April 24, 2023

1 Solution to excercise sheet 1, exercise 3

Solved by Jakub Dokulil

1.1 Theory

We have abservables

$$\underbrace{A_{1},A_{2},...A_{n}}_{A_{1}^{(n)}},A_{n+1},...A_{2n},...$$

The correlation of subsamples - blocks is

$$Var(A^{(n)}) = \frac{1}{n} Var(A)$$

However if the sample is correlated additional parameter s is needed

$$Var(A^{(n)}) = \frac{1}{n/s} Var(A)$$

Parameter s we can obtain from the equation

$$s = \lim_{n \to \infty} n \frac{Var(A^{(n)})}{Var(A)}$$

1.2 Demonstration of the second equation

The equation will be demonstrated on sets generated by random numbers generator.

Lets have APD monitoring photon counts with poissonian noise.

```
[]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from scipy import constants

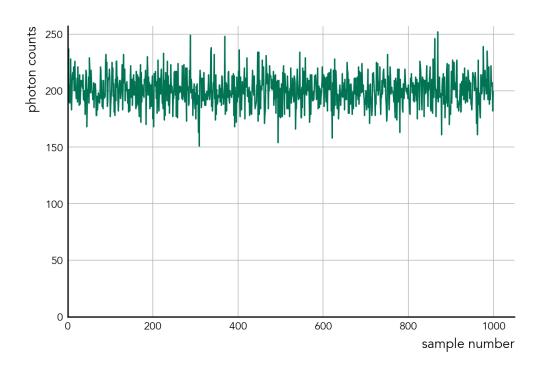
plt.style.use('scandic')
```

Duplicate key in file
PosixPath('/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/sitepackages/matplotlib/mpl-data/stylelib/scandic.mplstyle'), line 28
('xtick.major.size: 0 # major tick size in points')

```
Duplicate key in file
    PosixPath('/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
    packages/matplotlib/mpl-data/stylelib/scandic.mplstyle'), line 31
    ('ytick.major.size:
                                   # major tick size in points')
[]: def subsample_data(data, n):
         resample_shape = (sample_size//n, n)
         # print(resample_shape)
         resample_no_of_samples = np.product(resample_shape)
         subsample = data[:resample_no_of_samples]
         # print(subsample.shape)
         subsample = subsample.reshape(resample_shape)
         # print(subsample.shape)
         subsample = subsample.mean(axis=1)
         return subsample
[]: mu = 0
     sigma = 1
     sample_size = 1000
     signal_strength = 200
     # sample = np.random.default_rnq().normal(mu, sigma, sample_size)
     sample = np.ones(sample_size)*signal_strength
     # add poisson noise
     sample = np.random.default_rng().poisson(sample)
     # plot the sample
     plt.plot(sample)
     plt.xlabel('sample number')
     plt.ylabel('photon counts')
```

[]: (0.0, 1048.95)

plt.gca().set_ylim(bottom=0)
plt.gca().set_xlim(left=0)

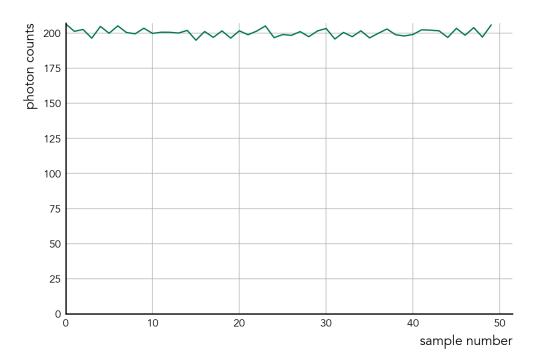


```
[]: n_min = 10
     n_max = 100
     step = 5
     n = np.arange(n_min, n_max, step).astype(int) # subsample sizes
     # create list of subsamples
     subsamples = []
     for i in n:
         resample_shape = (sample_size//i, i)
         # print(resample_shape)
         resample_no_of_samples = np.product(resample_shape)
         subsample = sample[:resample_no_of_samples]
         # print(subsample.shape)
         subsample = subsample.reshape(resample_shape)
         # print(subsample.shape)
         subsample = subsample.mean(axis=1)
         # print(subsample.shape)
         subsamples.append(subsample)
```

```
[]: # visualize one subsample
subspl_to_visualise = 2
# plot the sample
```

```
plt.plot(subsamples[subspl_to_visualise])
plt.xlabel('sample number')
plt.ylabel('photon counts')
plt.gca().set_ylim(bottom=0)
plt.gca().set_xlim(left=0)
```

