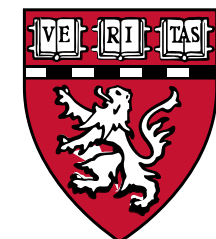




# Spatial statistics: Object-based colocalization







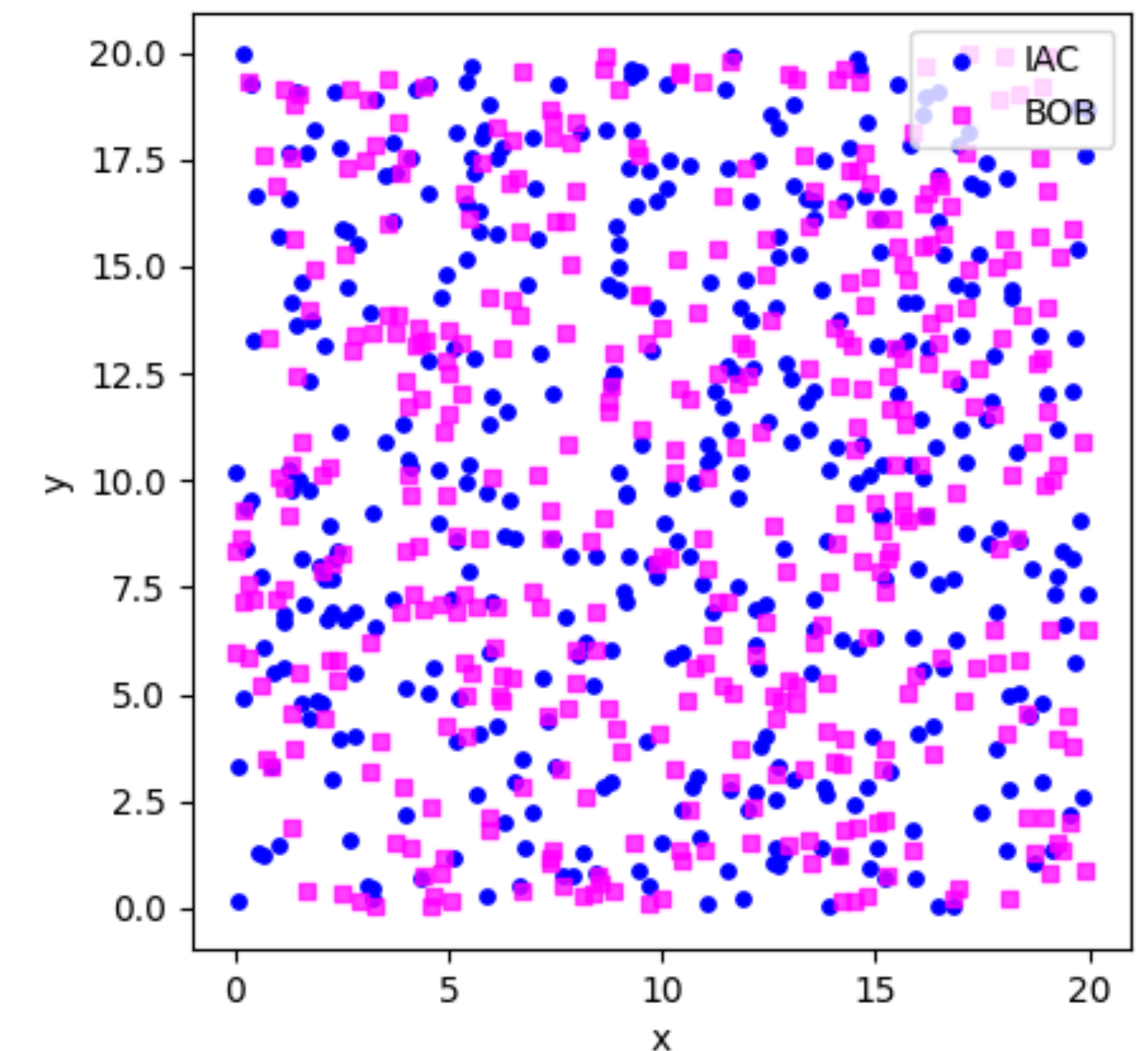
# The data



IAC and BOB are proteins in the eastern spruce budworm (*Choristoneura fumiferana*) epidermis

You hypothesize that the spatial interaction between IAC and BOB changes with temperature and season.

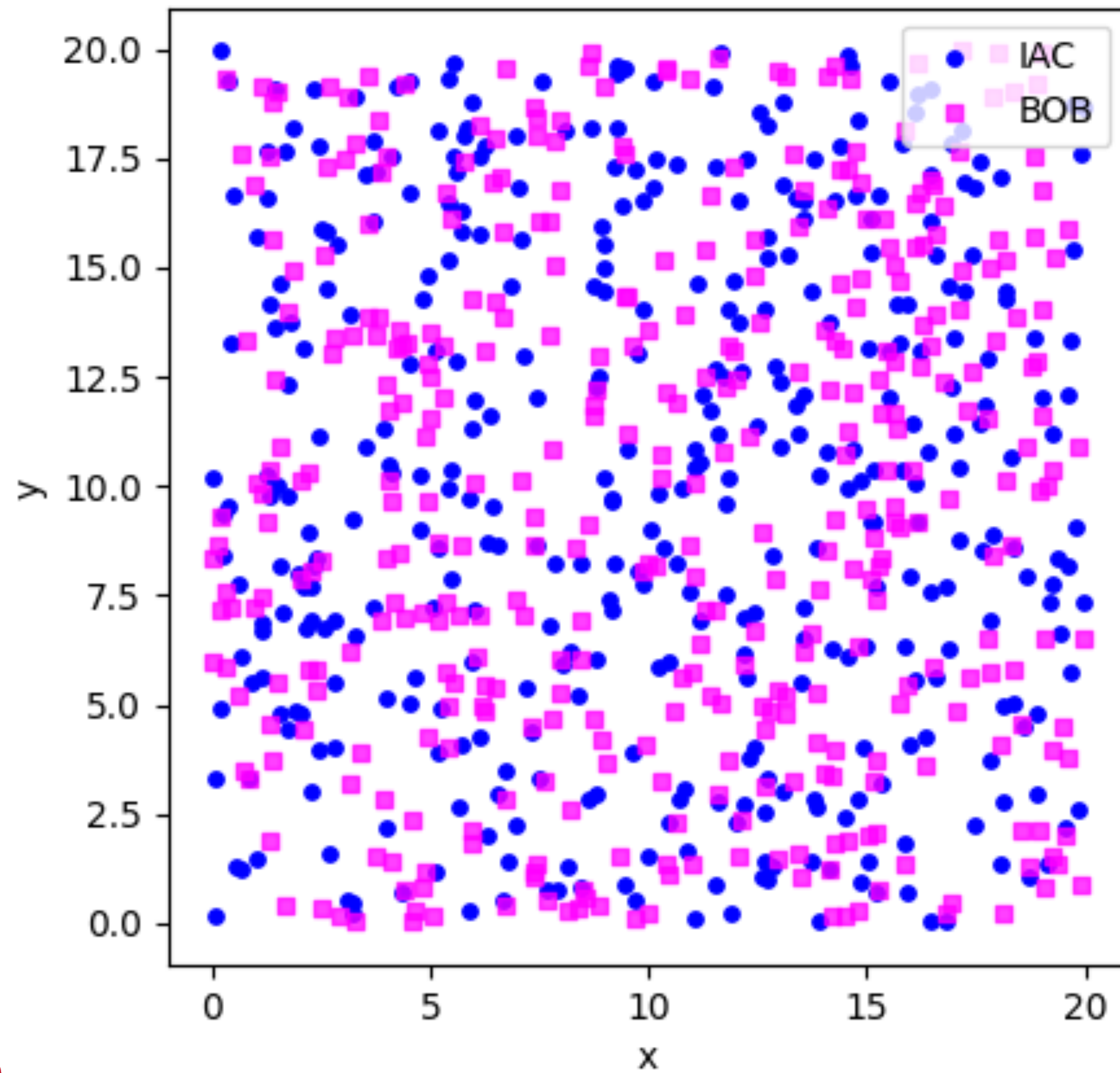
Extract coordinates







# The data



IAC

x y

1.6542, 4.98028  
2.64547, 4.95783  
6.90183, 17.5005  
6.98563, 17.8339  
7.24287, 17.1596  
6.57113, 17.3483  
6.41189, 16.8281  
6.62601, 17.4194  
6.21376, 17.4324  
6.74328, 16.7232  
7.0172, 17.5627  
6.52185, 16.5556  
5.93571, 17.4  
6.28006, 17.0457

... ..

BOB

x y

2.59176, 11.6148  
2.35522, 12.7033  
3.60981, 12.9357  
2.91734, 12.0081  
2.46703, 12.7667  
2.60448, 11.849  
2.36841, 12.6463  
1.24649, 11.4218  
3.67557, 4.29607  
2.63406, 4.7991  
2.77047, 4.19997  
2.90153, 4.83014  
2.45598, 4.98462  
4.02456, 4.89246

... ..







# The data — Fall epidermis samples

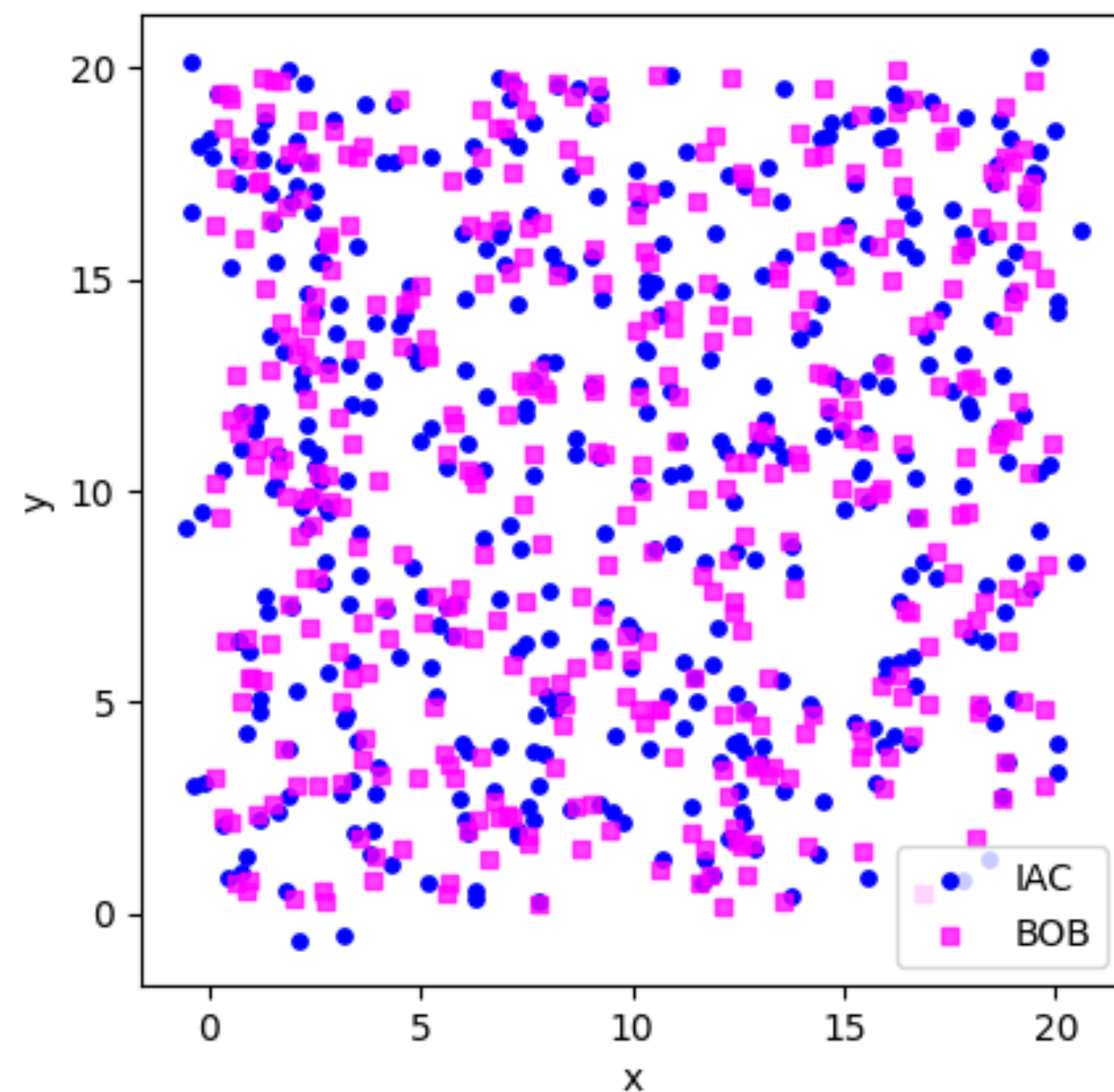




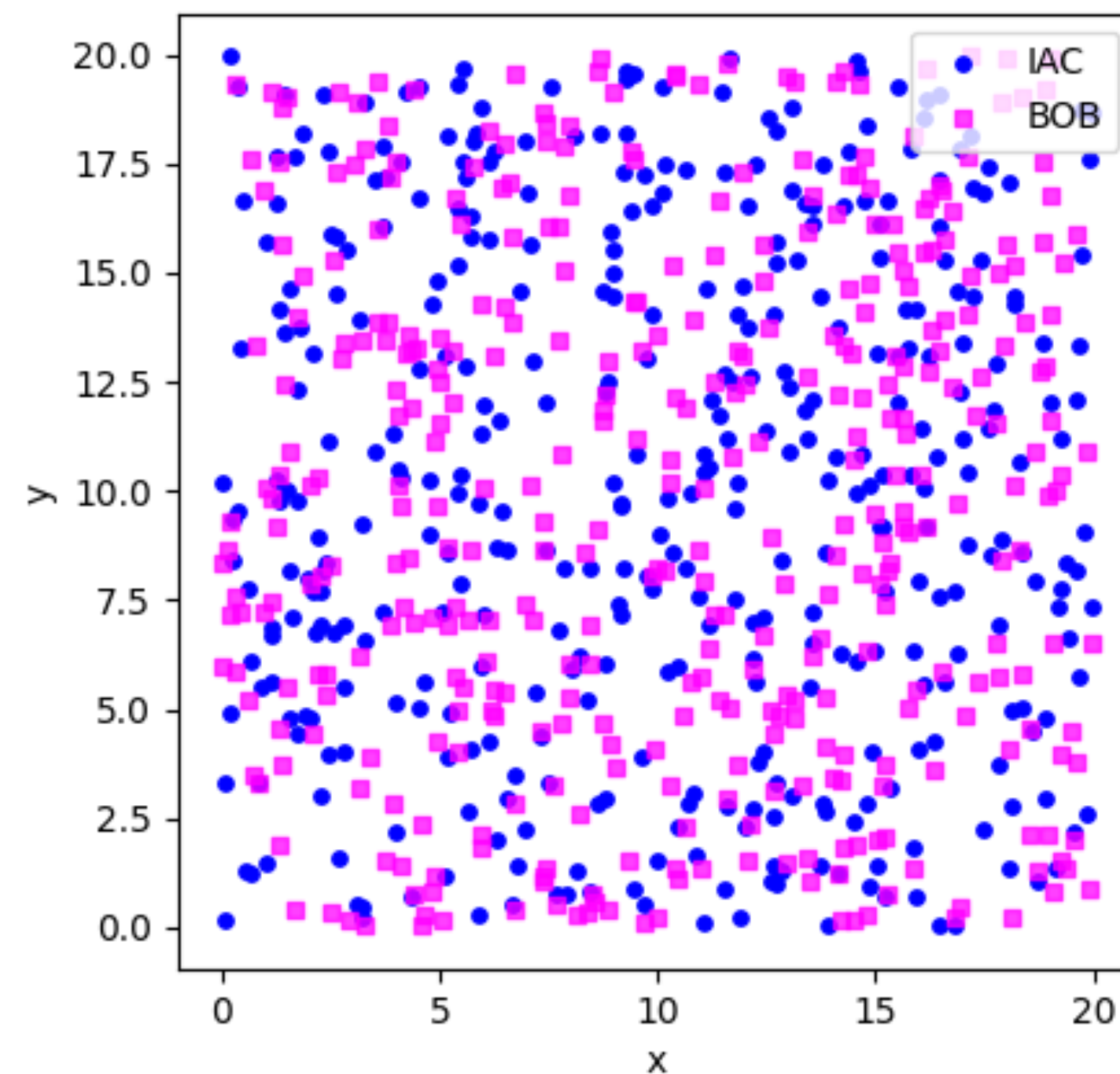


# The data — Fall epidermis samples

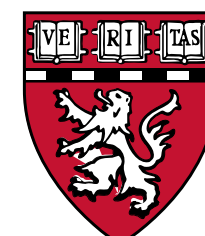
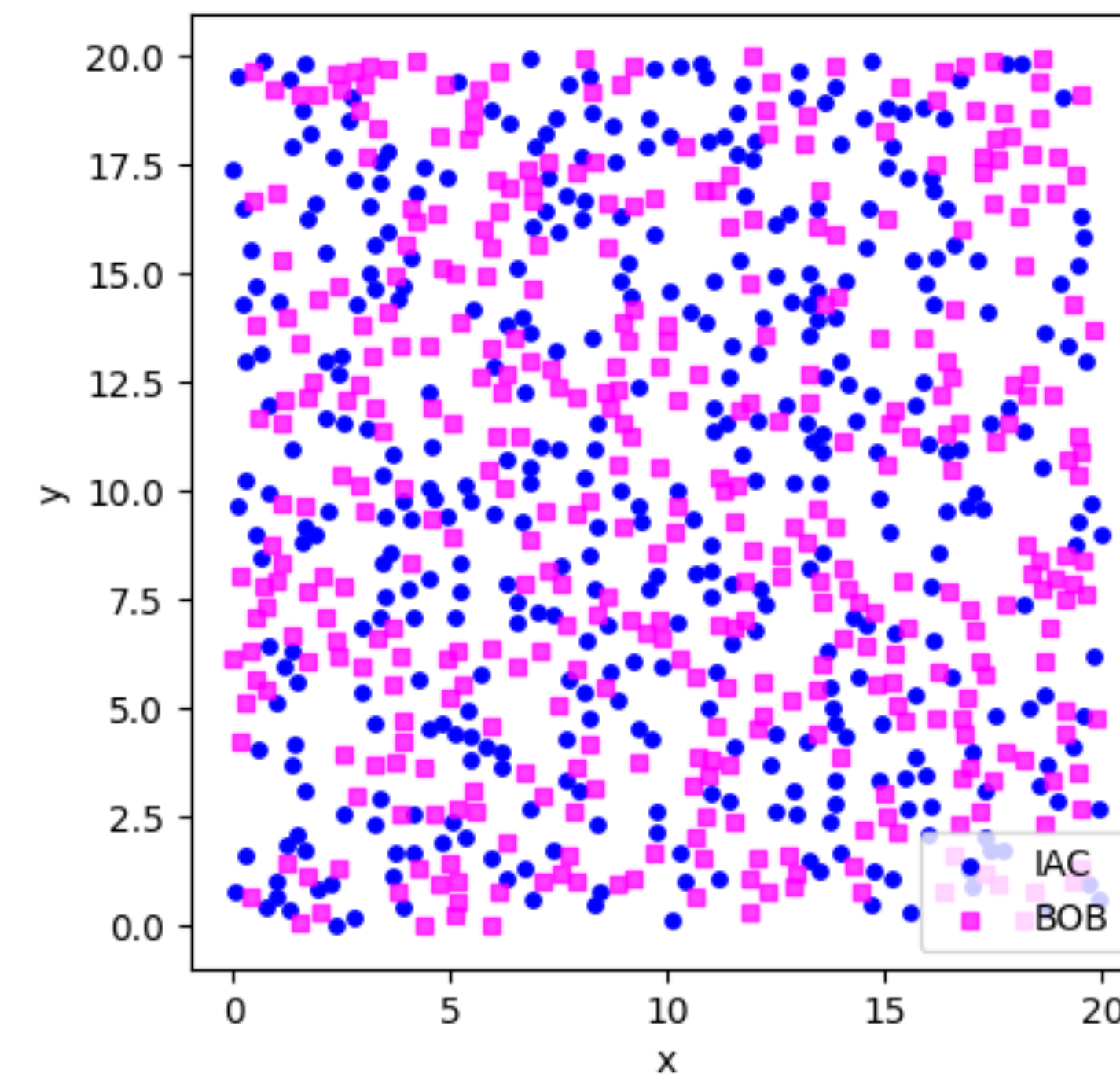
Cold



