

Effect of stiffness on phase separation

14.10.2025

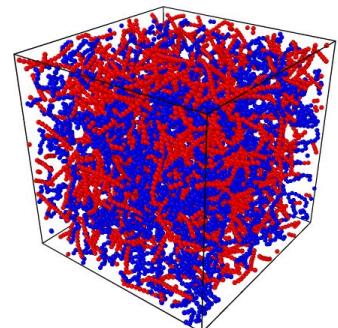
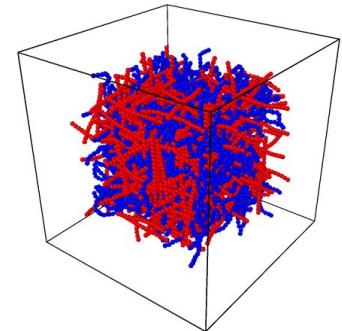
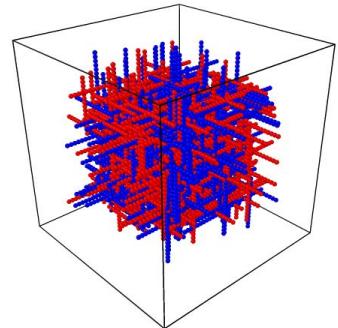
Parameters

- Number of chains (N - type A, M - type B)
- Particle types (T1(head), T2(body), T3(tail) - type A, T4(head, T5(body), T6(tail) - type B)
- Angle coefficients (a1 - type A, a2 - type B)

Pair coefficient - fixed 1.0 repulsive
FENE

Simulation setup

- Initial configuration - each chain contains 15 beads
- Relaxation - 10^5 steps
- Equilibration - 10^5 steps



**Data Analysis: Equilibration run
101 frames - 10^5 steps**

Data analysis methods

- End-to end distance (R)
- Number density (ρ)

End-to-End Distance

Measures the straight-line distance between the first and last monomer of a polymer chain. Useful for understanding chain conformation and flexibility.

$$R_{ee} = \|\mathbf{r}_N - \mathbf{r}_1\| \quad (1)$$

where:

- R_{ee} is the end-to-end distance
- \mathbf{r}_1 is the position vector of the first monomer
- \mathbf{r}_N is the position vector of the last monomer
- $\|\cdot\|$ denotes the Euclidean norm

1D Cartesian Number Density

Measures the actual concentration of particles along one coordinate axis. Gives the true number of particles per unit volume at each position.

$$\rho_\alpha(x) = \frac{N_\alpha(x)}{A \cdot \Delta x} \quad (5)$$

where:

- $\rho_\alpha(x)$ is the number density of type α at position x
- $N_\alpha(x)$ is the number of α particles in slab $[x, x + \Delta x]$
- $A = L_y \cdot L_z$ is the cross-sectional area perpendicular to x -axis
- Δx is the slab thickness ($\Delta x = \Delta y = \Delta z = 0.5\sigma$)

Data analysis methods

- Normalized probability density (p)
- Local composition fraction (ϕ)
- 2D density difference map ($p_B - p_A$)

Local Composition Fraction

Tells you the local concentration or fraction of a specific type of particle in a small region of space. It's especially useful in multicomponent systems (like polymer blends, colloids, or mixtures) to study phase separation, layering, or clustering. The local composition fraction of component A is given by:

$$\phi_A(\mathbf{r}) = \frac{p_A(\mathbf{r})}{p_A(\mathbf{r}) + p_B(\mathbf{r})} \quad (7)$$

where:

- $\phi_A(\mathbf{r})$ is the local composition fraction of component A at position \mathbf{r}
- $p_A(\mathbf{r})$ is the probability density of A particles at position \mathbf{r}
- $p_B(\mathbf{r})$ is the probability density of B particles at position \mathbf{r}
- where \mathbf{r} is x, y or z.

1D Cartesian Probability Density

Tells you the likelihood of finding a particle at each position along an axis, properly normalized. Useful for statistical analysis and comparing distributions.

$$p_\alpha(x) = \frac{N_\alpha(x)}{N_{\text{total}} \cdot A \cdot \Delta x} \quad (6)$$

where:

- $p_\alpha(x)$ is the probability density of finding type α at position x
- N_{total} is the total number of α particles in the system

2D Probability Density Difference Map

Provides a normalized view of spatial segregation patterns, showing where each particle type is more likely to be found. Values range from -1 to 1 for easy interpretation.

$$\Delta p(x, y) = \frac{p_A(x, y) - p_B(x, y)}{\max |p_A(x, y) - p_B(x, y)|} \quad (13)$$

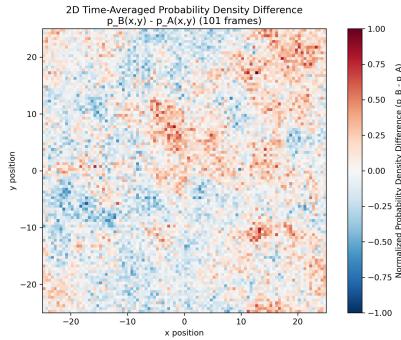
where:

- $p_A(x, y) = \frac{N_A(x, y)}{N_{\text{total}, A} \cdot \Delta x \Delta y L_z}$ is the 2D probability density of type A
- $p_B(x, y) = \frac{N_B(x, y)}{N_{\text{total}, B} \cdot \Delta x \Delta y L_z}$ is the 2D probability density of type B
- $\Delta p(x, y) \in [-1, 1]$ indicates spatial segregation
- Positive values: regions dominated by type A
- Negative values: regions dominated by type B

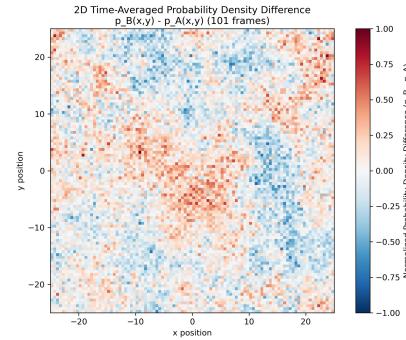
Effect of angle coefficient

$N = 50, M = 50$

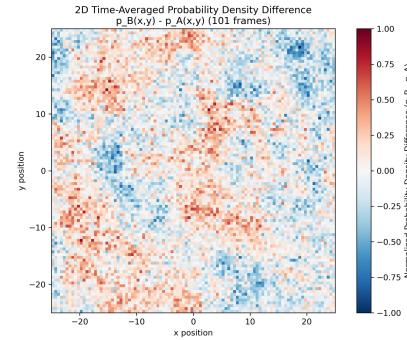
$a_1 = 1, a_2 = 1$



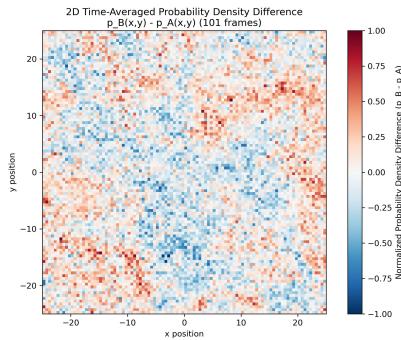
$a_1 = 1, a_2 = 20$



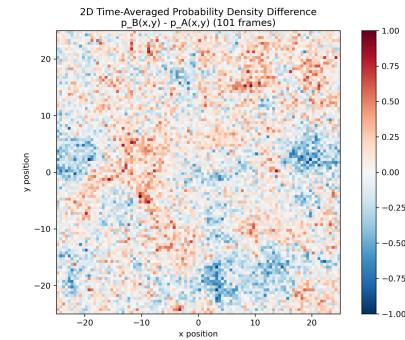
$a_1 = 1, a_2 = 60$



$a_1 = 20, a_2 = 20$



$a_1 = 20, a_2 = 40$



$a_1 = 20, a_2 = 60$

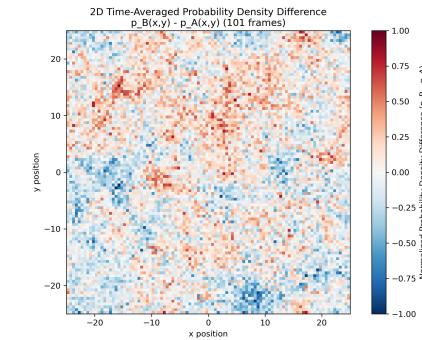
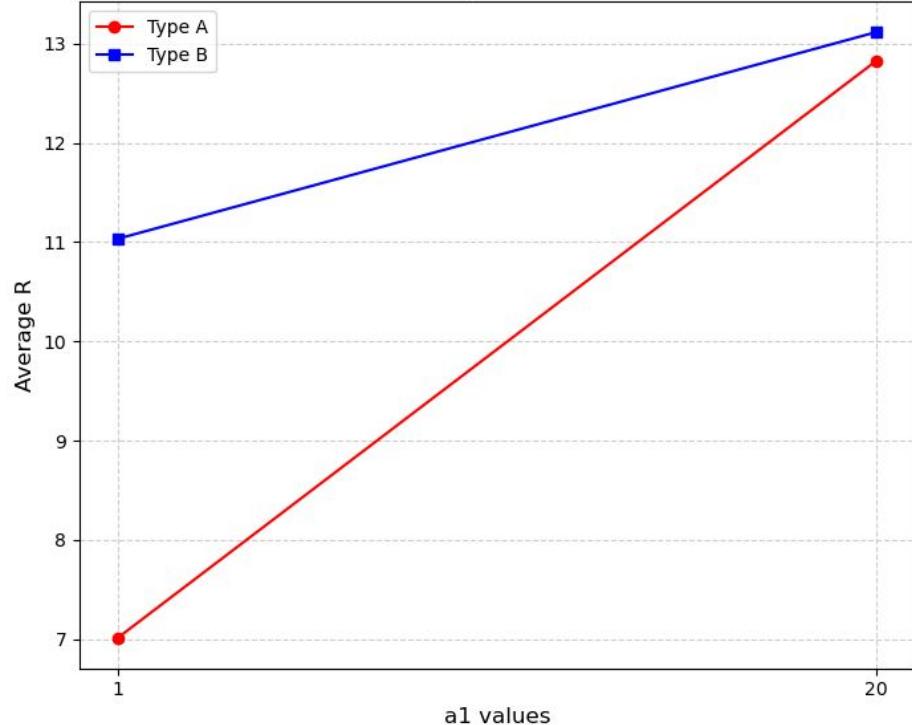


