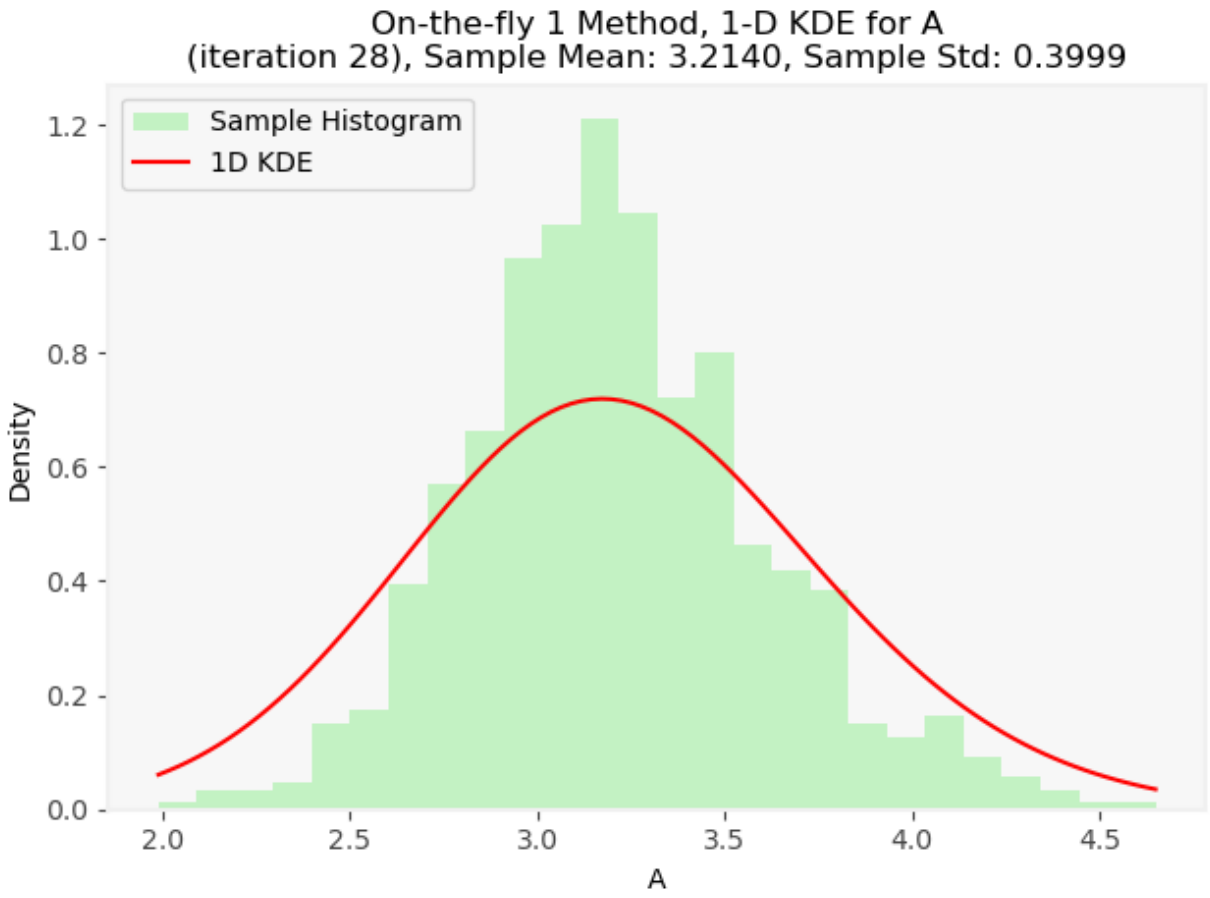

On-the-fly 1 Method, 1-D KDE for A
(iteration 23), Sample Mean: 3.2206, Sample Std: 0.5367
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5

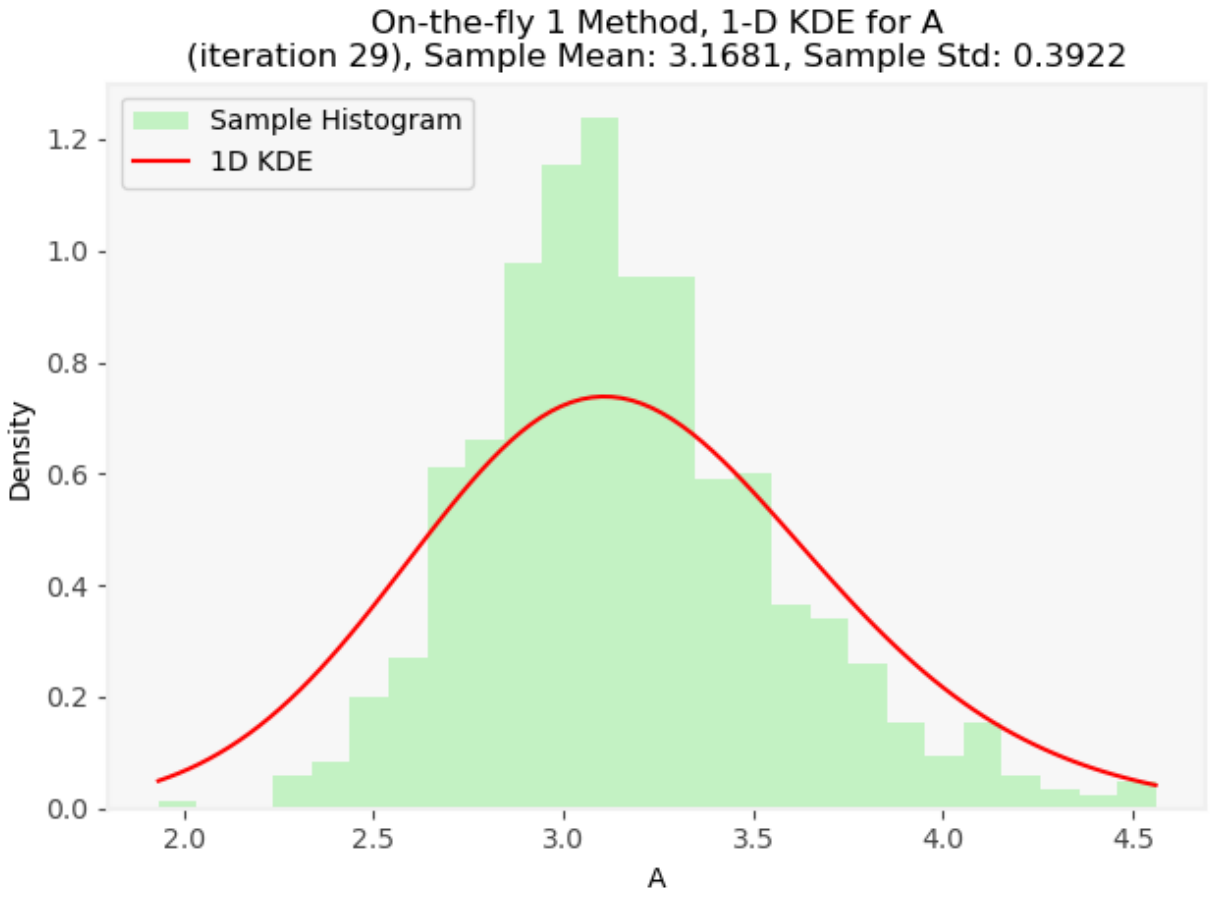

On-the-fly 1 Method, 1-D KDE for A
(iteration 24), Sample Mean: 3.1466, Sample Std: 0.5196
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
2.0
2.5
3.0
3.5
4.0
4.5
5.0

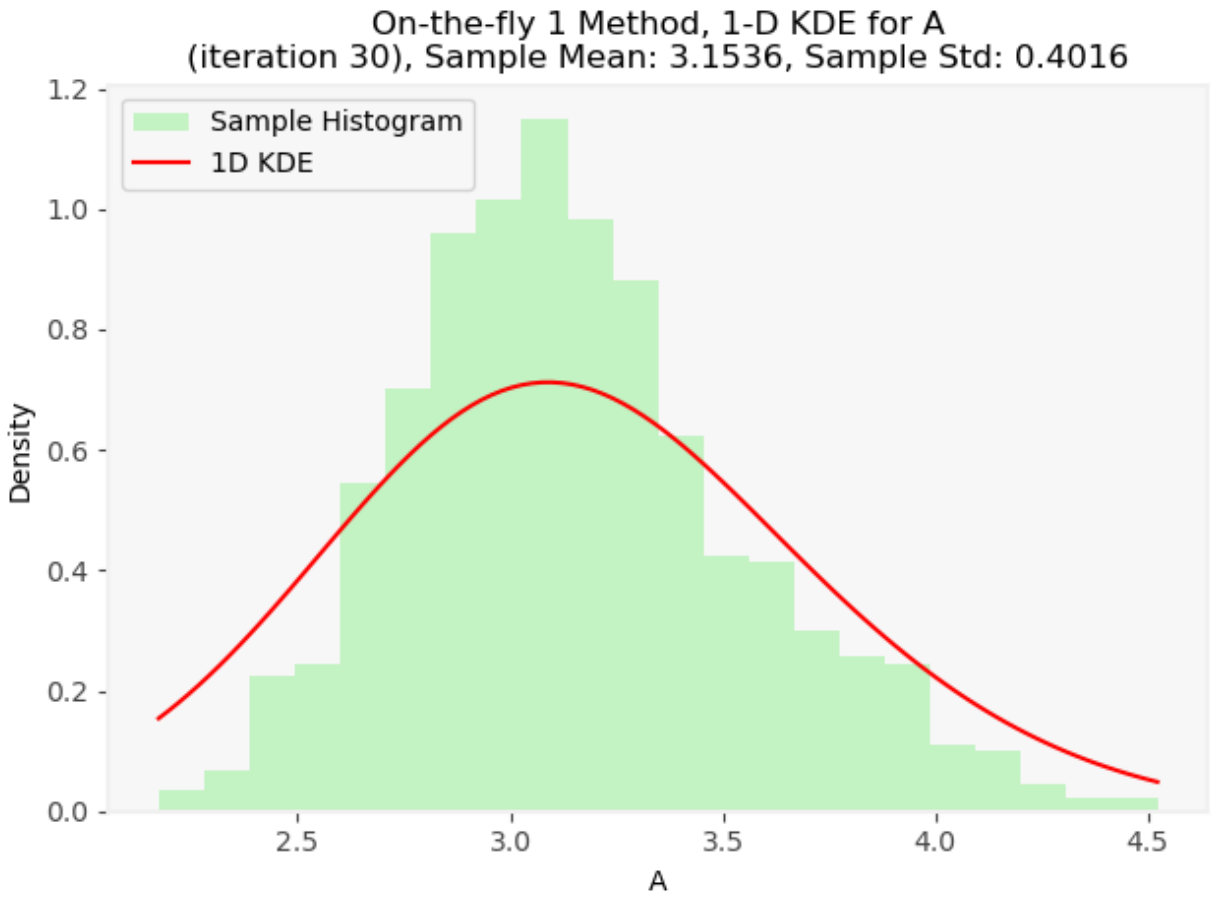

On-the-fly 1 Method, 1-D KDE for A
(iteration 25), Sample Mean: 3.2141, Sample Std: 0.5632
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

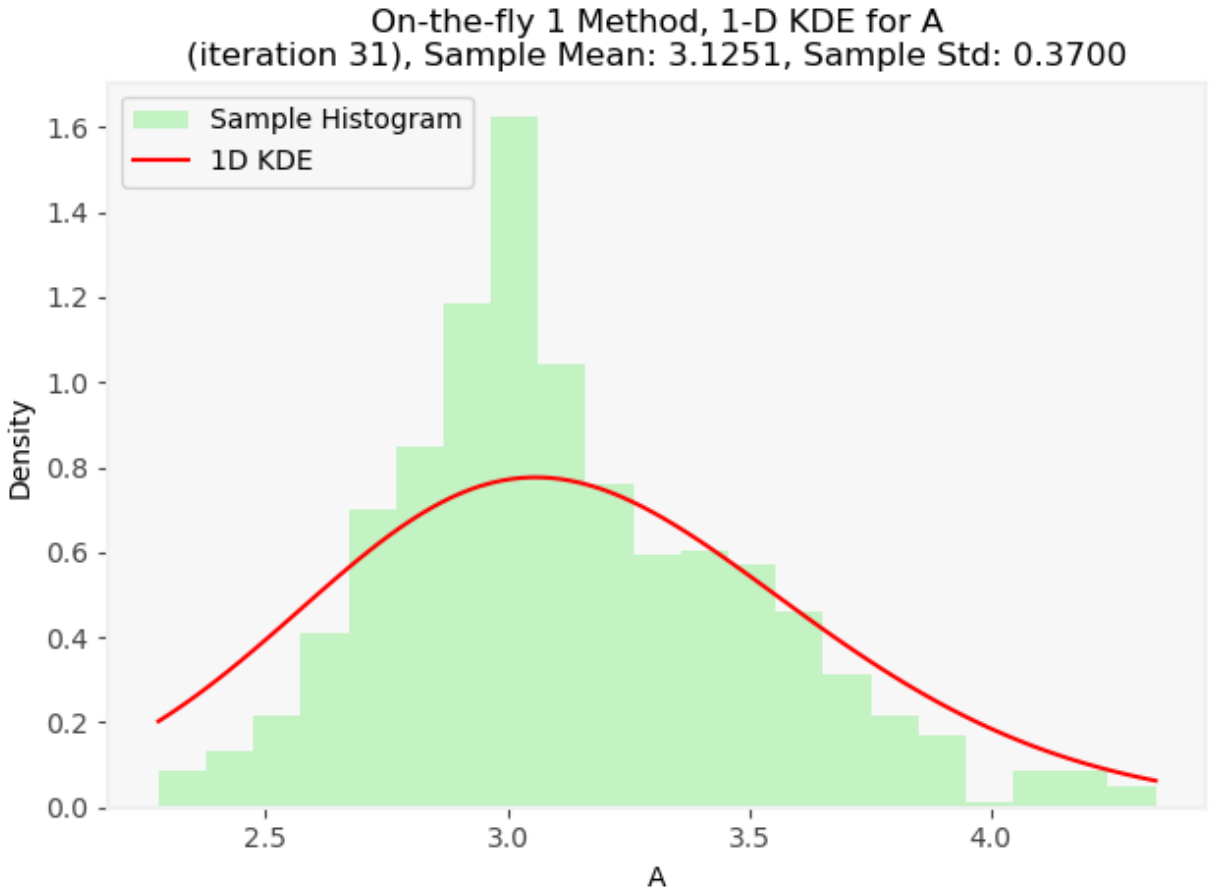

On-the-fly 1 Method, 1-D KDE for A
(iteration 26), Sample Mean: 3.1953, Sample Std: 0.5116
Sample Histogram
1D KDE
Density
0.0
0.2
0.4
0.6
0.8
2.0
2.5
3.0
3.5
4.0
4.5
5.0
A

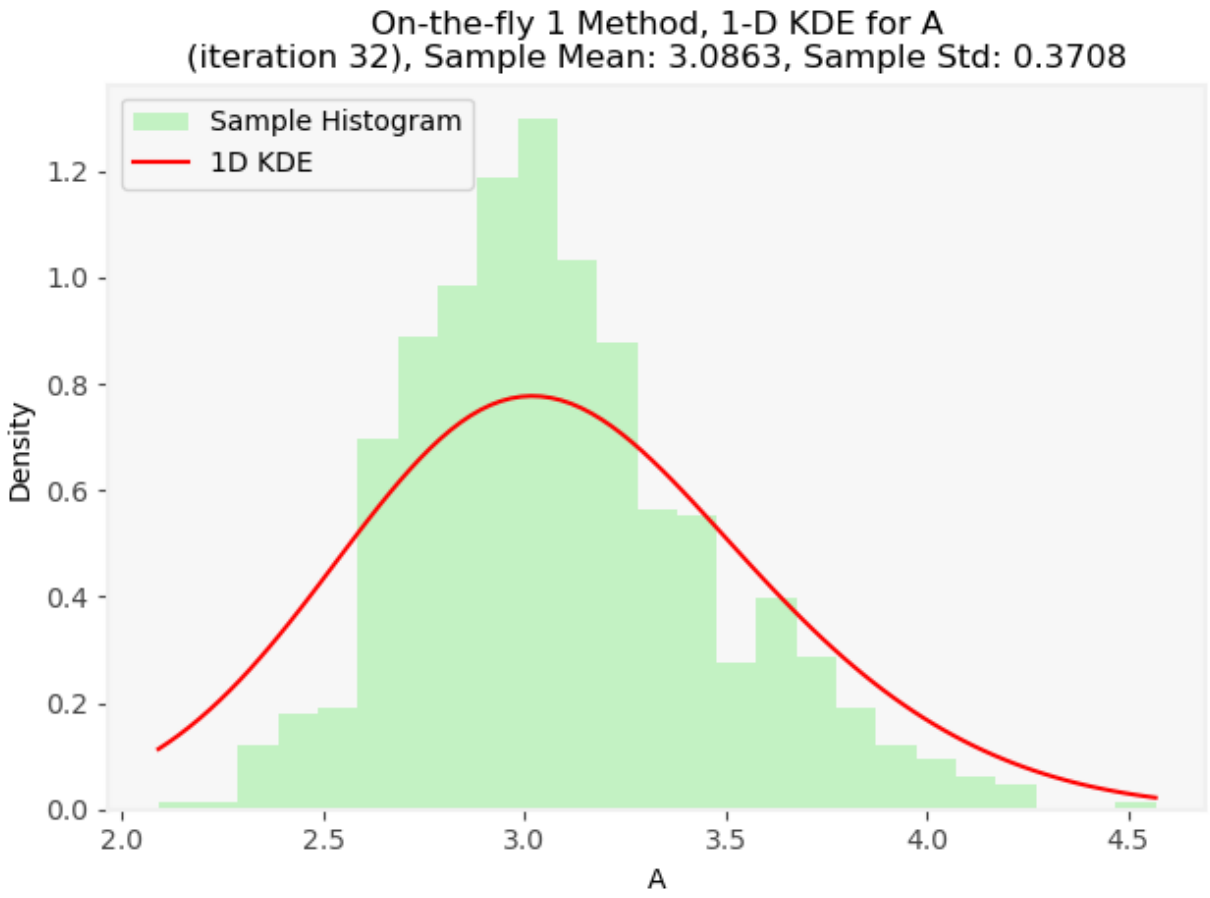

On-the-fly 1 Method, 1-D KDE for A
(iteration 27), Sample Mean: 3.3289, Sample Std: 0.4241
Sample Histogram
1D KDE
Density
0.0
0.2
0.4
0.6
0.8
2.5
3.0
3.5
4.0
4.5
A

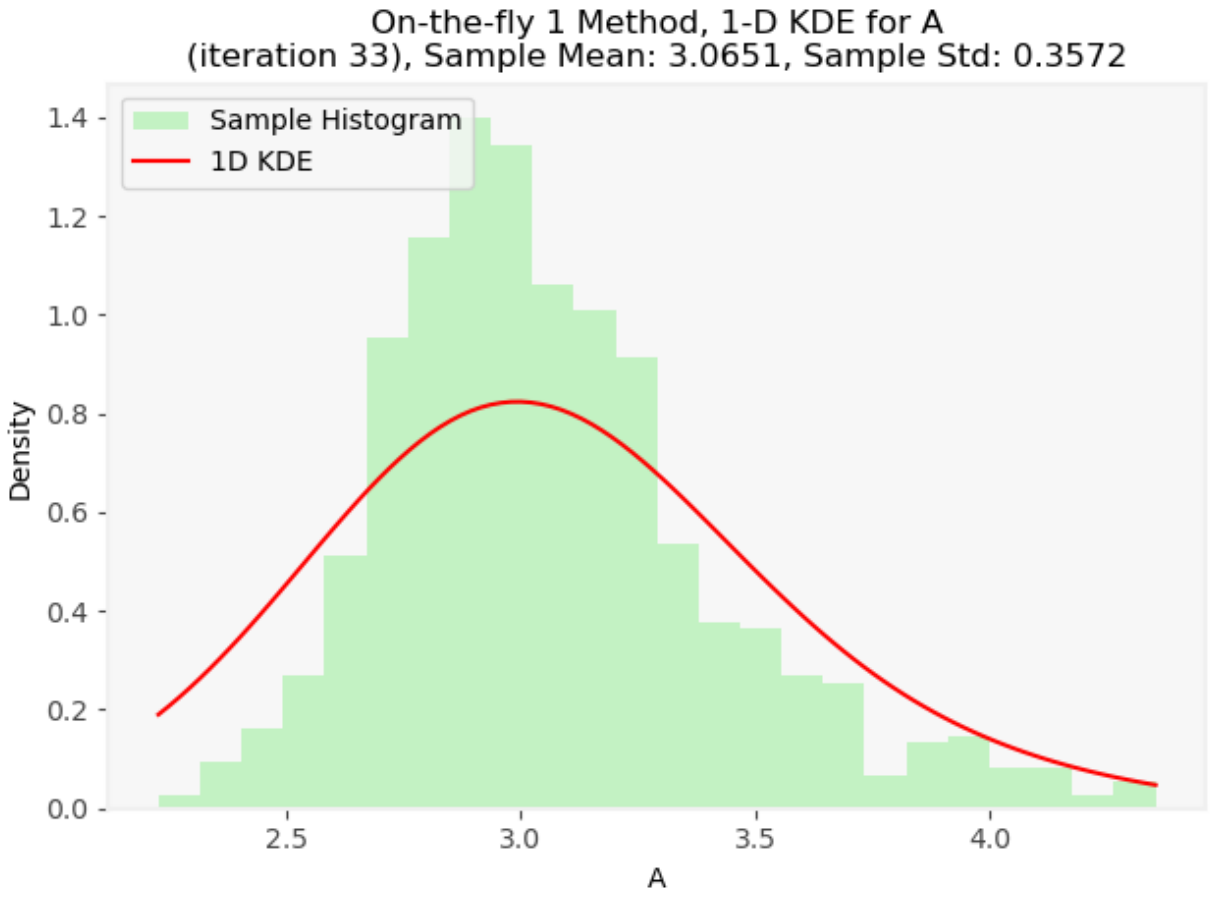

On-the-fly 1 Method, 1-D KDE for A
(iteration 28), Sample Mean: 3.2140, Sample Std: 0.3999
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.0
2.5
3.0
3.5
4.0
4.5