Medium



Warm





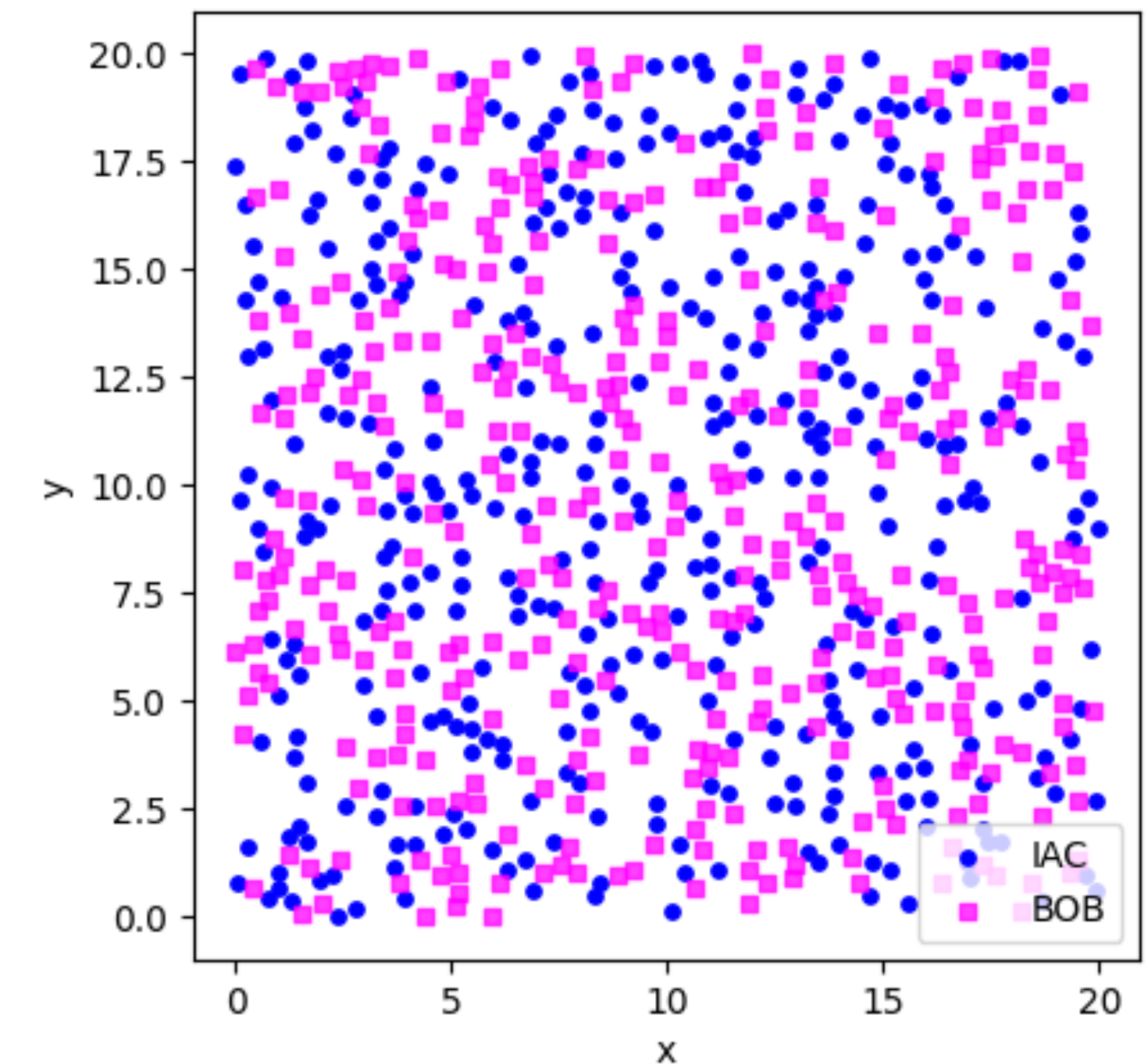
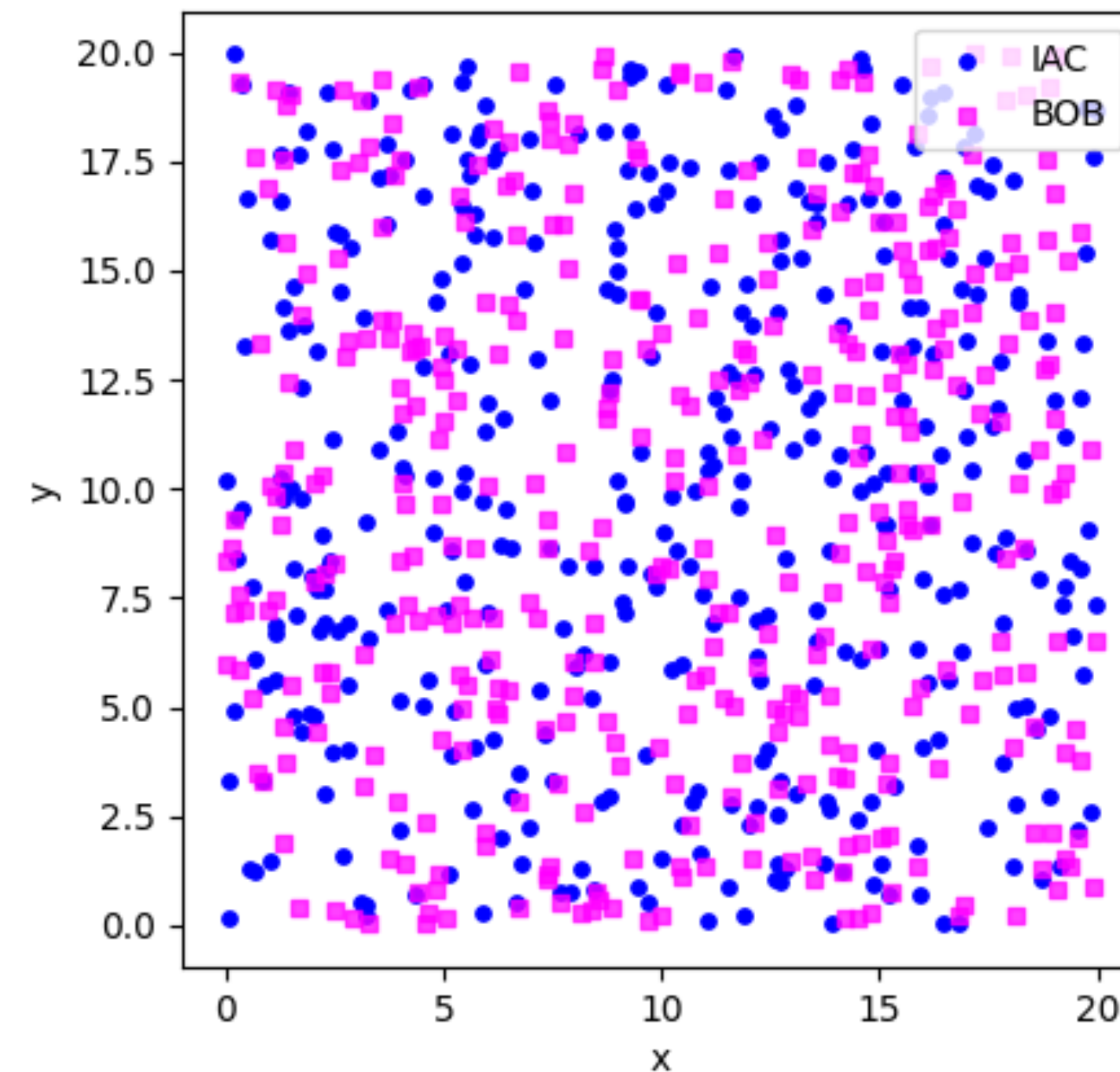
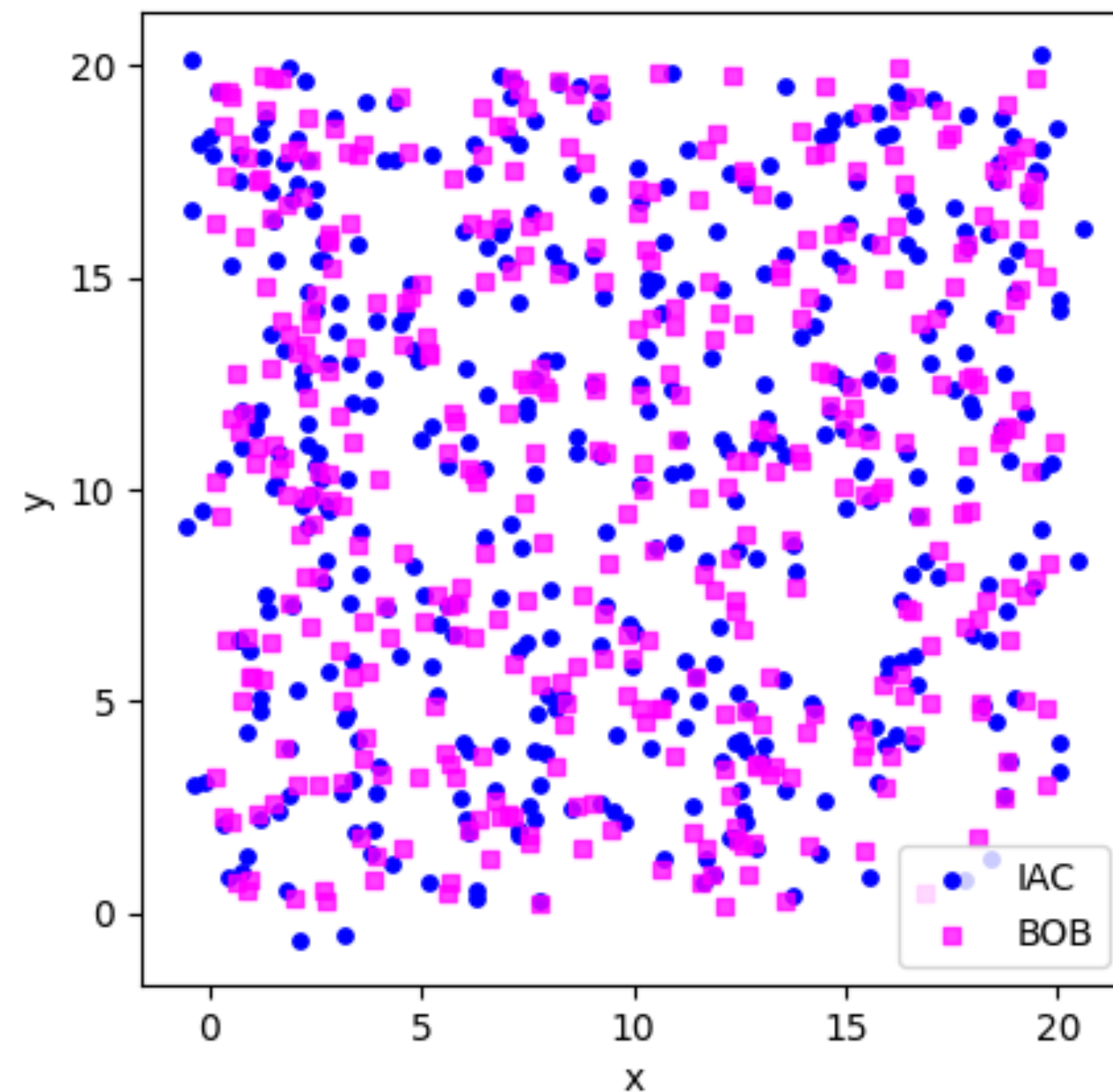


# The data — Fall epidermis samples

Cold

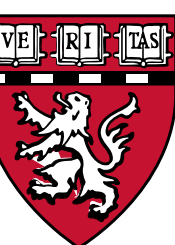
Medium

Warm



~~Do IAC and BOB attract or repulse each other depending on temperature?~~

Is there an association between attraction and repulsion and temperature?