Table 1: End-to-end distance analysis for different angle coefficient combinations

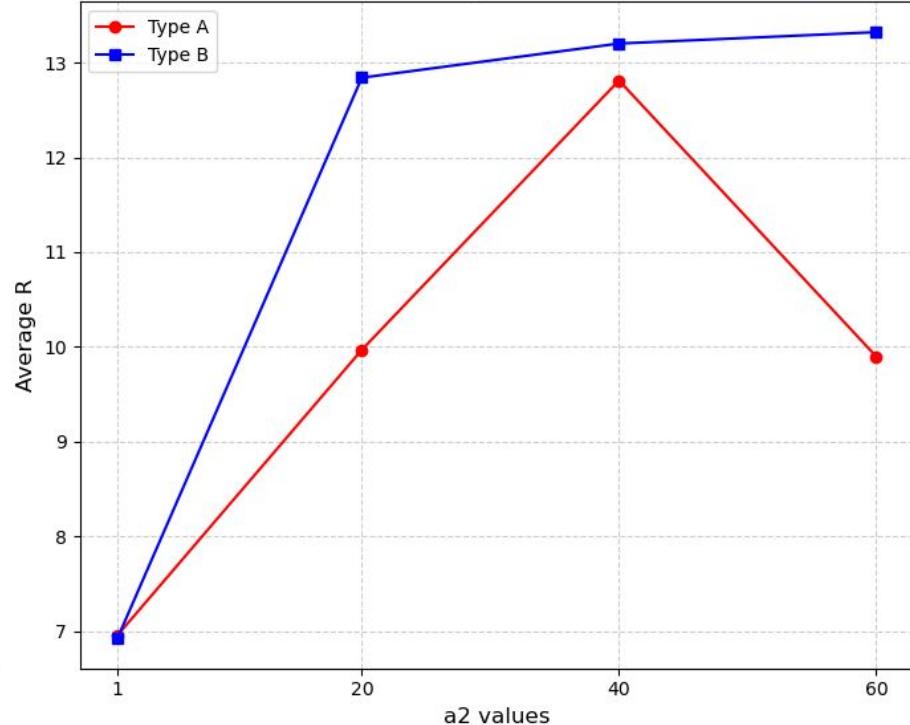
Angle Coefficients(a)		End-to-End Distance(R)	
a_1	a_2	$R_A(\sigma)$	$R_B(\sigma)$
1	1	6.904	6.861
1	20	7.081	12.845
1	60	6.965	13.315
20	20	12.839	12.826
20	40	12.810	13.196
20	60	12.827	13.315

Note: a_1 and a_2 represent the angle coefficients for type A and type B polymer chains, respectively. R_A and R_B denote the time-averaged end-to-end distances.

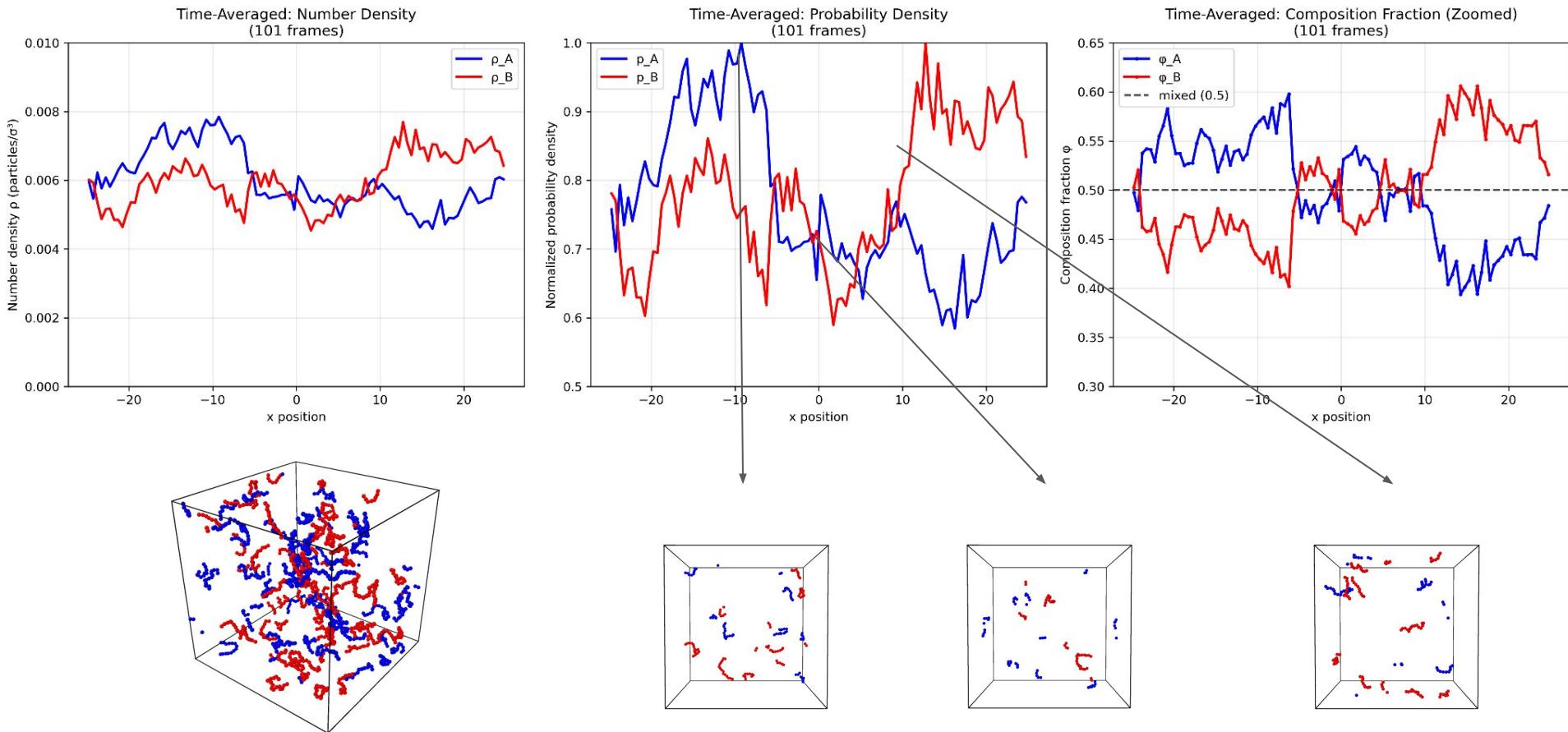
Average R vs a1

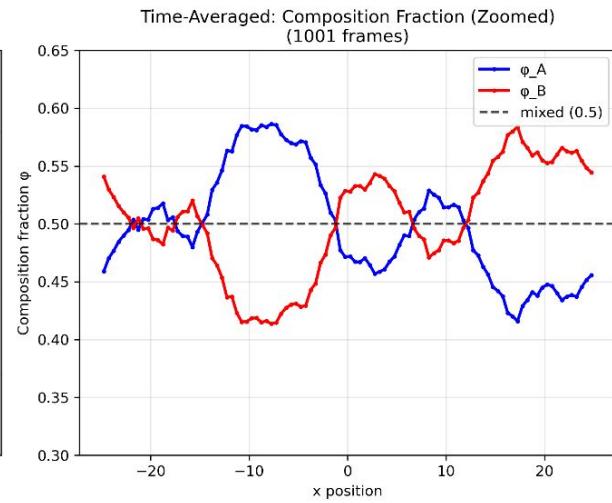
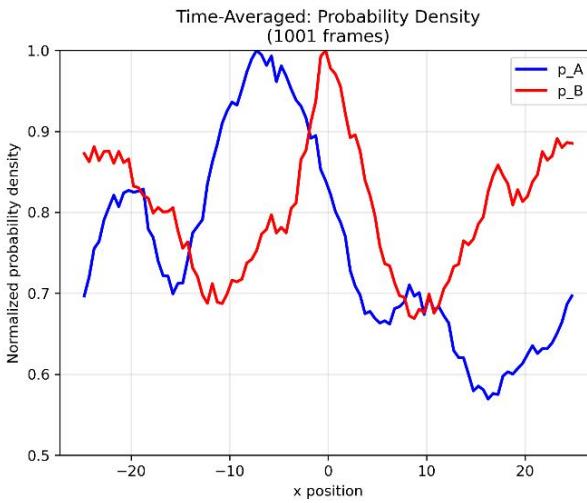
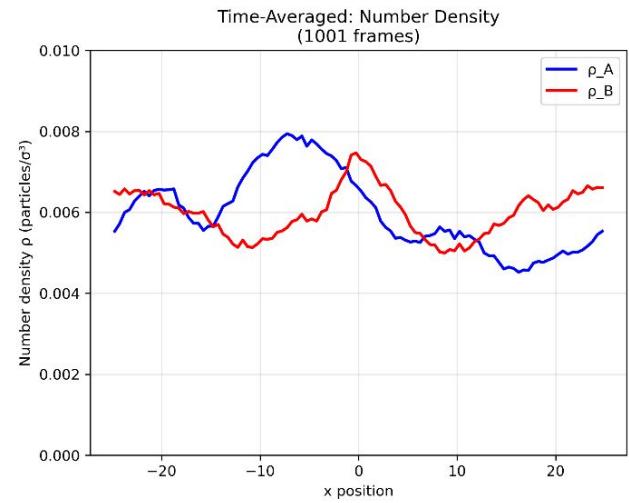