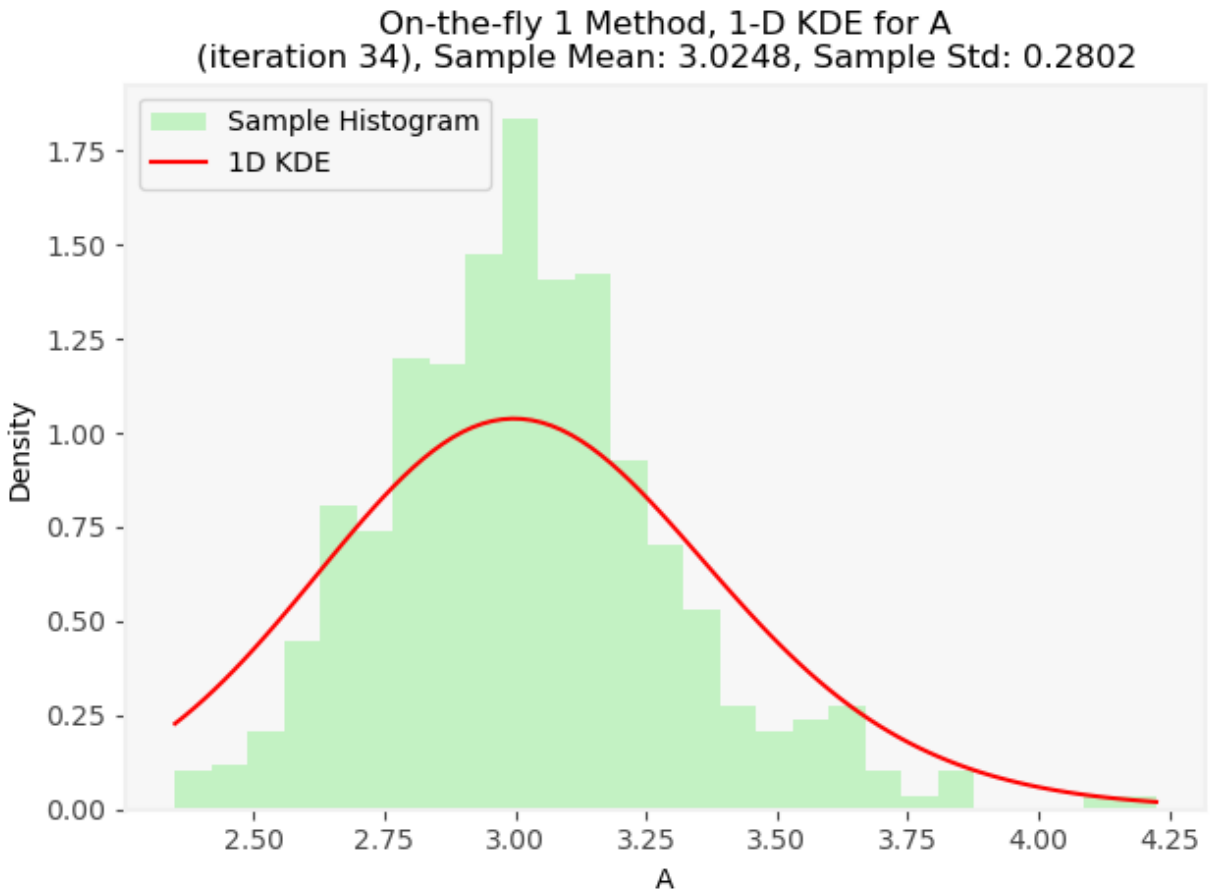

On-the-fly 1 Method, 1-D KDE for A
(iteration 29), Sample Mean: 3.1681, Sample Std: 0.3922
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.0
2.5
3.0
3.5
4.0
4.5

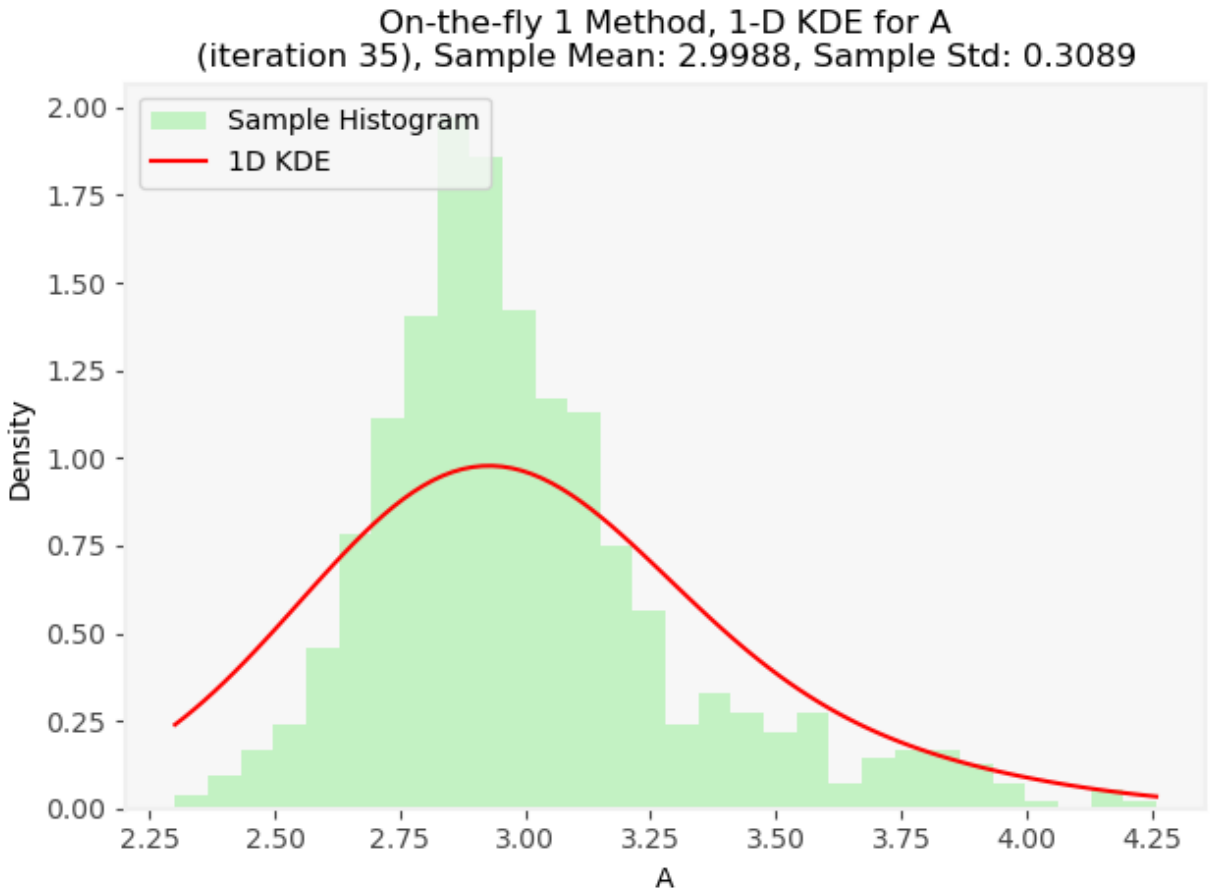

On-the-fly 1 Method, 1-D KDE for A
(iteration 30), Sample Mean: 3.1536, Sample Std: 0.4016
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0
4.5

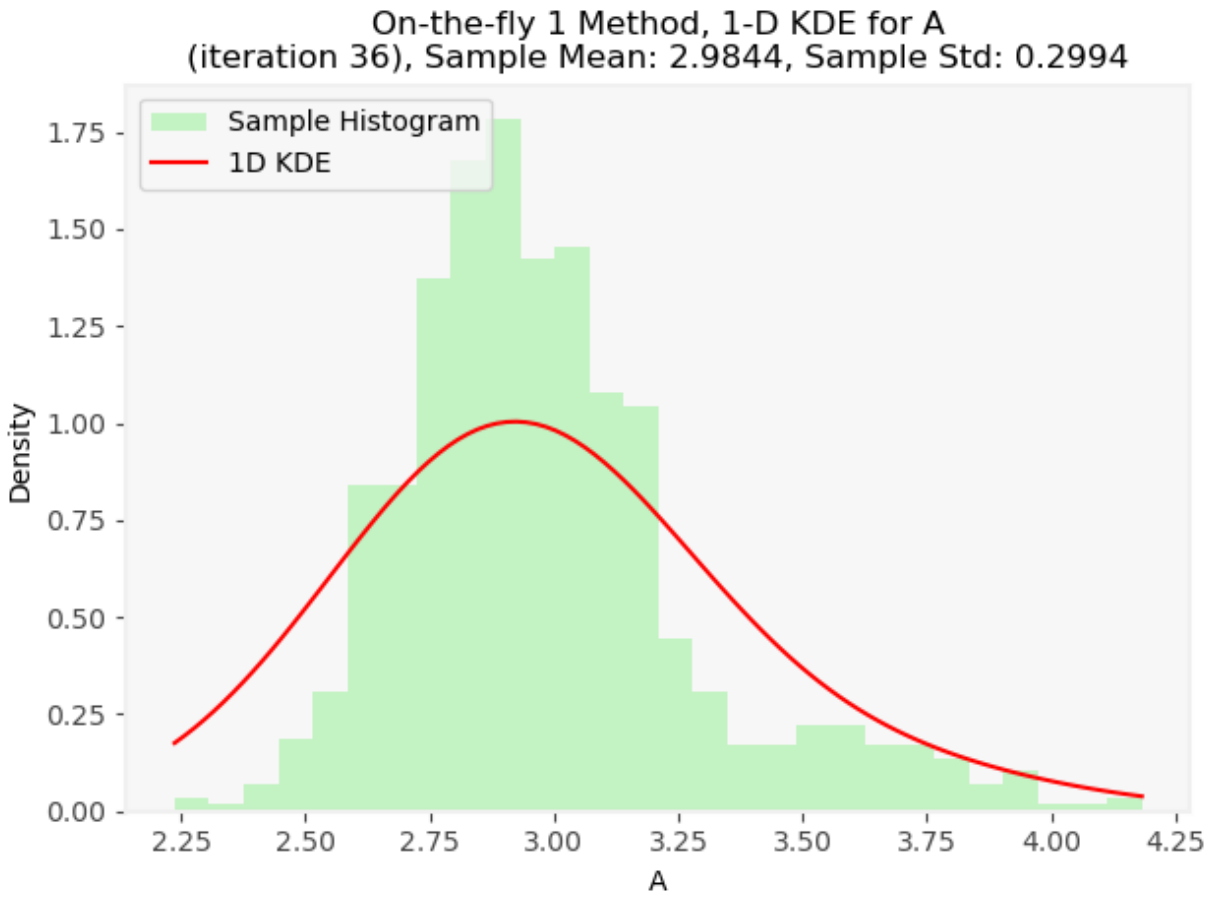

On-the-fly 1 Method, 1-D KDE for A
(iteration 31), Sample Mean: 3.1251, Sample Std: 0.3700
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.5
3.0
3.5
4.0


On-the-fly 1 Method, 1-D KDE for A
(iteration 32), Sample Mean: 3.0863, Sample Std: 0.3708
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.0
2.5
3.0
3.5
4.0
4.5

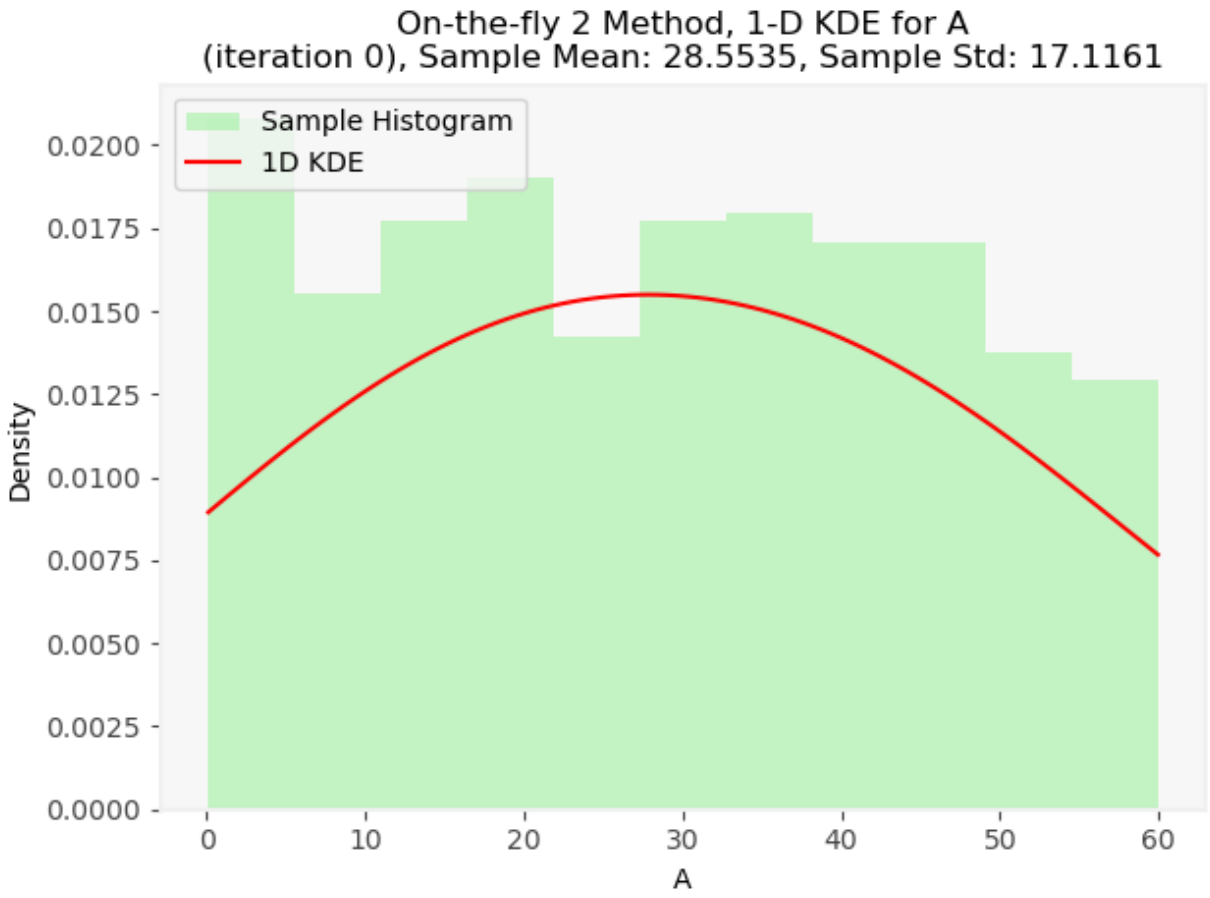

On-the-fly 1 Method, 1-D KDE for A
(iteration 33), Sample Mean: 3.0651, Sample Std: 0.3572
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.5
3.0
3.5
4.0

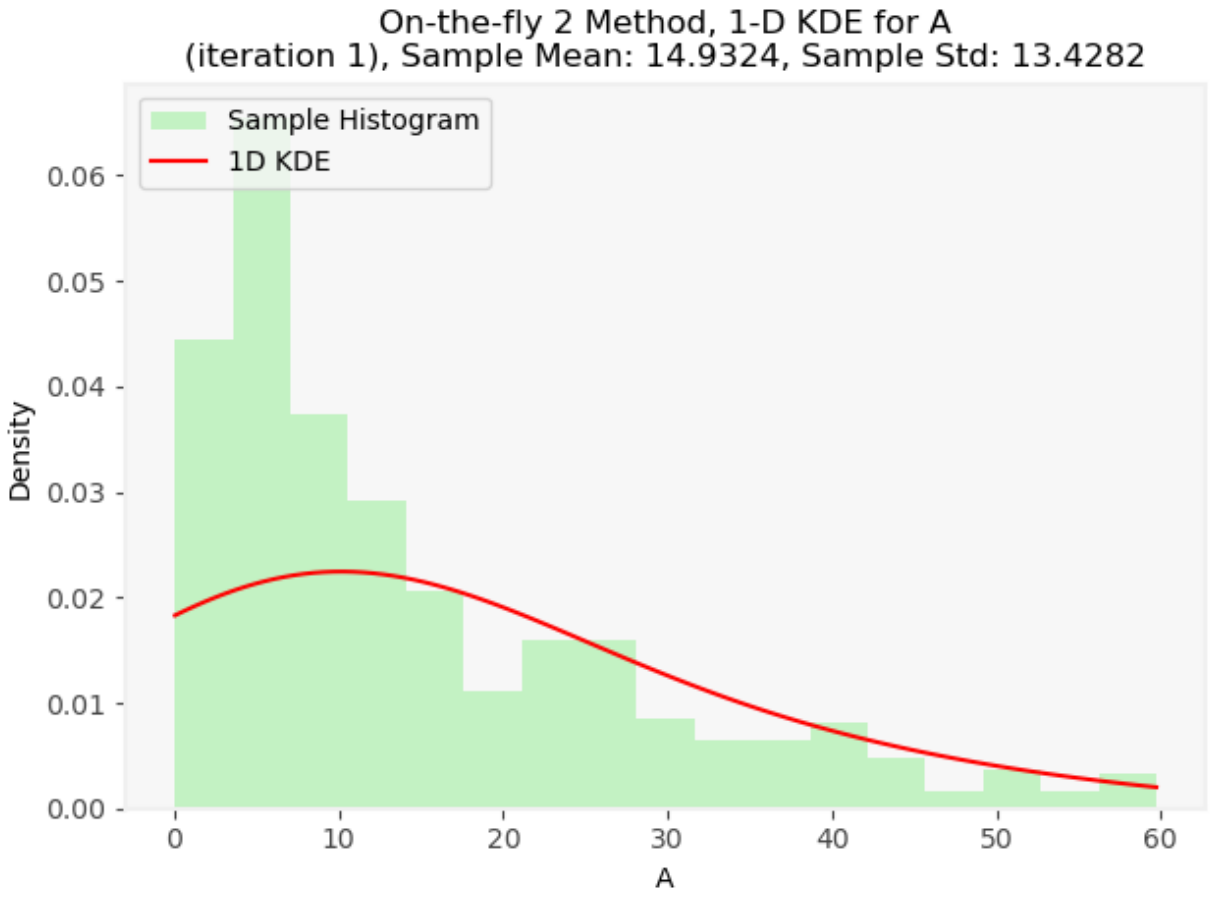

On-the-fly 1 Method, 1-D KDE for A
(iteration 34), Sample Mean: 3.0248, Sample Std: 0.2802
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25

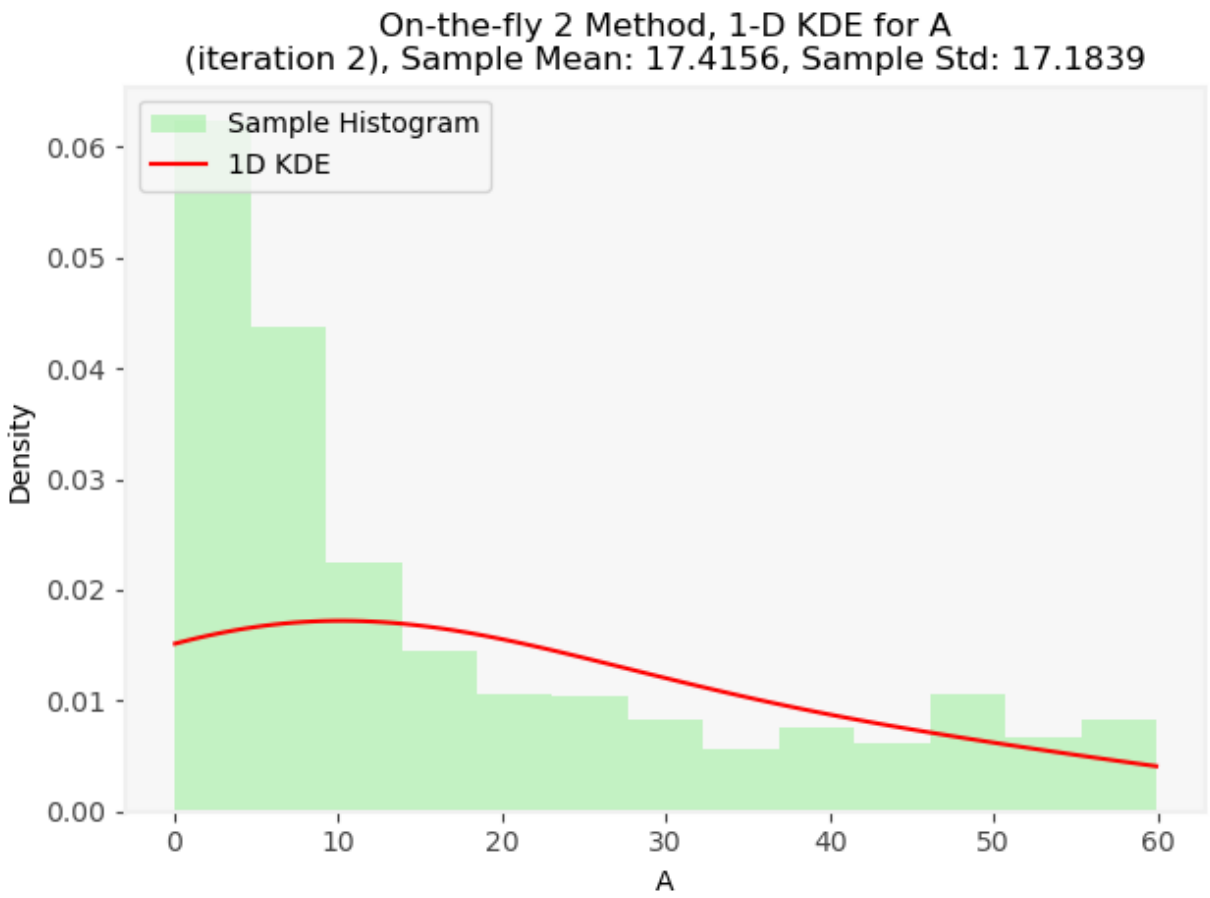

On-the-fly 1 Method, 1-D KDE for A
(iteration 35), Sample Mean: 2.9988, Sample Std: 0.3089
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25