# The data — Winter epidermis samples

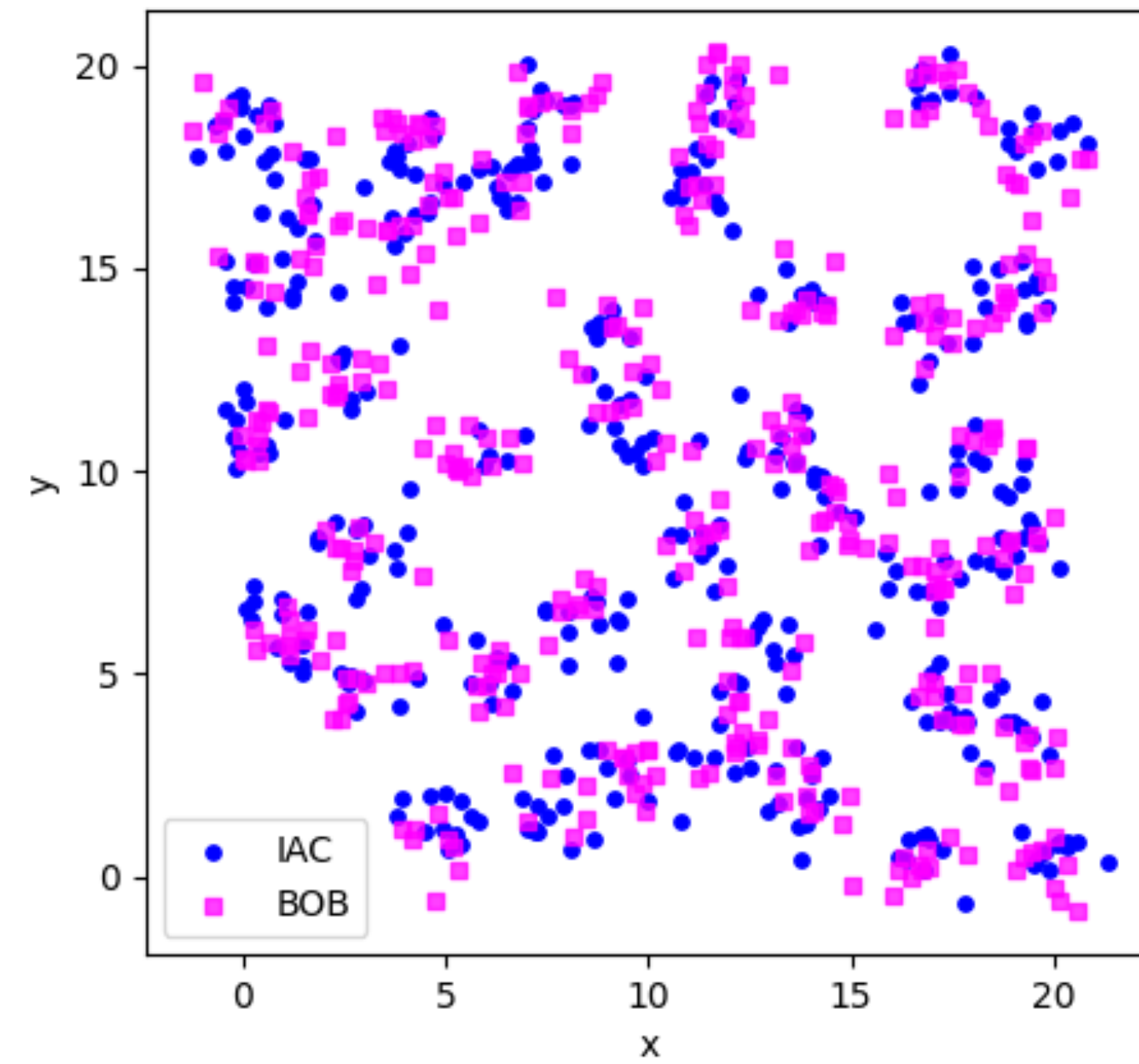




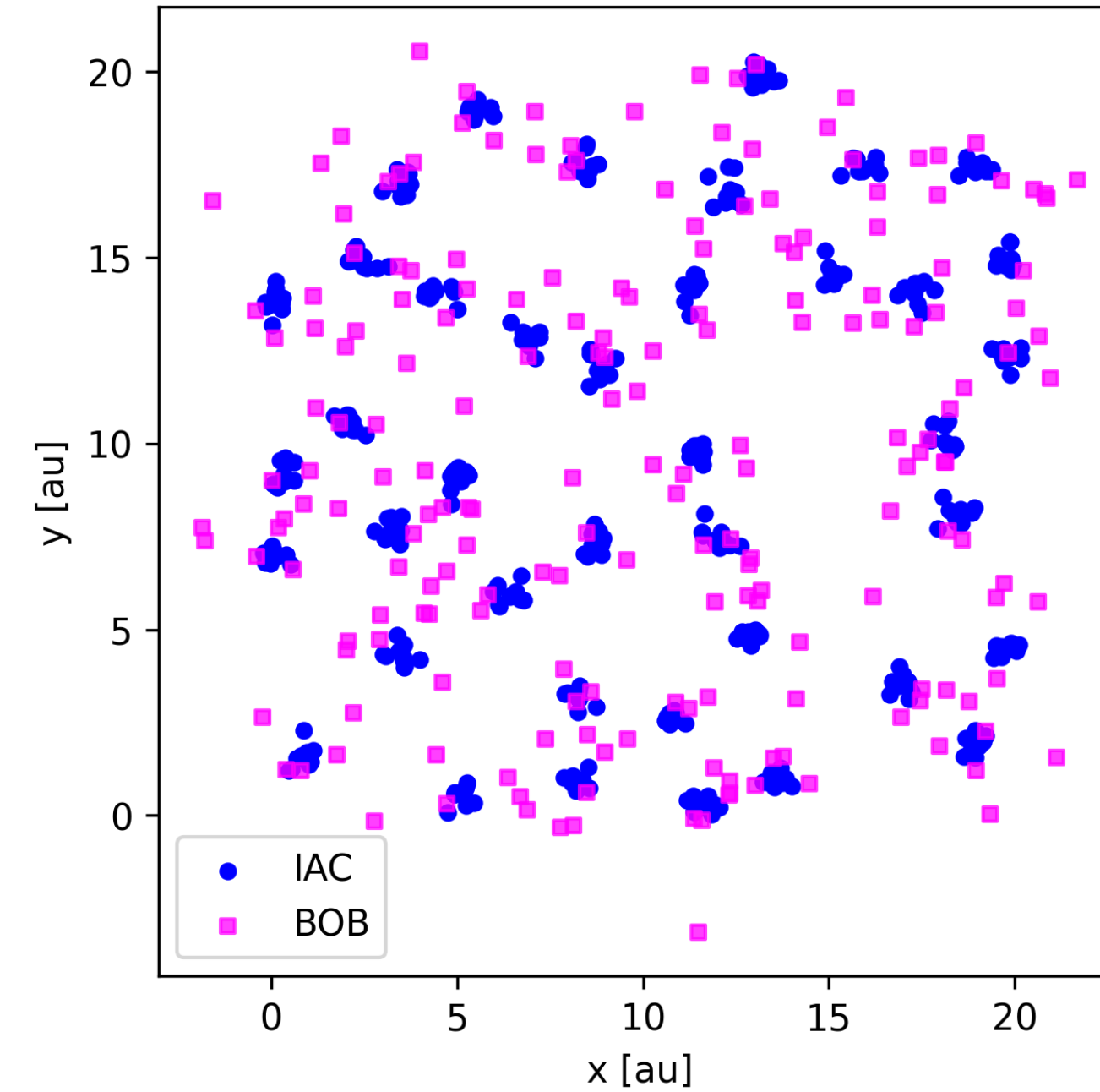


# The data — Winter epidermis samples

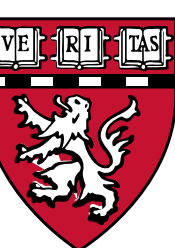
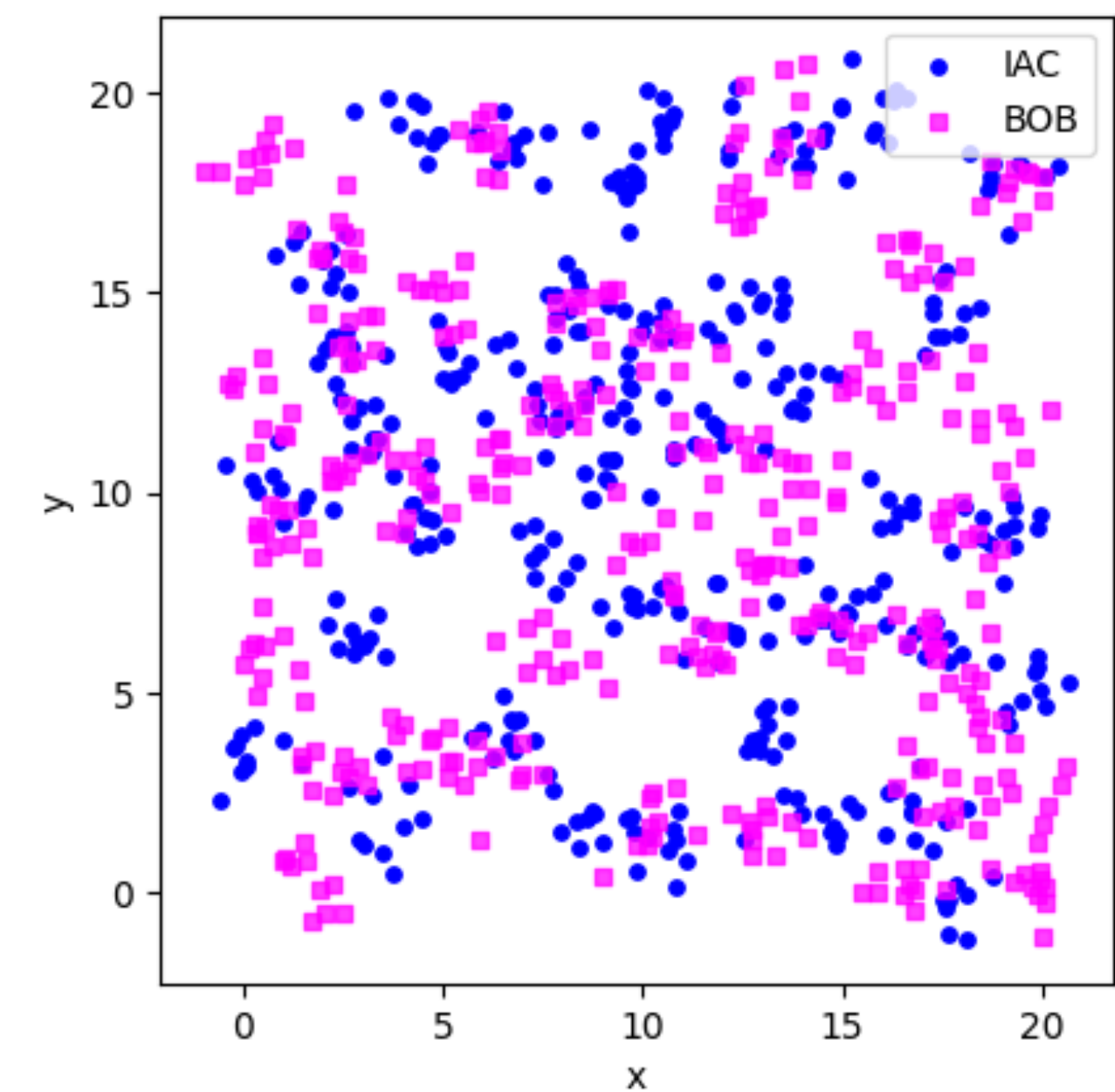
Cold



Medium



Warm

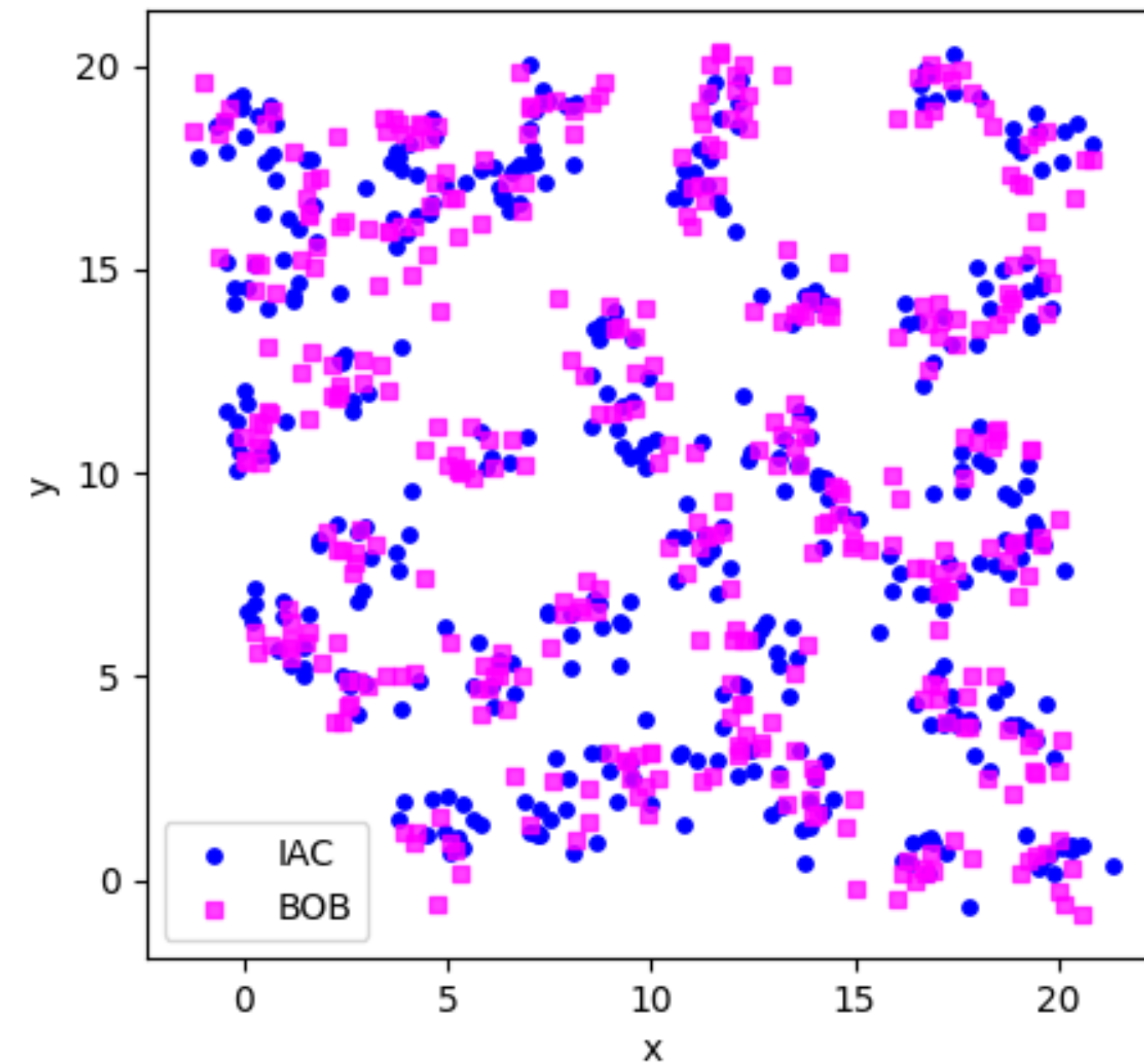




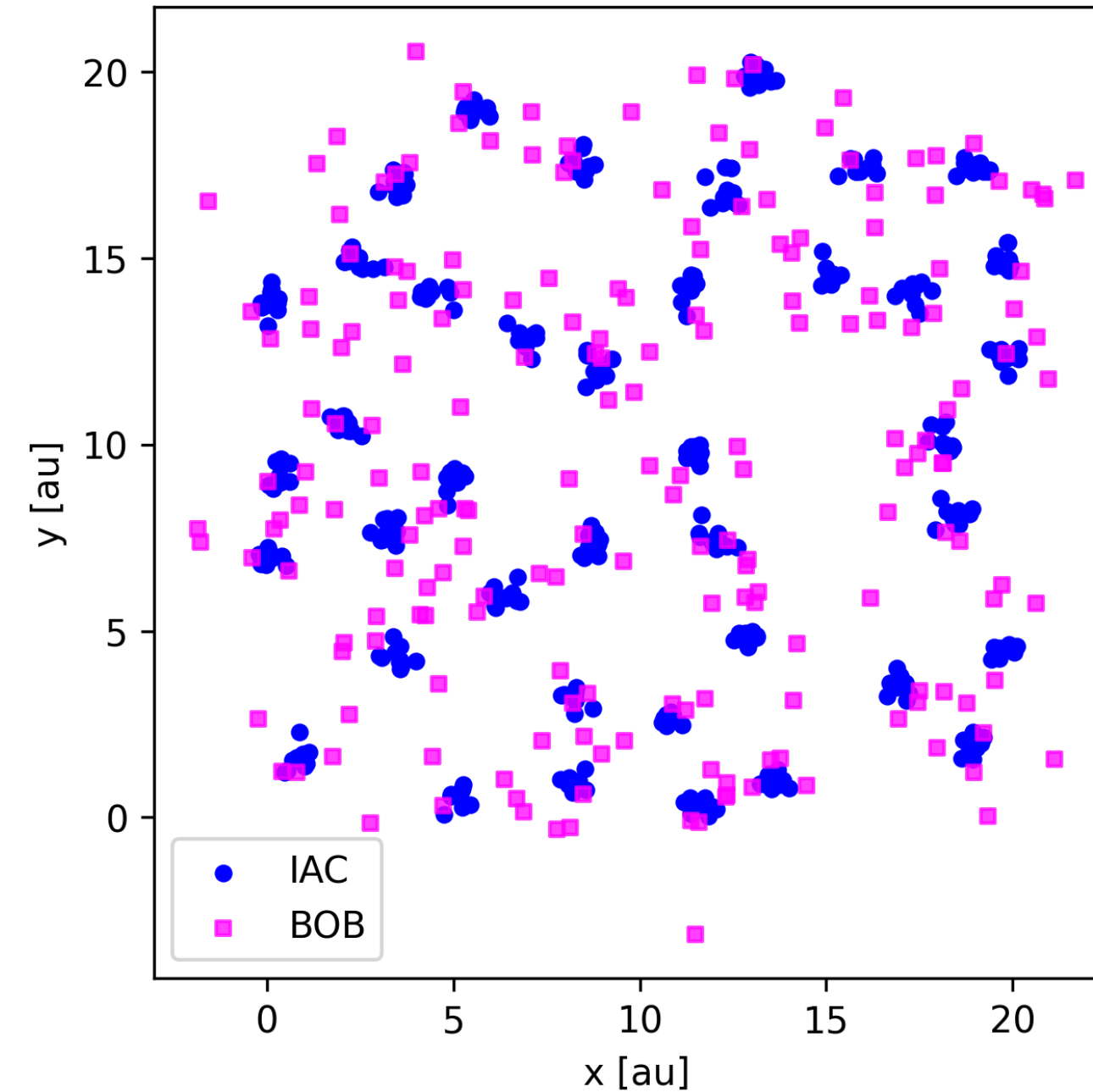


# The data — Winter epidermis samples

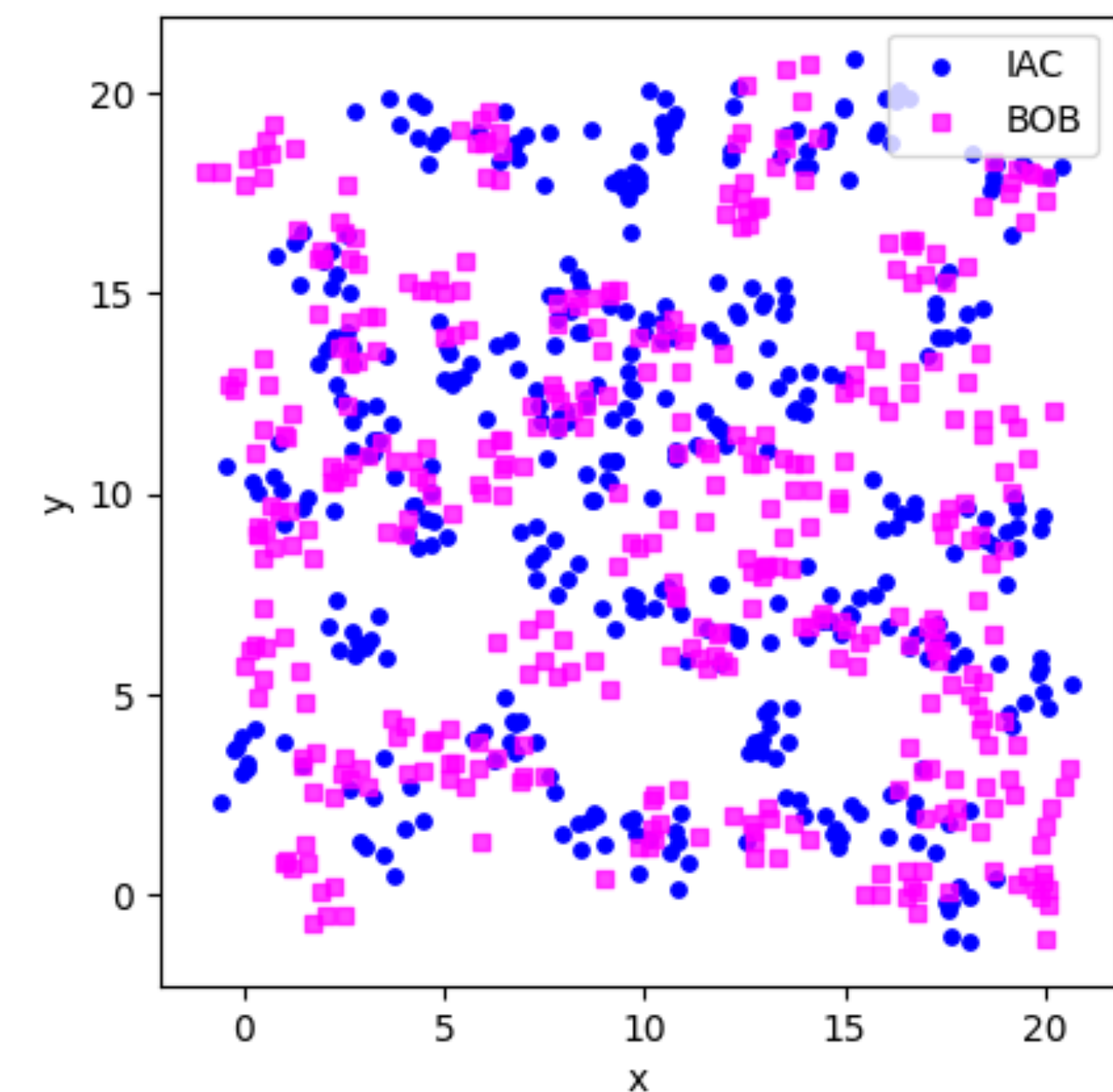
Cold



Medium



Warm

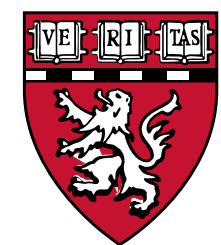


~~Do IAC and BOB attract or repulse each other depending on temperature?~~

Is there an association between attraction and repulsion and temperature?