Average R vs a2

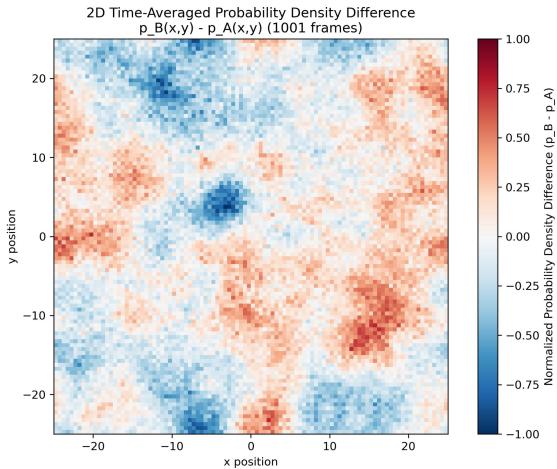


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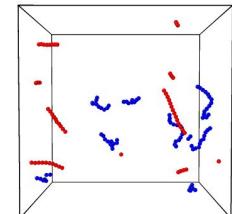
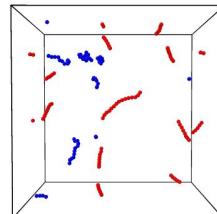
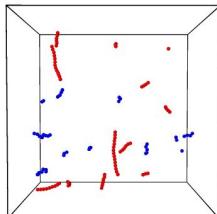
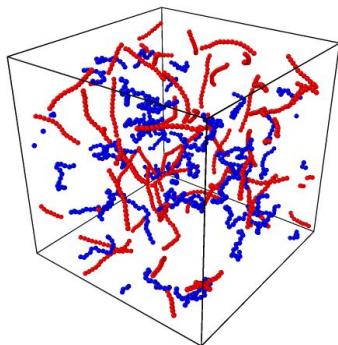
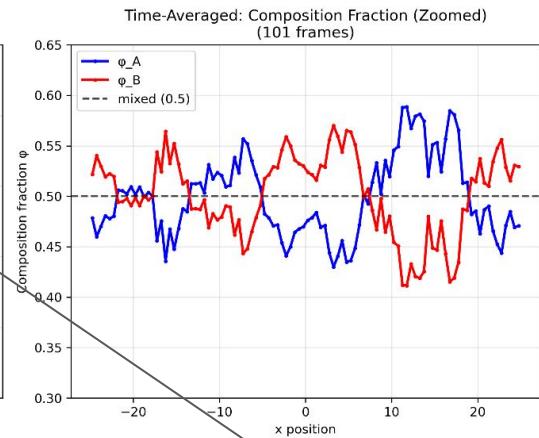
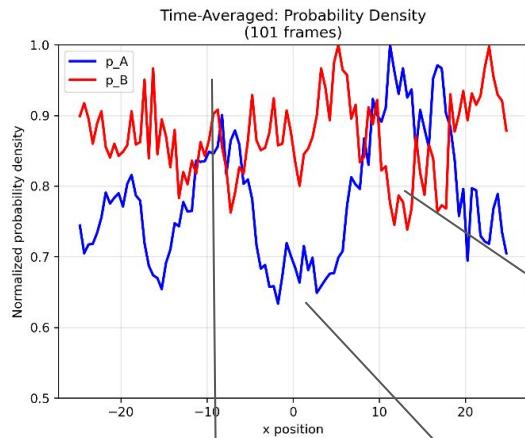
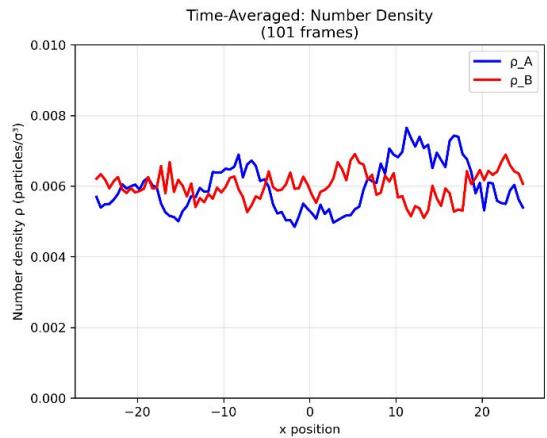




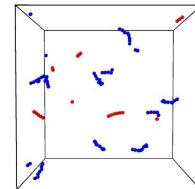
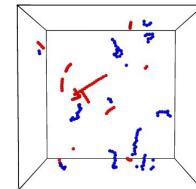
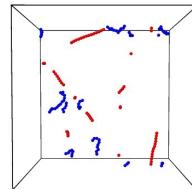
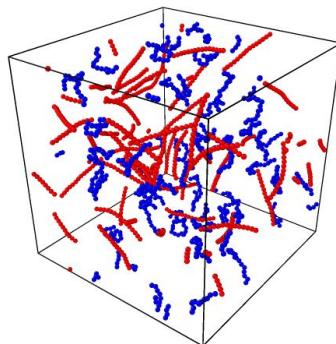
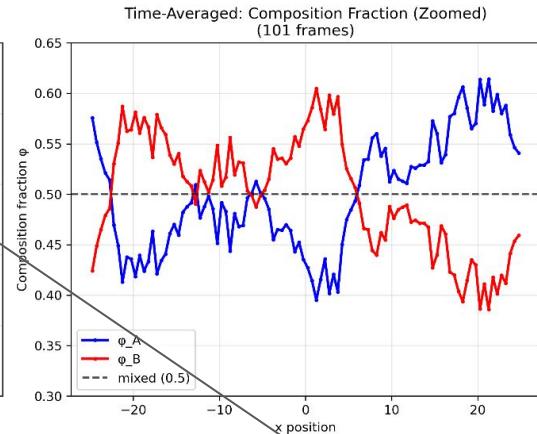
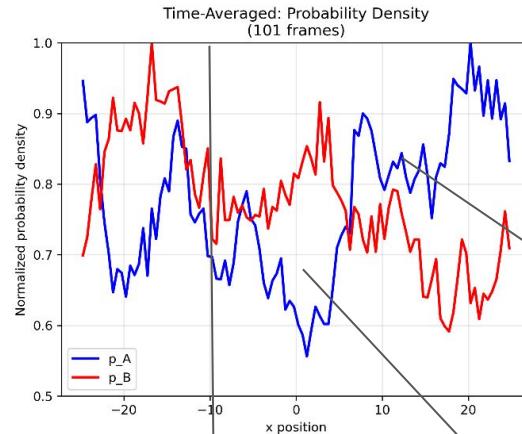
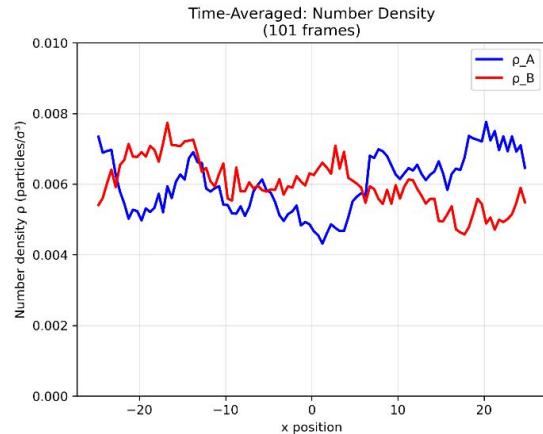
$a_1 = 1, a_2 = 1$
 Thermostat $\rightarrow 100$
 Timesteps $\rightarrow 10^6$



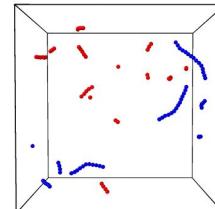
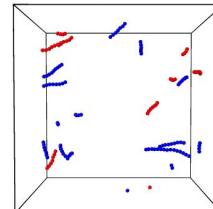
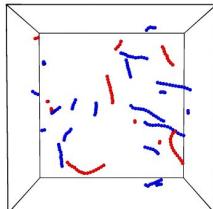
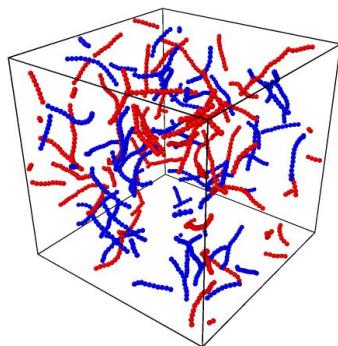
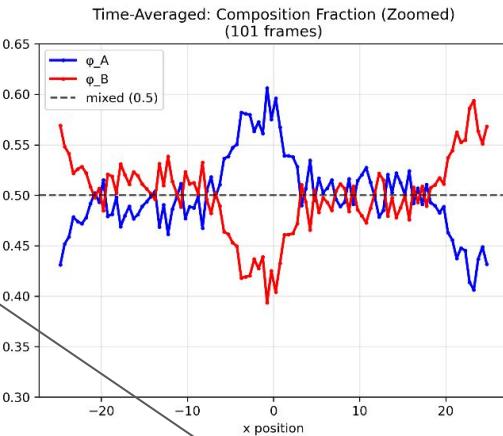
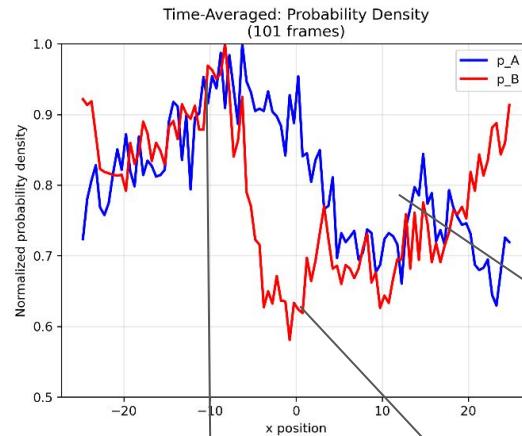
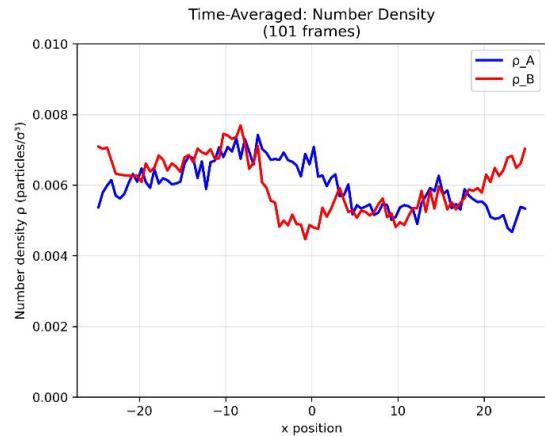
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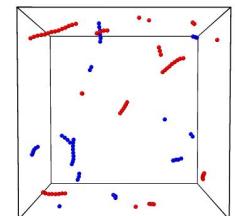
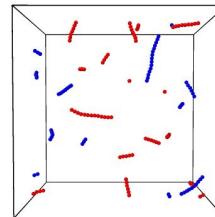
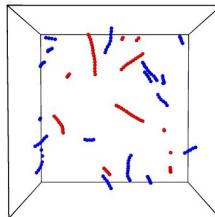
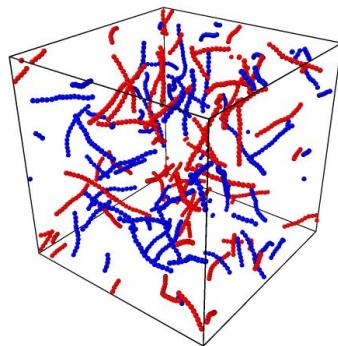
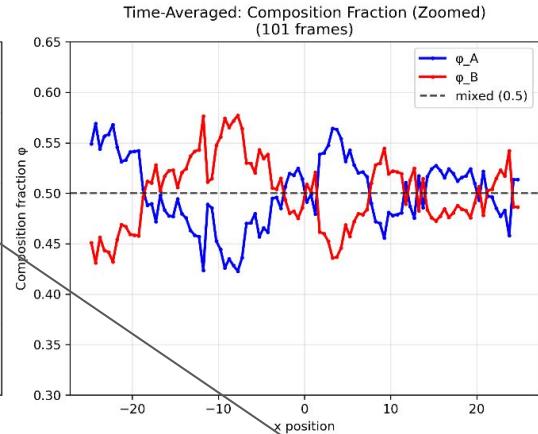
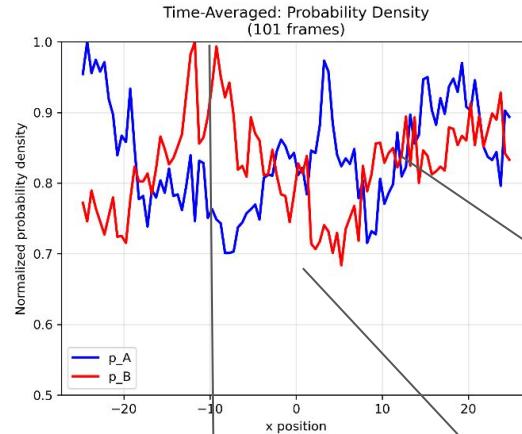
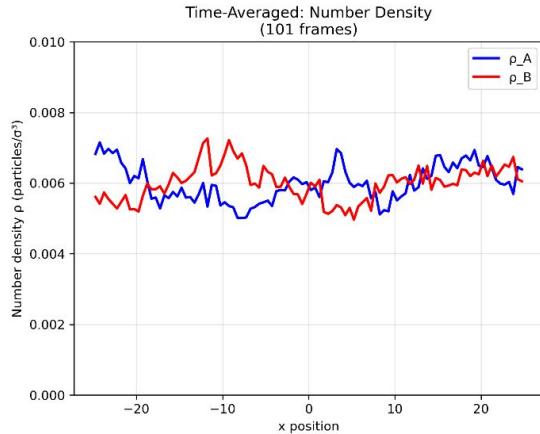
$$a_1 = 1, a_2 = 60$$