[]: (0.0, 51.45)



```
[]: print('sample mean: ', sample.mean())
    print('sample variance: ', sample.var())

# calculate the mean and variance of the subsamples
subsample_means = []
subsample_vars = []

for subsample in subsamples:
    subsample_means.append(subsample.mean())
    subsample_vars.append(subsample.var())

# plot the mean and variance of the subsamples
plt.plot(n, subsample_vars, 'o', label='variance')
plt.plot(n, sample.var()/n, 'o', label='$\sigma^2$/n - expected value')

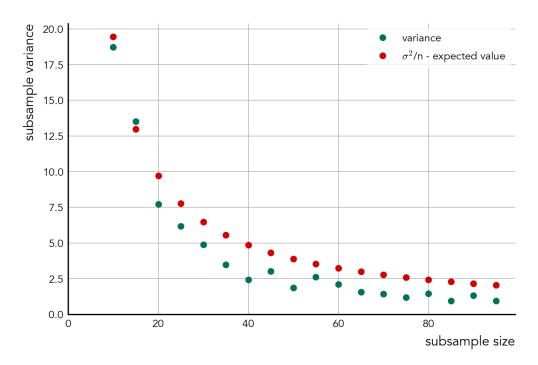
# plt.plot(n, n*subsample_vars, '.', label='n $\cdot$ variance')
plt.xlabel('subsample size')
```

```
plt.ylabel('subsample variance')
plt.gca().set_ylim(bottom=0)
plt.gca().set_xlim(left=0)
plt.legend()
```

sample mean: 200.374

sample variance: 194.48812399999997

[]: <matplotlib.legend.Legend at 0x7fe462625fd0>



1.2.1 Question for the excercise

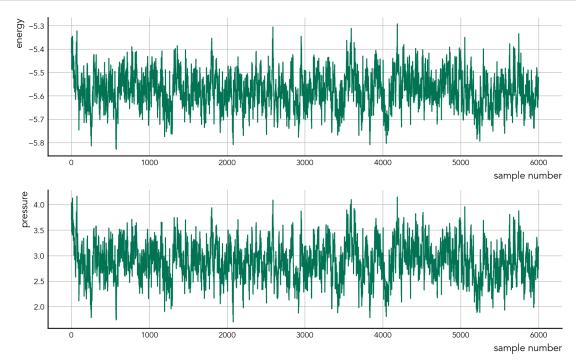
Why is it lower?

1.3 Implement procedure for err bar calculation

```
axs[0].set_xlabel('sample number')
axs[0].set_ylabel('energy')

axs[1].plot(pressure)
axs[1].set_xlabel('sample number')
axs[1].set_ylabel('pressure')

fig.tight_layout()
```



```
[]: n_min = 10
n_max = 6000
step = 10

n = list(np.arange(n_min, n_max, step).astype(int)) # subsample sizes

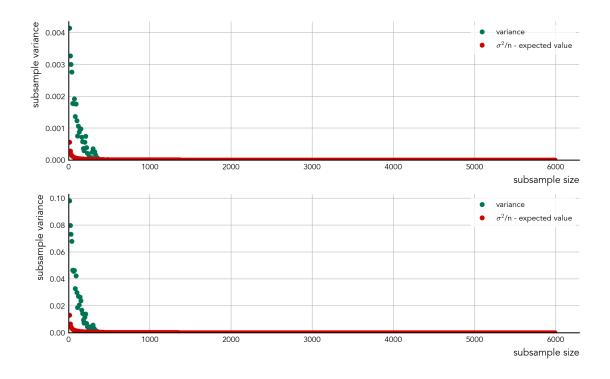
energy_subsamples = [subsample_data(energy, i) for i in n]
pressure_subsamples = [subsample_data(pressure, i) for i in n]

energy_variances = np.array([np.var(i) for i in energy_subsamples])
pressure_variances = np.array([np.var(i) for i in pressure_subsamples])

# plot the mean and variance of the subsamples
fig, axs = plt.subplots(2, 1, figsize=(8, 5))
```

```
axs[0].plot(n, energy_variances, 'o', label='variance')
axs[0].plot(n, np.var(energy)/np.array(n), 'o', label='$\sigma^2$/n - expected_
 ⇔value')
axs[0].set_xlabel('subsample size')
axs[0].set ylabel('subsample variance')
axs[0].set ylim(bottom=0)
axs[0].set xlim(left=0)
axs[0].legend()
axs[1].plot(n, pressure_variances, 'o', label='variance')
axs[1].plot(n, np.var(pressure)/np.array(n), 'o', label='$\sigma^2$/n -__
 ⇔expected value')
axs[1].set_xlabel('subsample size')
axs[1].set_ylabel('subsample variance')
axs[1].set_ylim(bottom=0)
axs[1].set_xlim(left=0)
axs[1].legend()
fig.tight_layout()
```

```
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/fromnumeric.py:3723: RuntimeWarning: Degrees of freedom <= 0
for slice
   return _methods._var(a, axis=axis, dtype=dtype, out=out, ddof=ddof,
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/_methods.py:222: RuntimeWarning: invalid value encountered
in true_divide
   arrmean = um.true_divide(arrmean, div, out=arrmean, casting='unsafe',
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/_methods.py:254: RuntimeWarning: invalid value encountered
in double_scalars
   ret = ret.dtype.type(ret / rcount)
```