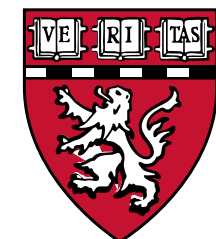
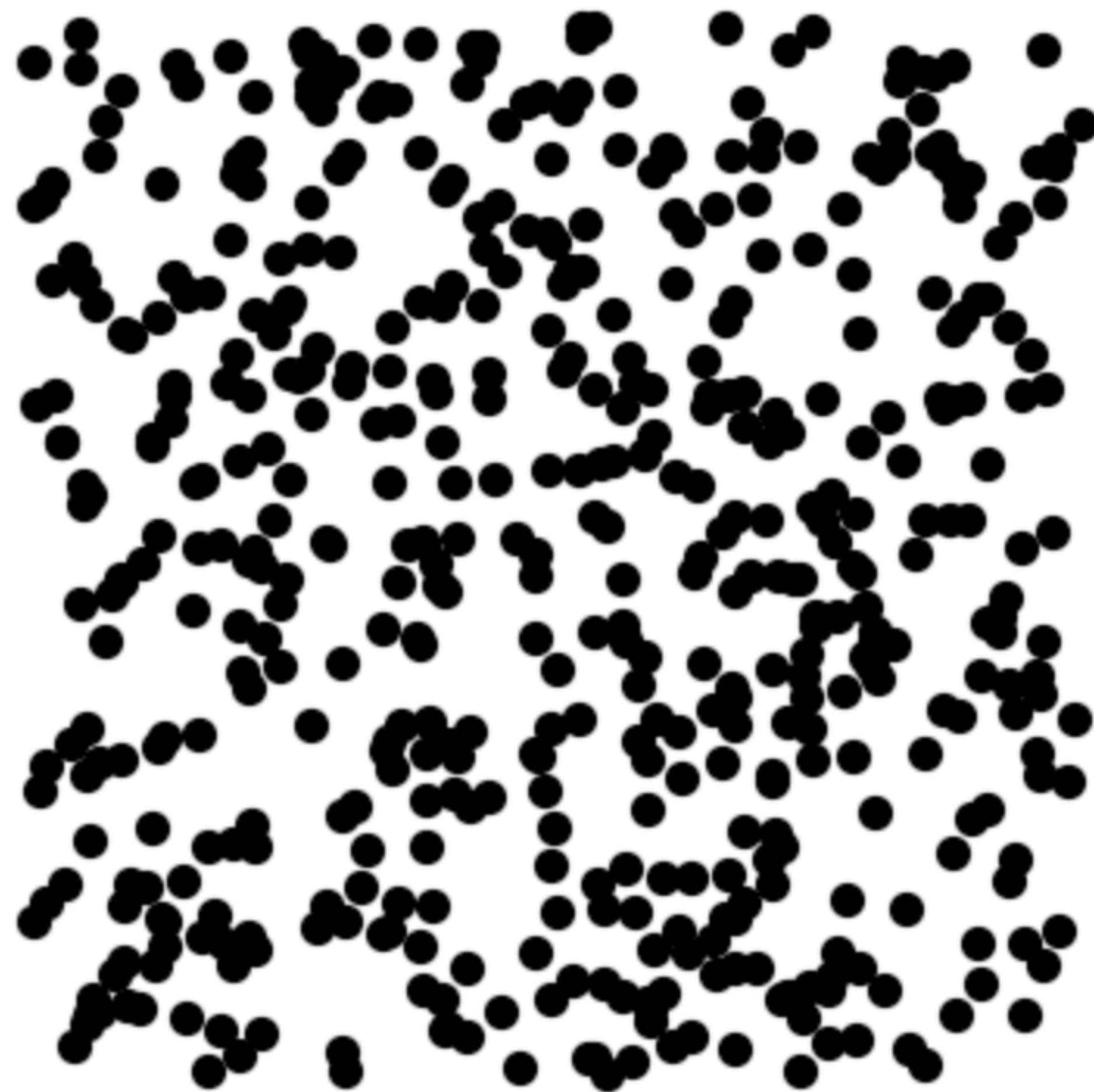
-> 0. Load the data, 1. plot the data







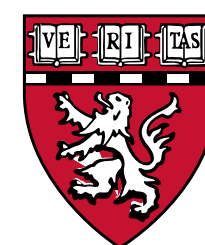
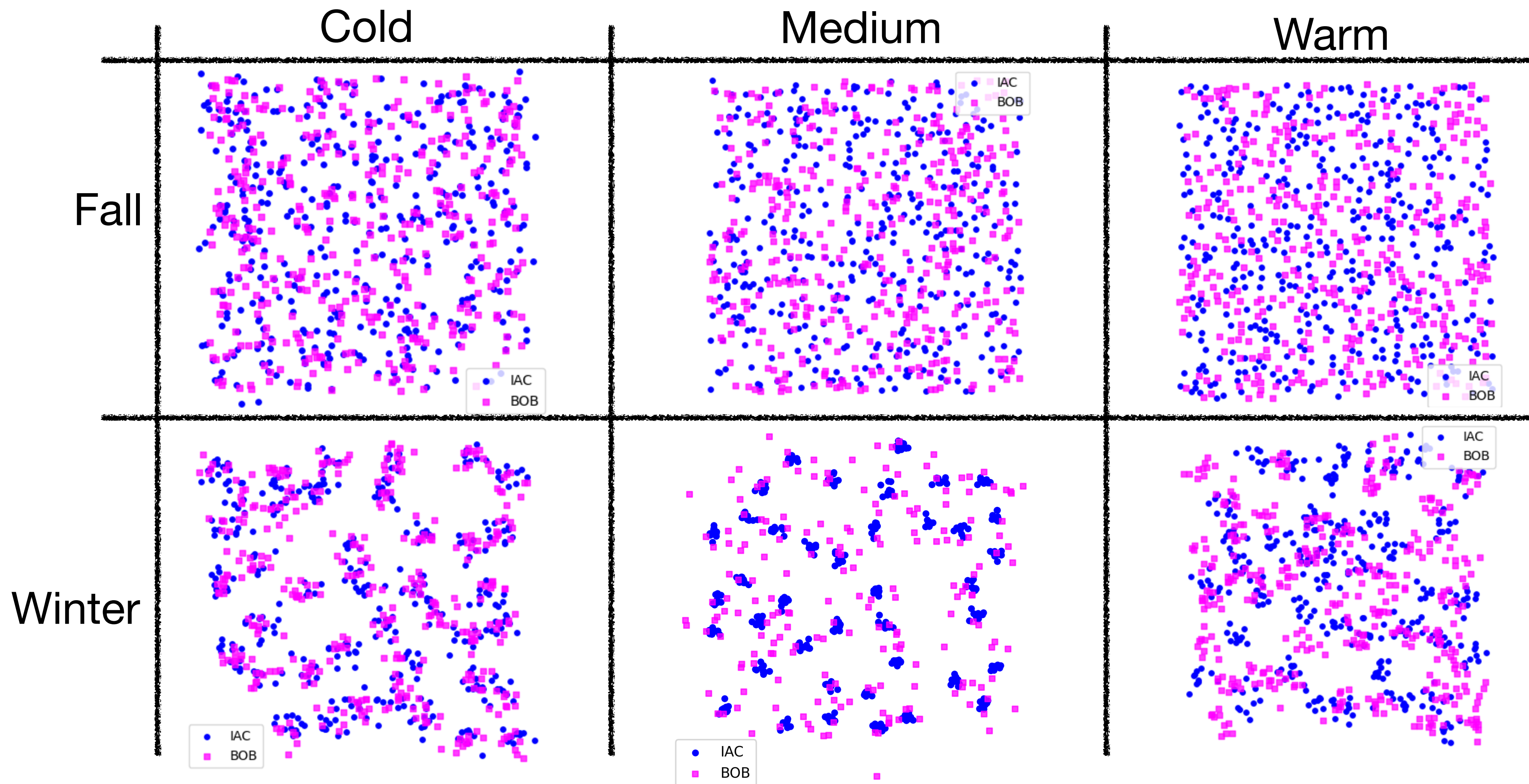
# Q: Do you see patterns?







# How would you analyze the data?

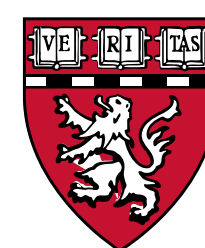






# Mean distance to nearest neighbor

IAC → BOB

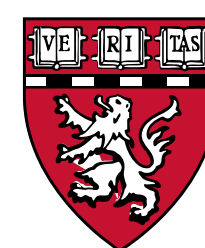
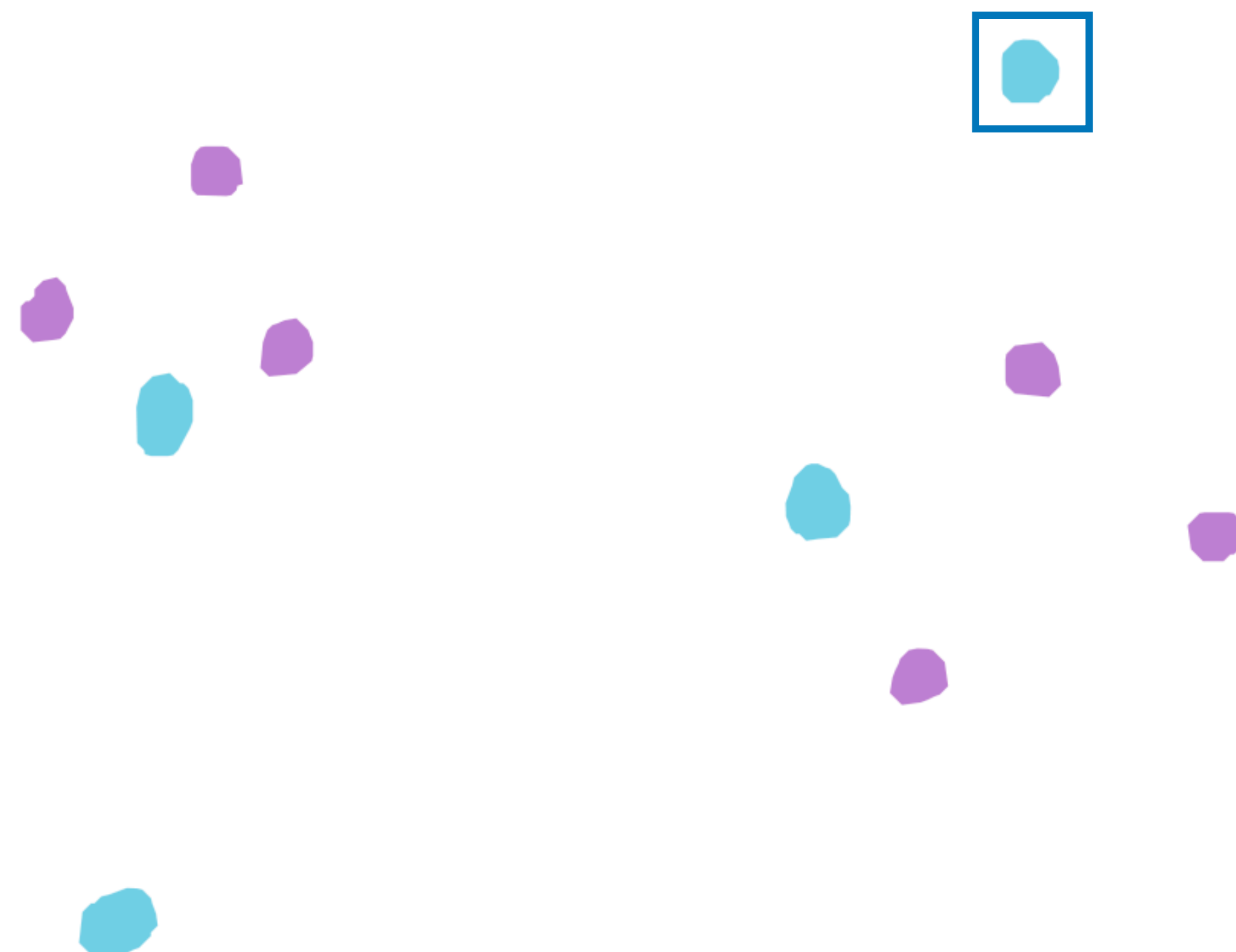






# Mean distance to nearest neighbor

IAC → BOB

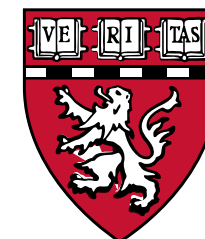
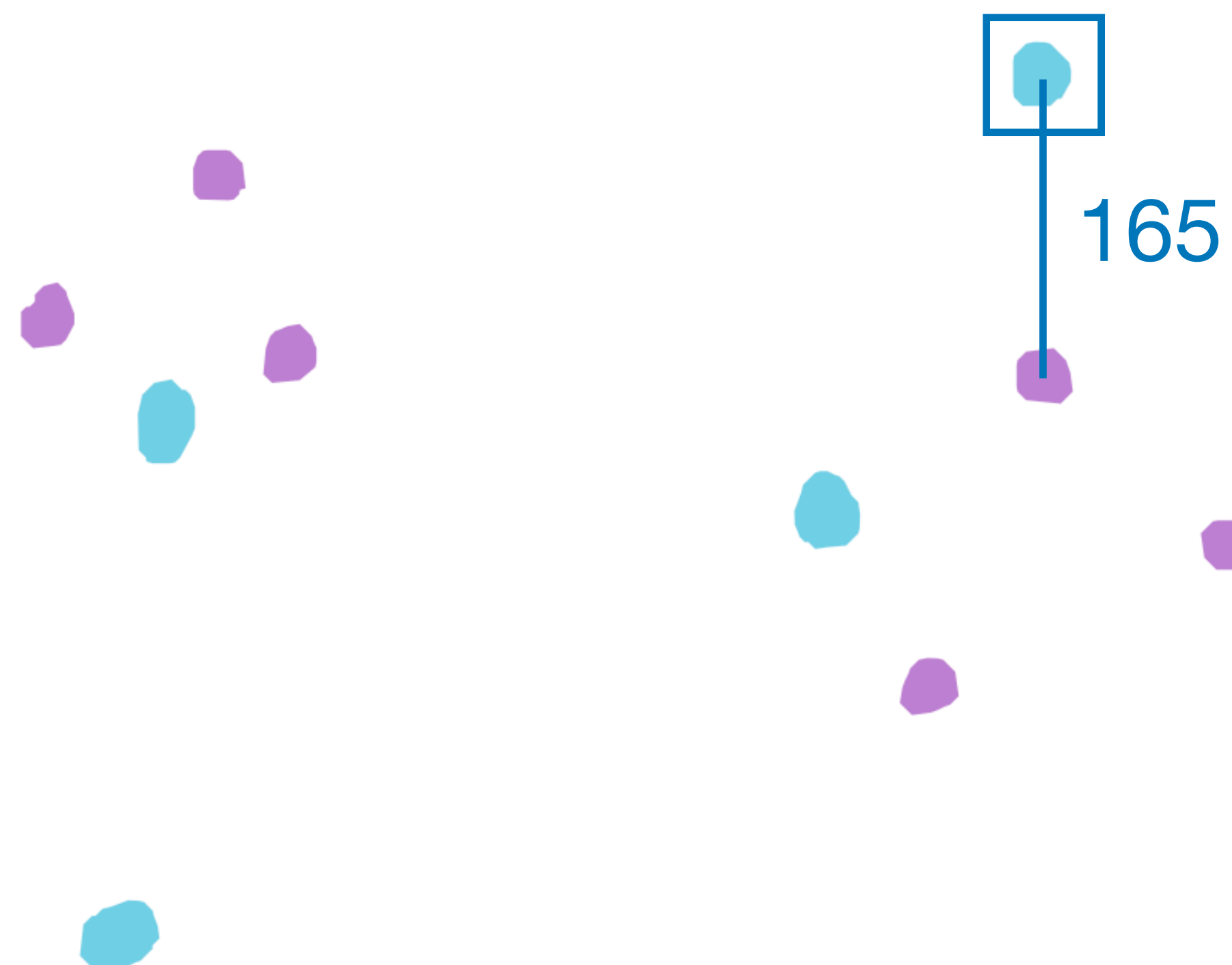