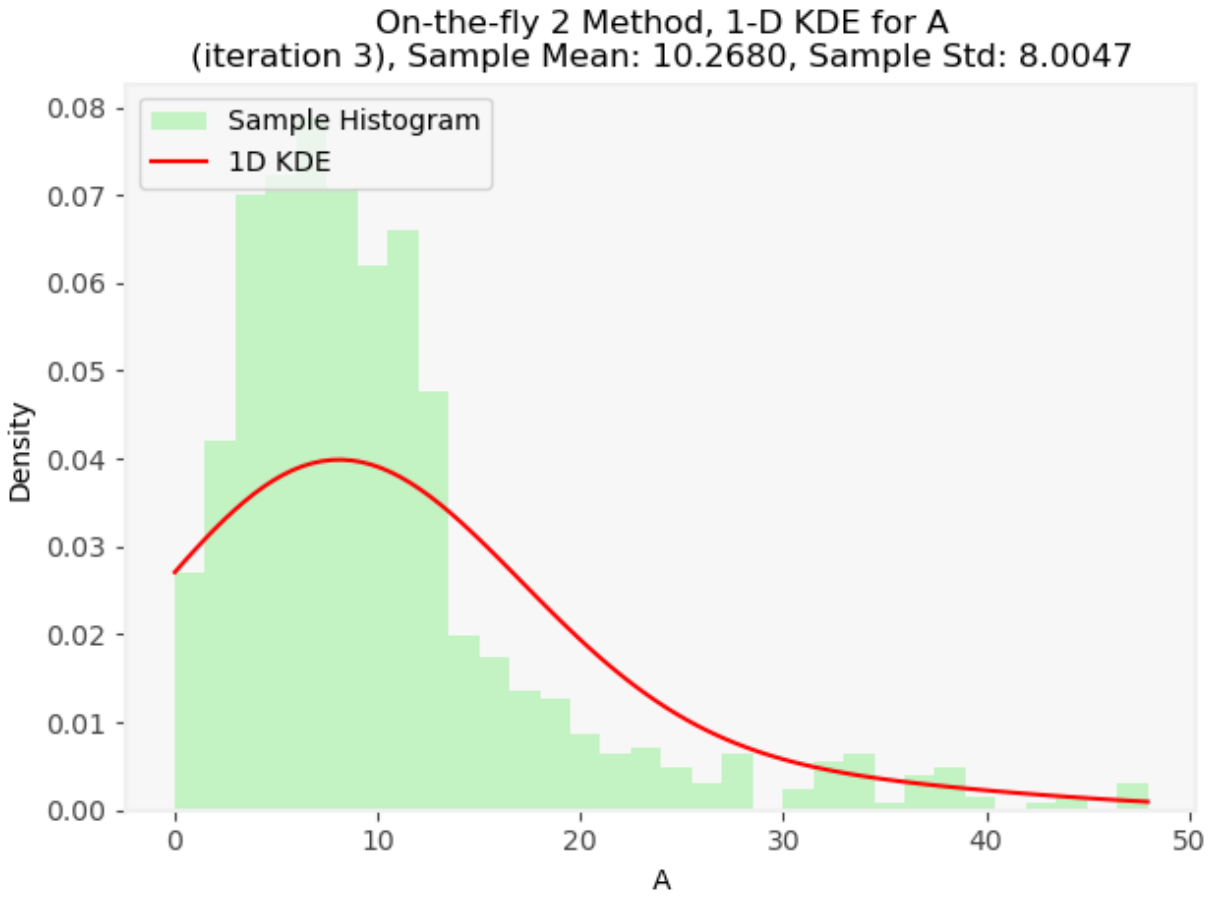


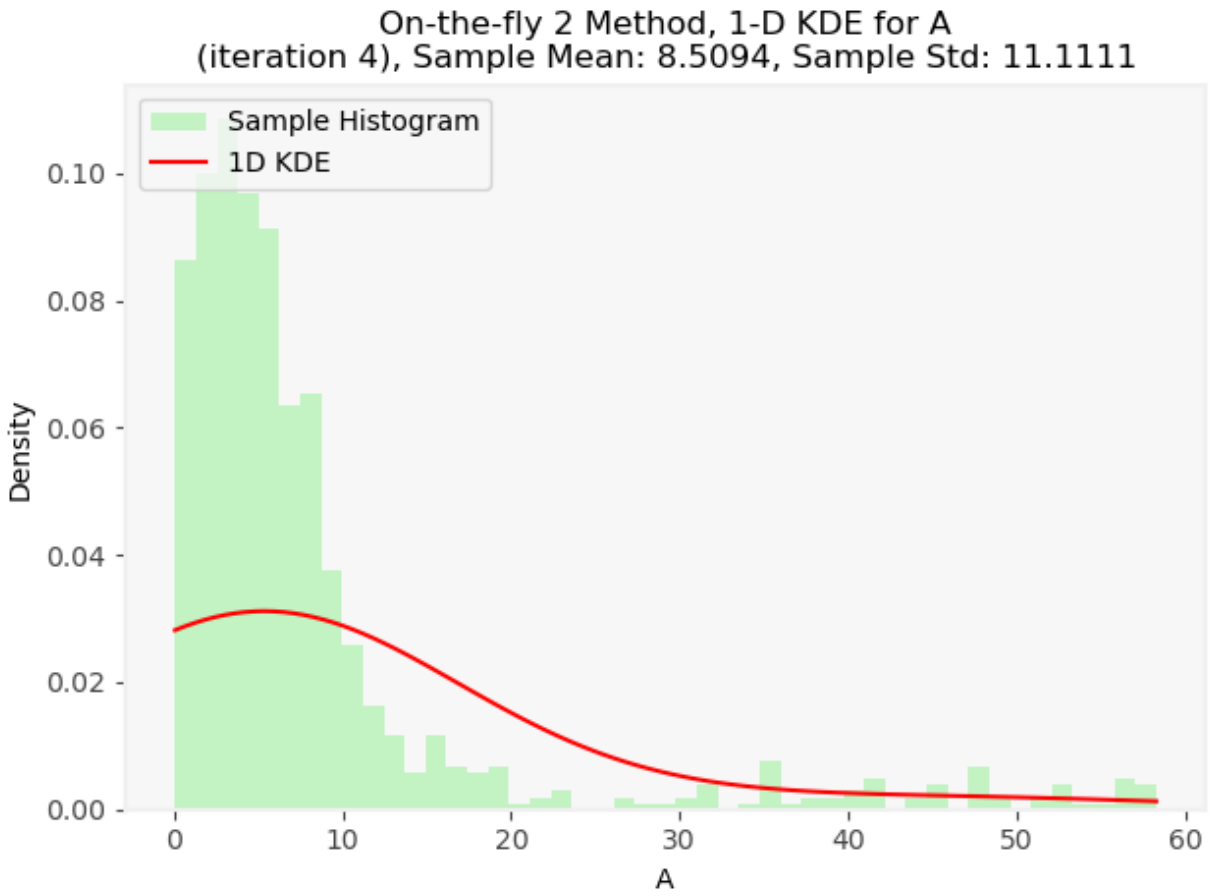
In [55]:
```
#Printing the evolution of parameter A for On-the-fly 2
for i in range(len(exp_on_the_fly2.totaltimes())):
    MyPlots.plot_hist_1d_kde(list_par_separated_o2[0][i], kdes_on_the_fly2[i,0],"On-th
```

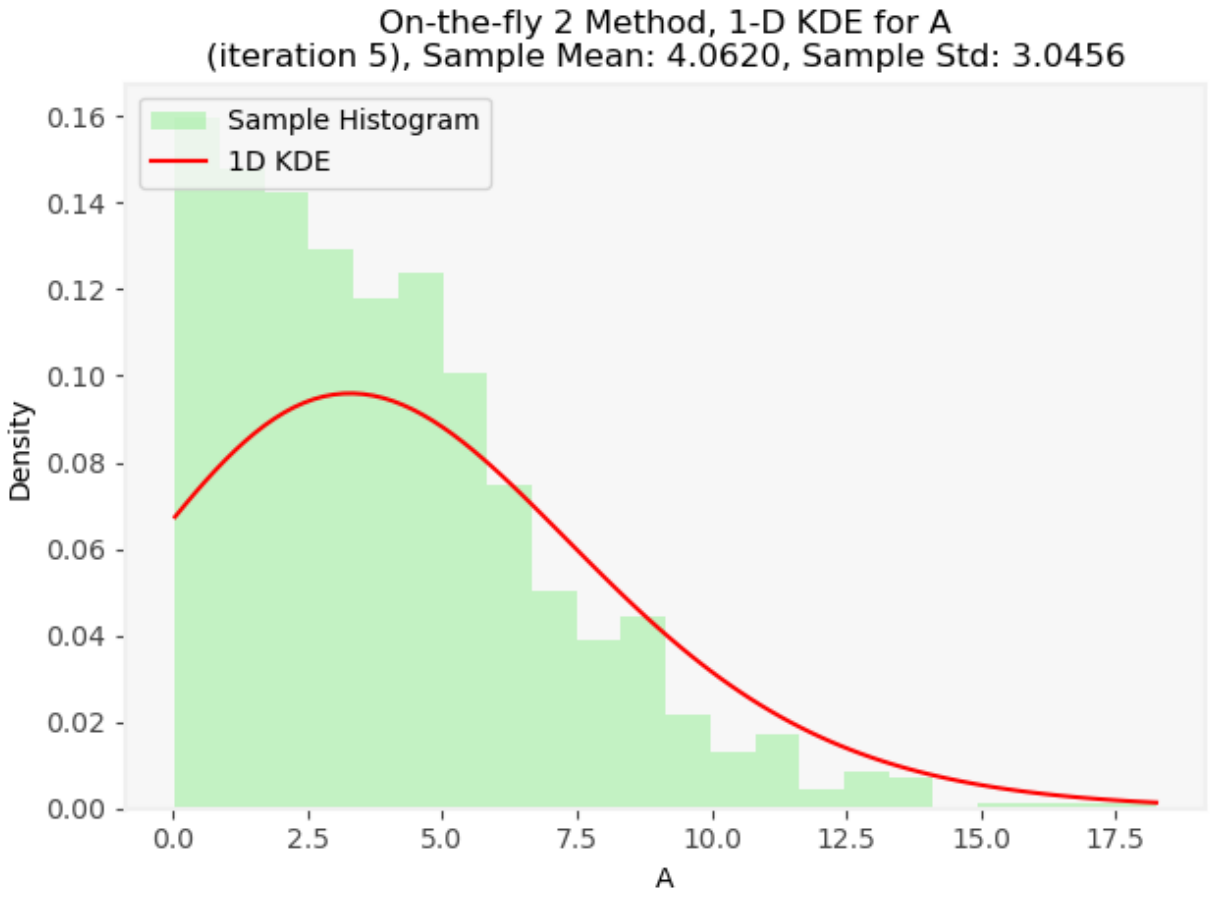

On-the-fly 2 Method, 1-D KDE for A
(iteration 0), Sample Mean: 28.5535, Sample Std: 17.1161
Sample Histogram
1D KDE
Density
0.0200
0.0175
0.0150
0.0125
0.0100
0.0075
0.0050
0.0025
0.0000
0
10
20
30
40
50
60
A

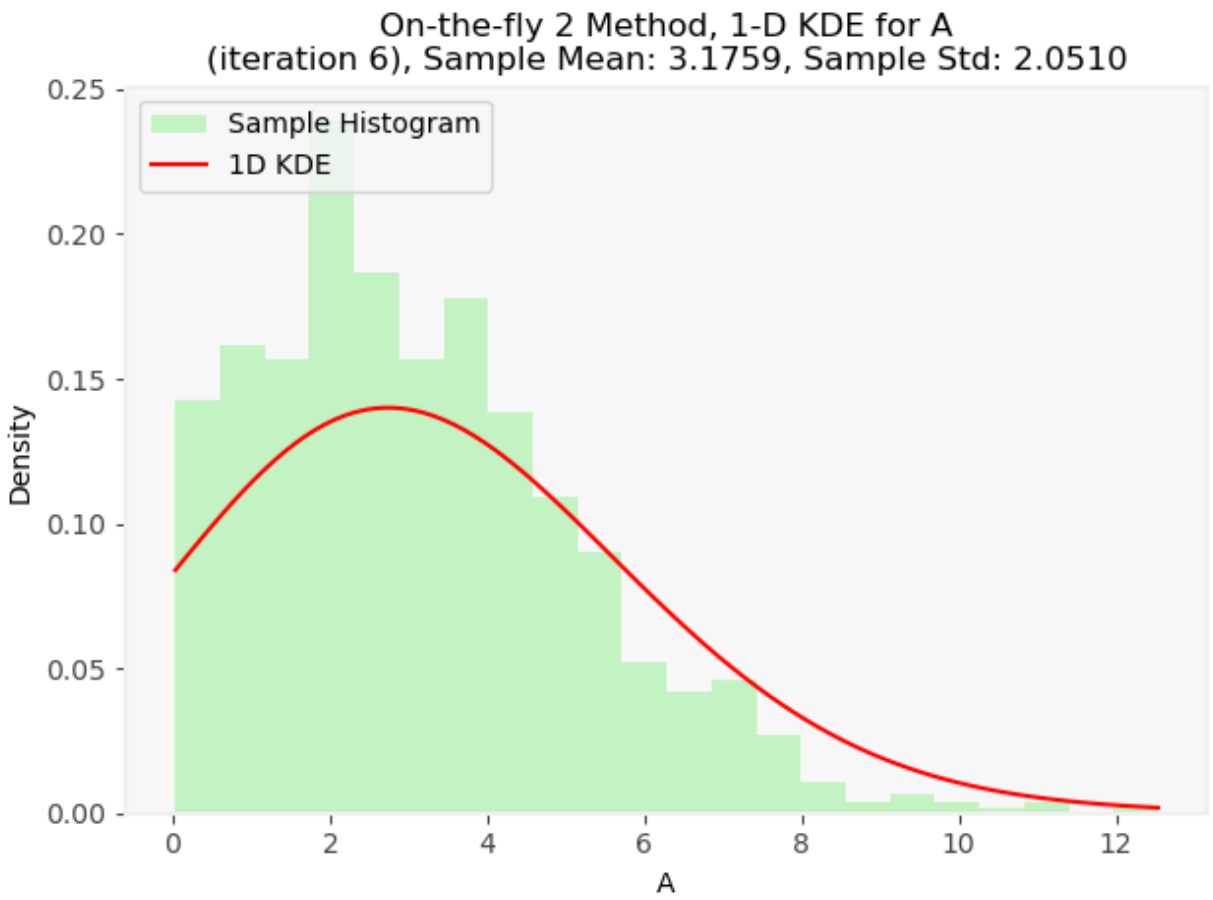

On-the-fly 2 Method, 1-D KDE for A
(iteration 1), Sample Mean: 14.9324, Sample Std: 13.4282
Sample Histogram
1D KDE
Density
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
10
20
30
40
50
60
A

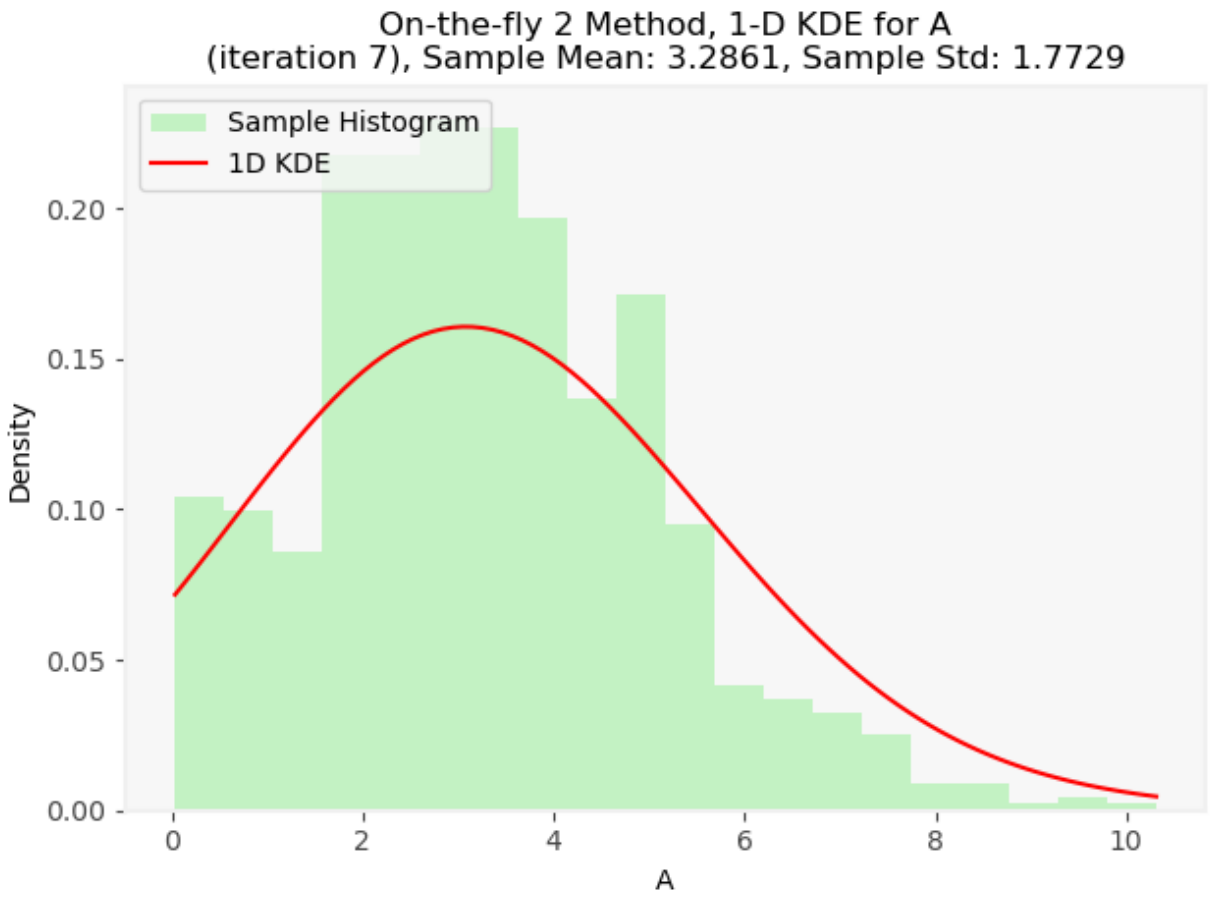

On-the-fly 2 Method, 1-D KDE for A
(iteration 2), Sample Mean: 17.4156, Sample Std: 17.1839
Sample Histogram
1D KDE
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0
10
20
30
40
50
60
A