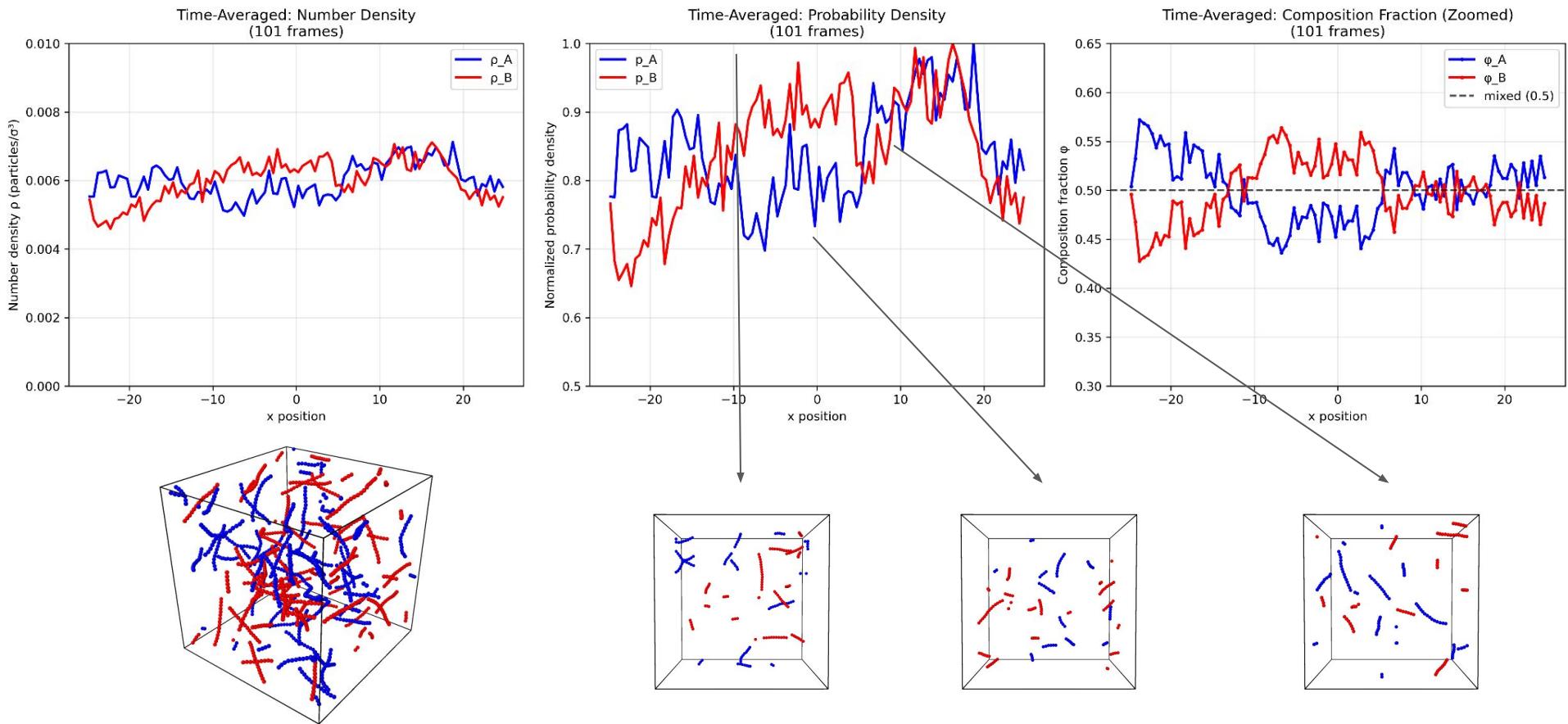
$$a_1 = 20, a_2 = 20$$

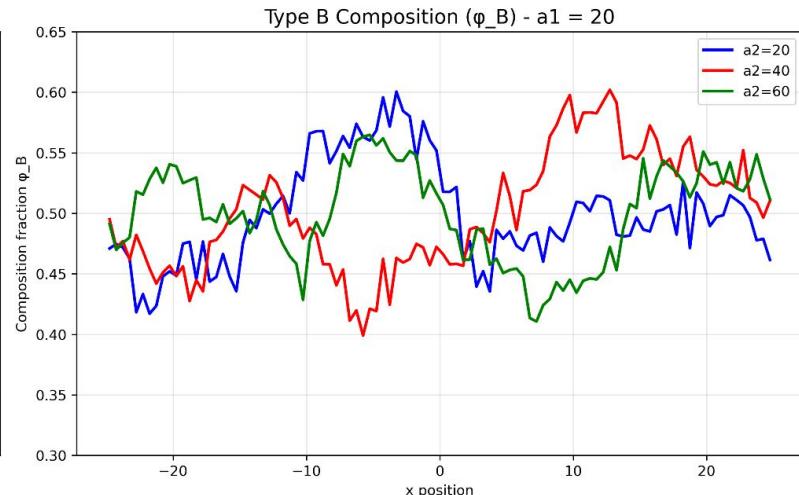
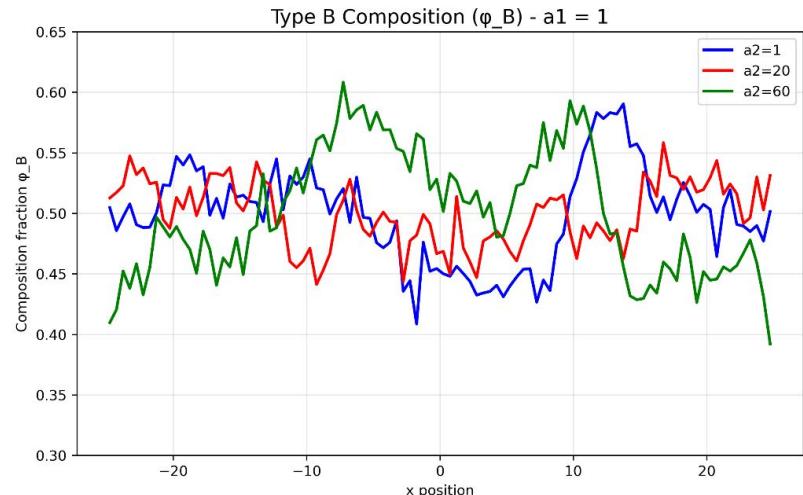
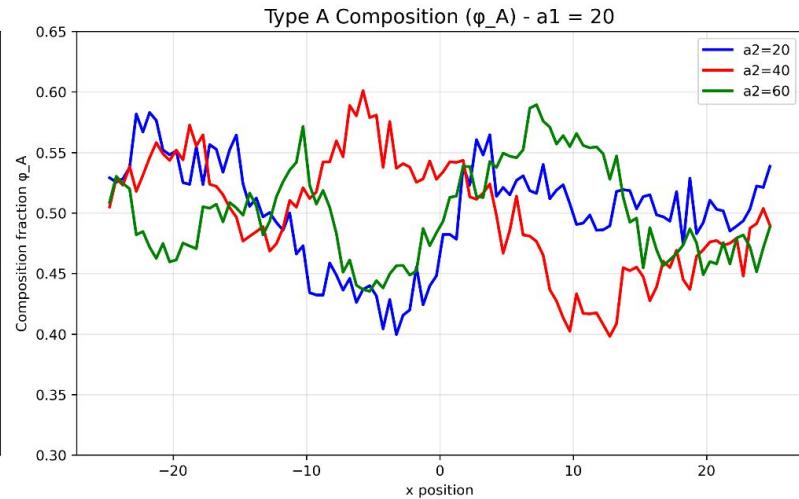
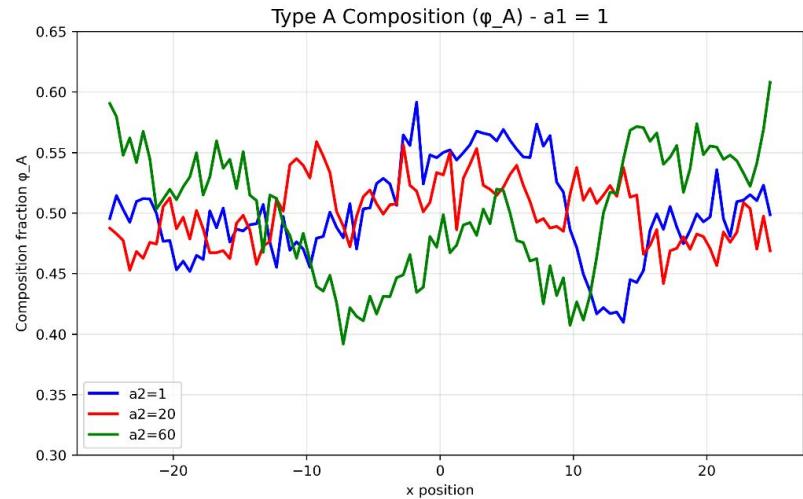