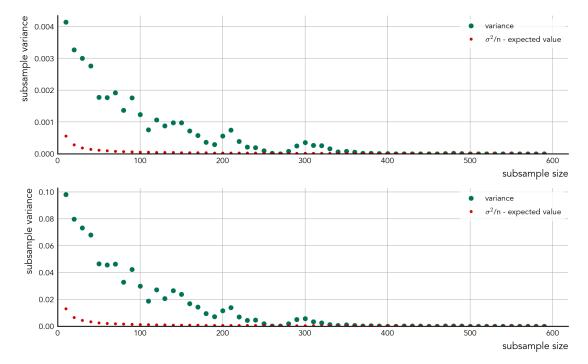


```
[]: n_min = 10
     n max = 600
     step = 10
     n = list(np.arange(n_min, n_max, step).astype(int)) # subsample sizes
     energy_subsamples = [subsample_data(energy, i) for i in n]
     pressure_subsamples = [subsample_data(pressure, i) for i in n]
     energy_variances = np.array([np.var(i) for i in energy_subsamples])
     pressure_variances = np.array([np.var(i) for i in pressure_subsamples])
     # plot the mean and variance of the subsamples
     fig, axs = plt.subplots(2, 1, figsize=(8, 5))
     axs[0].plot(n, [np.var(i) for i in energy_subsamples], 'o', label='variance')
     axs[0].plot(n, np.var(energy)/np.array(n), '.', label='$\sigma^2$/n - expected_
      ⇔value')
     axs[0].set_xlabel('subsample size')
     axs[0].set_ylabel('subsample variance')
     axs[0].set_ylim(bottom=0)
     axs[0].set xlim(left=0)
     axs[0].legend()
```

```
axs[1].plot(n, [np.var(i) for i in pressure_subsamples], 'o', label='variance')
axs[1].plot(n, np.var(pressure)/np.array(n), '.', label='$\sigma^2$/n -_
expected value')

axs[1].set_xlabel('subsample size')
axs[1].set_ylabel('subsample variance')
axs[1].set_ylim(bottom=0)
axs[1].set_xlim(left=0)
axs[1].legend()

fig.tight_layout()
```



```
[]: n_min = 10
n_max = 6000
step = 10

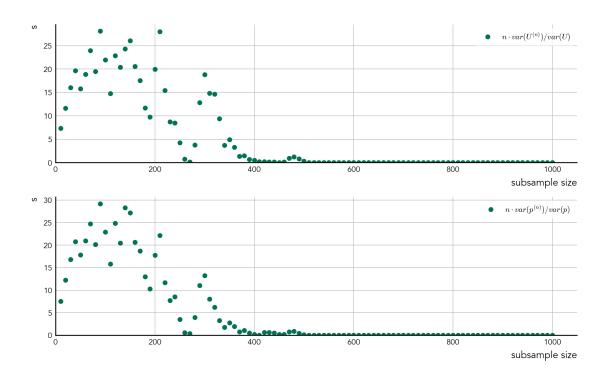
n = list(np.arange(n_min, n_max, step).astype(int)) # subsample sizes

energy_subsamples = [subsample_data(energy, i) for i in n]
pressure_subsamples = [subsample_data(pressure, i) for i in n]

energy_variances = np.array([np.var(i) for i in energy_subsamples])
pressure_variances = np.array([np.var(i) for i in pressure_subsamples])
```

```
s_energy = n*energy_variances/energy.var()
s_pressure = n*pressure_variances/pressure.var()
# plot the s vs n
fig, axs = plt.subplots(2, 1, figsize=(8, 5))
axs[0].plot(n, s_energy, 'o', label='$n \cdot <math>var(U^{(n)})/ var(U)$')
\# axs[0].plot(n, n, label='s = 1')
axs[0].set_xlabel('subsample size')
axs[0].set_ylabel('s')
axs[0].set_ylim(bottom=0)
axs[0].set_xlim(left=0)
axs[0].legend()
axs[1].plot(n, s_pressure, 'o', label='$n \cdot <math>var(p^{(n)}) / var(p)$')
\# axs[1].plot(n, n, label='s = 1')
axs[1].set_xlabel('subsample size')
axs[1].set_ylabel('s')
axs[1].set_ylim(bottom=0)
axs[1].set_xlim(left=0)
axs[1].legend()
fig.tight_layout()
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/fromnumeric.py:3723: RuntimeWarning: Degrees of freedom <= 0</pre>
for slice
  return _methods._var(a, axis=axis, dtype=dtype, out=out, ddof=ddof,
```

```
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/fromnumeric.py:3723: RuntimeWarning: Degrees of freedom <= 0
for slice
   return _methods._var(a, axis=axis, dtype=dtype, out=out, ddof=ddof,
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/_methods.py:222: RuntimeWarning: invalid value encountered
in true_divide
   arrmean = um.true_divide(arrmean, div, out=arrmean, casting='unsafe',
/Users/jakub.dokulil/opt/anaconda3/lib/python3.9/site-
packages/numpy/core/_methods.py:254: RuntimeWarning: invalid value encountered
in double_scalars
   ret = ret.dtype.type(ret / rcount)</pre>
```