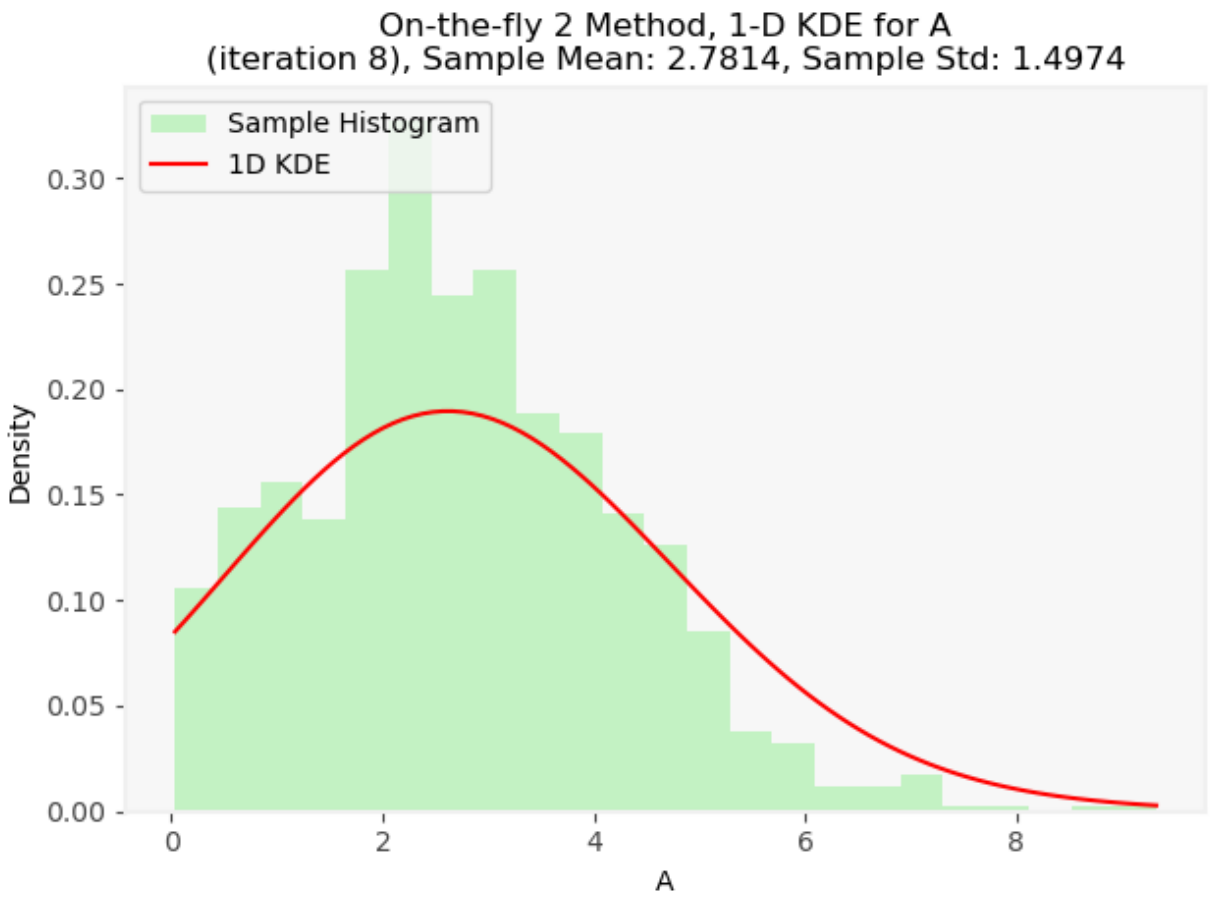

On-the-fly 2 Method, 1-D KDE for A
(iteration 3), Sample Mean: 10.2680, Sample Std: 8.0047
Sample Histogram
1D KDE
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0
10
20
30
40
50
A

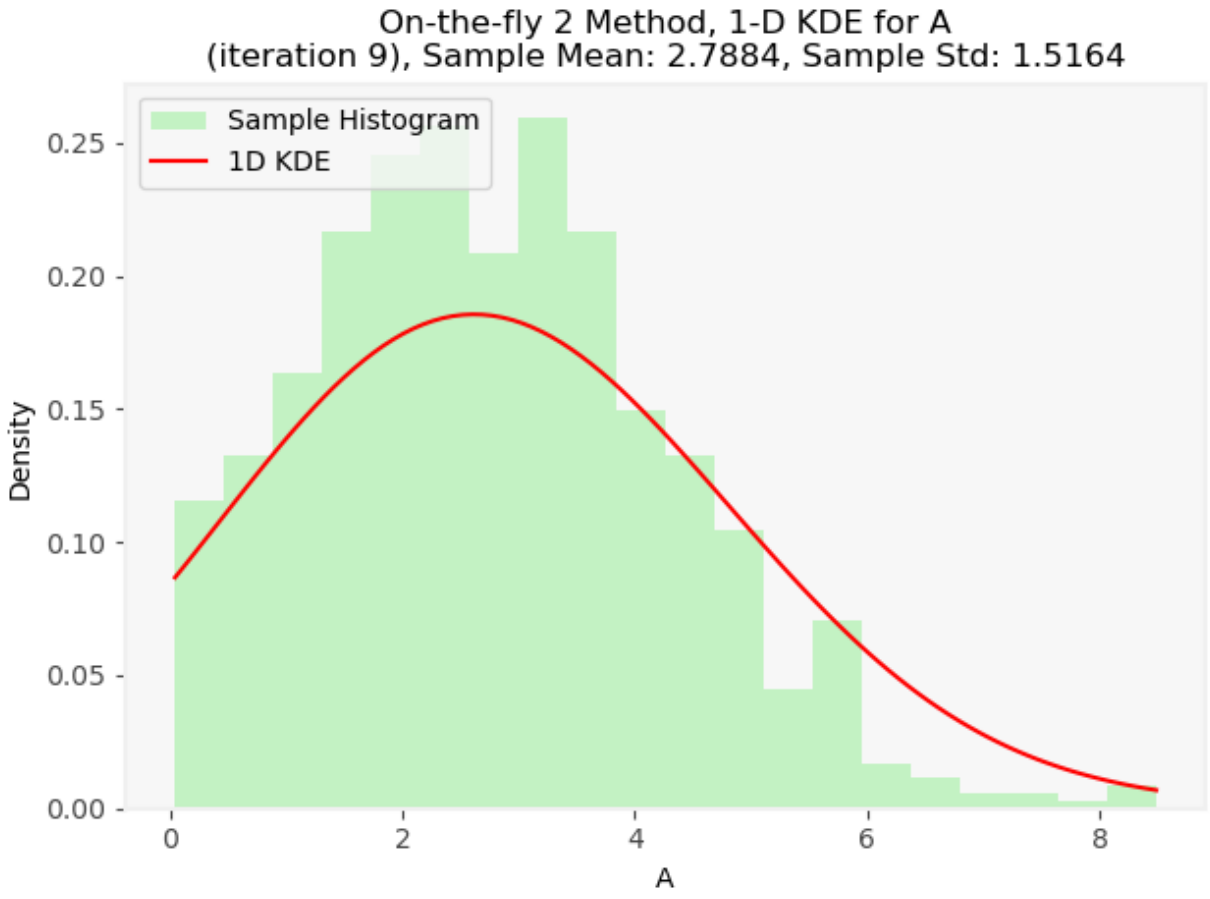

On-the-fly 2 Method, 1-D KDE for A
(iteration 4), Sample Mean: 8.5094, Sample Std: 11.1111
Sample Histogram
1D KDE
Density
0.00
0.02
0.04
0.06
0.08
0.10
0
10
20
30
40
50
60
A

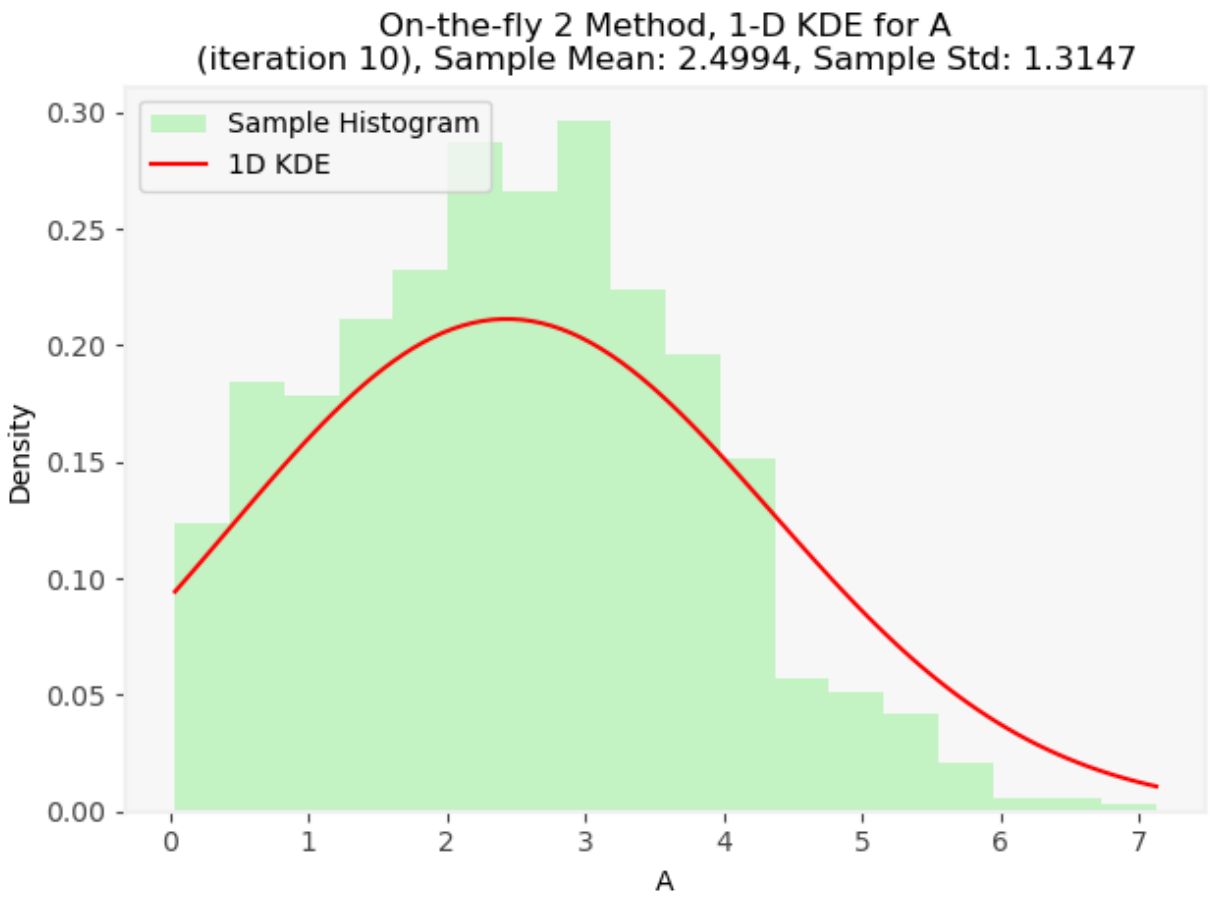

On-the-fly 2 Method, 1-D KDE for A
(iteration 5), Sample Mean: 4.0620, Sample Std: 3.0456
Sample Histogram
1D KDE
Density
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
0.16
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
A

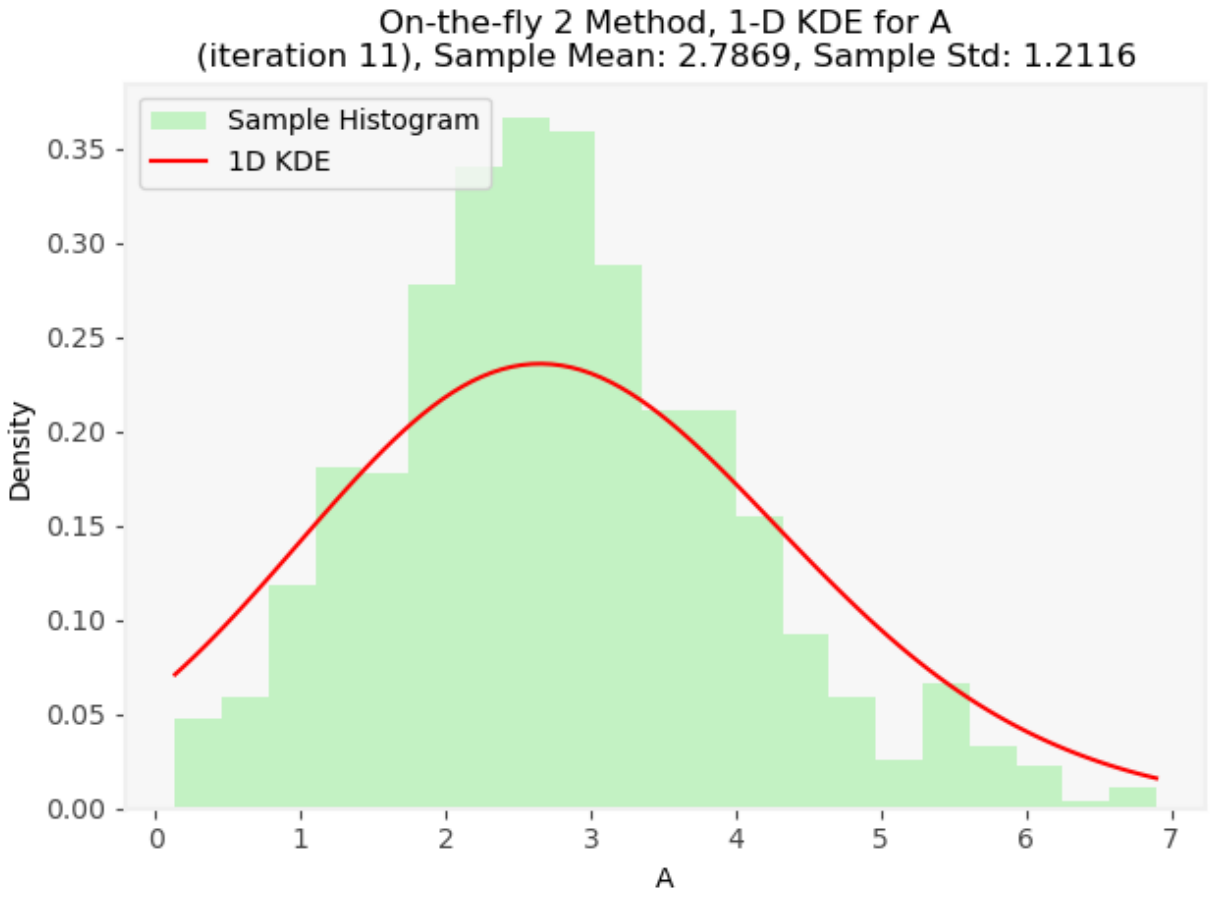

On-the-fly 2 Method, 1-D KDE for A
(iteration 6), Sample Mean: 3.1759, Sample Std: 2.0510
Sample Histogram
1D KDE
Density
A
0.25
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
10
12

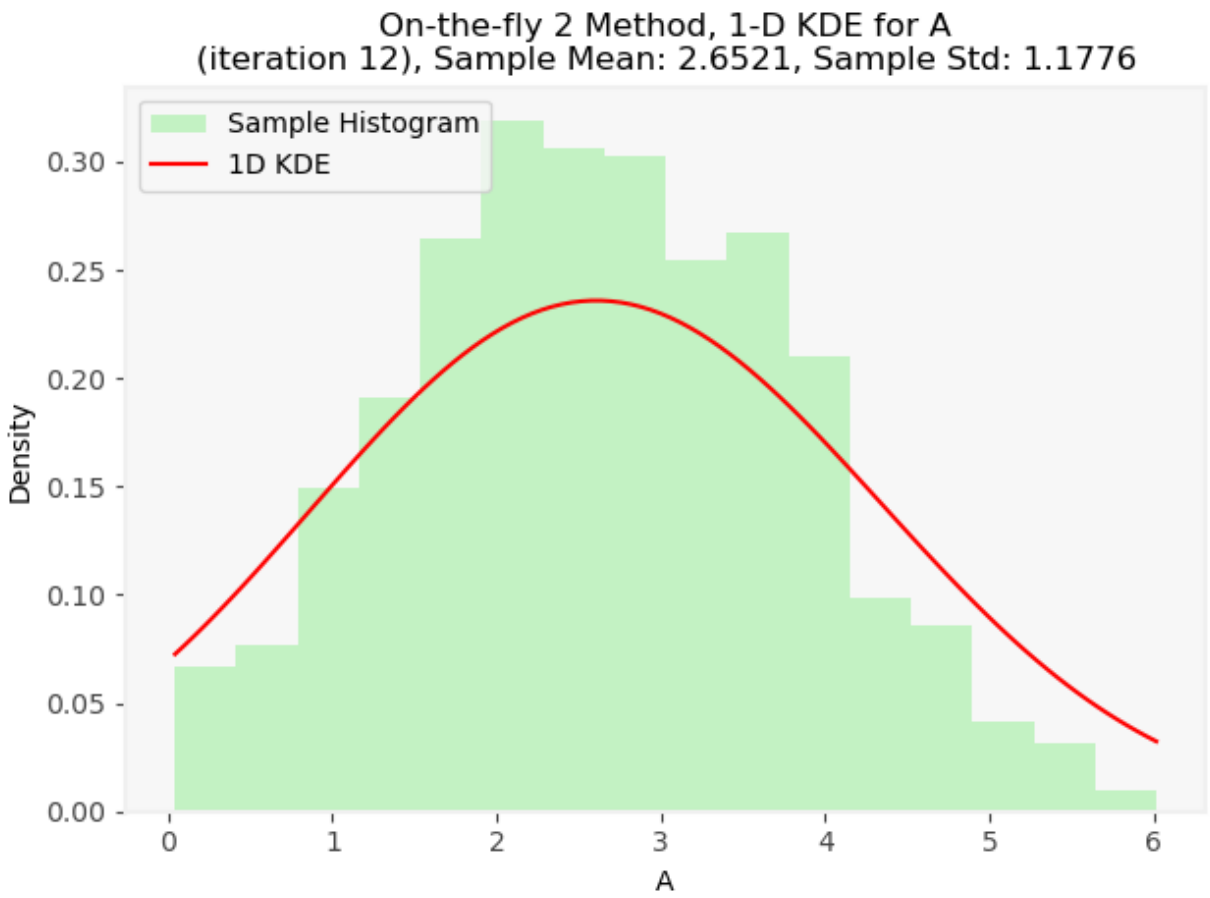

On-the-fly 2 Method, 1-D KDE for A
(iteration 7), Sample Mean: 3.2861, Sample Std: 1.7729
Sample Histogram
1D KDE
Density
A
0.20
0.15
0.10
0.05
0.00
0
2
4
6
8
10

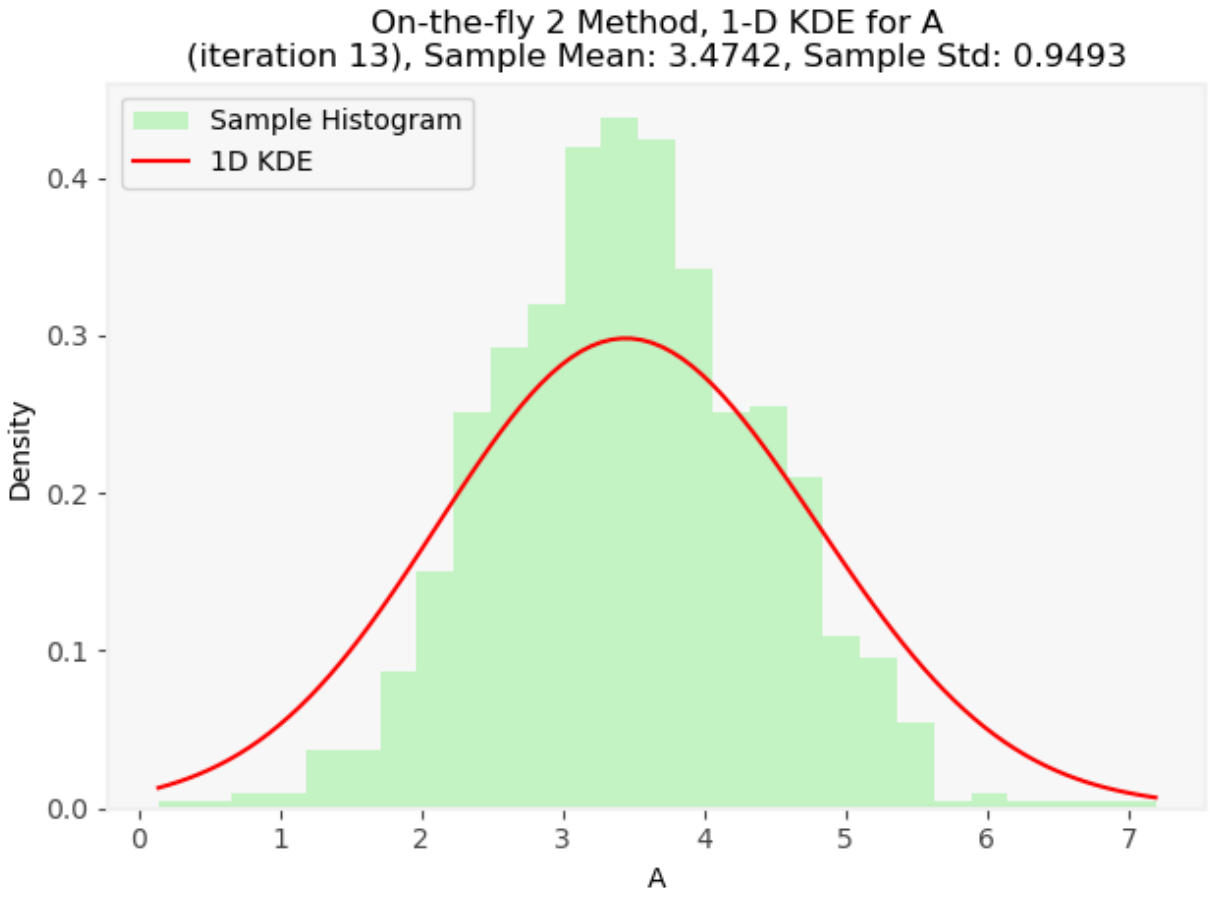

On-the-fly 2 Method, 1-D KDE for A
(iteration 8), Sample Mean: 2.7814, Sample Std: 1.4974
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
2
4
6
8
A