$$a_1 = 20, a_2 = 40$$



$a_1 = 20, a_2 = 60$



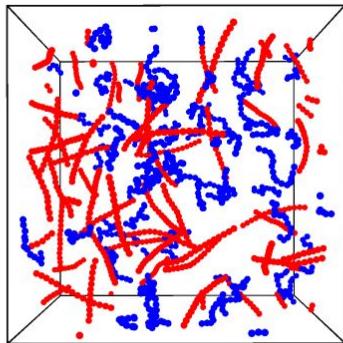


Effect of concentration

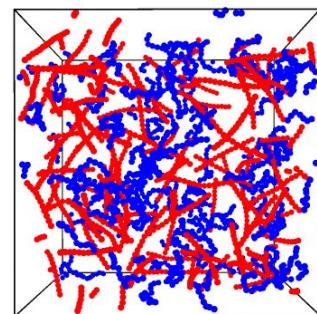
$a_1 = 1, a_2 = 60$

Comparison ($a_1 = 1$, $a_2 = 60$)

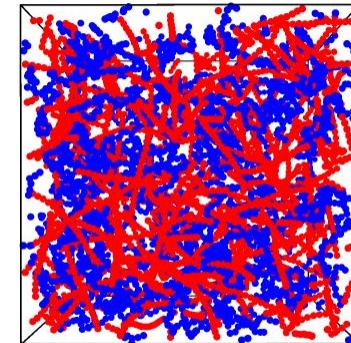
$N + M = 100$



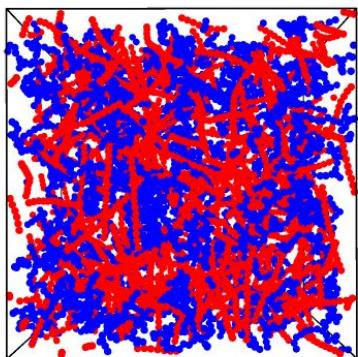
$N + M = 200$



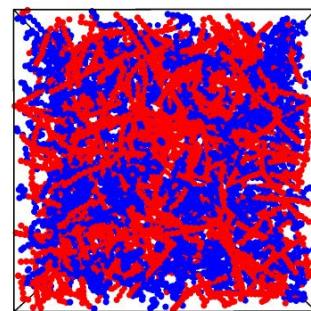
$N + M = 500$



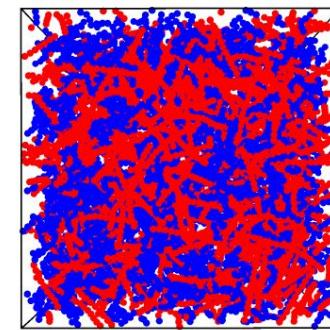
$N + M = 600$



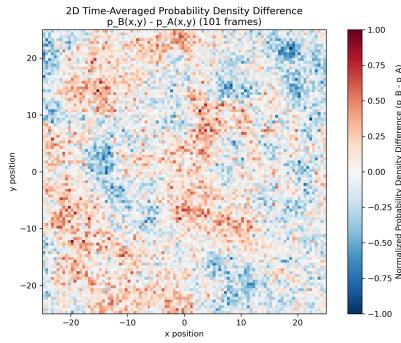
$N + M = 833$



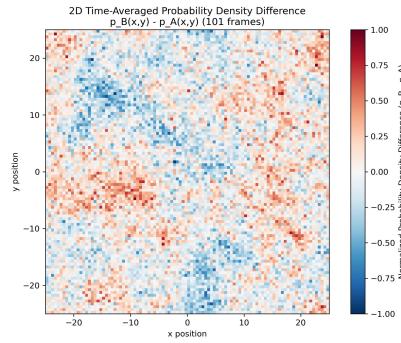
$N + M = 1000$



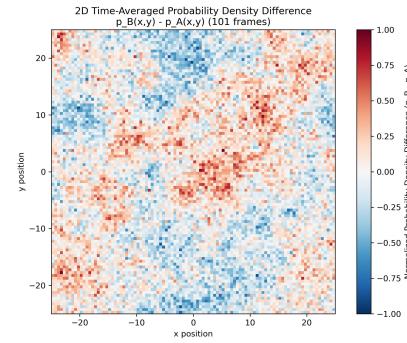
N + M = 100



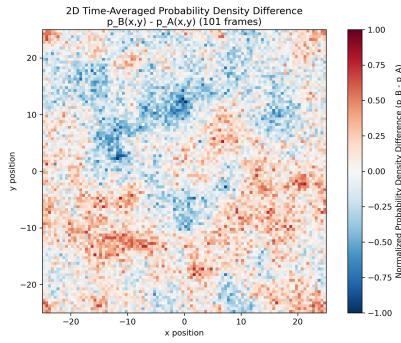
N + M = 200



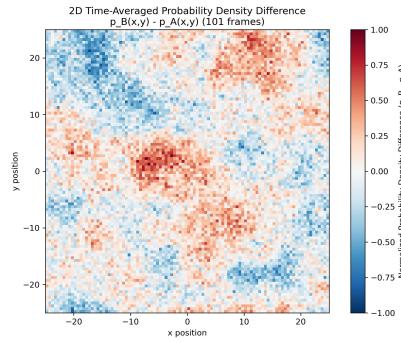
N + M = 500



N + M = 600



N + M = 833



N + M = 1000

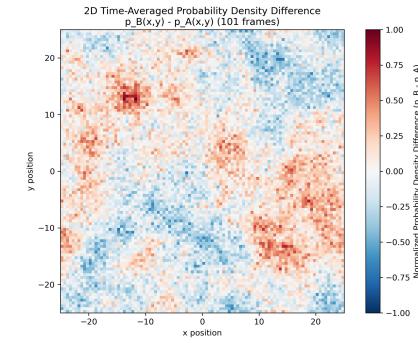
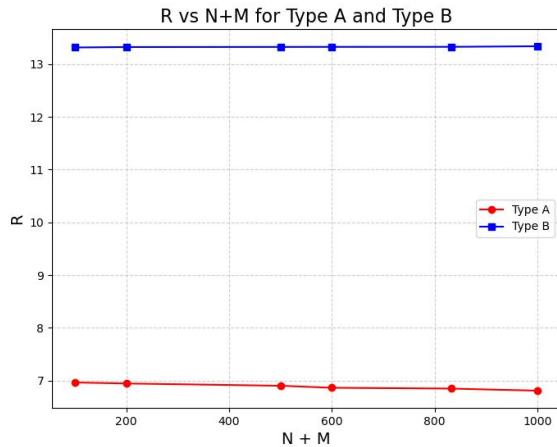


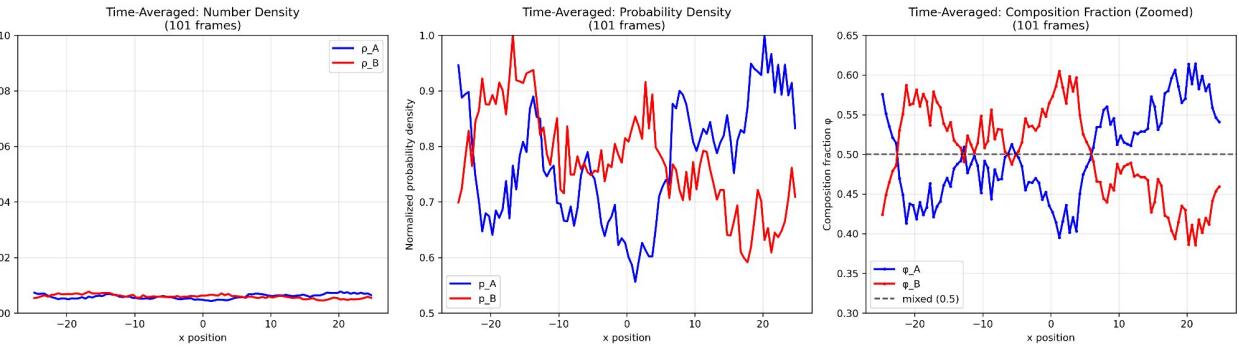
Table 2: End-to-end distance analysis for different concentrations

Angle Coefficients(a)		End-to-End Distance(R)	
N	M	$R_A(\sigma)$	$R_B(\sigma)$
50	50	6.965	13.315
100	100	6.946	13.323
250	250	6.903	13.325
300	300	6.865	13.326
416	417	6.849	13.327
500	500	6.810	13.338