# Mean distance to nearest neighbor

IAC → BOB

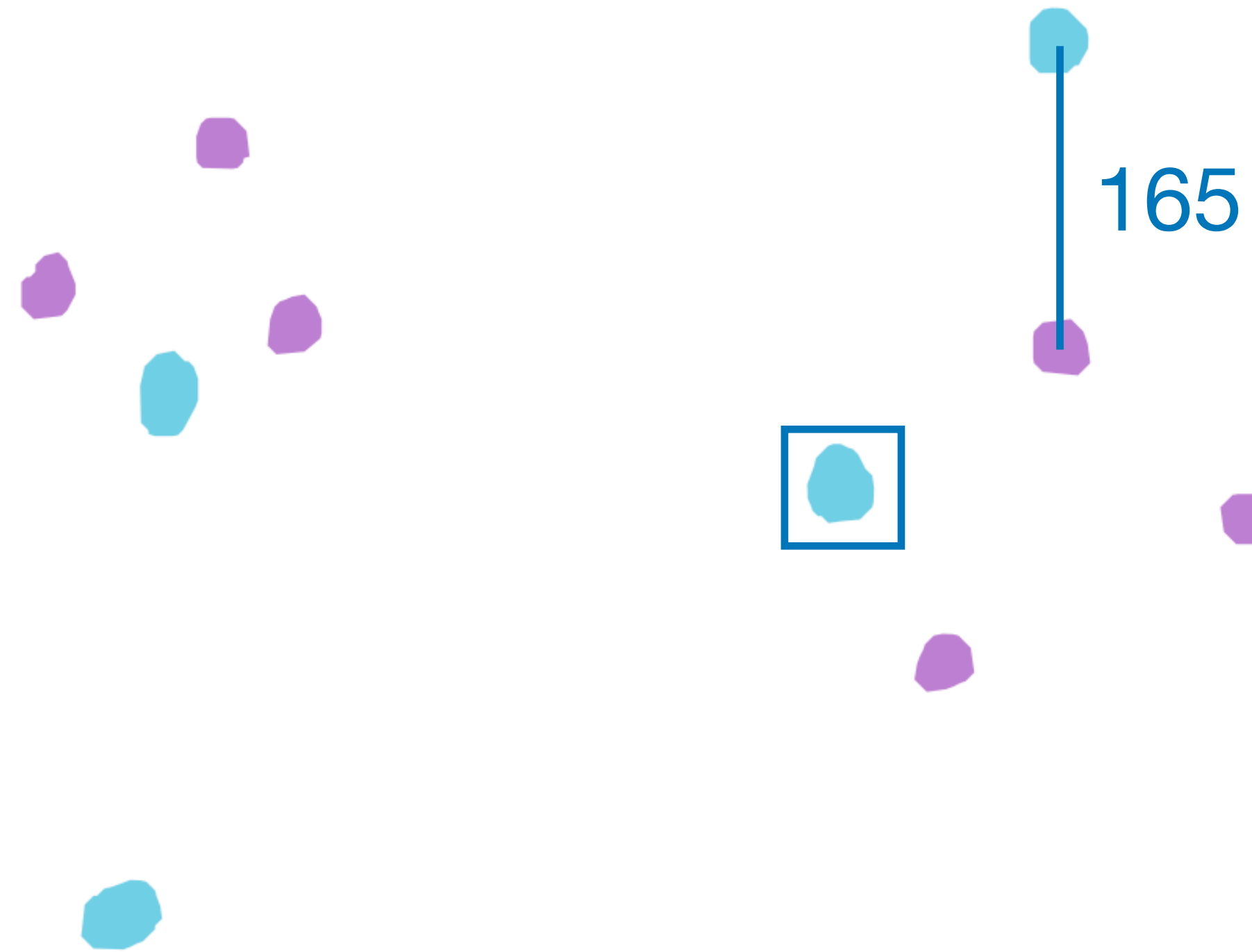






# Mean distance to nearest neighbor

IAC → BOB

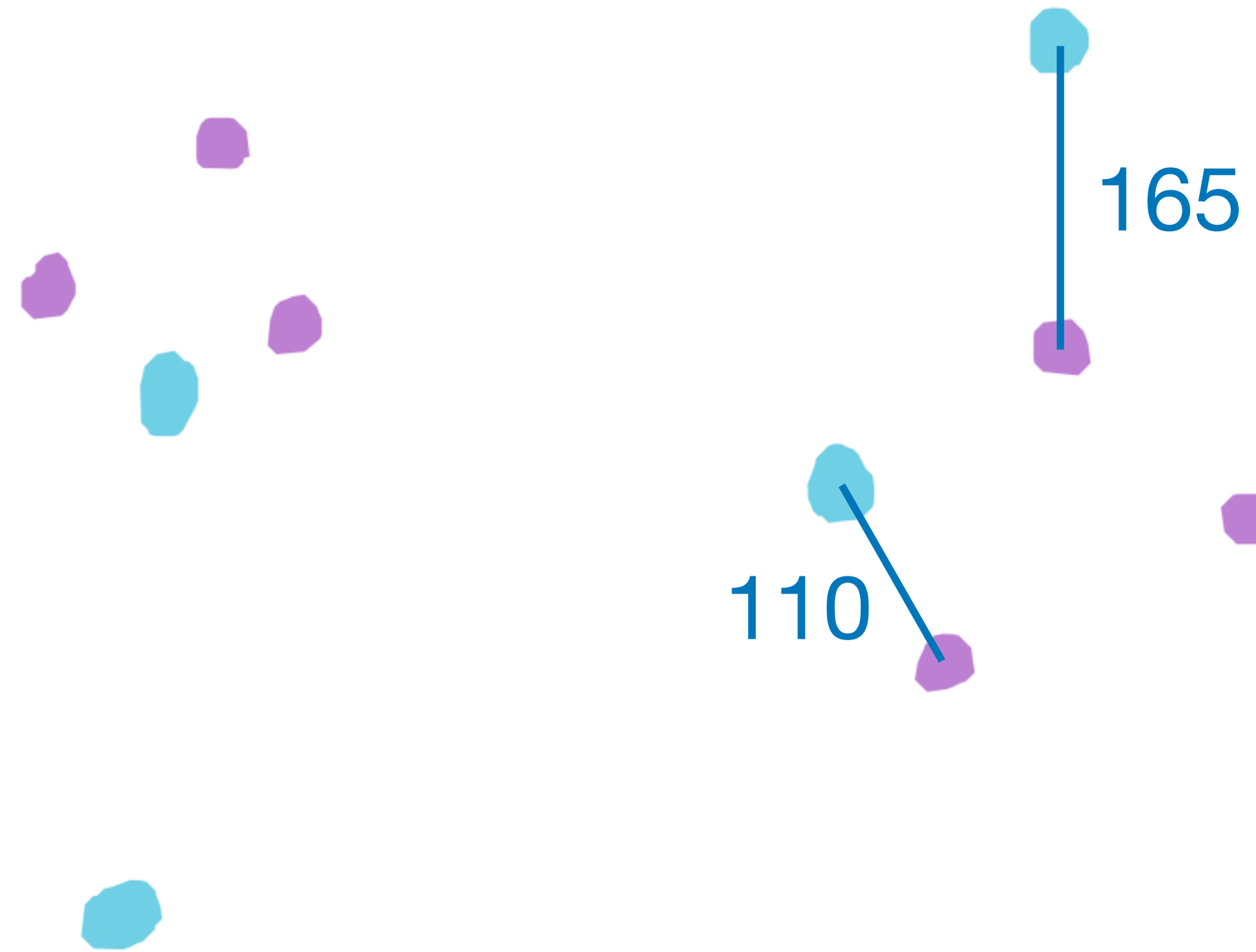






# Mean distance to nearest neighbor

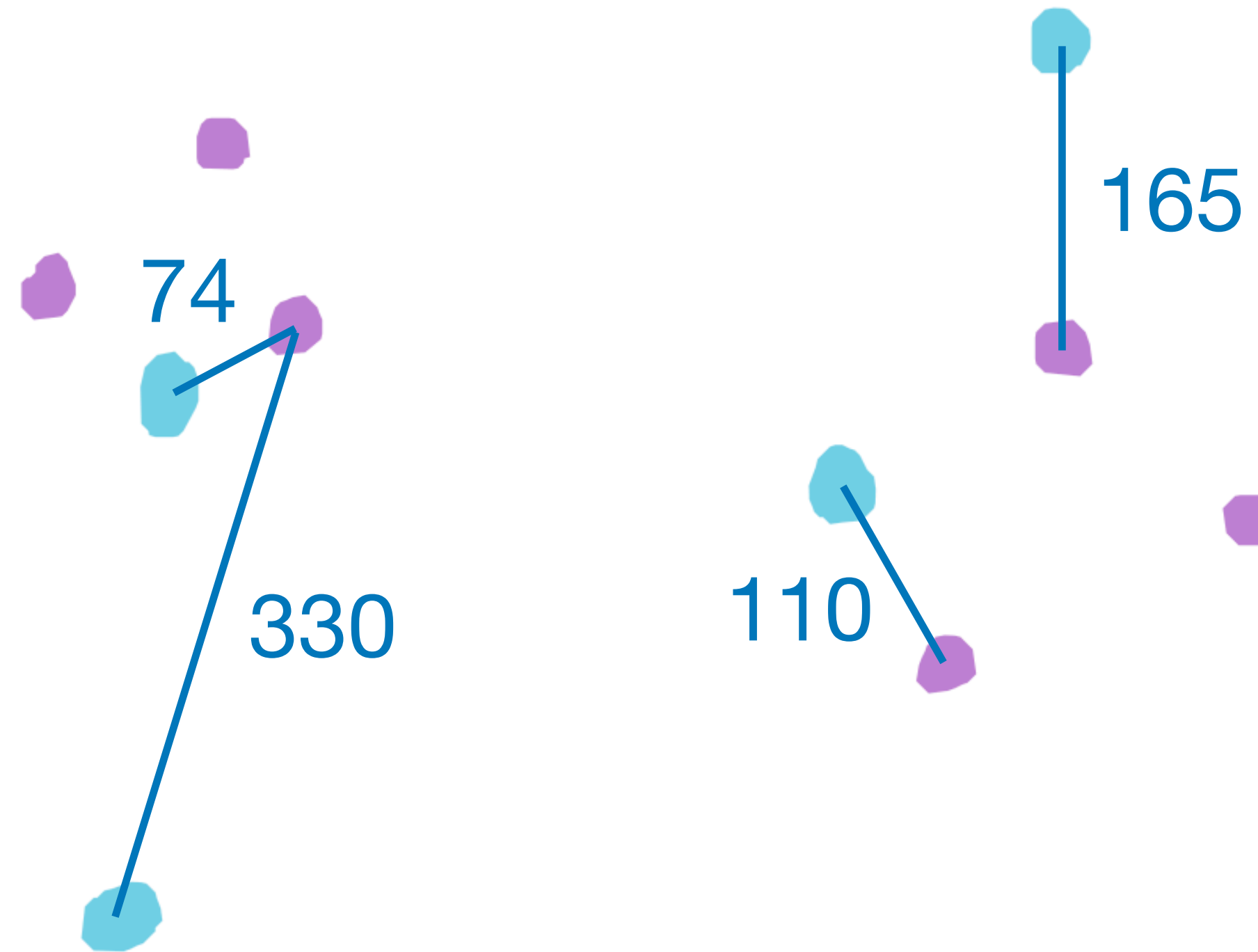
IAC → BOB







# Mean distance to nearest neighbor



IAC → BOB

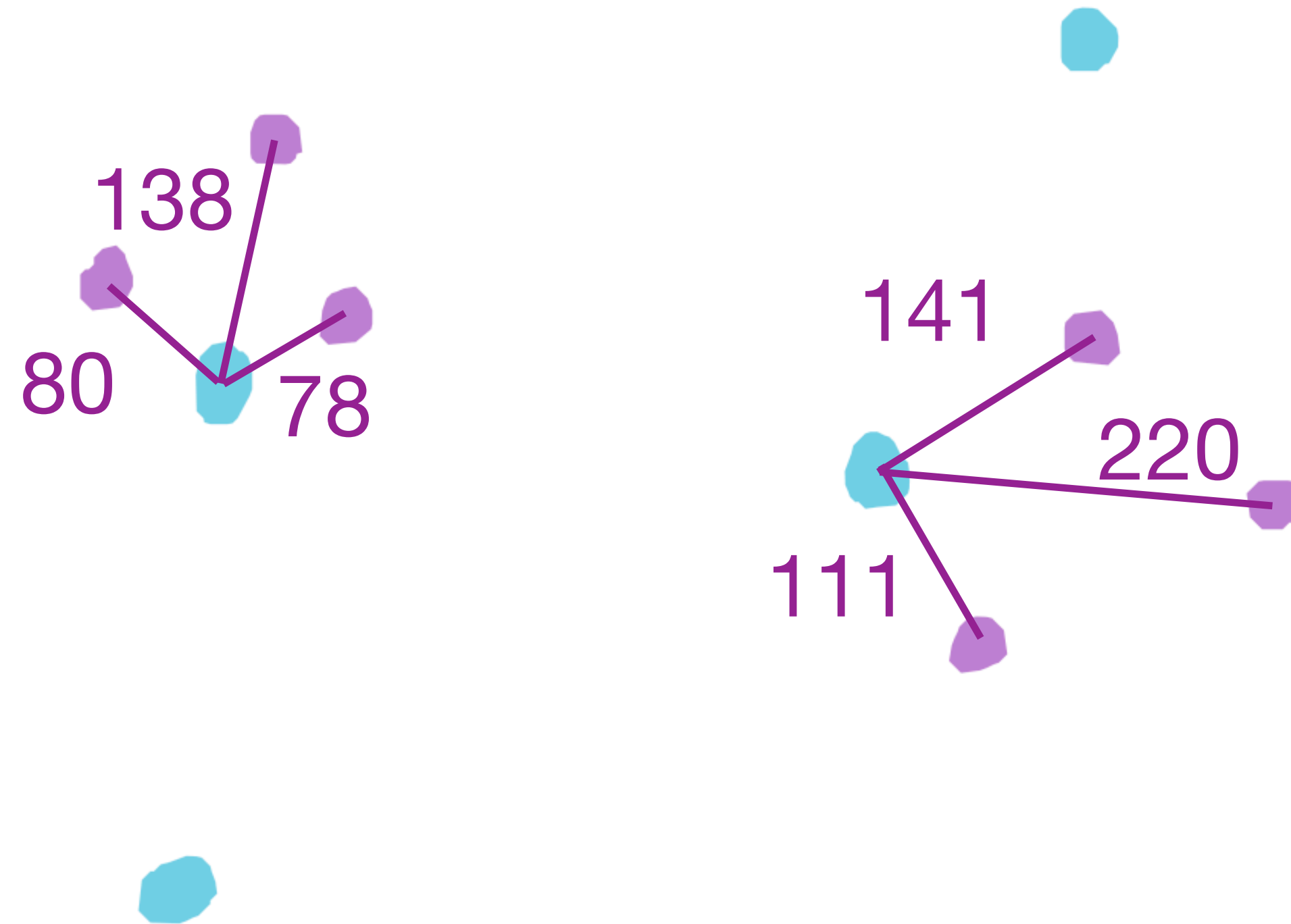
$$\frac{74 + 330 + 110 + 165}{4} = 169.75$$







# Mean distance to nearest neighbor



IAC → BOB

$$\frac{74 + 330 + 110 + 165}{4} = 169.75$$

BOB → IAC

$$\frac{80 + 138 + 78 + 111 + 141 + 220}{6} = 121$$

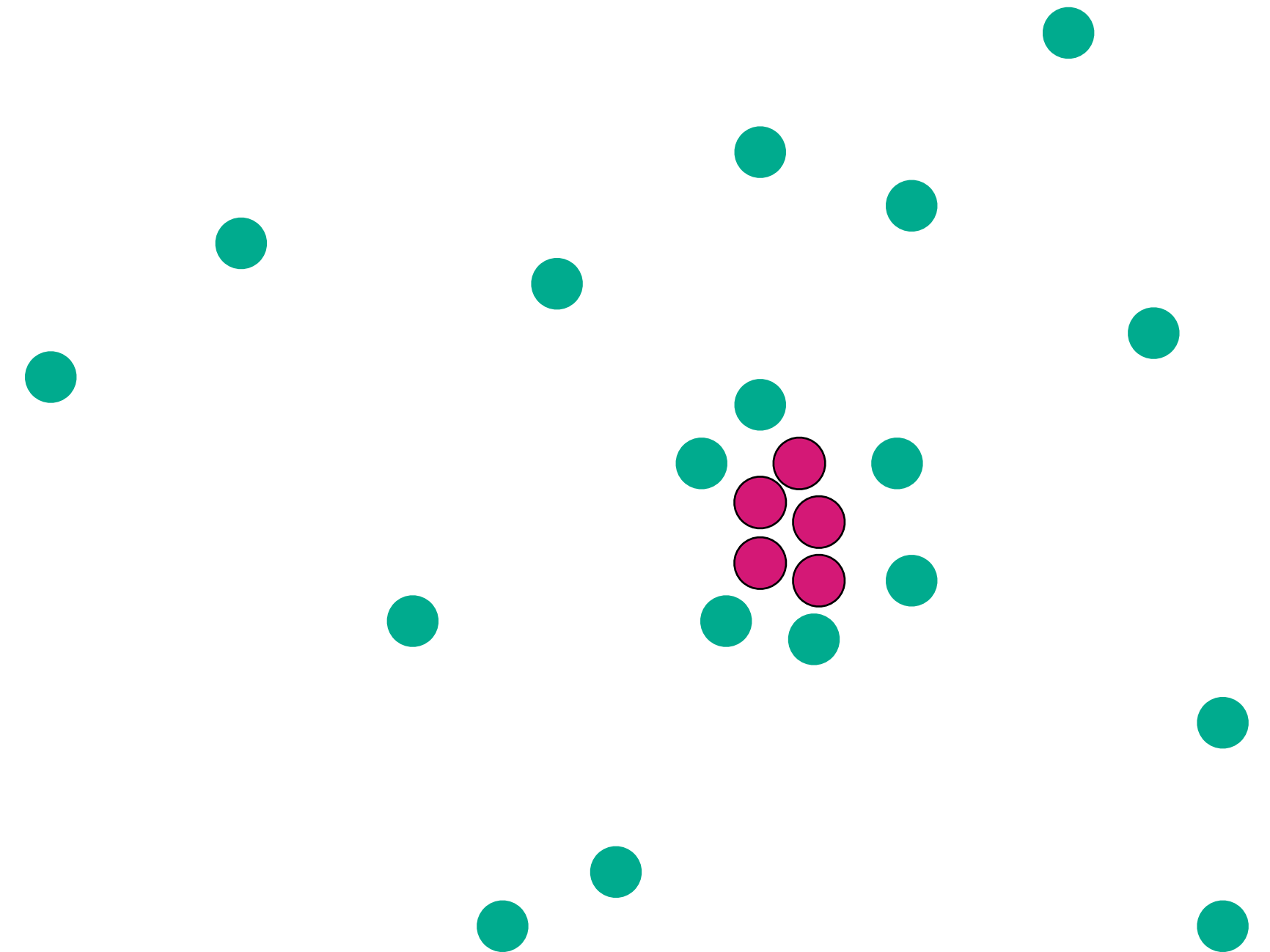




# Mean distance to nearest neighbor

   = Small mean distance

   = Large mean distance







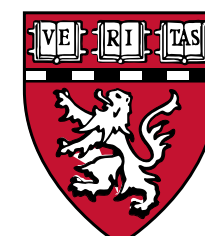
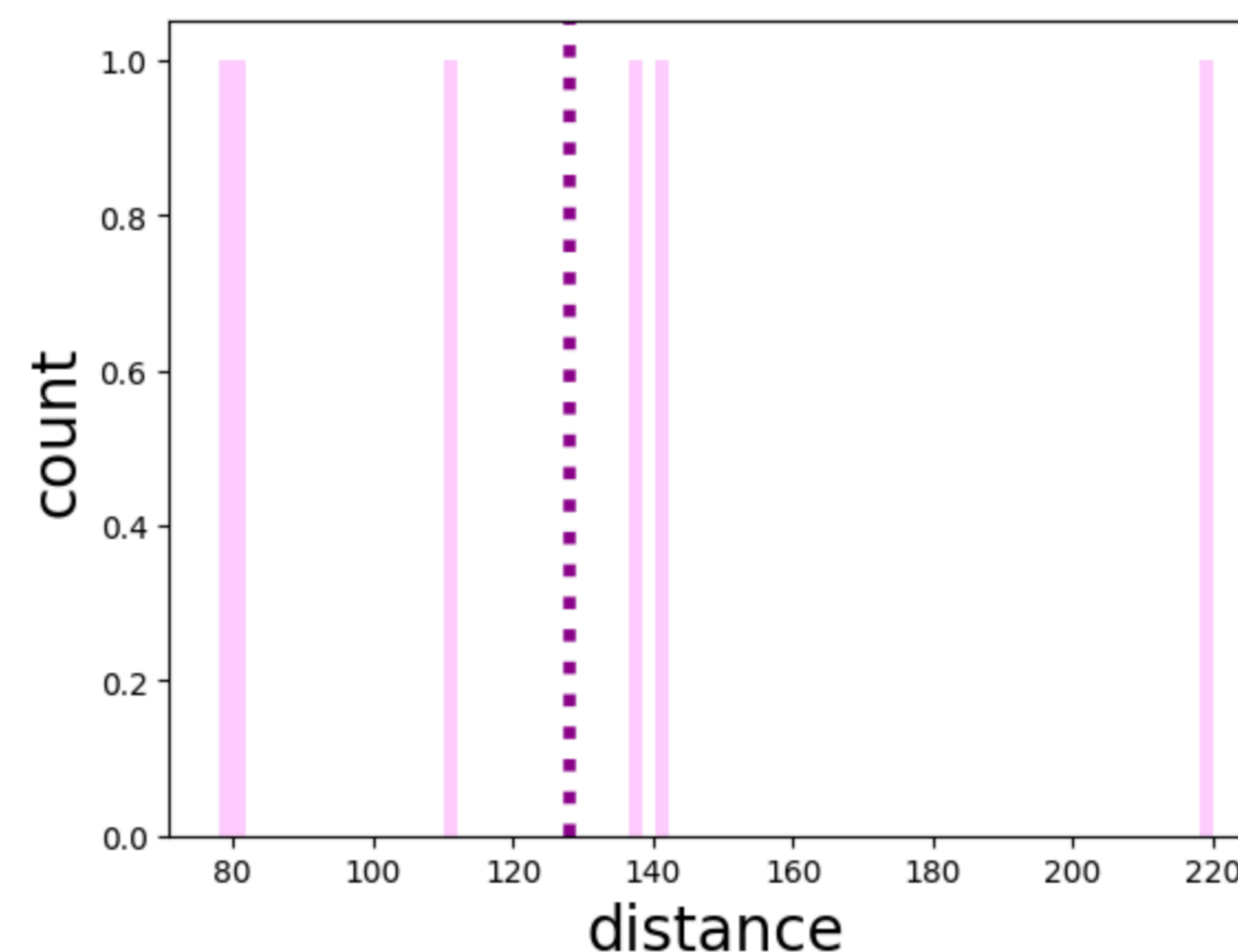
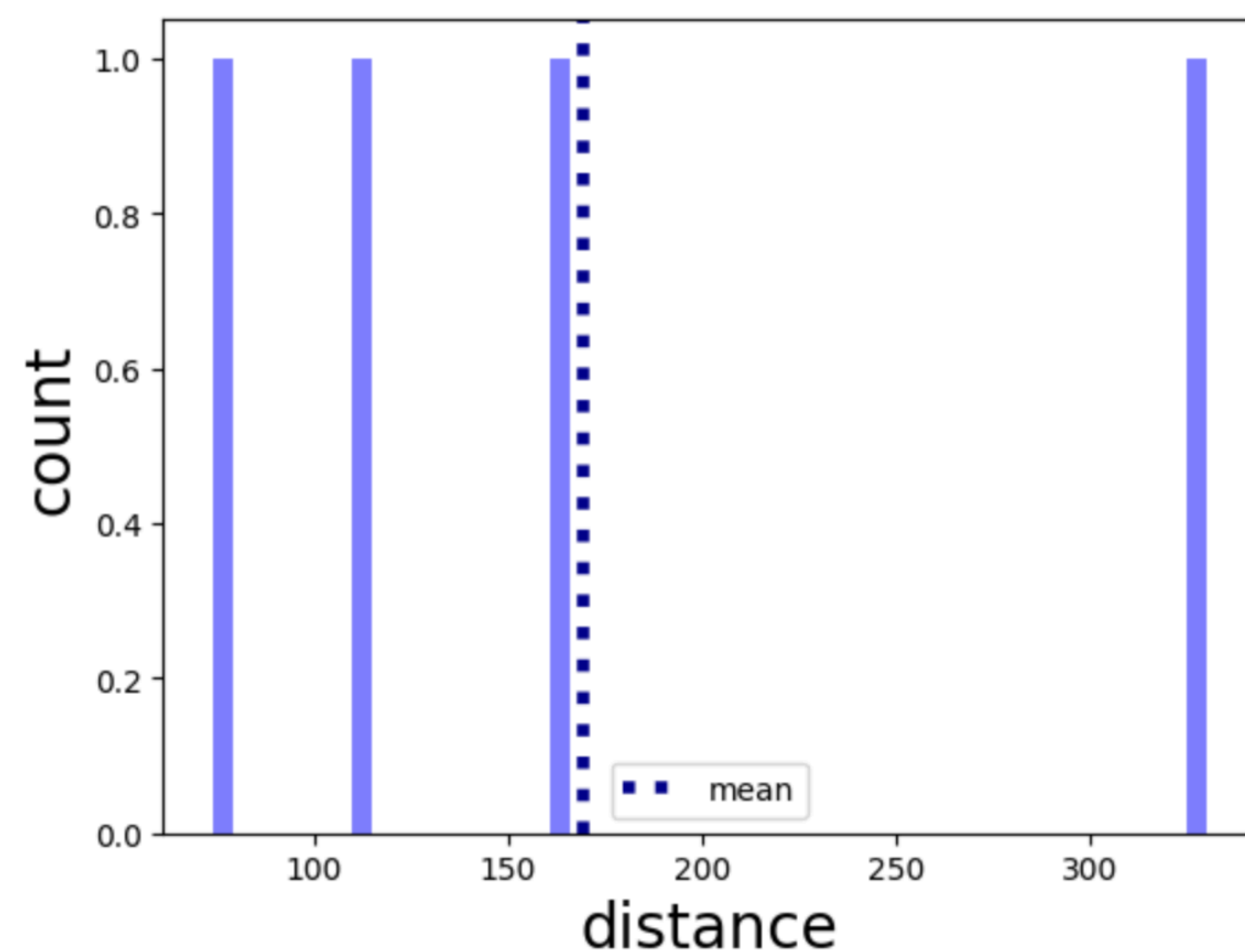
# Mean distance to nearest neighbor