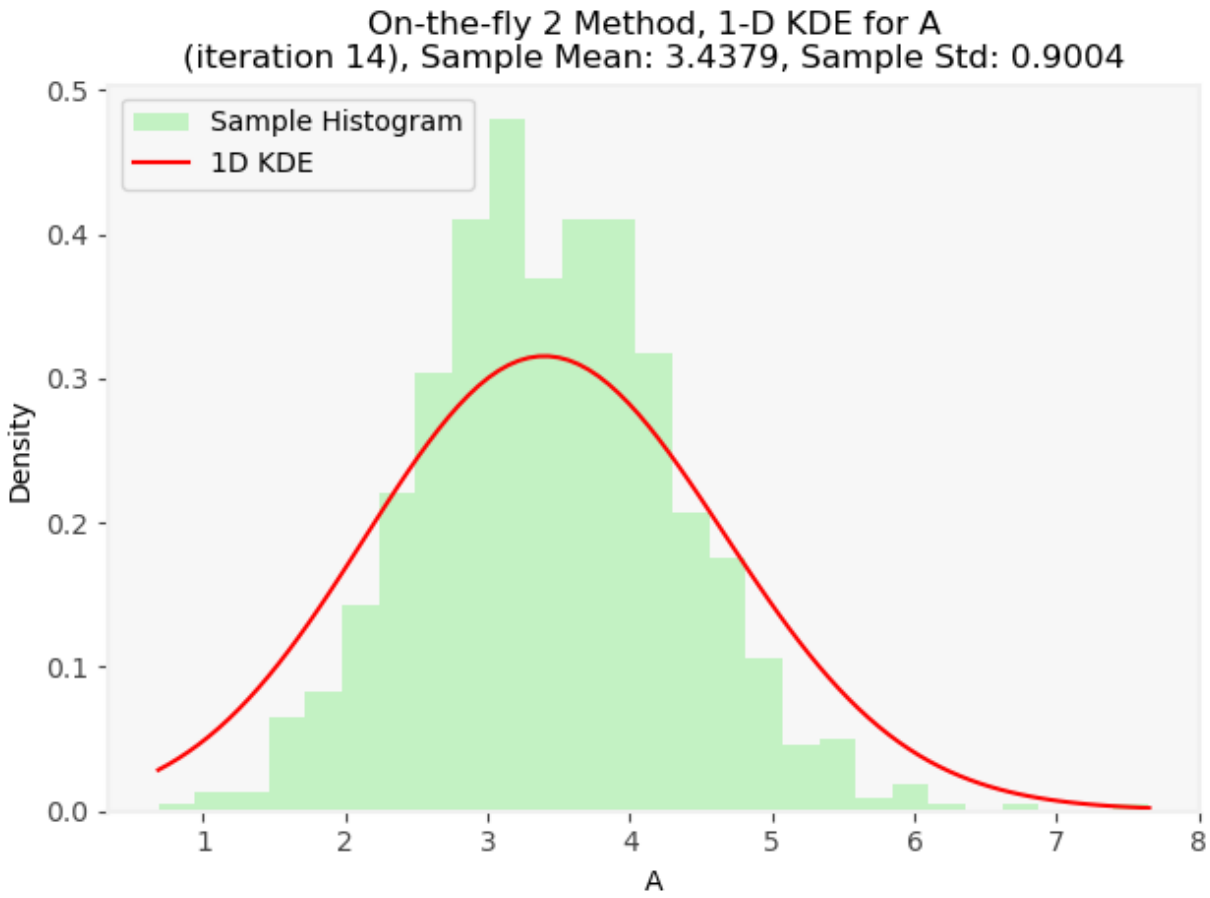

On-the-fly 2 Method, 1-D KDE for A
(iteration 9), Sample Mean: 2.7884, Sample Std: 1.5164
Sample Histogram
1D KDE
Density
0.00
0.05
0.10
0.15
0.20
0.25
0
2
4
6
8
A

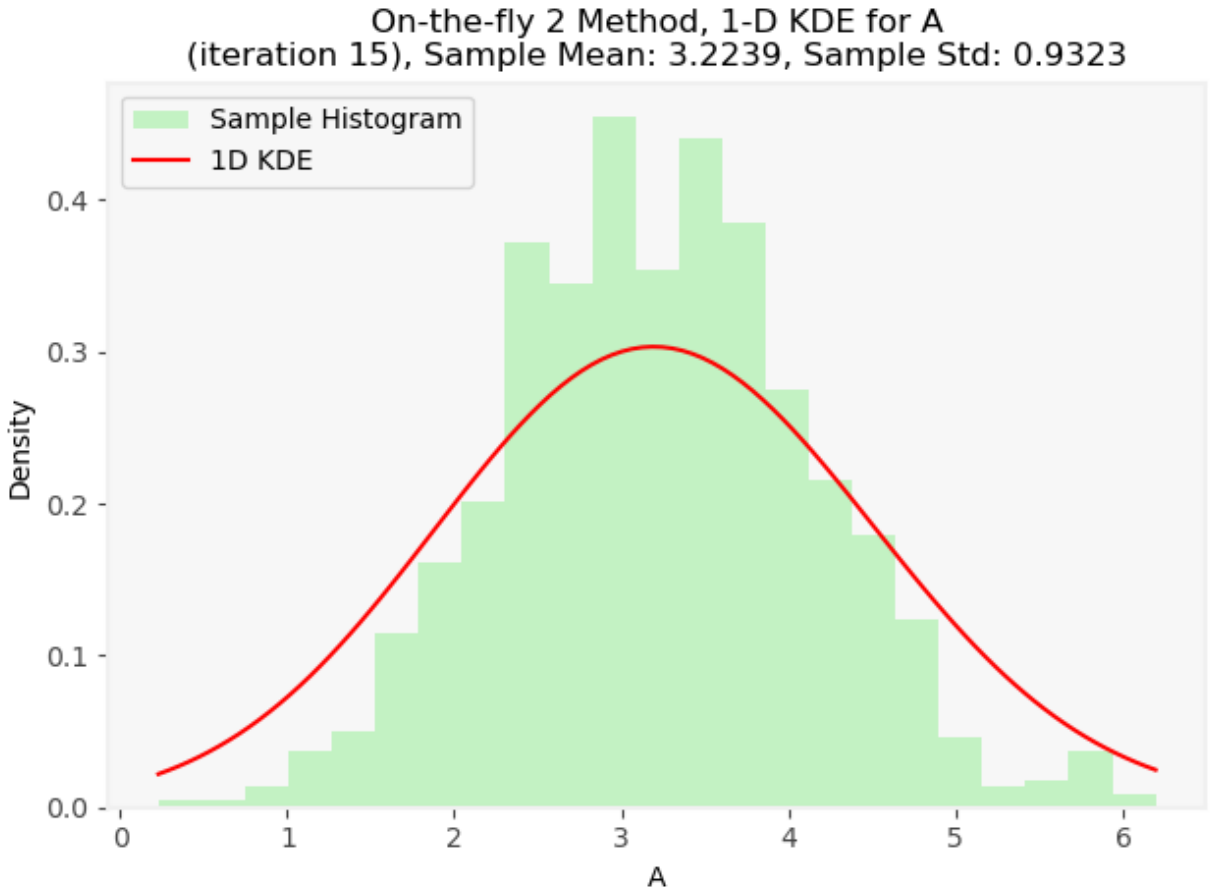

On-the-fly 2 Method, 1-D KDE for A
(iteration 10), Sample Mean: 2.4994, Sample Std: 1.3147
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
1
2
3
4
5
6
7

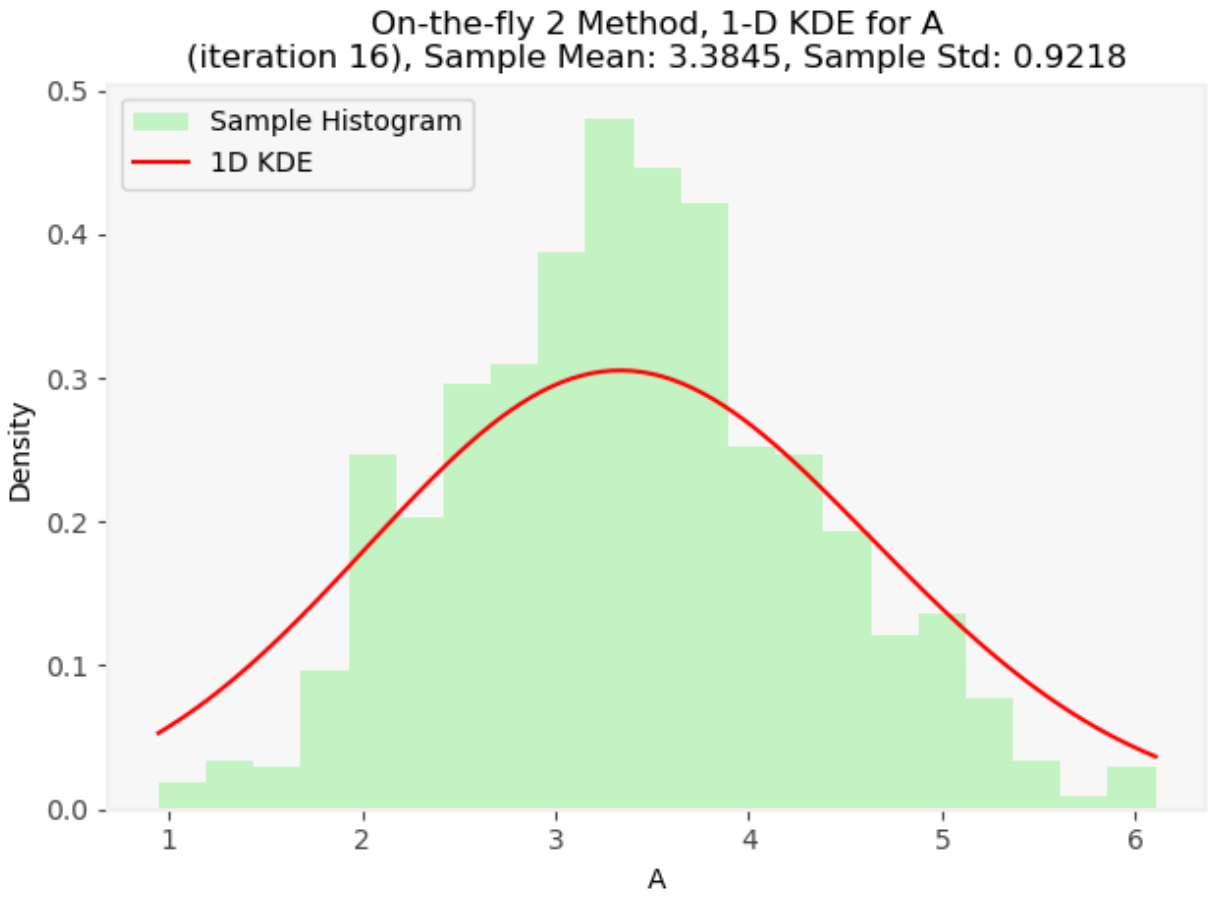

On-the-fly 2 Method, 1-D KDE for A
(iteration 11), Sample Mean: 2.7869, Sample Std: 1.2116
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0
1
2
3
4
5
6
7

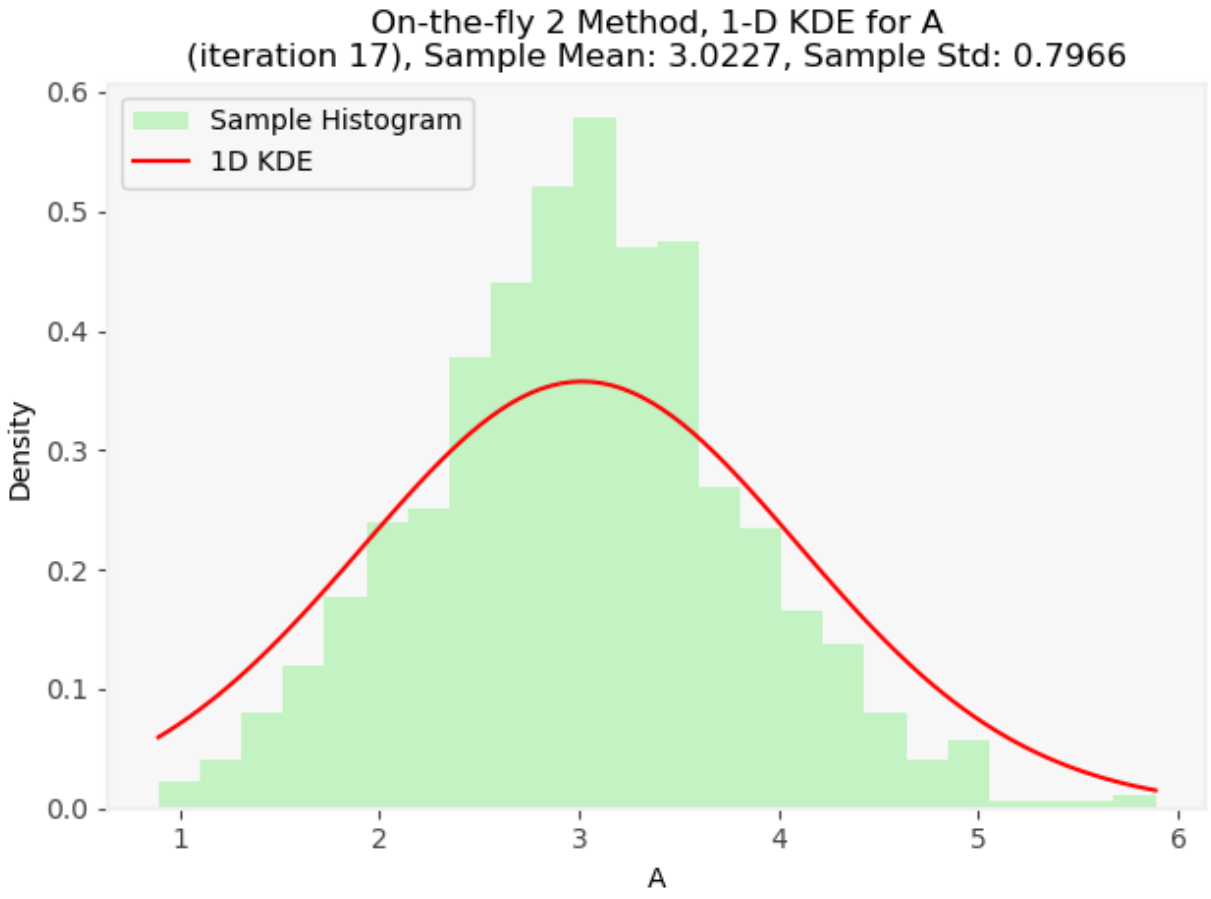

On-the-fly 2 Method, 1-D KDE for A
(iteration 12), Sample Mean: 2.6521, Sample Std: 1.1776
Sample Histogram
1D KDE
Density
A
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0
1
2
3
4
5
6

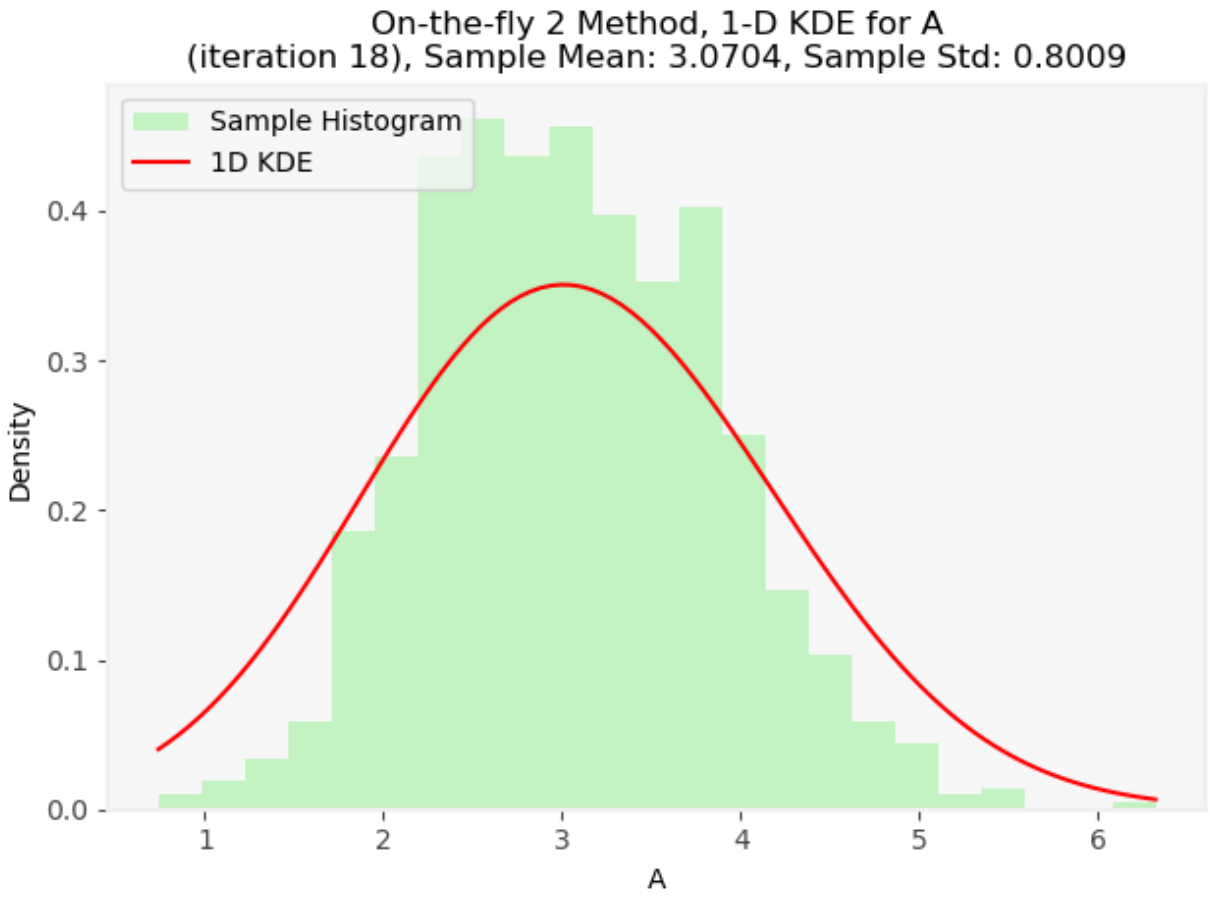

On-the-fly 2 Method, 1-D KDE for A
(iteration 13), Sample Mean: 3.4742, Sample Std: 0.9493
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0
1
2
3
4
5
6
7

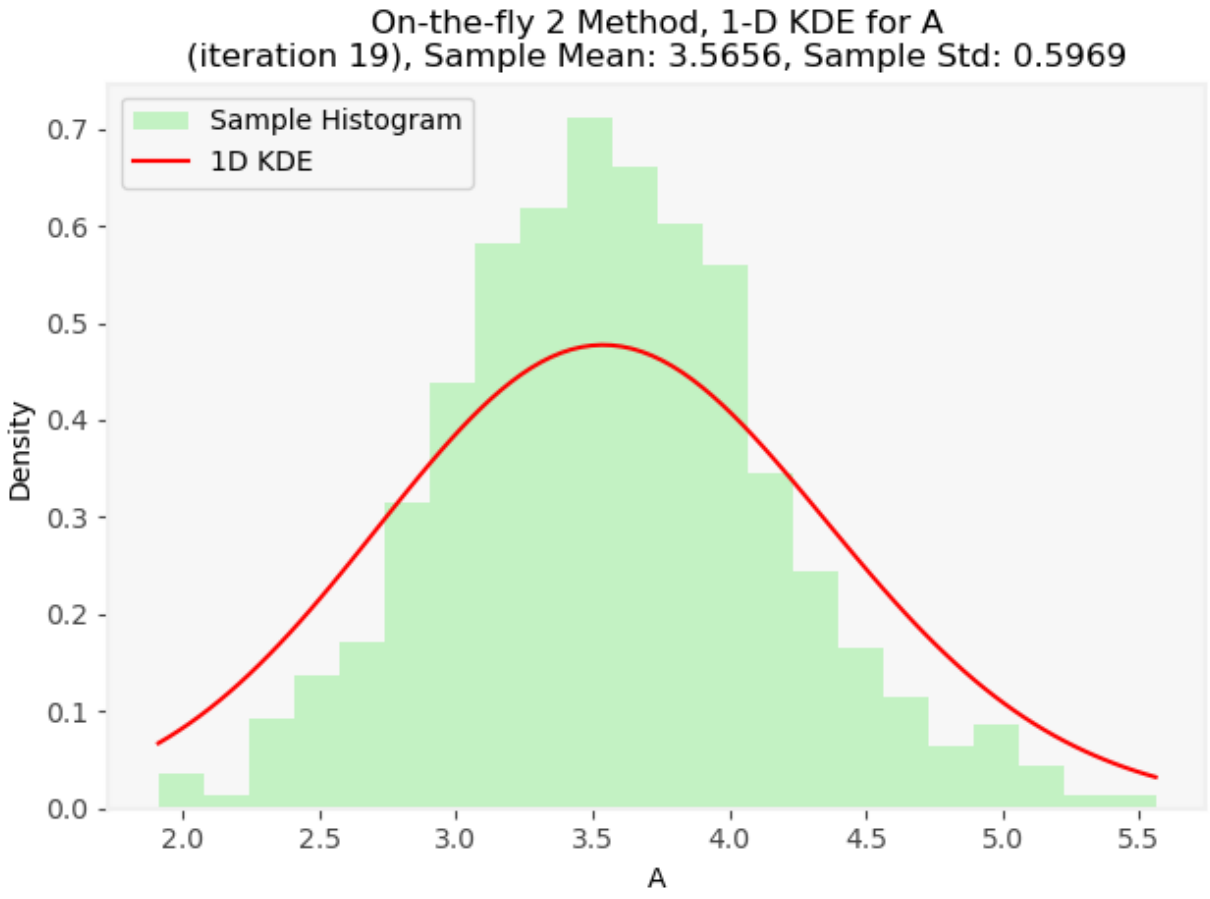

On-the-fly 2 Method, 1-D KDE for A
(iteration 14), Sample Mean: 3.4379, Sample Std: 0.9004
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6
7
8