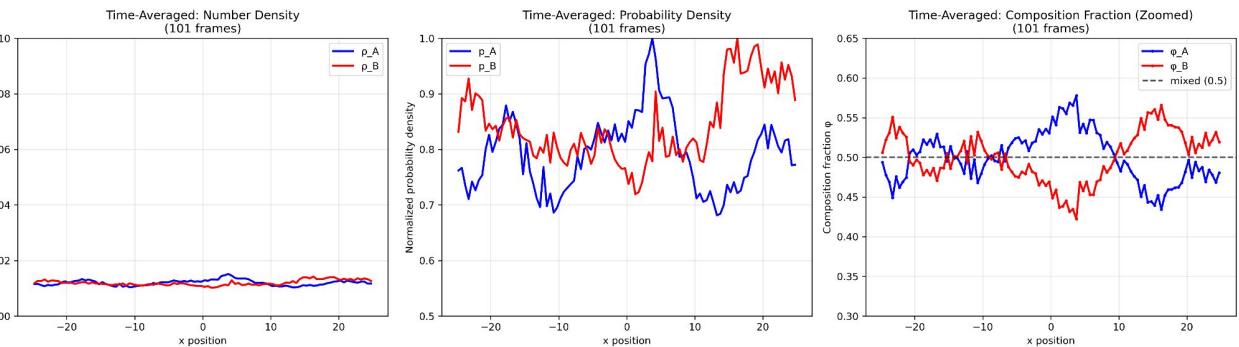
Note: N and M represent the chain numbers for type A and type B polymer chains, respectively. R_A and R_B denote the time-averaged end-to-end distances.