IAC → BOB

BOB → IAC

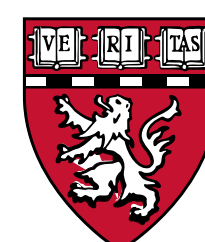
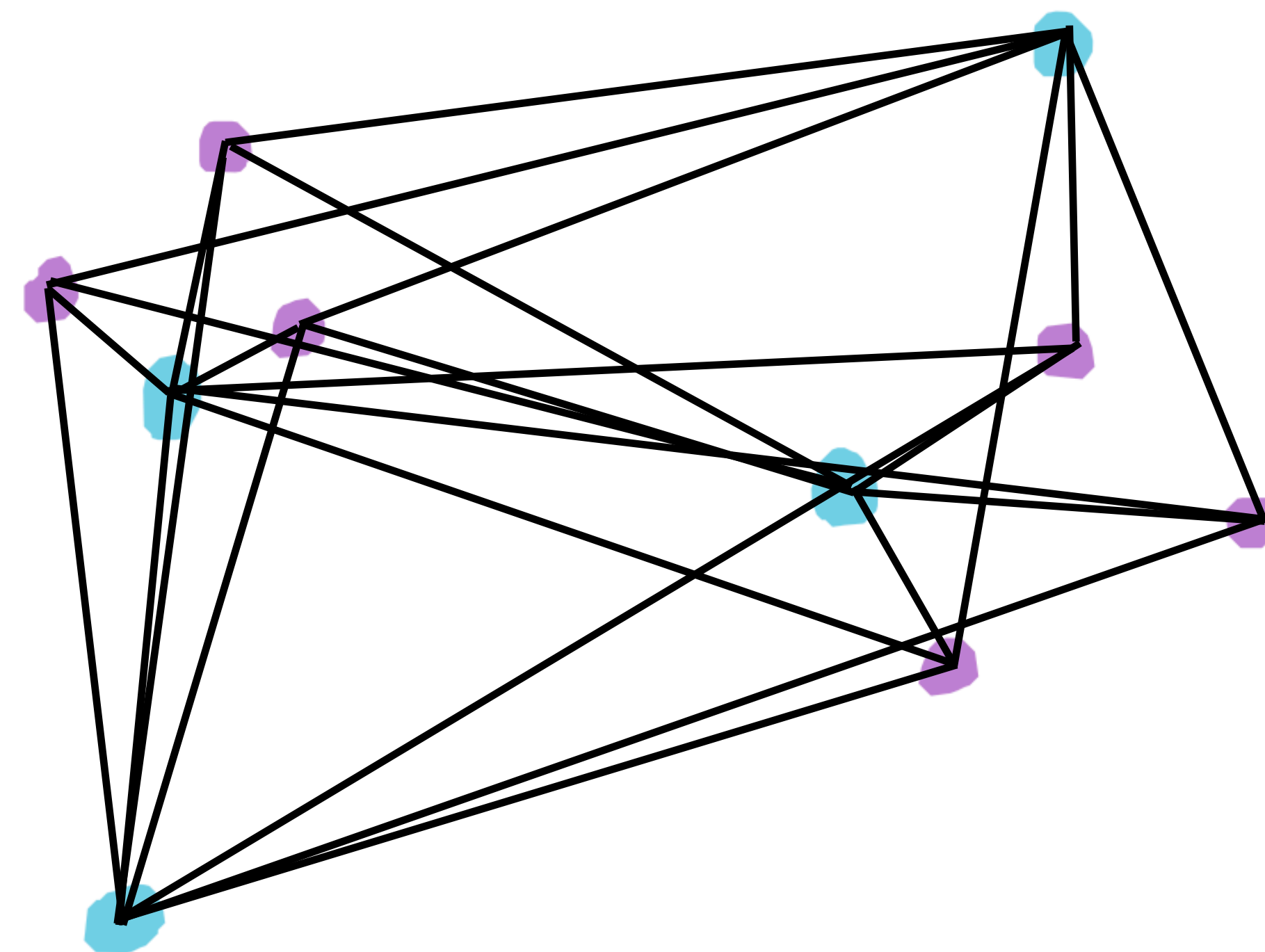
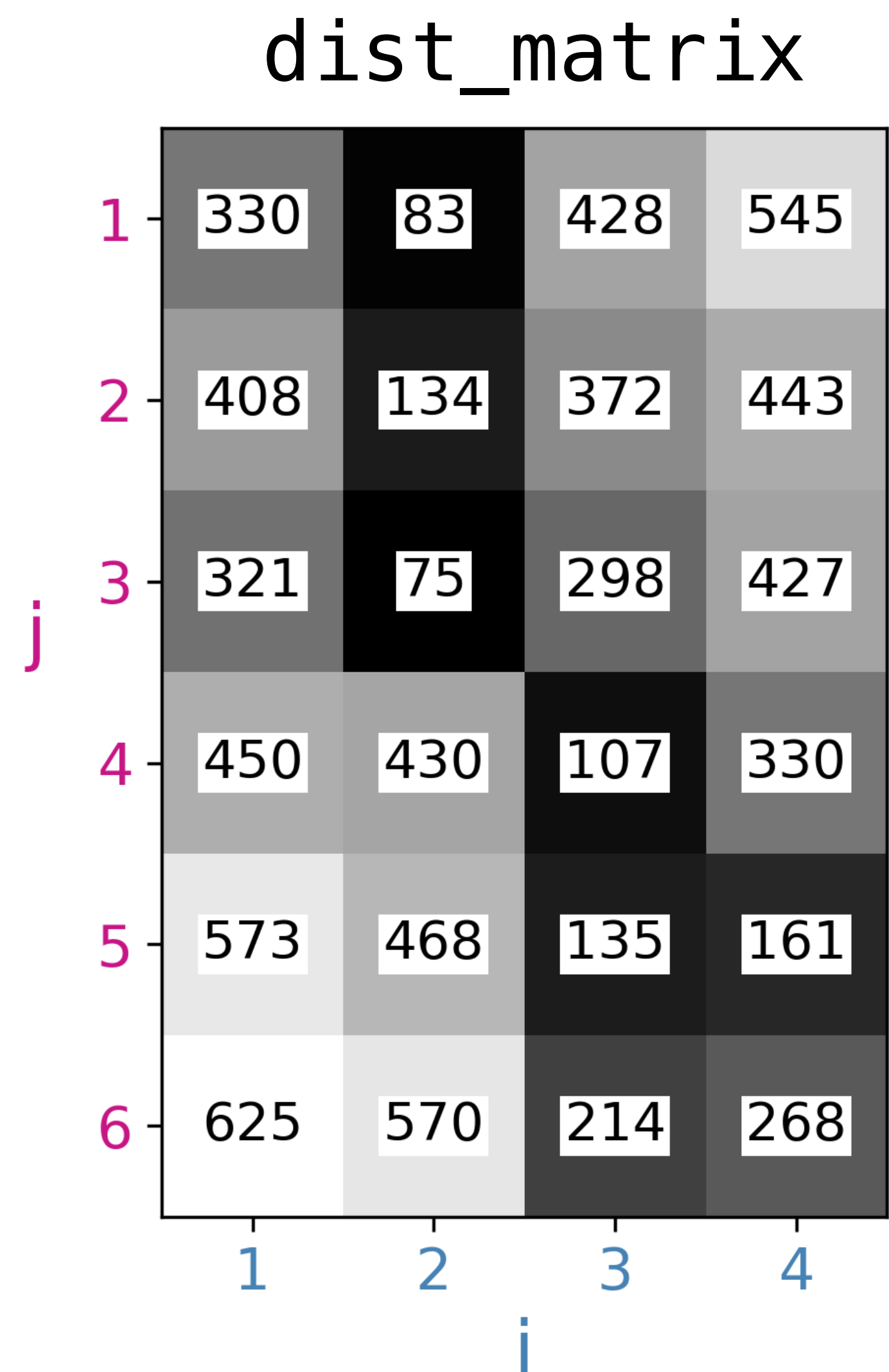
Distances	Mean
74, 330, 110, 165	169.75