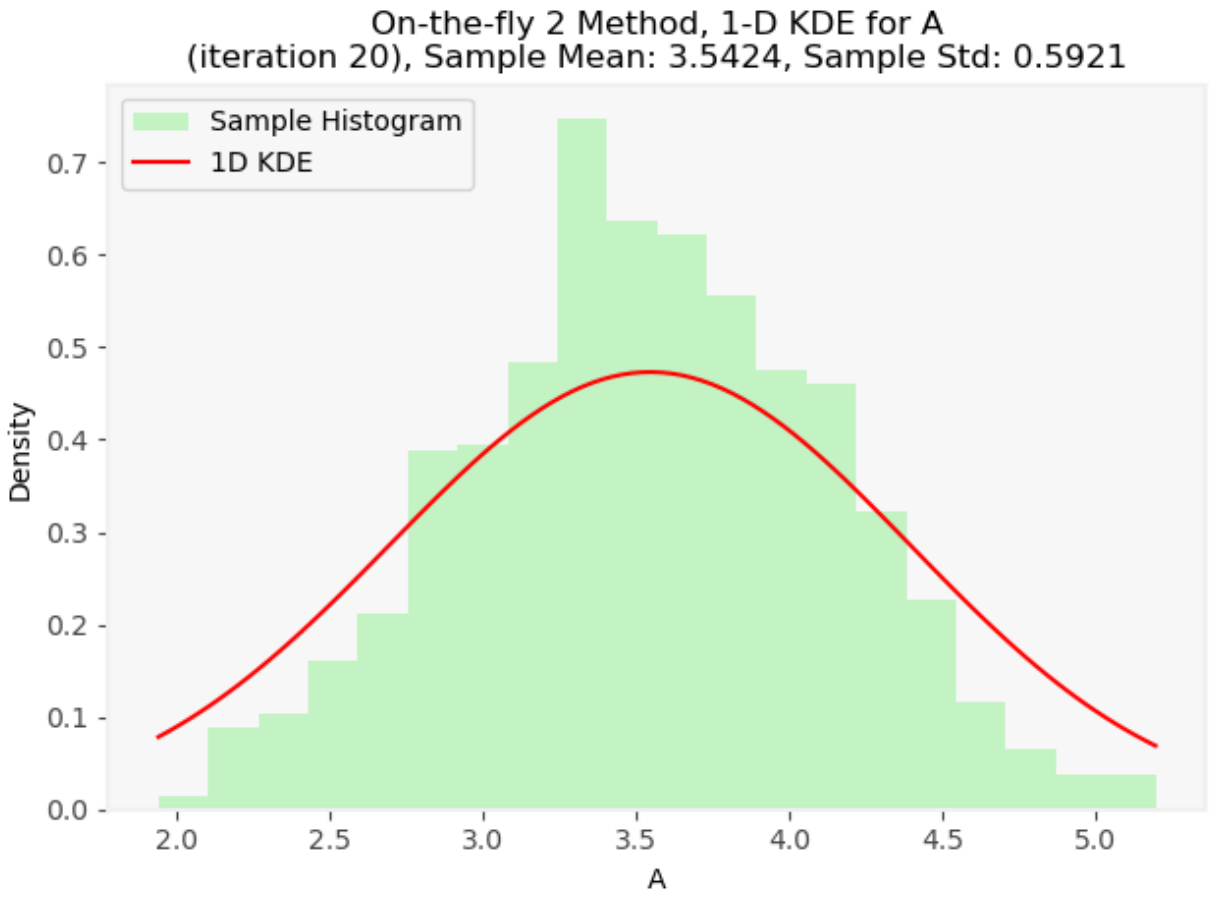

On-the-fly 2 Method, 1-D KDE for A
(iteration 15), Sample Mean: 3.2239, Sample Std: 0.9323
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0
1
2
3
4
5
6

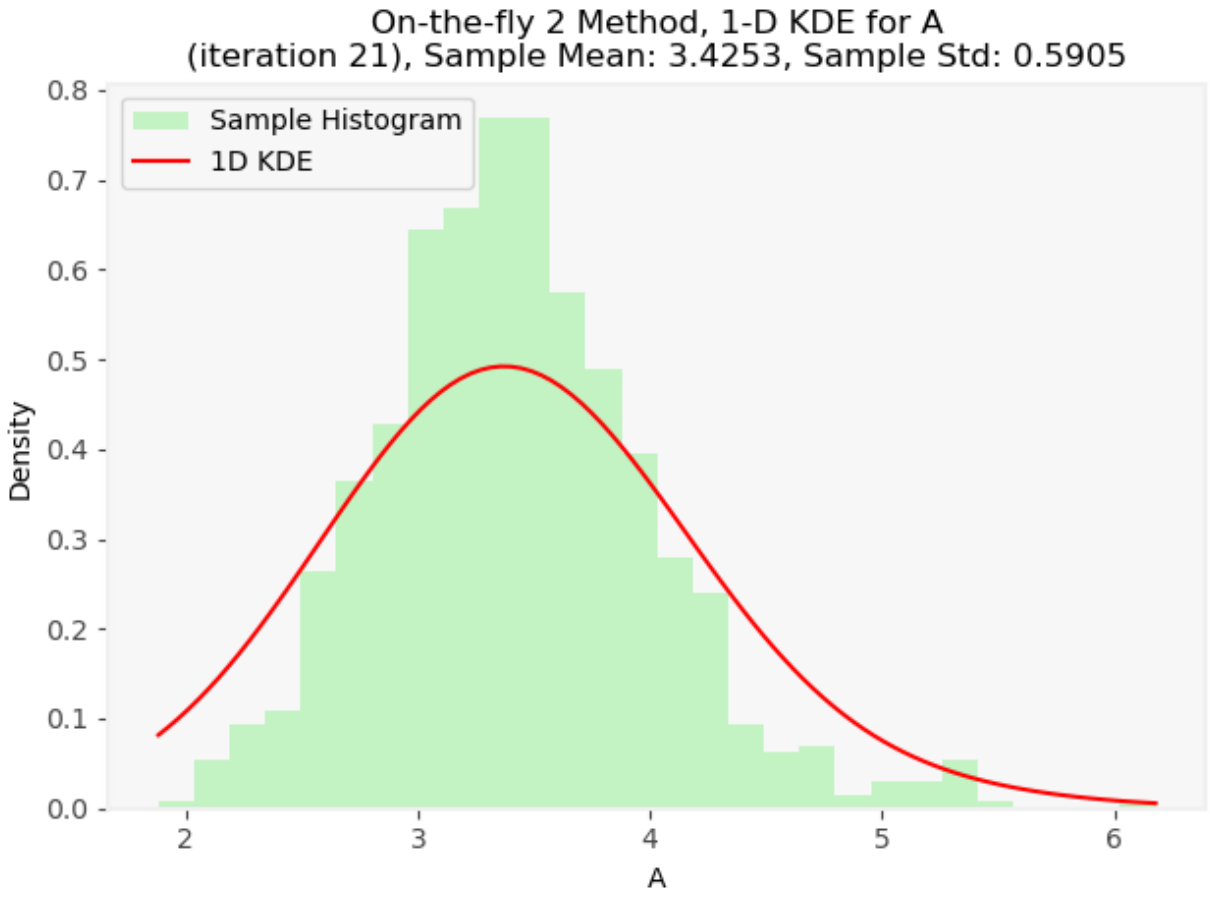

On-the-fly 2 Method, 1-D KDE for A
(iteration 16), Sample Mean: 3.3845, Sample Std: 0.9218
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
1
2
3
4
5
6

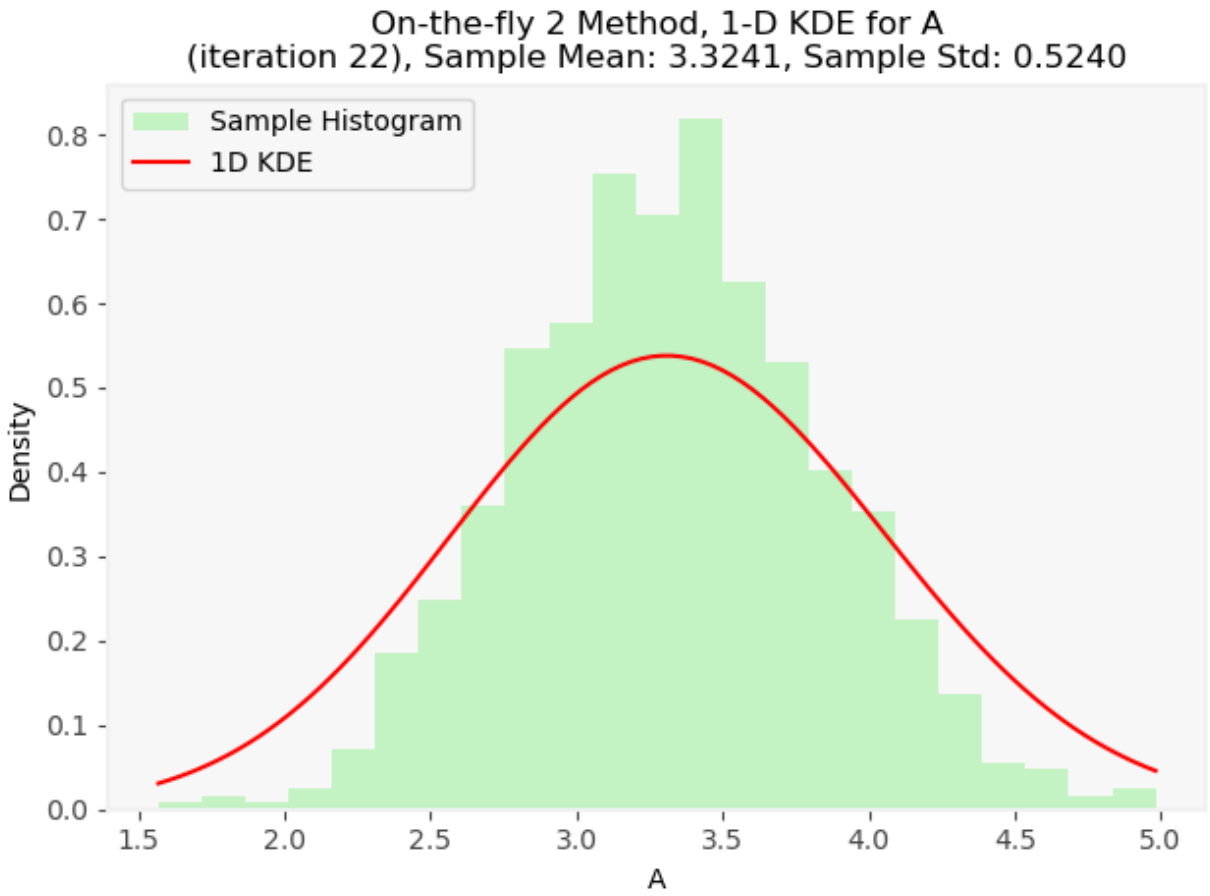

On-the-fly 2 Method, 1-D KDE for A
(iteration 17), Sample Mean: 3.0227, Sample Std: 0.7966
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
1
2
3
4
5
6

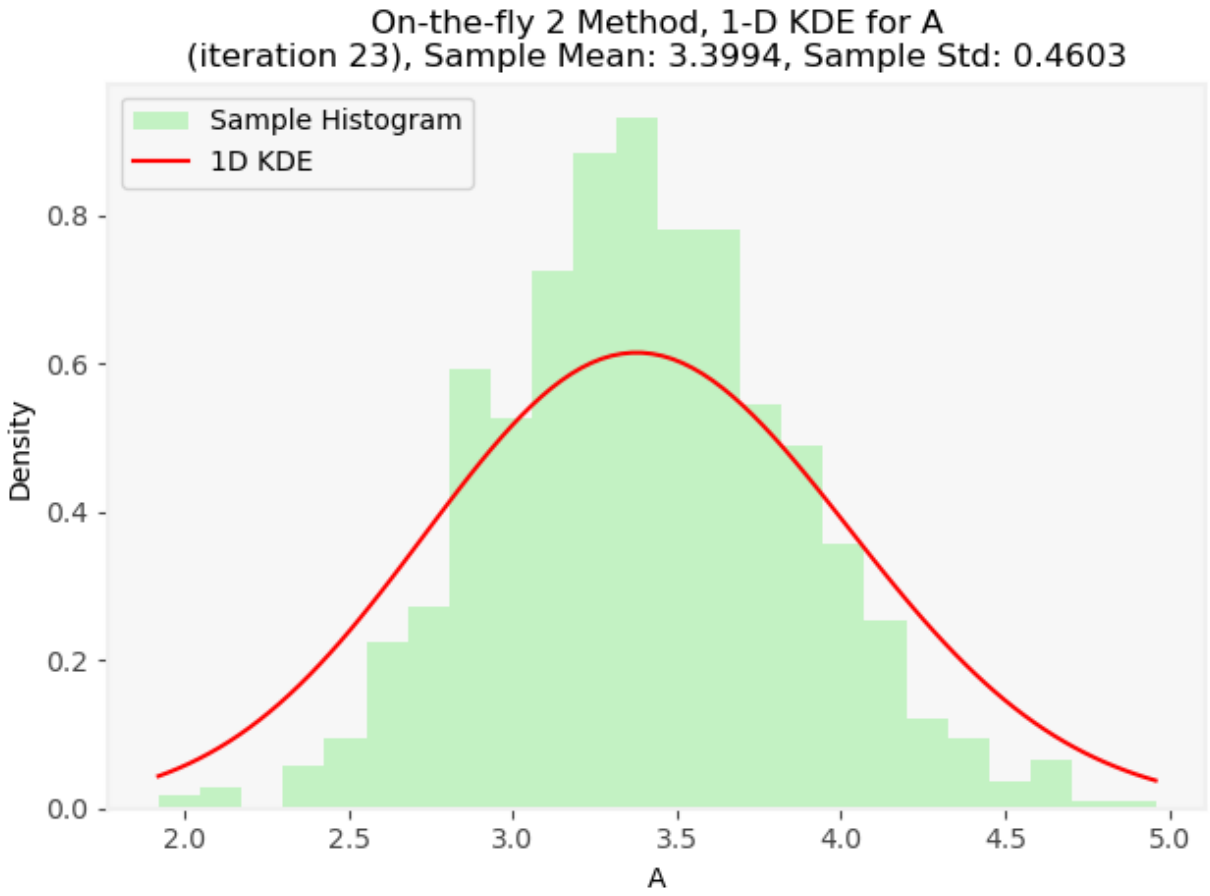

On-the-fly 2 Method, 1-D KDE for A
(iteration 18), Sample Mean: 3.0704, Sample Std: 0.8009
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
1
2
3
4
5
6

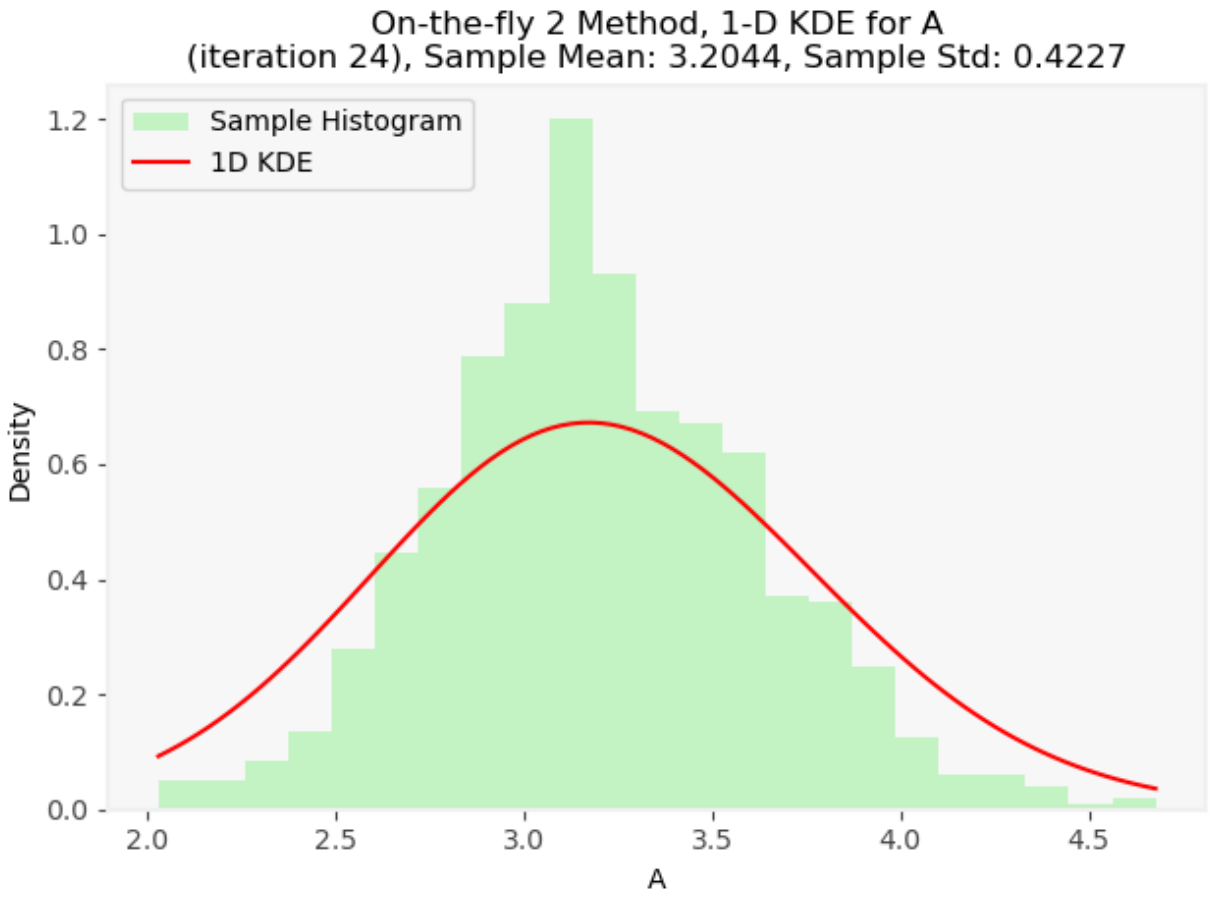

On-the-fly 2 Method, 1-D KDE for A
(iteration 19), Sample Mean: 3.5656, Sample Std: 0.5969
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5

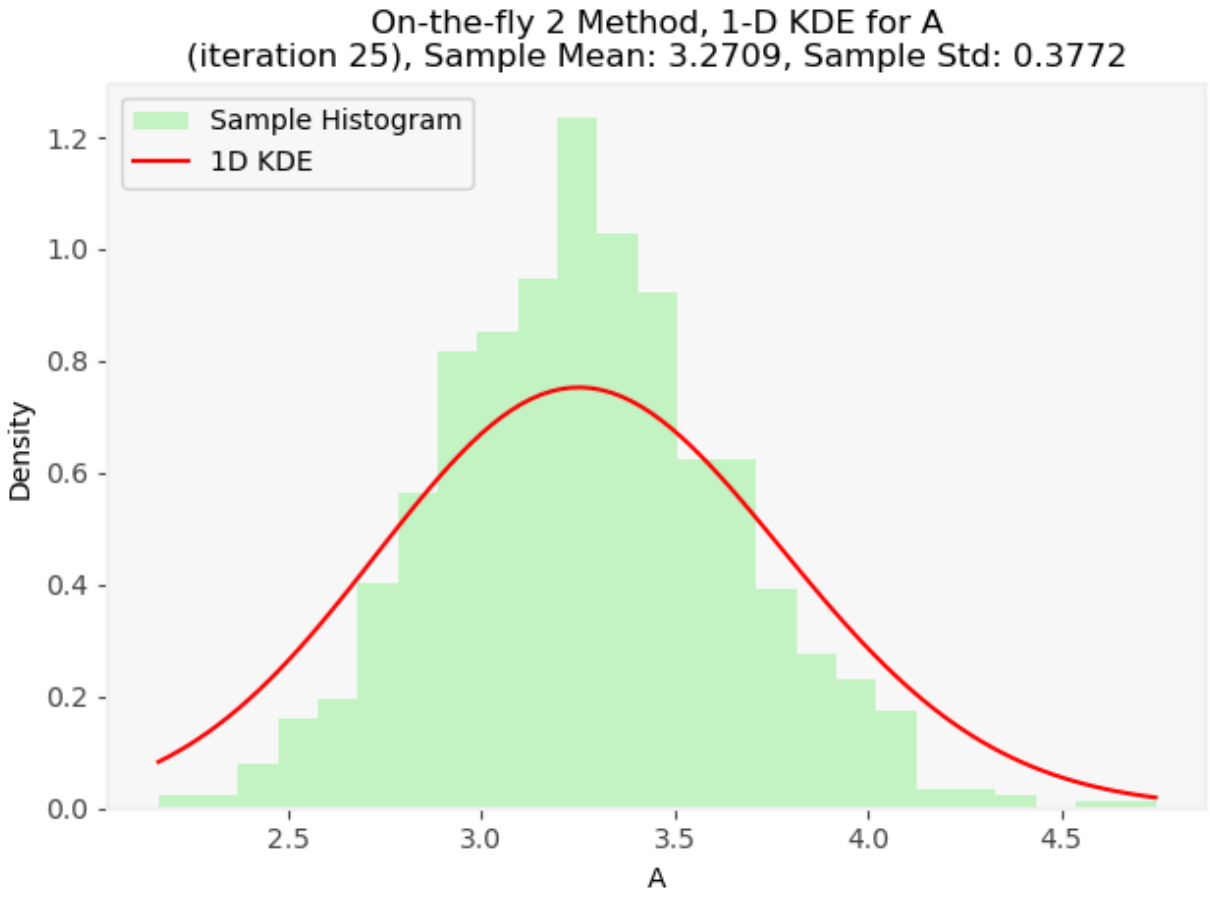

On-the-fly 2 Method, 1-D KDE for A
(iteration 20), Sample Mean: 3.5424, Sample Std: 0.5921
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
2.0
2.5
3.0
3.5
4.0
4.5
5.0