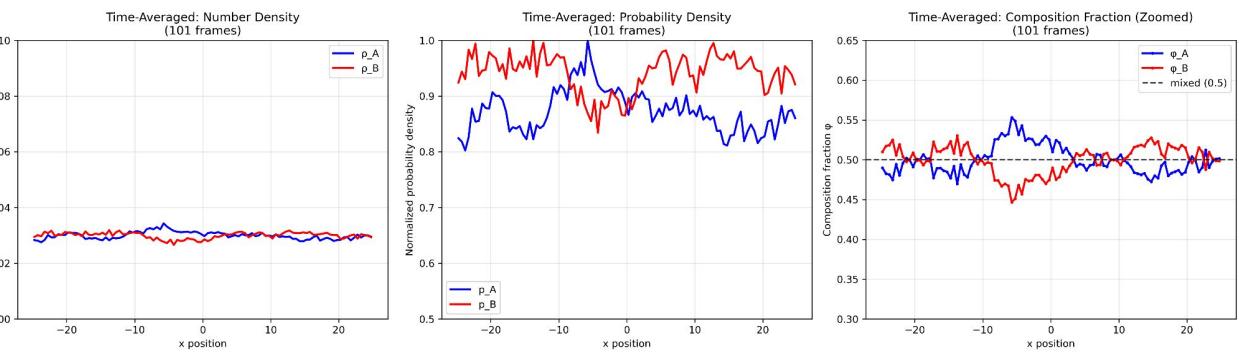
$N = 50$
 $M = 50$
 X



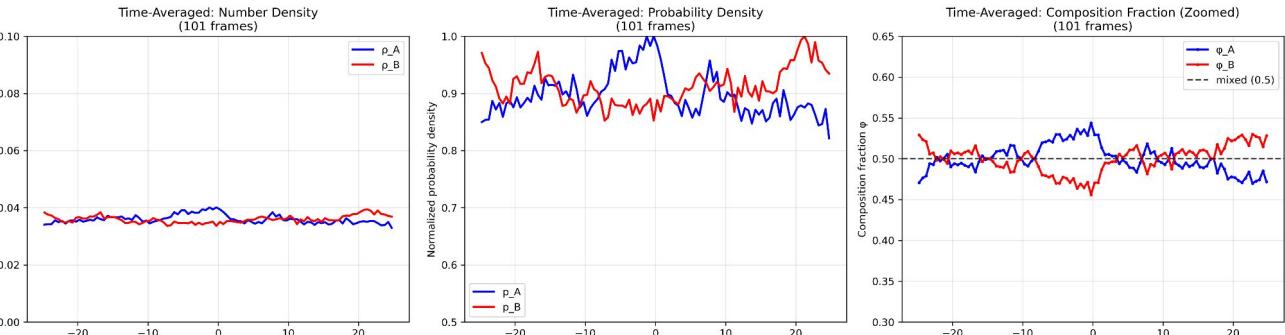
$N = 100$
 $M = 100$
 X



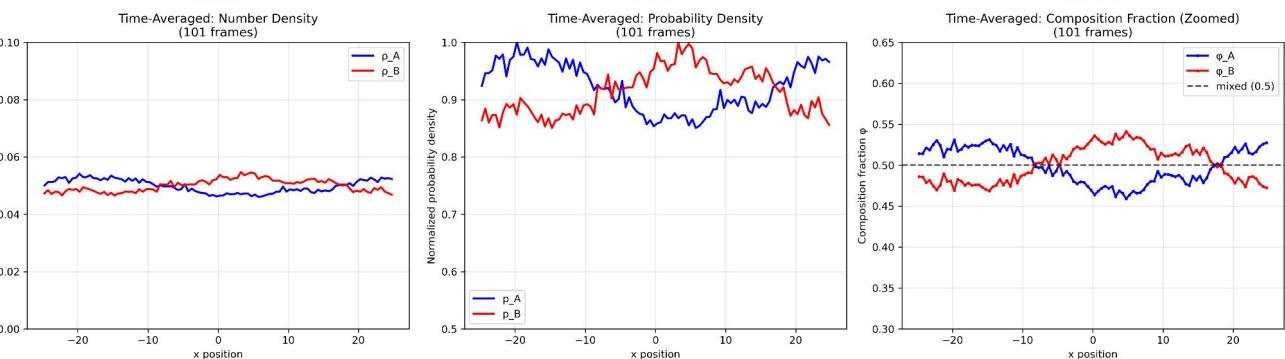
$N = 250$
 $M = 250$
 X



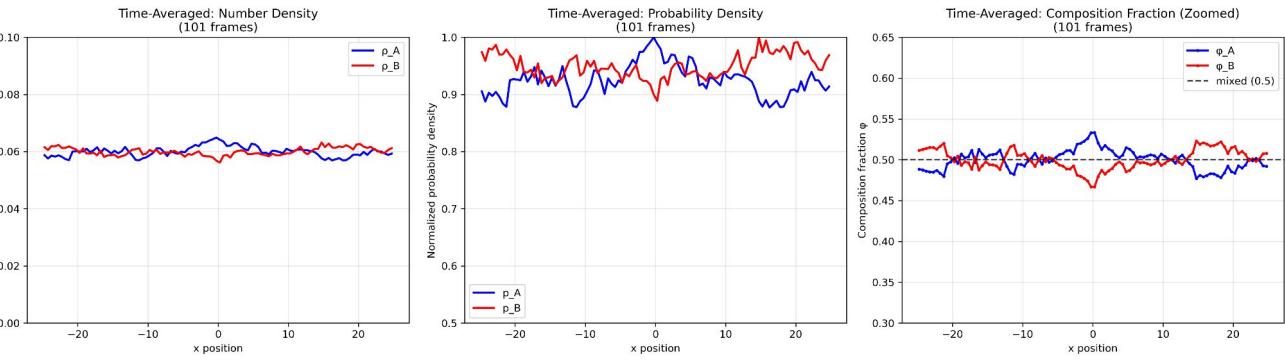
$N = 300$
 $M = 300$
 X



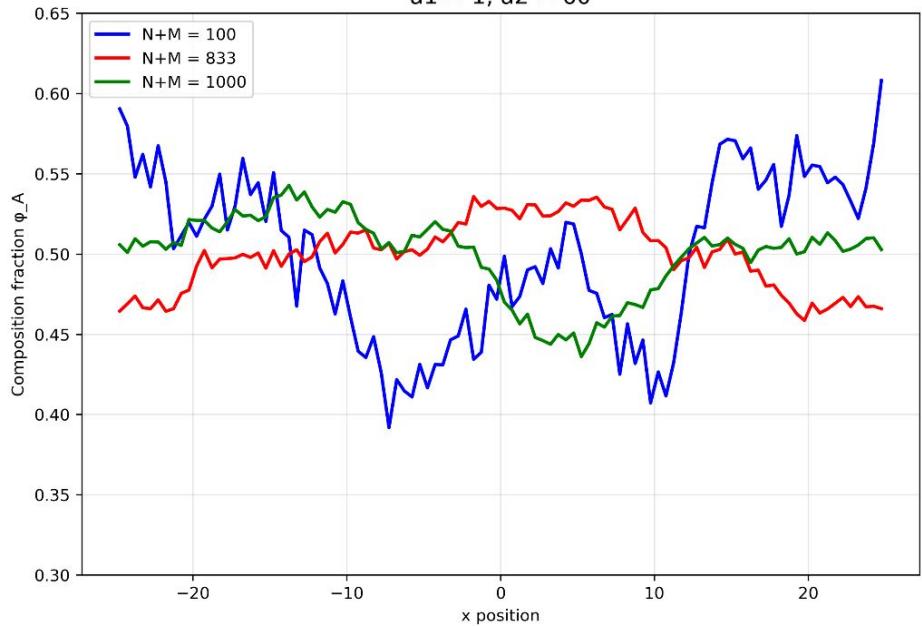
$N = 417$
 $M = 416$
 X



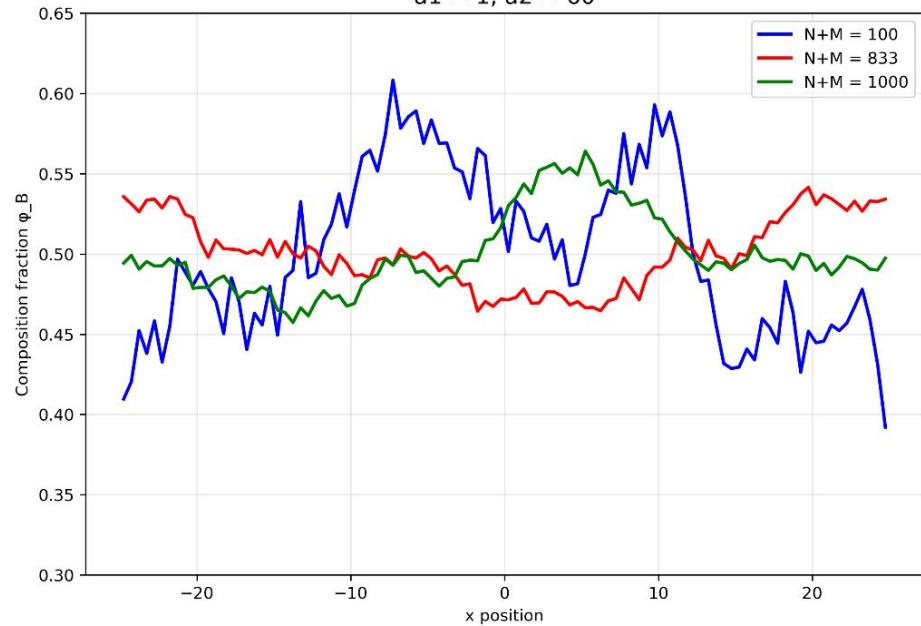
$N = 500$
 $M = 500$
 X



Type A Composition (ϕ_A)
 $a_1 = 1, a_2 = 60$



Type B Composition (ϕ_B)
 $a_1 = 1, a_2 = 60$



Analysis

```
# Slab profile functions with 0.5σ bin size
def slab_profile_number_density(coords, mask, axis=0, R=25.0):
    """Formula 1: 1D Number Density  $\rho_{\alpha}(x) = N_{\alpha}(x) / (A * \Delta x)$ """
    dx = 0.5 # σ = 0.5
    bins = np.arange(-R, R + dx, dx)

    # Cross-sectional area
    area = (2 * R) * (2 * R)

    vals = coords[:, axis]
    cnt, _ = np.histogram(vals[mask], bins=bins)
    density = cnt / (area * dx) # Number density

    centers = 0.5 * (bins[:-1] + bins[1:])
    return centers, density

def slab_profile_probability_density(coords, mask, total_particles, axis=0, R=25.0):
    """Formula 2: 1D Probability Density  $p_{\alpha}(x) = N_{\alpha}(x) / (N_{total}, \alpha * A * \Delta x)$ """
    dx = 0.5 # σ = 0.5
    bins = np.arange(-R, R + dx, dx)

    # Cross-sectional area
    area = (2 * R) * (2 * R)

    vals = coords[:, axis]
    cnt, _ = np.histogram(vals[mask], bins=bins)
    probability_density = cnt / (total_particles * area * dx) # Probability density

    centers = 0.5 * (bins[:-1] + bins[1:])
    return centers, probability_density

def calculate_composition_fraction_probability(p_A, p_B):
    """Calculate composition fraction using probability density:  $\varphi_A = p_A / (p_A + p_B)$ """
    phi_A = np.zeros_like(p_A)
    phi_B = np.zeros_like(p_B)
    nonzero = (p_A + p_B) > 0
    phi_A[nonzero] = p_A[nonzero] / (p_A[nonzero] + p_B[nonzero])
    phi_B[nonzero] = p_B[nonzero] / (p_A[nonzero] + p_B[nonzero])
    return phi_A, phi_B
```

Simulation input file

Relaxation and repulsive run

```
1 # --- Initialization ---
2 units      lj
3 boundary   p p p
4
5 atom_style angle
6 pair_style lj/cut 1.12246
7 pair_modify shift yes
8 bond_style fene
9 angle_style harmonic
10
11 # --- Read structure ---
12 read_data solution.data
13
14 # --- Bonded Interactions ---
15 bond_coeff 1 30.0 1.5 1.0 1.0
16 bond_coeff 2 30.0 1.5 1.0 1.0
17 angle_coeff 1 1.0 180.0
18 angle_coeff 2 60.0 180.0
19
20 pair_coeff * * 1.0 1.0
21
22 # --- Energy Minimization ---
23 minimize 1e-6 1e-8 10000 100000
24
25 # --- Neighbor setup ---
26 neighbor    0.4 bin
27 neigh_modify delay 10
28
29 # --- Velocity Initialization & Dynamics ---
30 velocity all create 1.0 12345 rot yes dist gaussian
31
32 fix integrator all nve
33 fix thermostat all langevin 1.0 1.0 100.0 12345
34
35 # --- Output settings ---
36 thermo_style multi
37 thermo 500
38
39 # --- Dump unwrapped coordinates for python analysis ---
40 dump 1 all atom 1000 dump.relaxation
41 dump_modify 1 scale yes
42
43 # Run simulation
44 run 100000
45
46 # --- Save final configuration ---
47 write_data data.relaxation
48
49
```

```
in.task_1_60 •
2 types > _Task1000 > _60 > in.task_1_60
1 # --- Initialization ---
2 units      lj
3 boundary   p p p
4
5 atom_style angle
6 pair_style lj/cut 1.12246
7 pair_modify shift yes
8 bond_style fene
9 angle_style harmonic
10
11 # --- Read structure ---
12 read_data data.relaxation
13
14 # --- Bonded Interactions ---
15 bond_coeff 1 30.0 1.5 1.0 1.0
16 bond_coeff 2 30.0 1.5 1.0 1.0
17 angle_coeff 1 1.0 180.0
18 #angle_coeff 2 60.0 180.0
19
20 pair_coeff * * 1.0 1.0
21
22 # --- Neighbor setup ---
23 neigh_modify delay 10
24
25 # --- Velocity Initialization & Dynamics ---
26 velocity all create 1.0 12345 rot yes dist gaussian
27
28 fix integrator all nve
29 fix thermostat all langevin 1.0 1.0 100.0 12345
30
31 # --- Output settings ---
32 thermo_style multi
33 thermo 500
34
35 # --- Dump unwrapped coordinates for python analysis ---
36 dump 1 all atom 1000 dump.task
37 dump_modify 1 scale yes
38
39 # Run simulation
40 run 100000
41
42 # --- Save final configuration ---
43 write_data data.task
44
45
46
47 print "Simulation done"
48
```

1D Cartesian Probability Density

Tells you the likelihood of finding a particle at each position along an axis, properly normalized. Useful for statistical analysis and comparing distributions.

$$p_\alpha(x) = \frac{N_\alpha(x)}{N_{\text{total},\alpha} \cdot A \cdot \Delta x} \quad (6)$$

where:

- $p_\alpha(x)$ is the probability density of finding type α at position x
- $N_{\text{total},\alpha}$ is the total number of α particles in the system

```
N_total_A = len(coords_transformed[A_mask])
N_total_B = len(coords_transformed[B_mask])

for axis_idx, axis_name in enumerate(['x', 'y', 'z']):
    # Calculate instantaneous profiles
    centers, rho_A_inst = slab_profile_number_density(coords_transformed, A_mask, axis=axis_idx)
    centers, rho_B_inst = slab_profile_number_density(coords_transformed, B_mask, axis=axis_idx)
    centers, p_A_inst = slab_profile_probability_density(coords_transformed, A_mask, N_total_A)
    centers, p_B_inst = slab_profile_probability_density(coords_transformed, B_mask, N_total_B)
```

Local Composition Fraction

Tells you the local concentration or fraction of a specific type of particle in a small region of space. It's especially useful in multicomponent systems (like polymer blends, colloids, or mixtures) to study phase separation, layering, or clustering. The local composition fraction of component A is given by:

$$\phi_A(\mathbf{r}) = \frac{\rho_A(\mathbf{r})}{\rho_A(\mathbf{r}) + \rho_B(\mathbf{r})} \quad (7)$$

where:

- $\phi_A(\mathbf{r})$ is the local composition fraction of component A at position \mathbf{r}
- $\rho_A(\mathbf{r})$ is the number density of A particles at position \mathbf{r}
- $\rho_B(\mathbf{r})$ is the number density of B particles at position \mathbf{r}
- where \mathbf{r} is x, y or z.

```
def calculate_composition_fraction(rho_A, rho_B):
    """Calculate composition fraction: phi_A = p_A / (p_A + p_B)"""
    phi_A = np.zeros_like(rho_A)
    phi_B = np.zeros_like(rho_B)
    nonzero = (rho_A + rho_B) > 0
    phi_A[nonzero] = rho_A[nonzero] / (rho_A[nonzero] + rho_B[nonzero])
    phi_B[nonzero] = rho_B[nonzero] / (rho_A[nonzero] + rho_B[nonzero])
    return phi_A, phi_B
```

1D Cartesian Probability Density

Tells you the likelihood of finding a particle at each position along an axis, properly normalized. Useful for statistical analysis and comparing distributions.

$$p_\alpha(x) = \frac{N_\alpha(x)}{N_{\text{total}} \cdot A \cdot \Delta x} \quad (6)$$

where:

- $p_\alpha(x)$ is the probability density of finding type α at position x
- N_{total} is the total number of α particles in the system

```
coords_transformed = (coords - 0.5) * 2 * R
A_mask = np.isin(types, [1, 2, 3])
B_mask = ~A_mask

N_total = len(coords_transformed[A_mask]) + len(coords_transformed[B_mask])

for axis_idx, axis_name in enumerate(['x', 'y', 'z']):
    # Calculate instantaneous profiles
    centers, rho_A_inst = slab_profile_number_density(coords_transformed, A_mask, axis=axis_idx)
    centers, rho_B_inst = slab_profile_number_density(coords_transformed, B_mask, axis=axis_idx)
    centers, p_A_inst = slab_profile_probability_density(coords_transformed, A_mask, N_total)
    centers, p_B_inst = slab_profile_probability_density(coords_transformed, B_mask, N_total)
```

Proper fixes

Local Composition Fraction

Tells you the local concentration or fraction of a specific type of particle in a small region of space. It's especially useful in multicomponent systems (like polymer blends, colloids, or mixtures) to study phase separation, layering, or clustering. The local composition fraction of component A is given by:

$$\phi_A(\mathbf{r}) = \frac{p_A(\mathbf{r})}{p_A(\mathbf{r}) + p_B(\mathbf{r})} \quad (7)$$