Distances	Mean
80, 138, 78, 111, 141, 220	121





# Exercise: Code along: Mean nearest neighbor distance

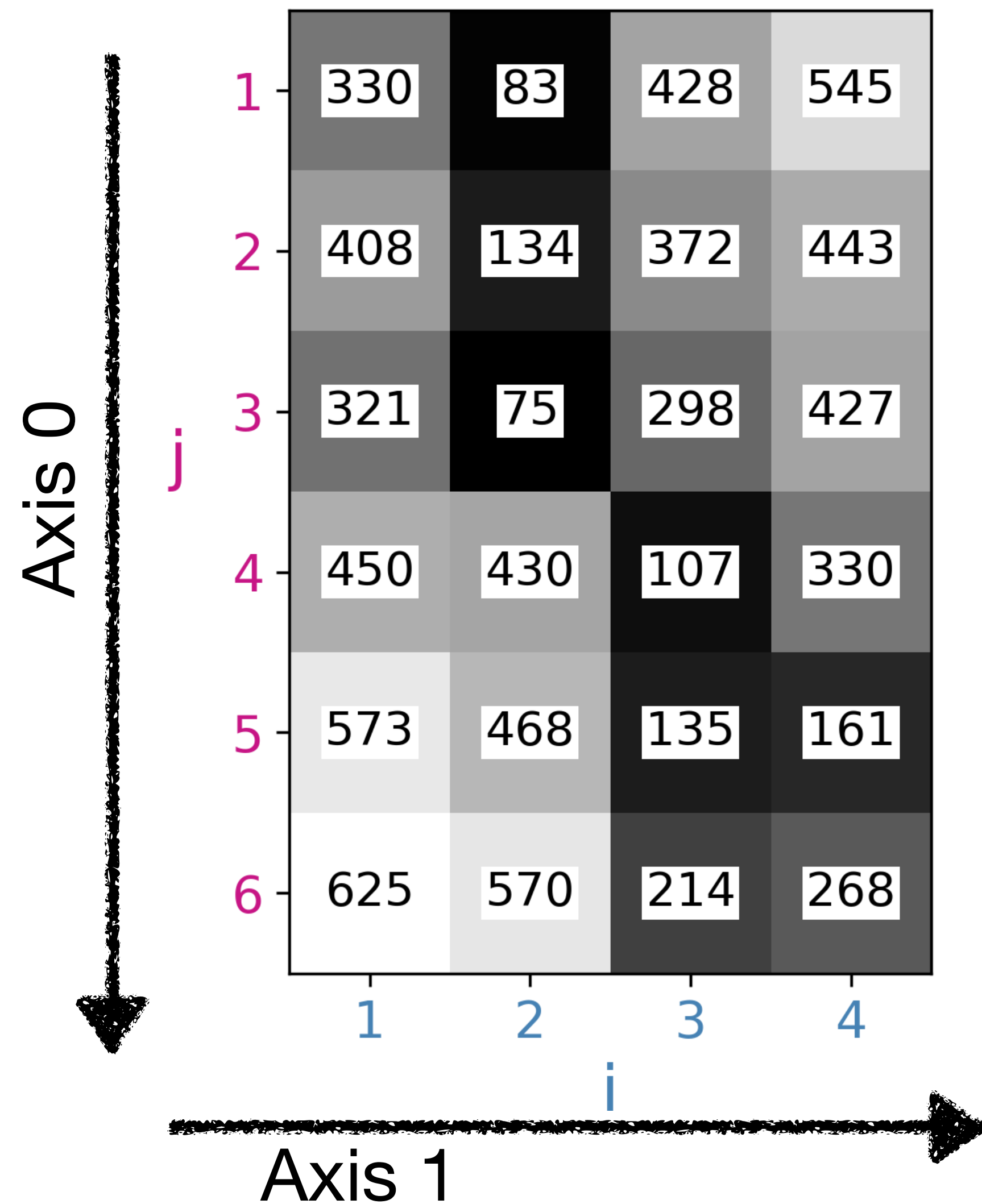




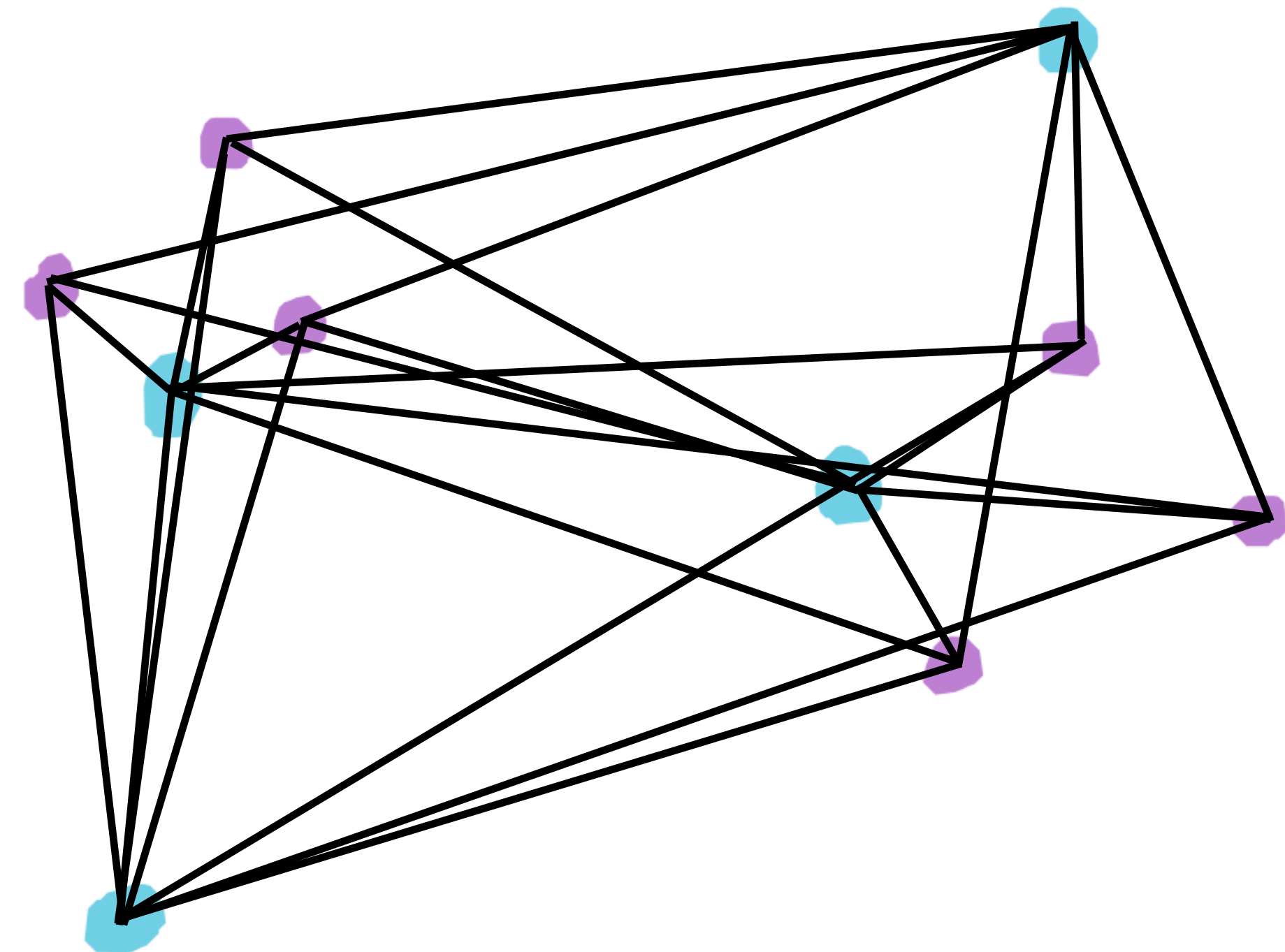


# Exercise: Code along: Mean nearest neighbor distance

dist\_matrix



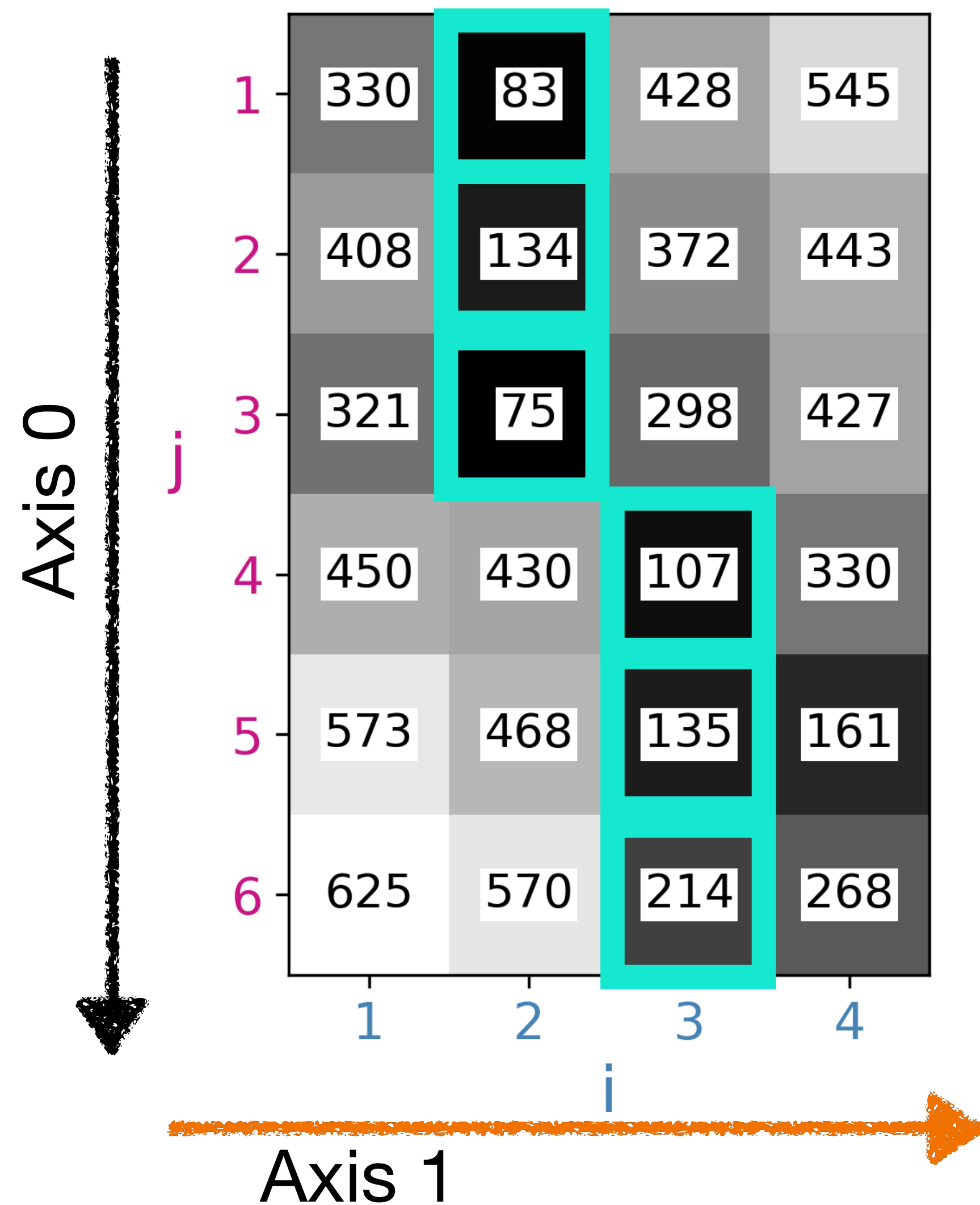
```
np.min(dist_matrix, axis = 1)
```



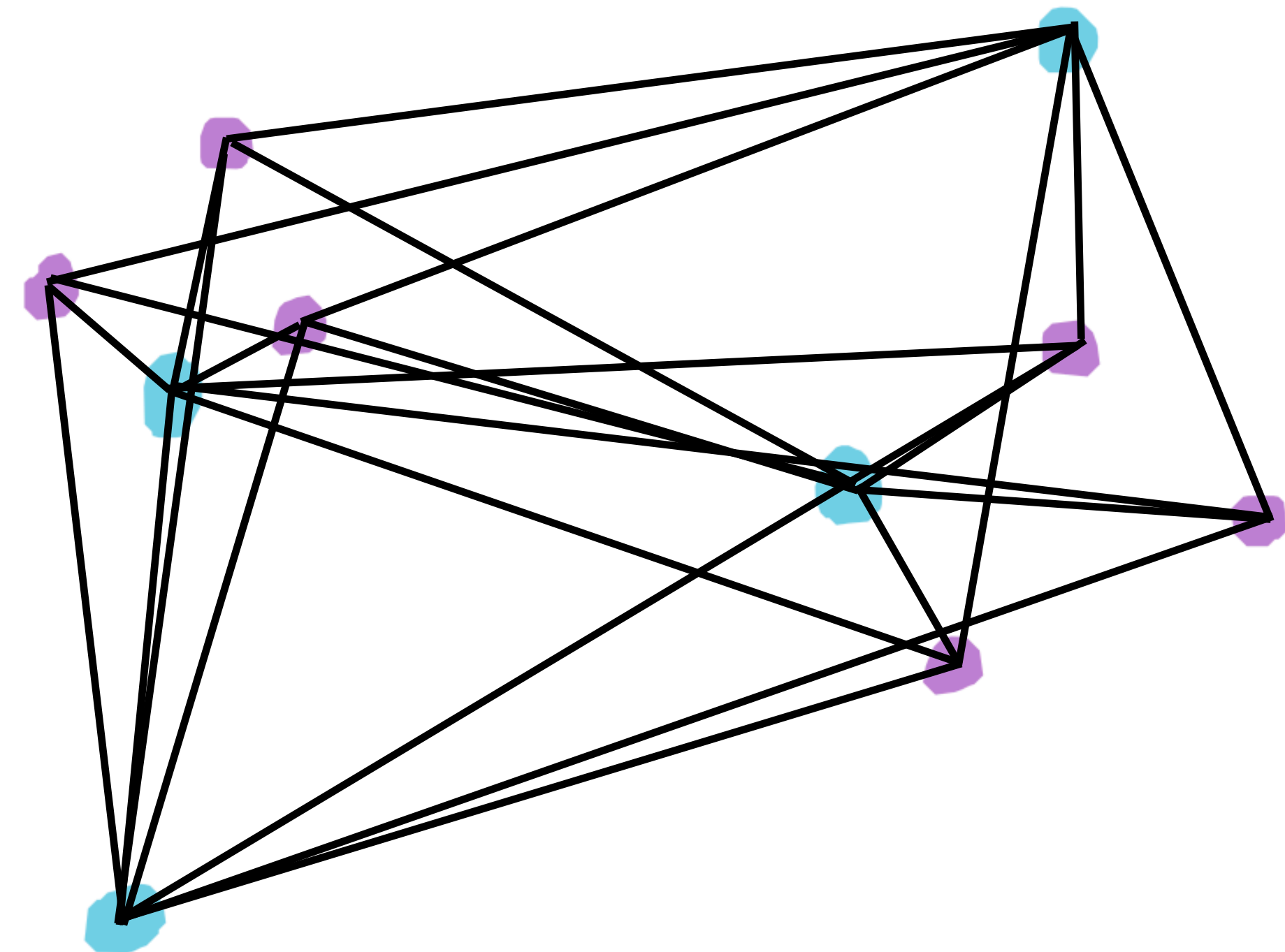


# Exercise: Code along: Mean nearest neighbor distance

dist\_matrix



```
np.min(dist_matrix, axis = 1)
```

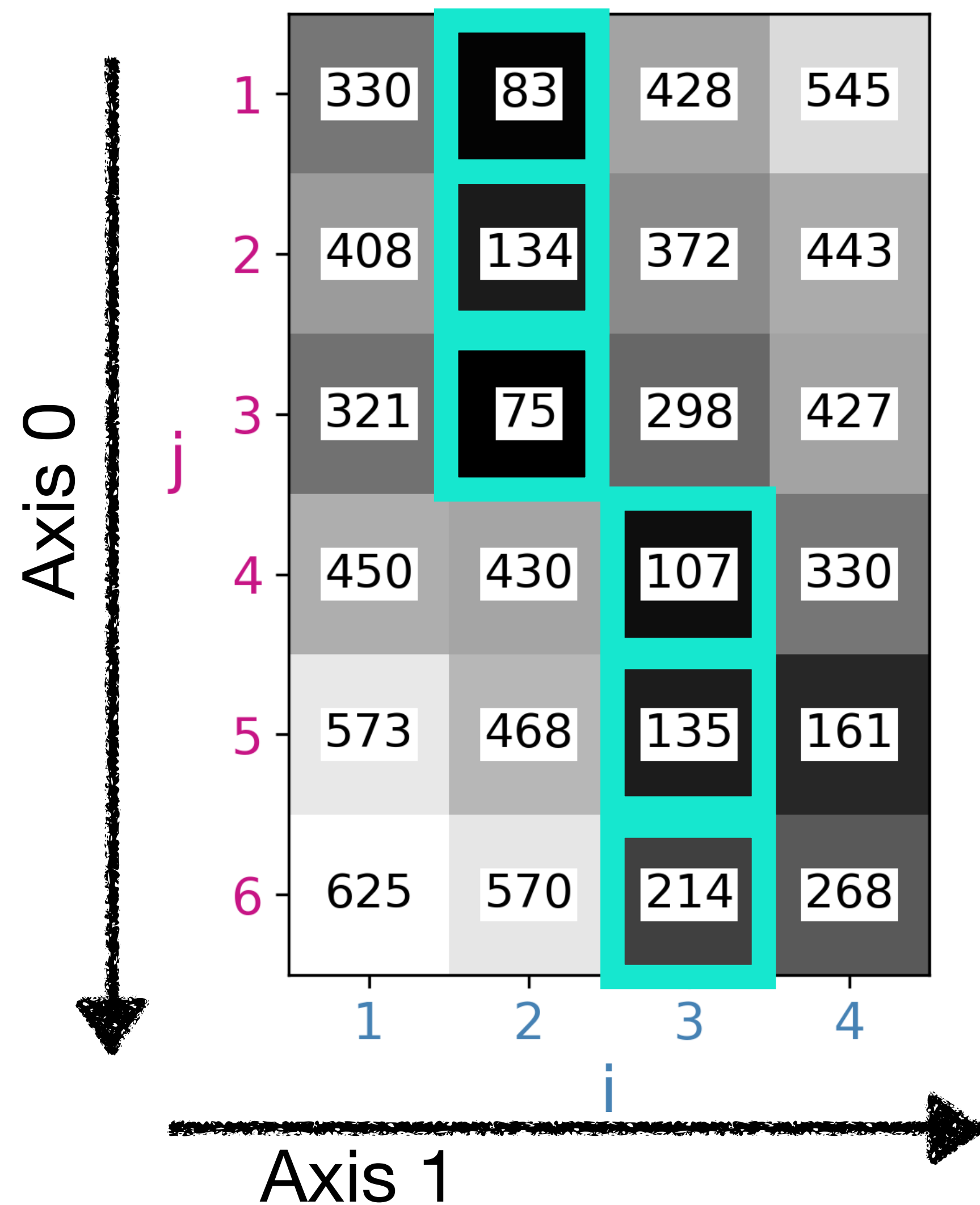




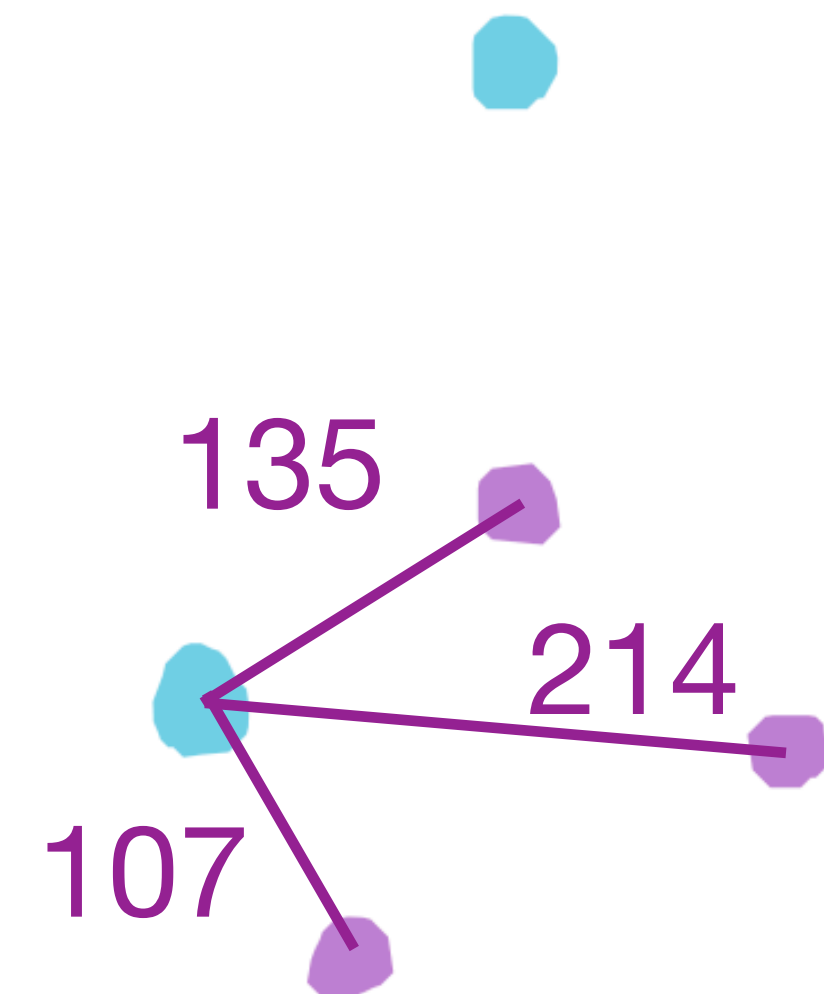
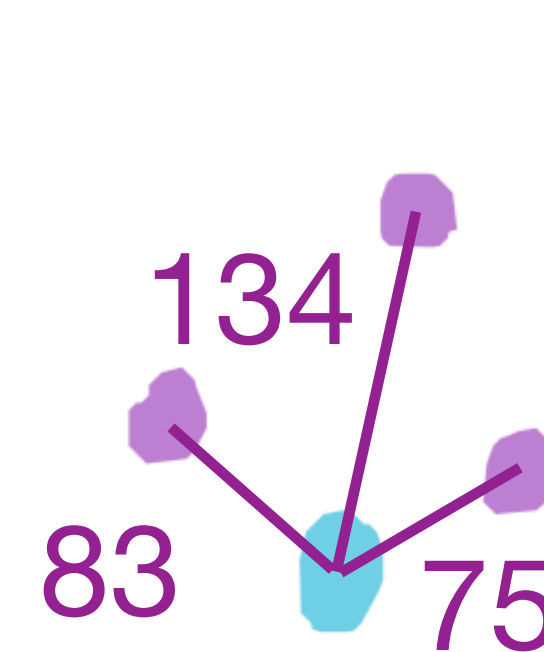


# Exercise: Code along: Mean nearest neighbor distance

dist\_matrix



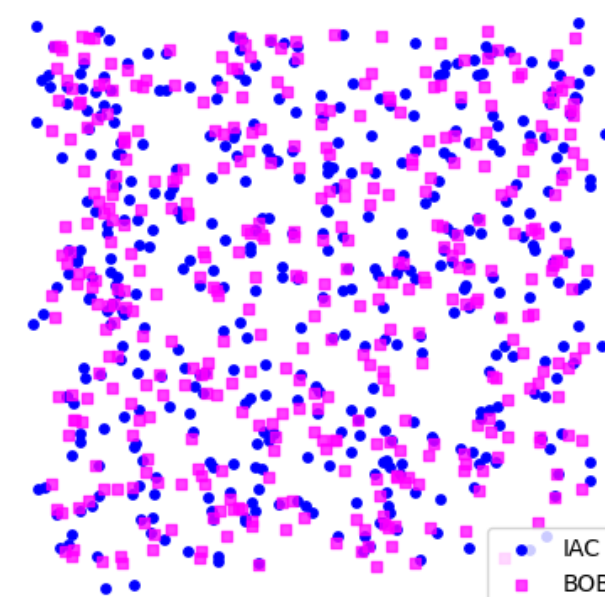
```
np.min(dist_matrix, axis = 1)
```



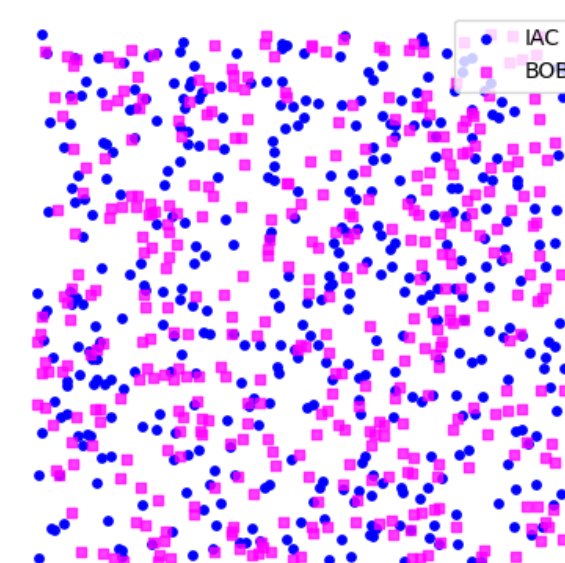


# Results: Mean distance **IAC** -> **BOB**

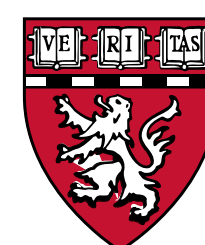
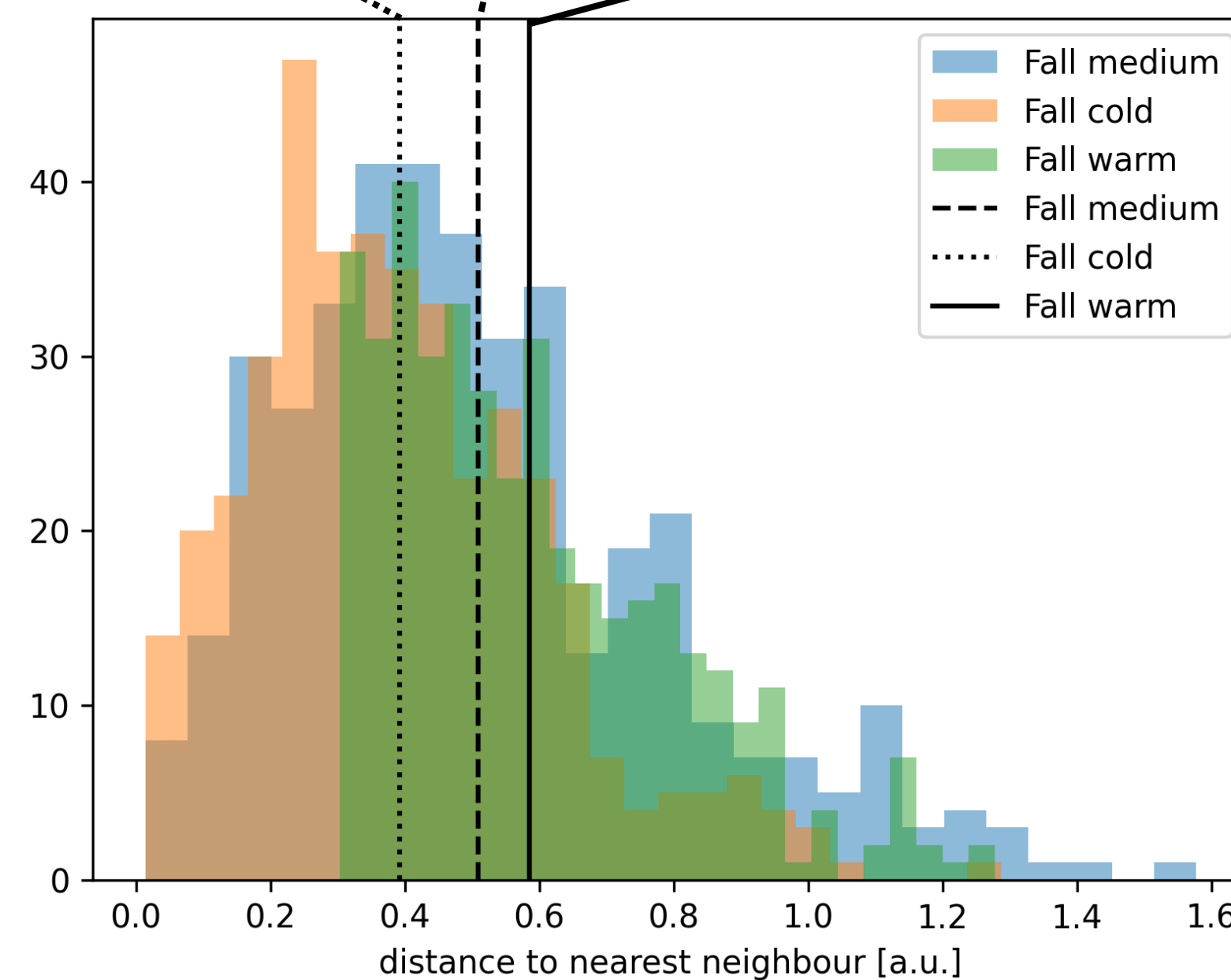
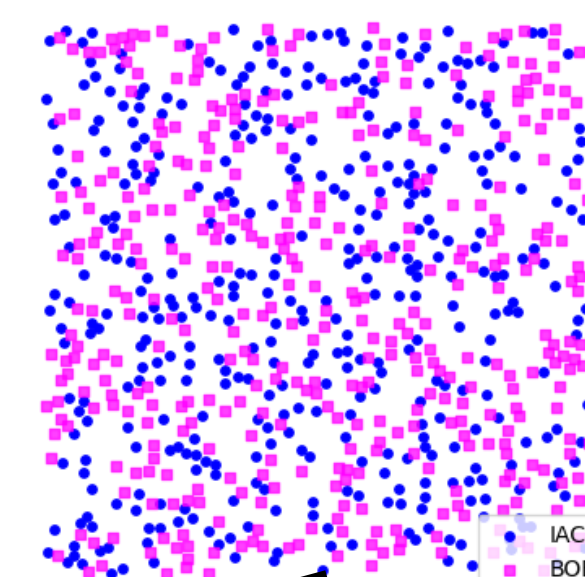
Cold