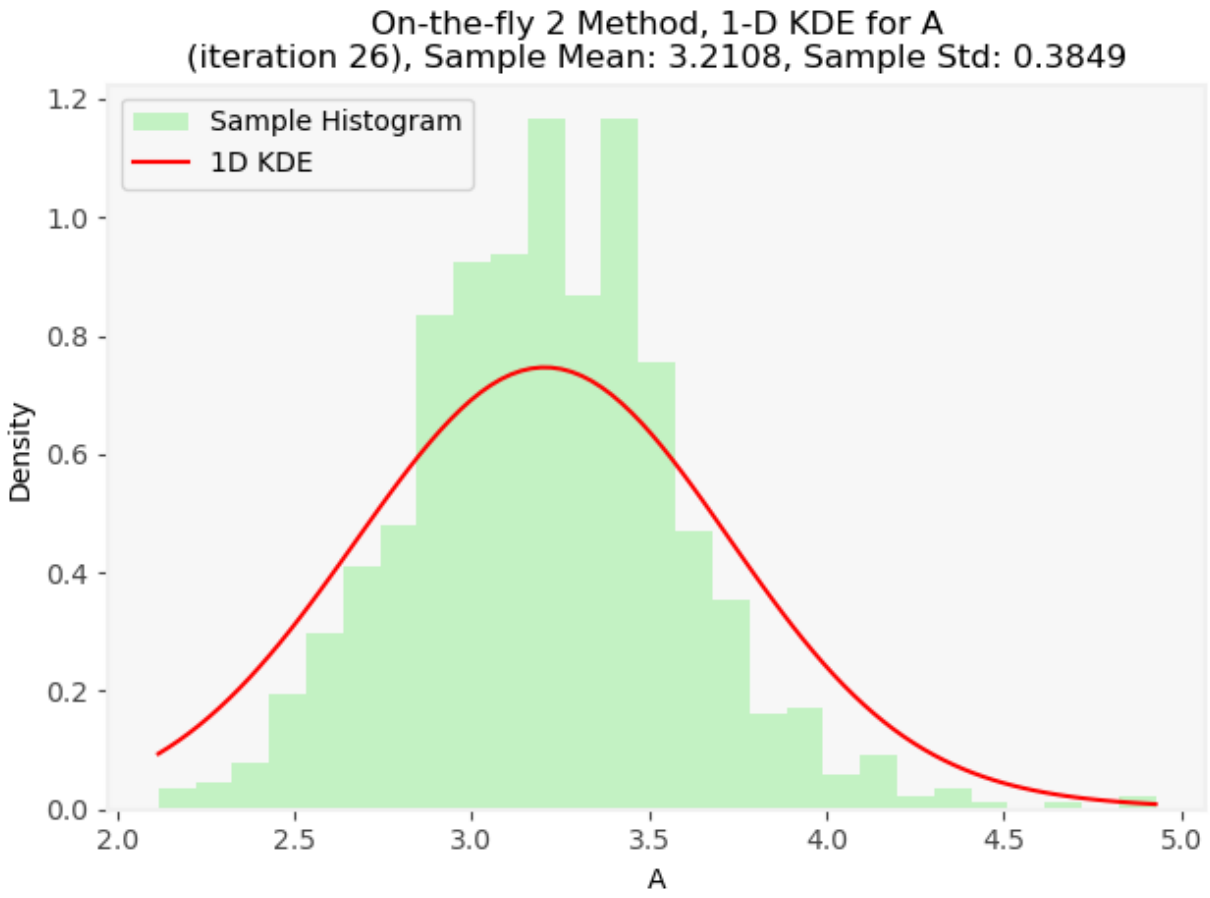

On-the-fly 2 Method, 1-D KDE for A
(iteration 21), Sample Mean: 3.4253, Sample Std: 0.5905
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
2
3
4
5
6

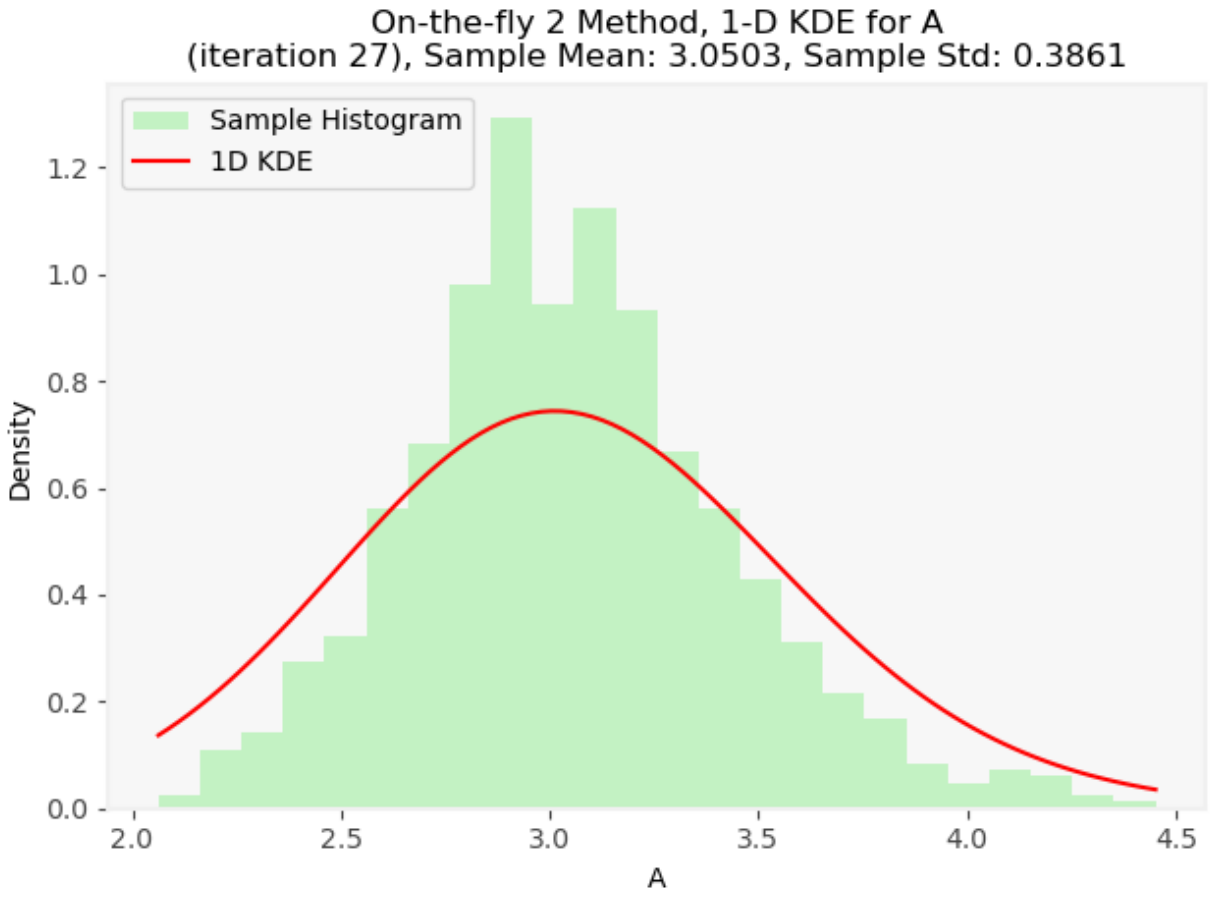

On-the-fly 2 Method, 1-D KDE for A
(iteration 22), Sample Mean: 3.3241, Sample Std: 0.5240
Sample Histogram
1D KDE
Density
A
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

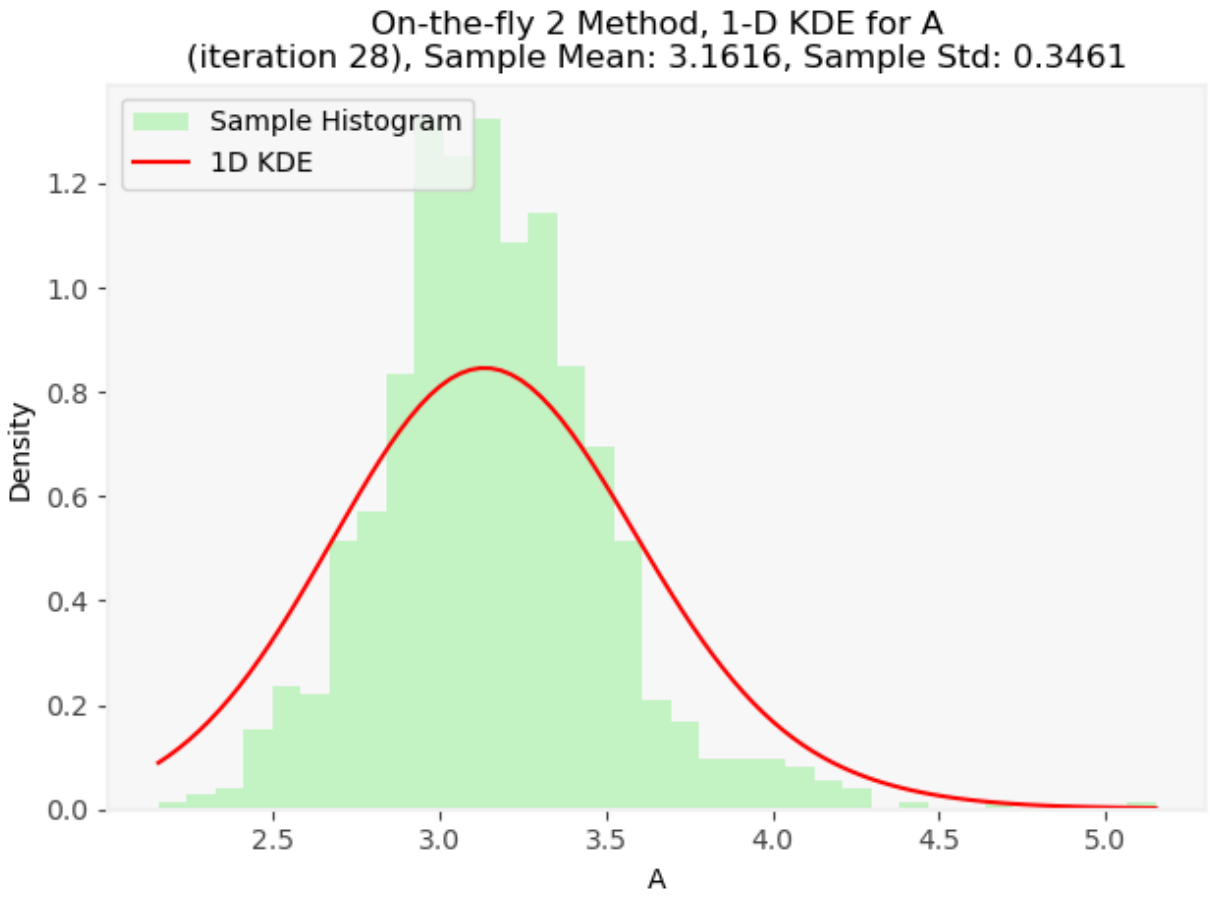

On-the-fly 2 Method, 1-D KDE for A
(iteration 23), Sample Mean: 3.3994, Sample Std: 0.4603
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
2.0
2.5
3.0
3.5
4.0
4.5
5.0

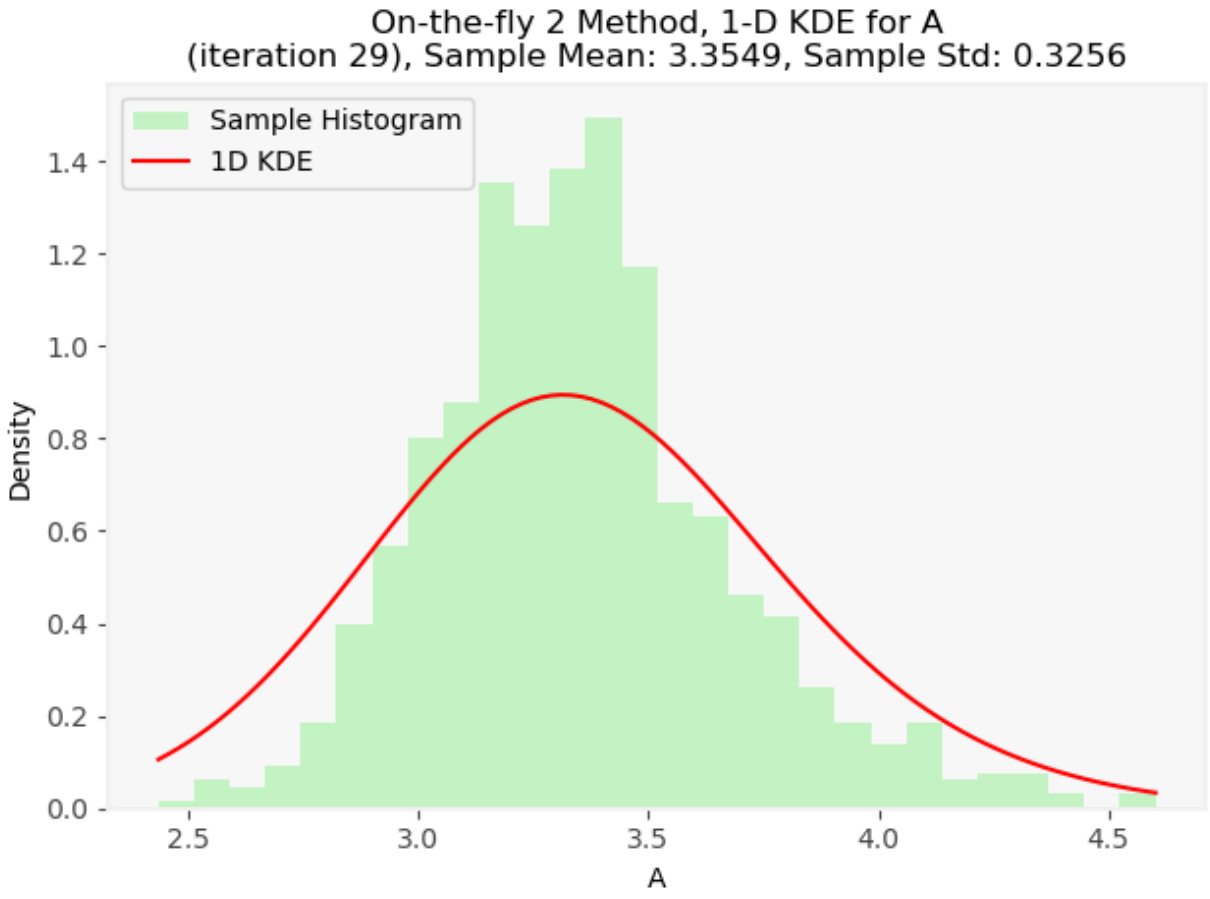

On-the-fly 2 Method, 1-D KDE for A
(iteration 24), Sample Mean: 3.2044, Sample Std: 0.4227
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.0
2.5
3.0
3.5
4.0
4.5

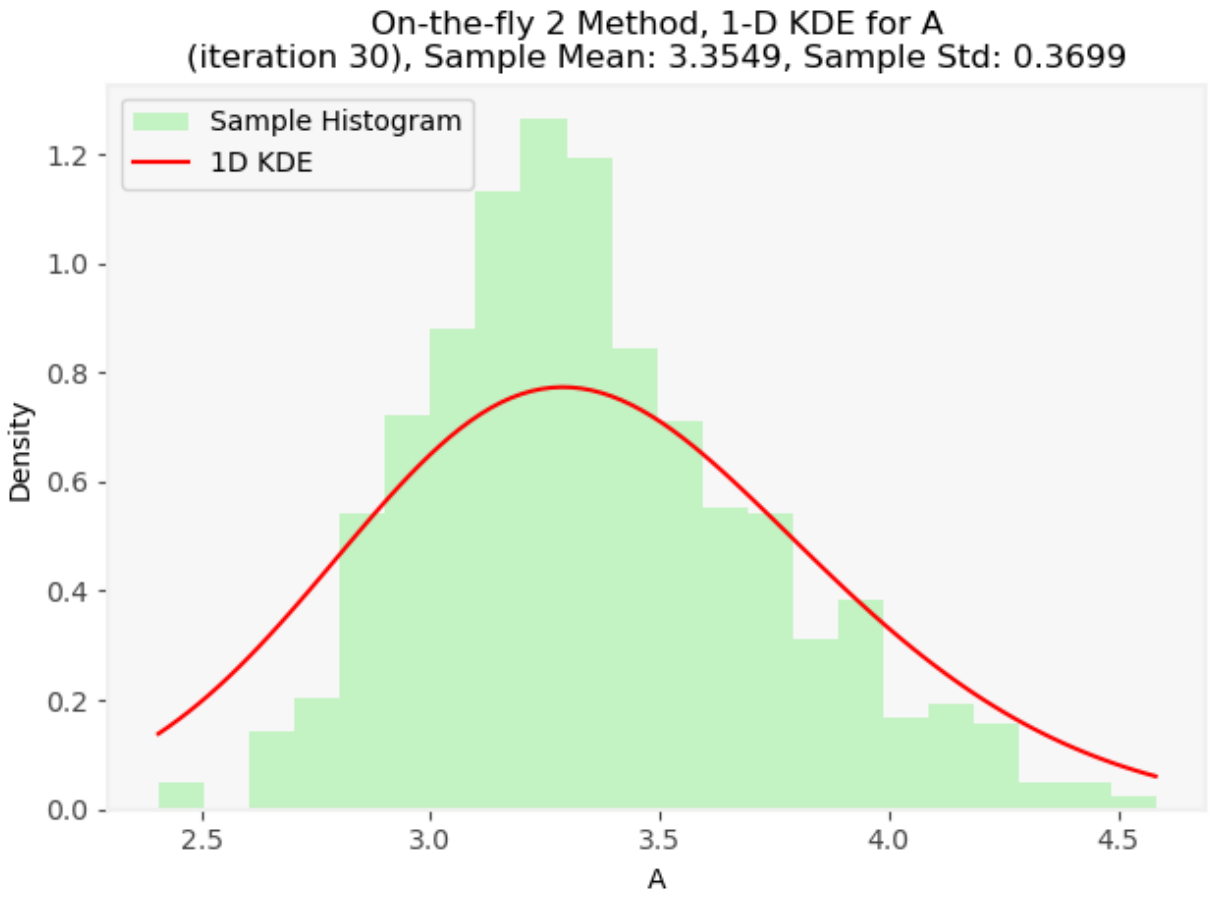

On-the-fly 2 Method, 1-D KDE for A
(iteration 25), Sample Mean: 3.2709, Sample Std: 0.3772
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0
4.5