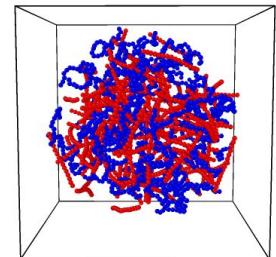
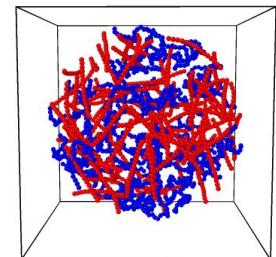
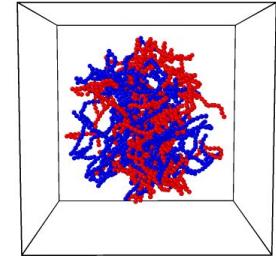
where:

- $\phi_A(\mathbf{r})$ is the local composition fraction of component A at position \mathbf{r}
- $p_A(\mathbf{r})$ is the probability density of A particles at position \mathbf{r}
- $p_B(\mathbf{r})$ is the probability density of B particles at position \mathbf{r}
- where \mathbf{r} is x, y or z.

```
calculate_composition_fraction_probability(p_A, p_B):
    """Calculate composition fraction using probability density: phi_A = p_A / (p_A + p_B)"""
    phi_A = np.zeros_like(p_A)
    phi_B = np.zeros_like(p_B)
    nonzero = (p_A + p_B) > 0
    phi_A[nonzero] = p_A[nonzero] / (p_A[nonzero] + p_B[nonzero])
    phi_B[nonzero] = p_B[nonzero] / (p_A[nonzero] + p_B[nonzero])
    return phi_A, phi_B
```

Simulation setup

- Initial configuration - each chain contains 15 beads
- Relaxation - 10^6 steps
- Equilibration - 10^6 steps



Data Analysis: Equilibration run
101 frames - 10^6 steps

Data analysis methods

- Radial Distribution Function($g(r)$)
- Radial probability density (p)
- Local composition fraction (ϕ)

Radial Probability Density

*I should have used this formula, however I used normalized radial number density. The radial probability density is given by:

$$p(r) = \frac{n(r)}{4\pi R_0^2 \Delta r}. \quad (3)$$

where:

- $p(r)$ is the radial probability density at distance r
- $n(r)$ is the number of particles in the spherical shell at radius r
- R_0 is the reference radius
- Δr is $R_0 - r$
- r is the position

Radial Distribution Function

The radial distribution function answers: "Given a particle here, how likely am I to find another particle at distance r from it compared to a completely random distribution (ideal gas distribution)?"

$$g(r) = \frac{1}{\rho N} \left\langle \sum_{i=1}^N \sum_{j \neq i}^N \delta(r - r_{ij}) \right\rangle \quad (2)$$

where:

- N = total number of particles
- $\rho = \frac{N}{V}$ = number density (particles per unit volume)
- r_{ij} = distance between particles i and j
- δ = Dirac delta function
- $\langle \dots \rangle$ = ensemble or time average

Local Composition Fraction

Tells you the local concentration or fraction of a specific type of particle in a small region of space. It's especially useful in multicomponent systems (like polymer blends, colloids, or mixtures) to study phase separation, layering, or clustering. The local composition fraction of component A is given by:

$$\phi_A(\mathbf{r}) = \frac{p_A(\mathbf{r})}{p_A(\mathbf{r}) + p_B(\mathbf{r})} \quad (7)$$

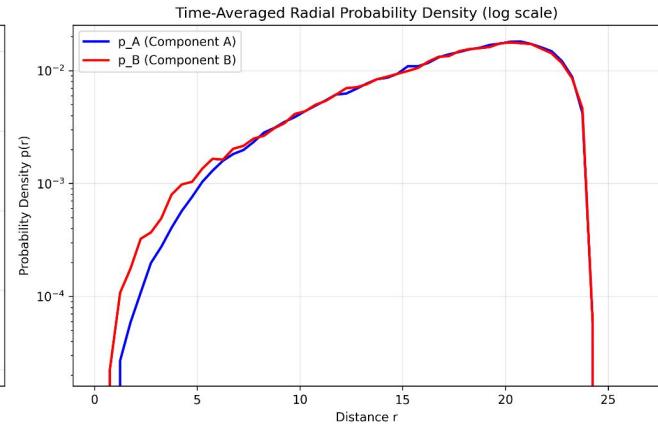
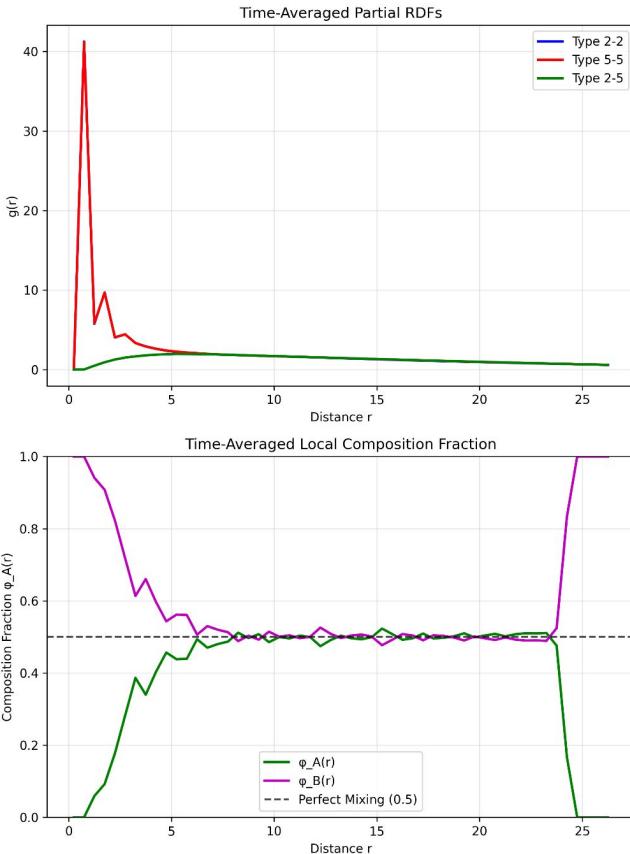
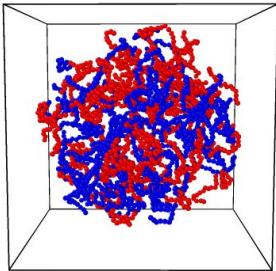
where:

- $\phi_A(\mathbf{r})$ is the local composition fraction of component A at position \mathbf{r}
- $p_A(\mathbf{r})$ is the probability density of A particles at position \mathbf{r}
- $p_B(\mathbf{r})$ is the probability density of B particles at position \mathbf{r}
- where \mathbf{r} is x, y or z.

Effect of angle coefficient

$N = 100, M = 100$

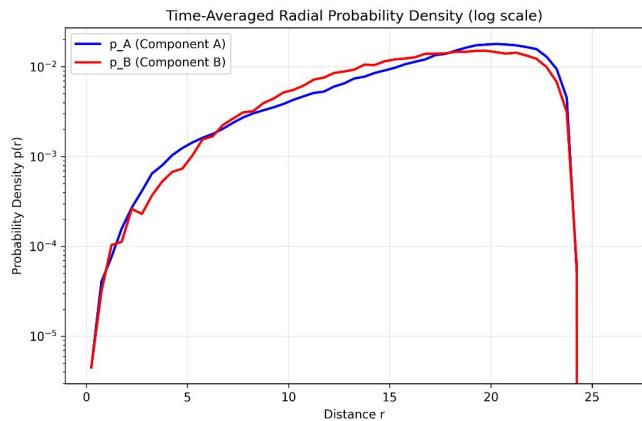
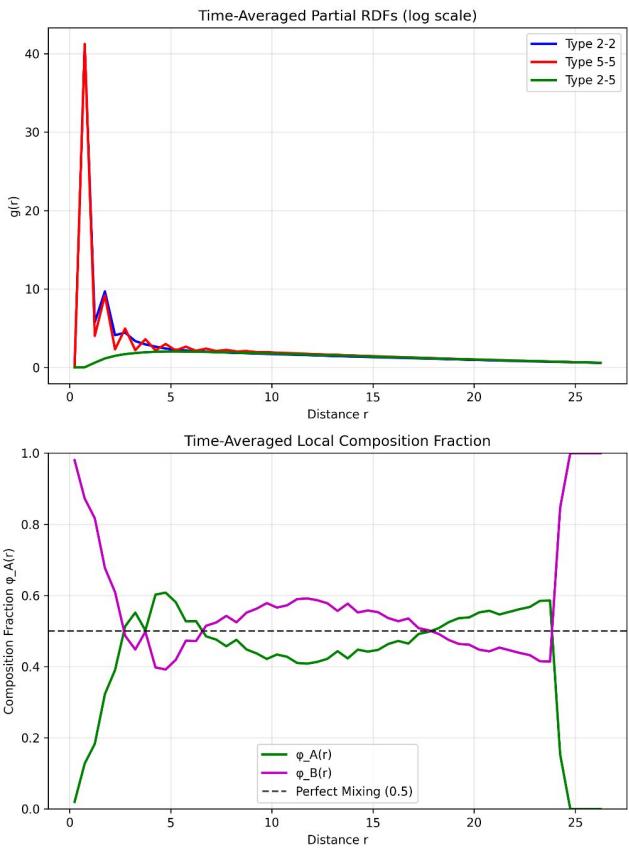
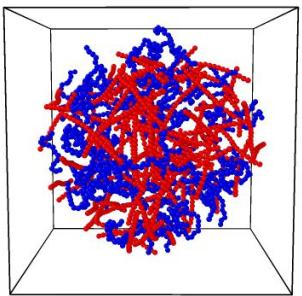
$a_1 = 1, a_2 = 1$



System Summary:

- Total particles: 3000
- Component A types: 1, 2, 3
- Component B types: 4, 5, 6
- Sphere radius: 26.33
- Box size: 50.00
- Frames averaged: 51
- Using second half of trajectory

$a_1 = 1$, $a_2 = 60$



System Summary:

- Total particles: 3000
- Component A types: 1, 2, 3
- Component B types: 4, 5, 6
- Sphere radius: 26.32
- Box size: 50.00
- Frames averaged: 51
- Using second half of trajectory