The variance decreases with n. Therefore for 'larger' n we are effectively dividing

$$\frac{\text{small number}}{\text{large number}} \to 0$$

```
[]: n_min = 5
    n_max = 400
    step = 1

    n = list(np.arange(n_min, n_max, step).astype(int)) # subsample sizes

energy_subsamples = [subsample_data(energy, i) for i in n]
    pressure_subsamples = [subsample_data(pressure, i) for i in n]

energy_variances = np.array([np.var(i) for i in energy_subsamples])

pressure_variances = np.array([np.var(i) for i in pressure_subsamples]))

s_energy = n*energy_variances/energy.var()
s_pressure = n*pressure_variances/pressure.var()

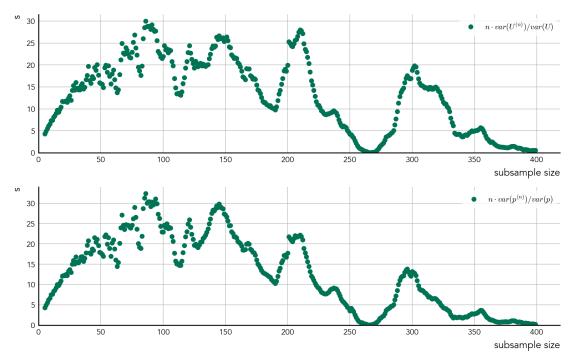
# plot the s vs n

fig, axs = plt.subplots(2, 1, figsize=(8, 5))
```

```
axs[0].plot(n, s_energy, 'o', label='\nabla \cdot var(U^{(n)})/ var(U)\nabla')
# axs[0].plot(n, n, label='s = 1')
axs[0].set_xlabel('subsample size')
axs[0].set_ylabel('s')
axs[0].set_ylim(bottom=0)
axs[0].set_xlim(left=0)
axs[0].legend()

axs[1].plot(n, s_pressure, 'o', label='\nabla \cdot var(p^{(n)})/ var(p)\nabla')
# axs[1].plot(n, n, label='s = 1')
axs[1].set_xlabel('subsample size')
axs[1].set_ylabel('s')
axs[1].set_ylim(bottom=0)
axs[1].set_xlim(left=0)
axs[1].legend()

fig.tight_layout()
```