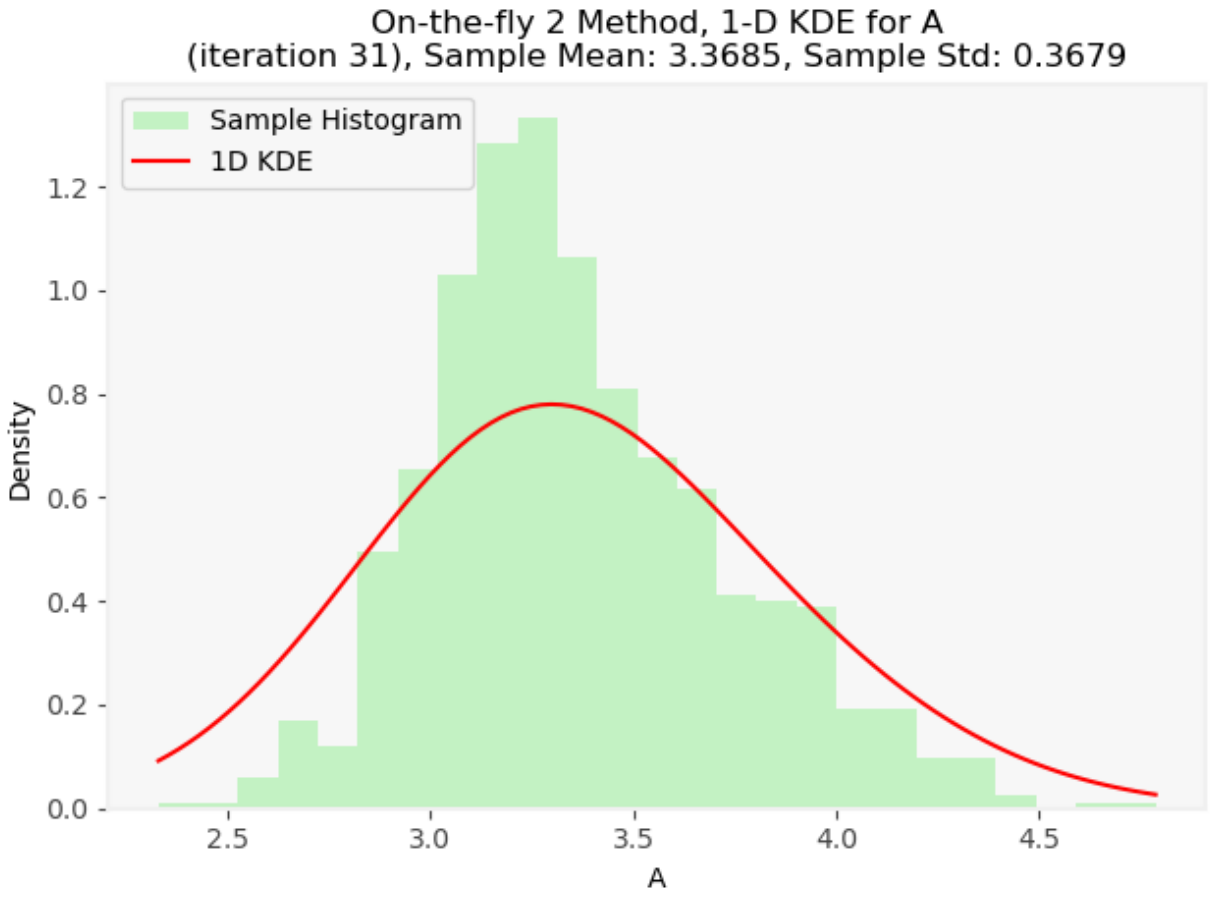

On-the-fly 2 Method, 1-D KDE for A
(iteration 26), Sample Mean: 3.2108, Sample Std: 0.3849
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.0
2.5
3.0
3.5
4.0
4.5
5.0

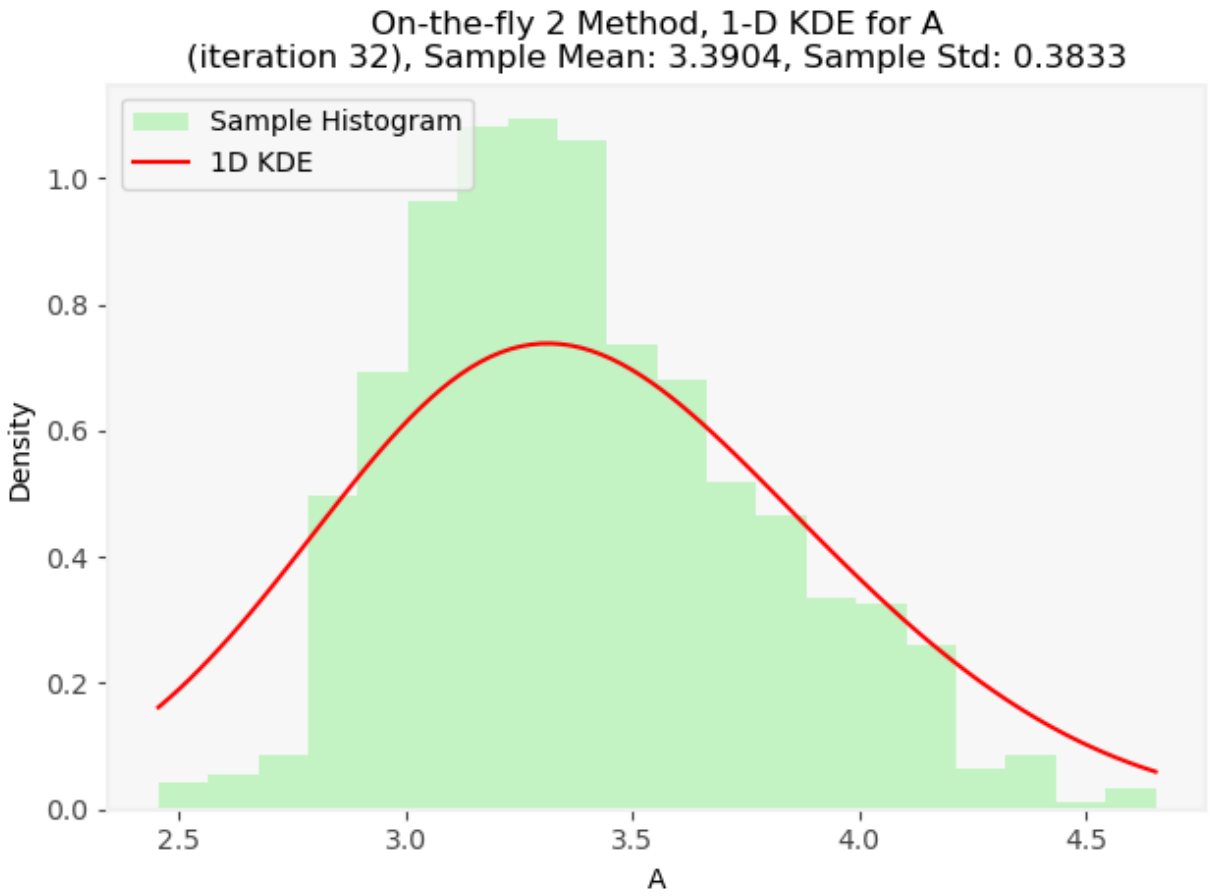

On-the-fly 2 Method, 1-D KDE for A
(iteration 27), Sample Mean: 3.0503, Sample Std: 0.3861
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.0
2.5
3.0
3.5
4.0
4.5

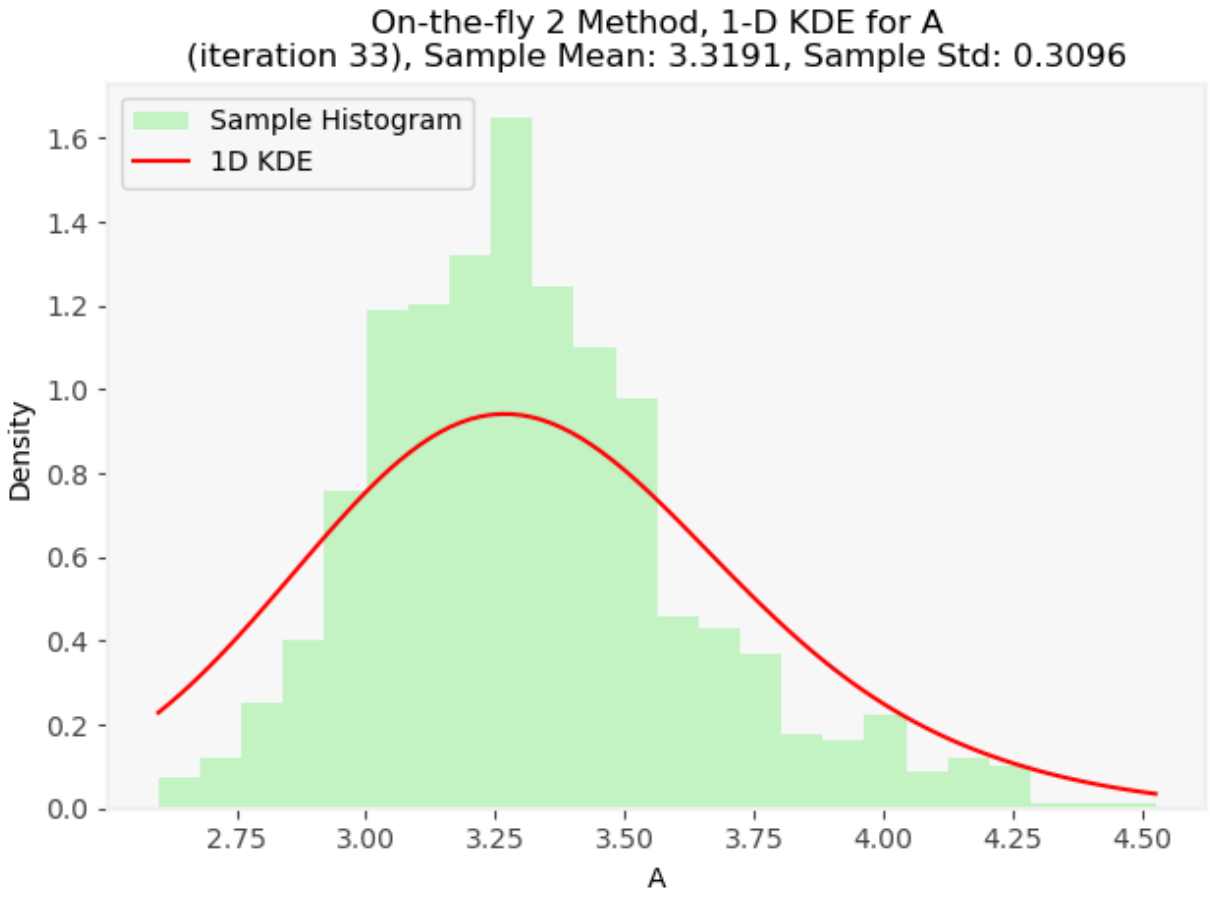

On-the-fly 2 Method, 1-D KDE for A
(iteration 28), Sample Mean: 3.1616, Sample Std: 0.3461
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0
4.5
5.0

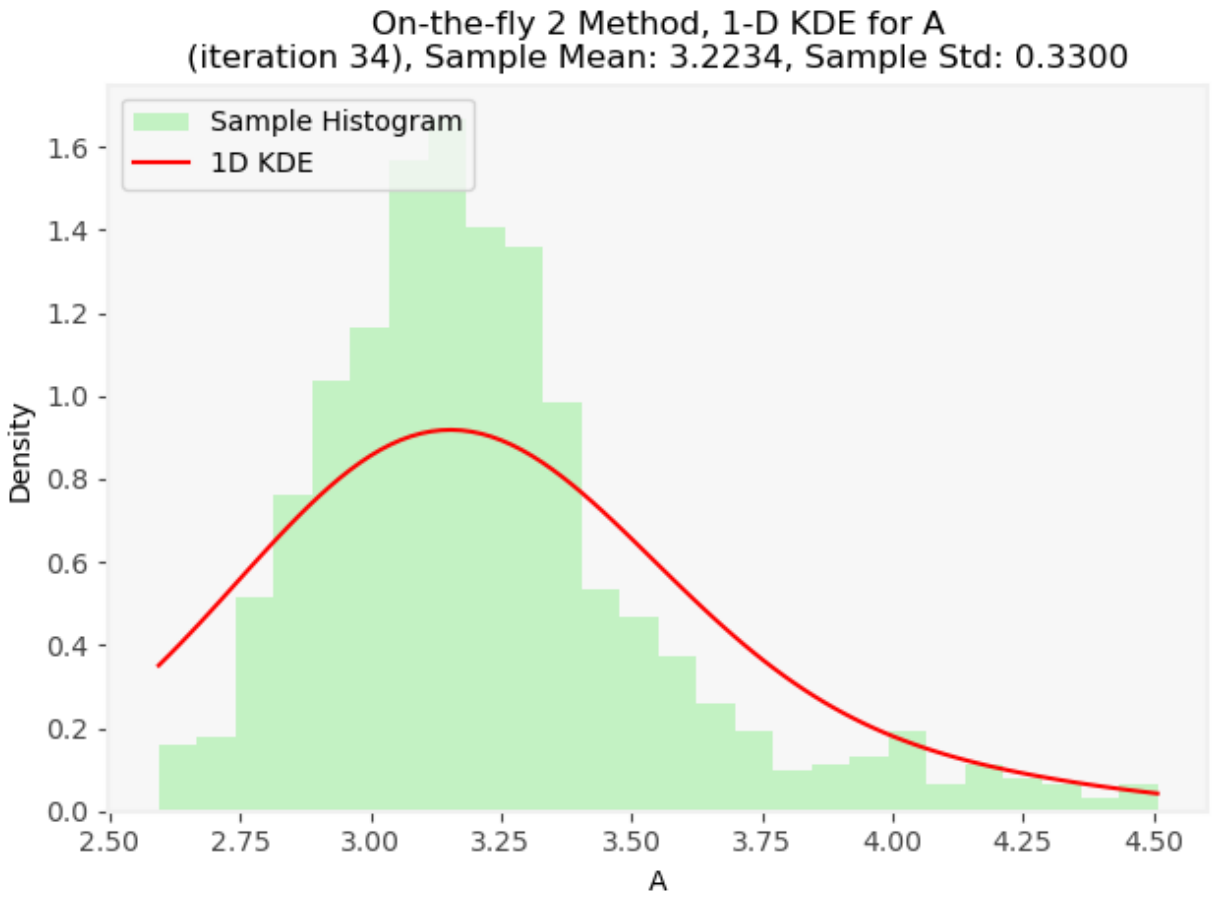

On-the-fly 2 Method, 1-D KDE for A
(iteration 29), Sample Mean: 3.3549, Sample Std: 0.3256
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
2.5
3.0
3.5
4.0
4.5

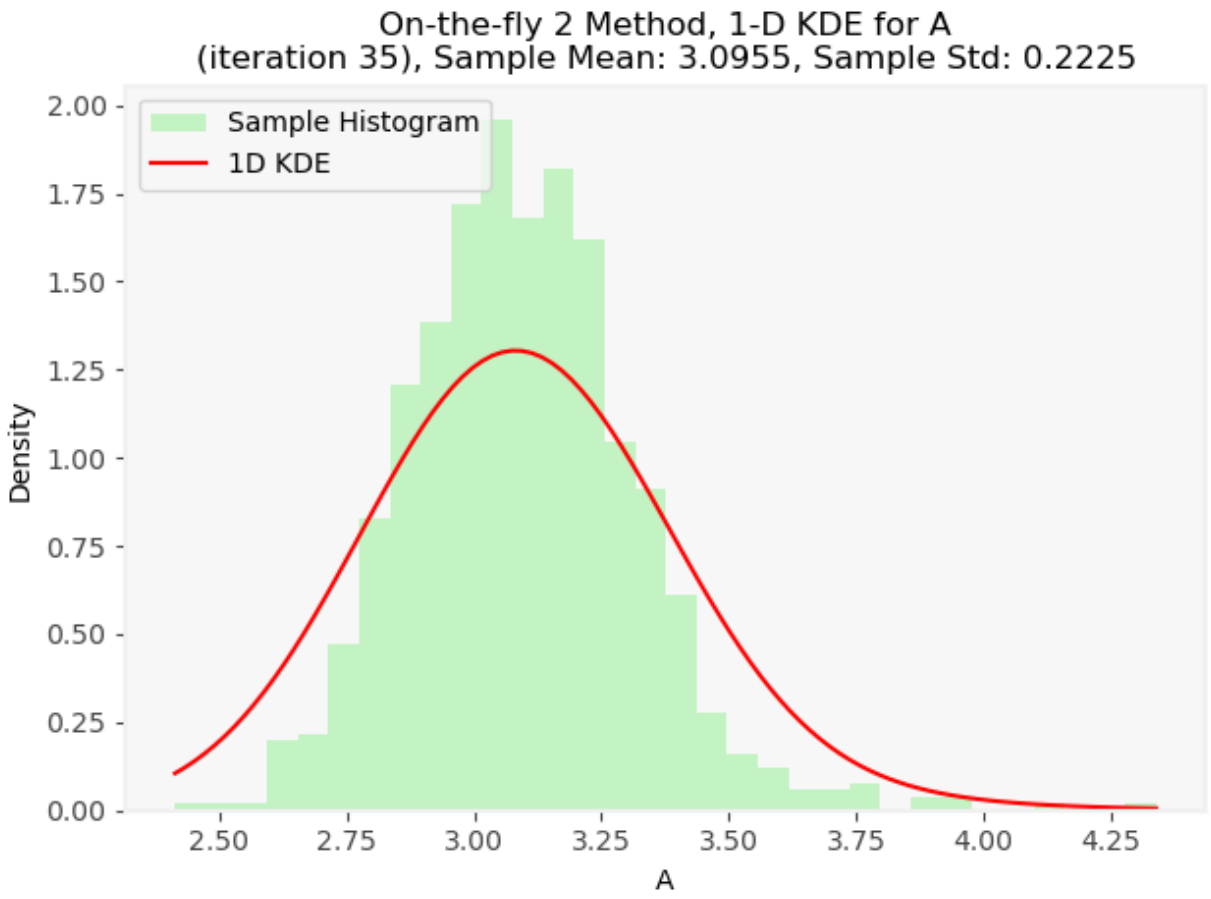

On-the-fly 2 Method, 1-D KDE for A
(iteration 30), Sample Mean: 3.3549, Sample Std: 0.3699
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0
4.5

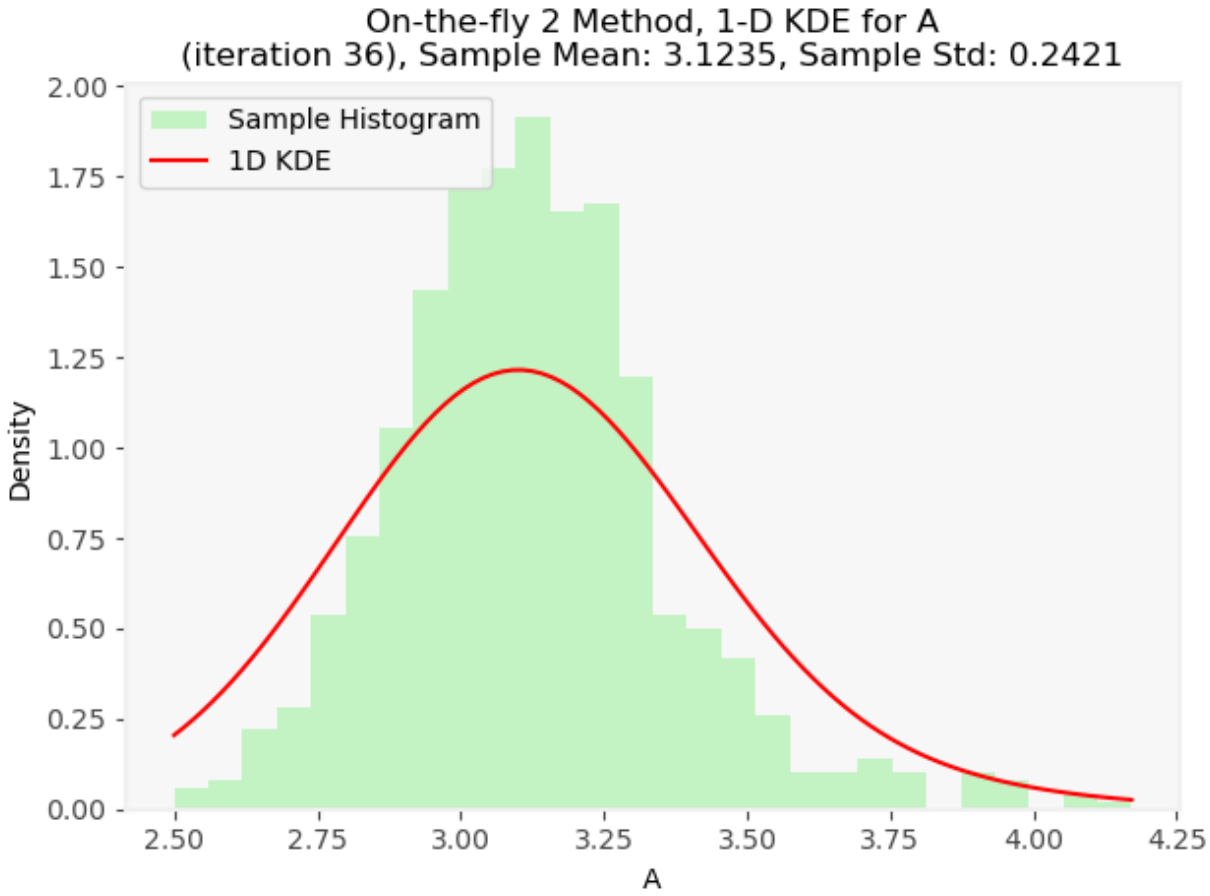

On-the-fly 2 Method, 1-D KDE for A
(iteration 31), Sample Mean: 3.3685, Sample Std: 0.3679
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
2.5
3.0
3.5
4.0
4.5


On-the-fly 2 Method, 1-D KDE for A
(iteration 32), Sample Mean: 3.3904, Sample Std: 0.3833
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
2.5
3.0
3.5
4.0
4.5


On-the-fly 2 Method, 1-D KDE for A
(iteration 33), Sample Mean: 3.3191, Sample Std: 0.3096
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50


On-the-fly 2 Method, 1-D KDE for A
(iteration 34), Sample Mean: 3.2234, Sample Std: 0.3300
Sample Histogram
1D KDE
Density
A
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25
4.50


On-the-fly 2 Method, 1-D KDE for A
(iteration 35), Sample Mean: 3.0955, Sample Std: 0.2225
Sample Histogram
1D KDE
Density
A
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
2.50
2.75
3.00
3.25
3.50
3.75
4.00
4.25



Playground

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