For further calculations lets choose s = 125.

```
[]: s = 125
energy_subsample = subsample_data(energy, s)
pressure_subsample = subsample_data(pressure, s)
```

```
energy_mean = np.mean(energy_subsample)
pressure_mean = np.mean(pressure_subsample)
energy_variance = np.var(energy_subsample)
pressure_variance = np.var(pressure_subsample)
print(f'energy U*: {energy_mean} +- {np.sqrt(energy_variance)}')
print(f'pressure p*: {pressure_mean} +- {np.sqrt(pressure_variance)}')
energy U*: -5.5679165799999994 +- 0.02948127051421655
pressure p*: 2.9280593 +- 0.14348167591431454
1.4 Effect of displacement
originally chosen to 0.4. Lets run the simultions for values from 0.1 to 0.6.
output for 0.1
fname=[mclj_out.dat]
```

```
256
     n=
  rho= 0.84186
     t = 1.20000
  disp= 0.10000
               6000 (*
                          1)
   nt=
  accr= 7.15899e-01
 <U>/N=-5.56697e+00
  Cv/N = 2.90678e + 00
     p= 2.91892e+00
 Write g(r) to 'amclj.dat? [y] y
Write PDB format to amclj.pdb? [y] y
output for r = 0.2
```

```
[]: s = 125
     disp = 1
     energies_mean = []
     energies_variance = []
     pressures_mean = []
     pressures_variance = []
     for disp in range(1, 5):
         df = pd.read_csv(f"results/sim_0{disp}_run_2.dat", header=None, sep="\s+",u
      →index_col=0)
```

```
energy = df[2].to_numpy()
    pressure = df[3].to_numpy()
    energy_subsample = subsample_data(energy, s)
    pressure_subsample = subsample_data(pressure, s)
    energy_mean = np.mean(energy_subsample)
    pressure_mean = np.mean(pressure_subsample)
    energy_variance = np.var(energy_subsample)
    pressure_variance = np.var(pressure_subsample)
    print(f'energy U*: {energy_mean} +- {np.sqrt(energy_variance)}')
    print(f'pressure p*: {pressure_mean} +- {np.sqrt(pressure_variance)}')
    print()
    energies_mean.append(energy_mean)
    energies_variance.append(energy_variance)
    pressures_mean.append(pressure_mean)
    pressures_variance.append(pressure_variance)
displacement = np.arange(1, 5, 1)/10
fig, axs = plt.subplots(1, 2, figsize=(8, 3))
axs[0].errorbar(displacement, energies_mean, yerr=np.sqrt(energies_variance),_

fmt='o')
axs[0].set_xlabel('$\Delta$')
axs[0].set ylabel('U*')
axs[1].errorbar(displacement, pressures_mean, yerr=np.sqrt(pressures_variance),_

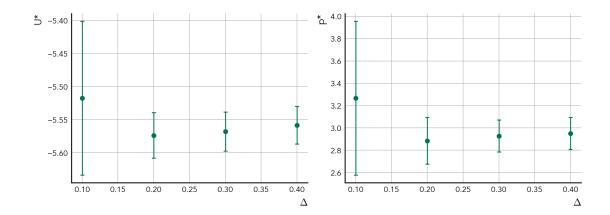
fmt='o')
axs[1].set_xlabel('$\Delta$')
axs[1].set_ylabel('p*')
fig.tight_layout()
energy U*: -5.5173435600000005 +- 0.11615562042799624
pressure p*: 3.2675371900000005 +- 0.6889600524554783
energy U*: -5.573679 +- 0.0344007331277921
pressure p*: 2.88579925 +- 0.20790188196841702
```

energy U*: -5.5679165799999994 +- 0.02948127051421655

pressure p*: 2.9280593 +- 0.14348167591431454

energy U*: -5.558228639999999 +- 0.02849613077154221

pressure p*: 2.95132061 +- 0.14376239065420635



2 Solution to excercise sheet 1, exercise 4

2.1 (a) background corrections

$$\frac{A V_{c}}{N} = 2 \pi \varrho \int_{r_{c}}^{\infty} dr \, r^{2} \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{6}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \left(\frac{\sigma}{r} \right)^{\frac{1}{2}} \right] = 2 \pi \varrho \, 4 \varepsilon \left[\left(\frac{\sigma}{r} \right)^{\frac$$

2.2 (b) background corrections application

From the previous calculations we can see
$$r_c = 3.345\sigma$$
.

 $V_c = 3_c 24C\sigma = \sum \frac{AU_c}{N} = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \frac{1}{3}\right) = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{3}\right)$

$$\frac{\Delta U_c}{N} = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \right) = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \right) = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \right) = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \right) = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \right) = 2\pi \zeta 4\varepsilon \left(\frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \cdot \frac{1}{4\sigma} + \frac{\pi^{\frac{1}{2}}^3}{(3_c 3 4r)^3 \sigma^{\frac{1}{3}}} \right)$$

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