Medium



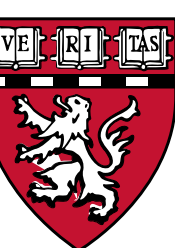
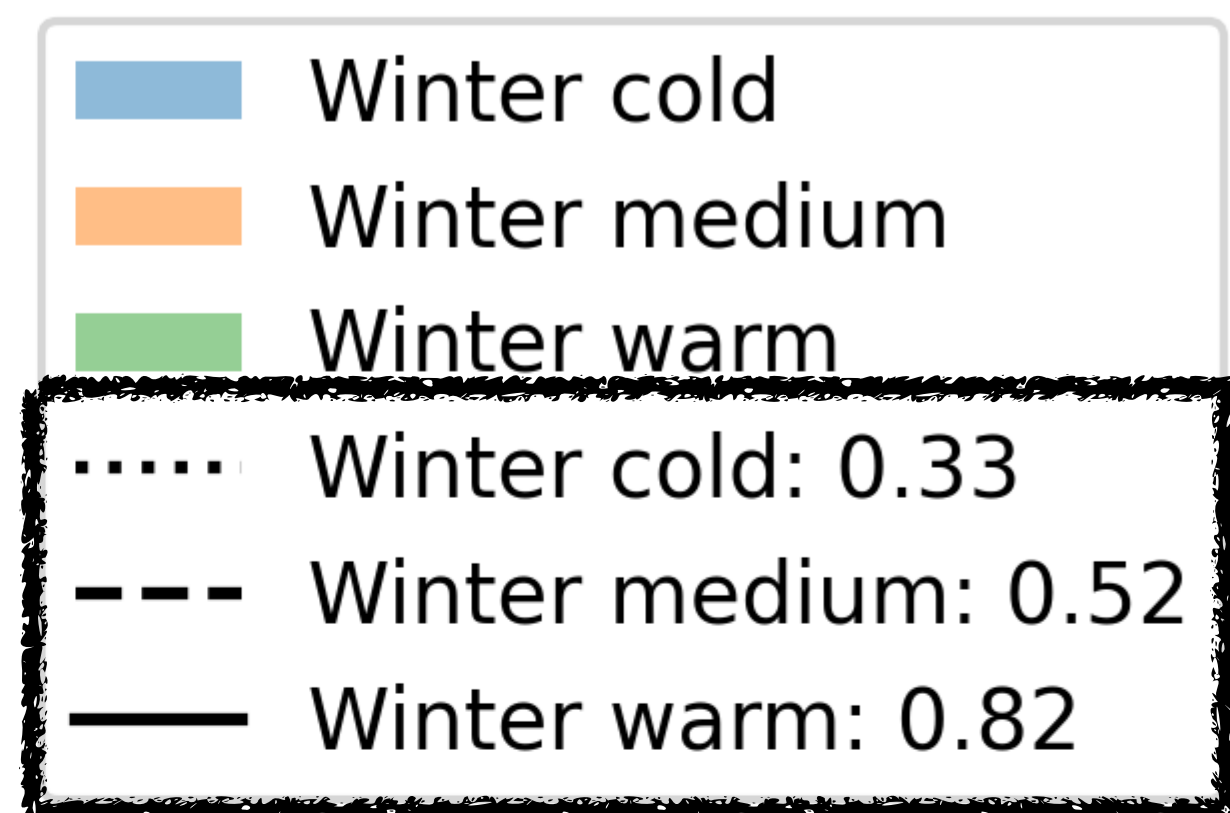
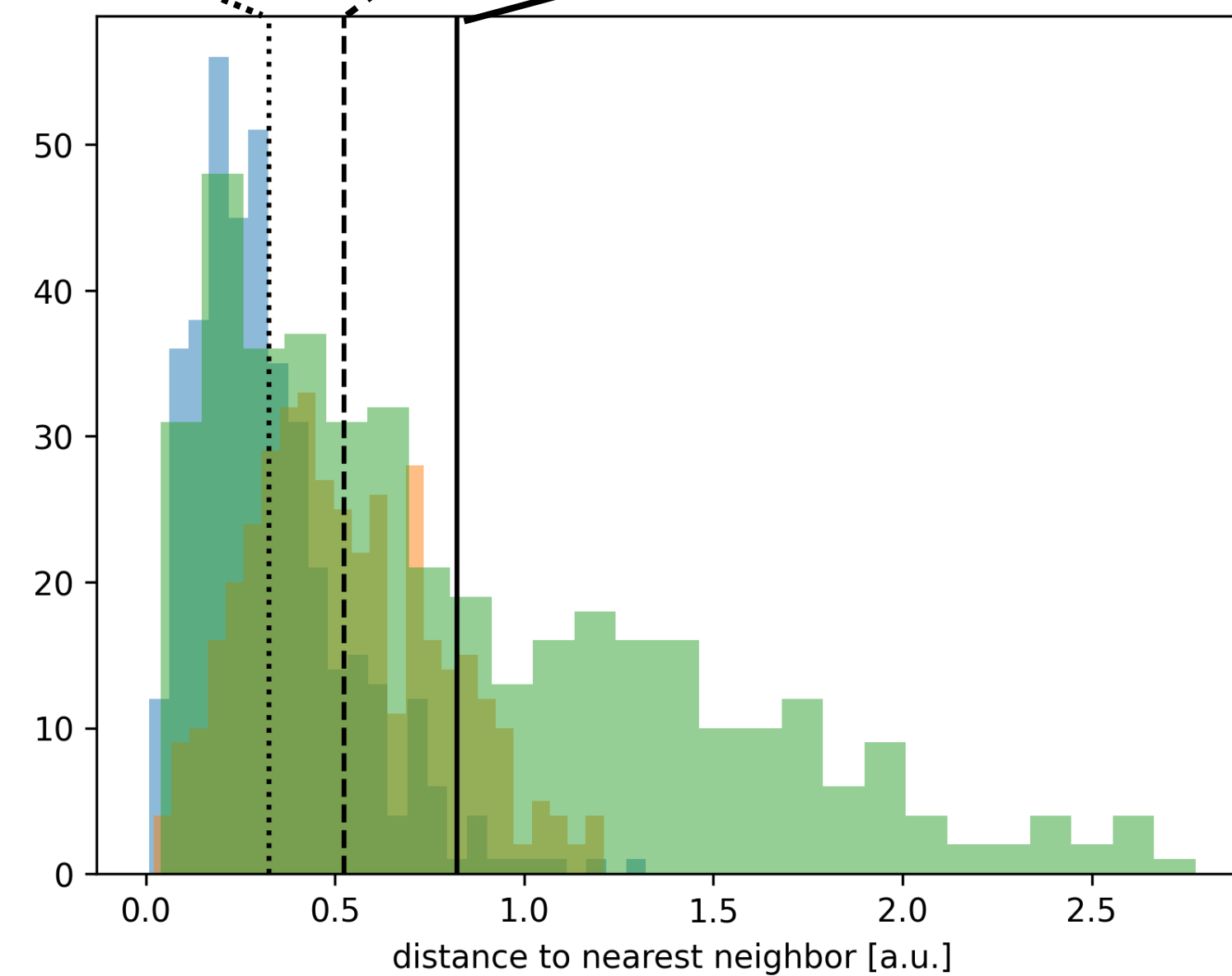
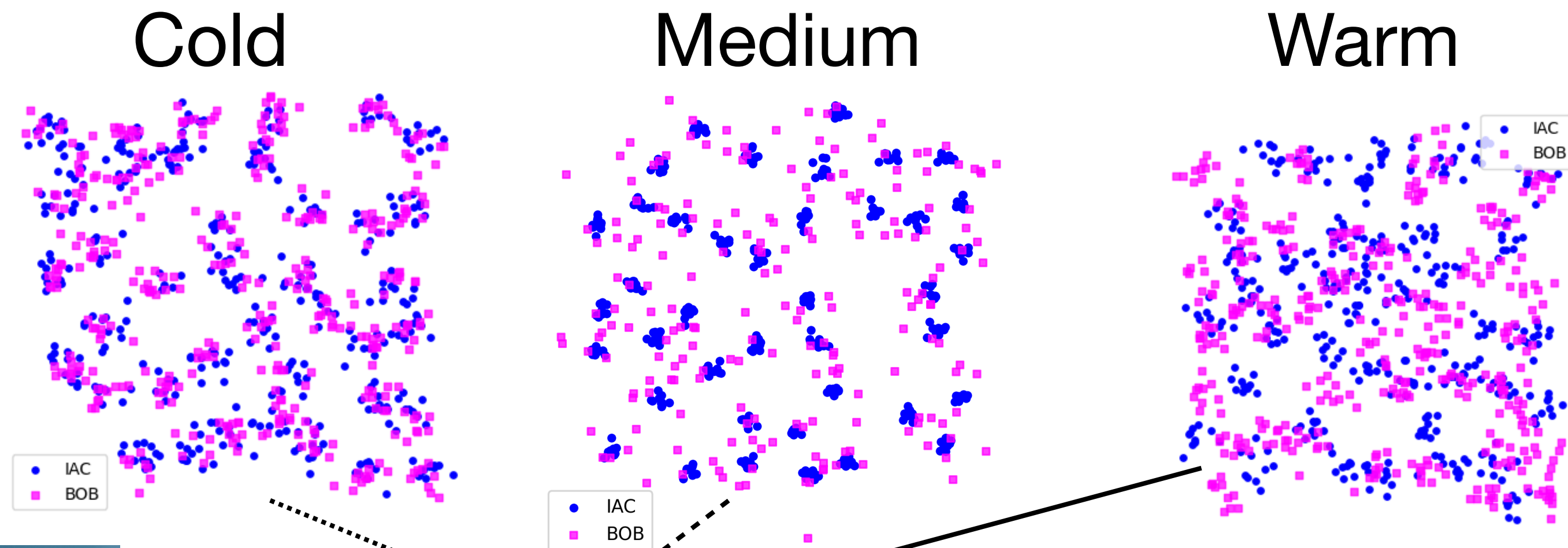
Warm







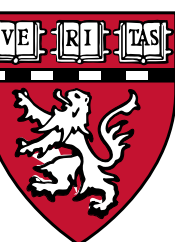
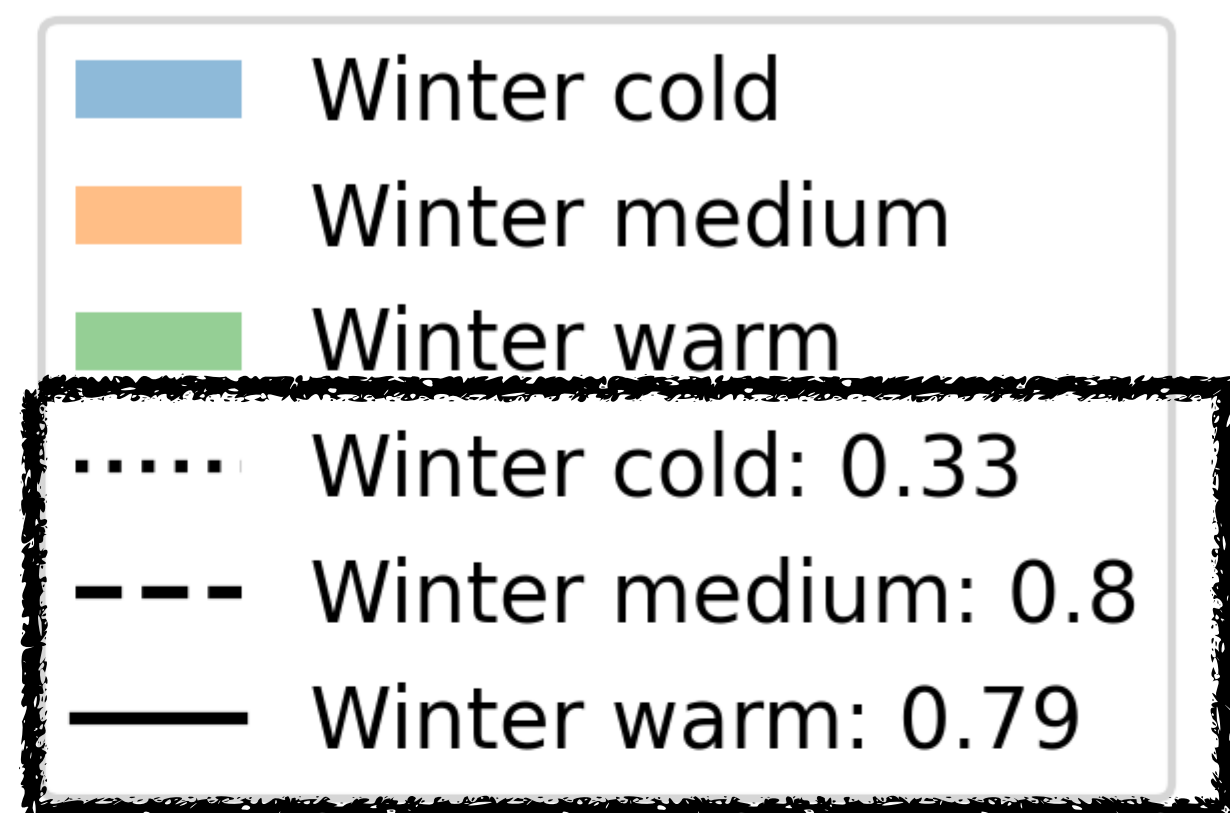
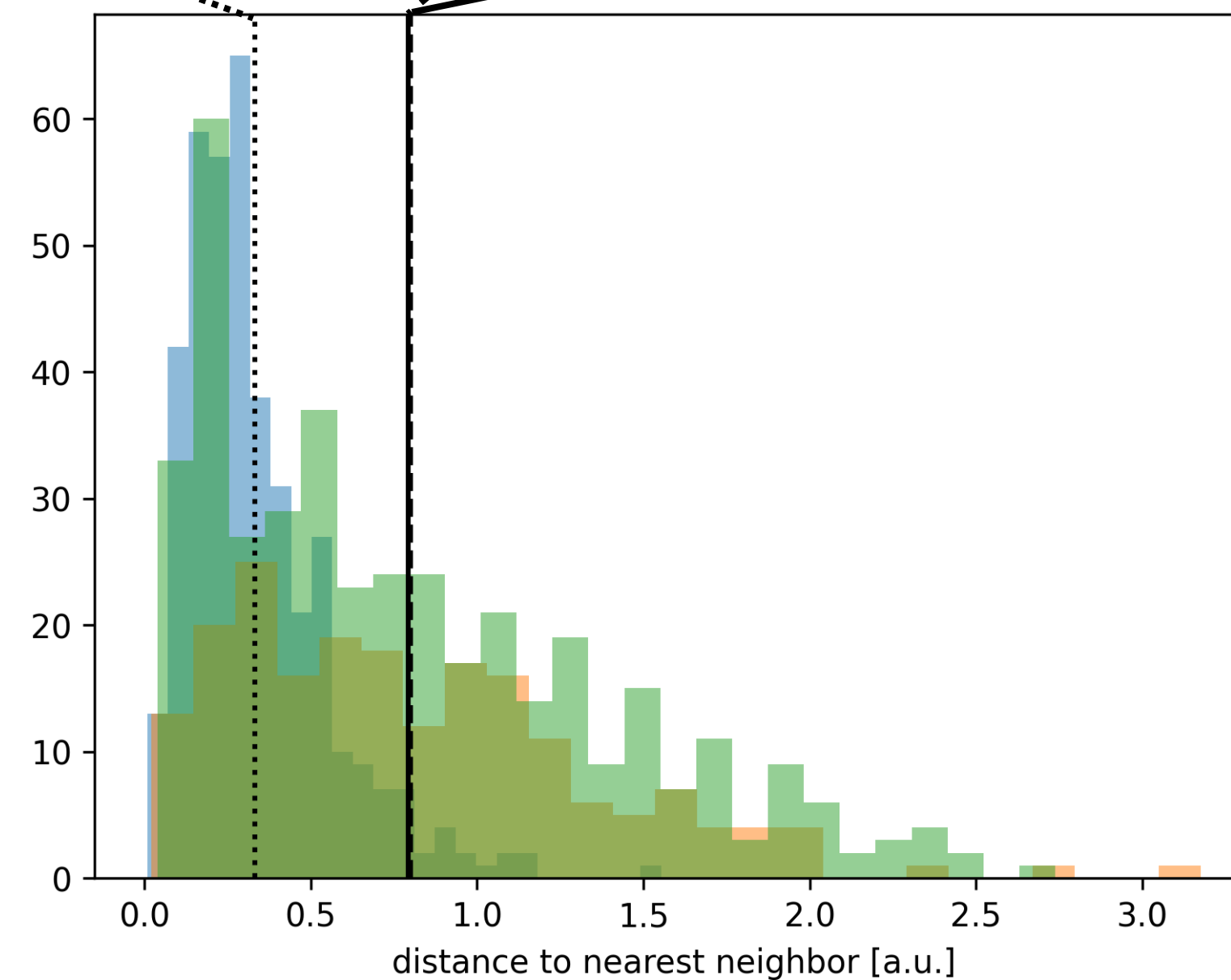
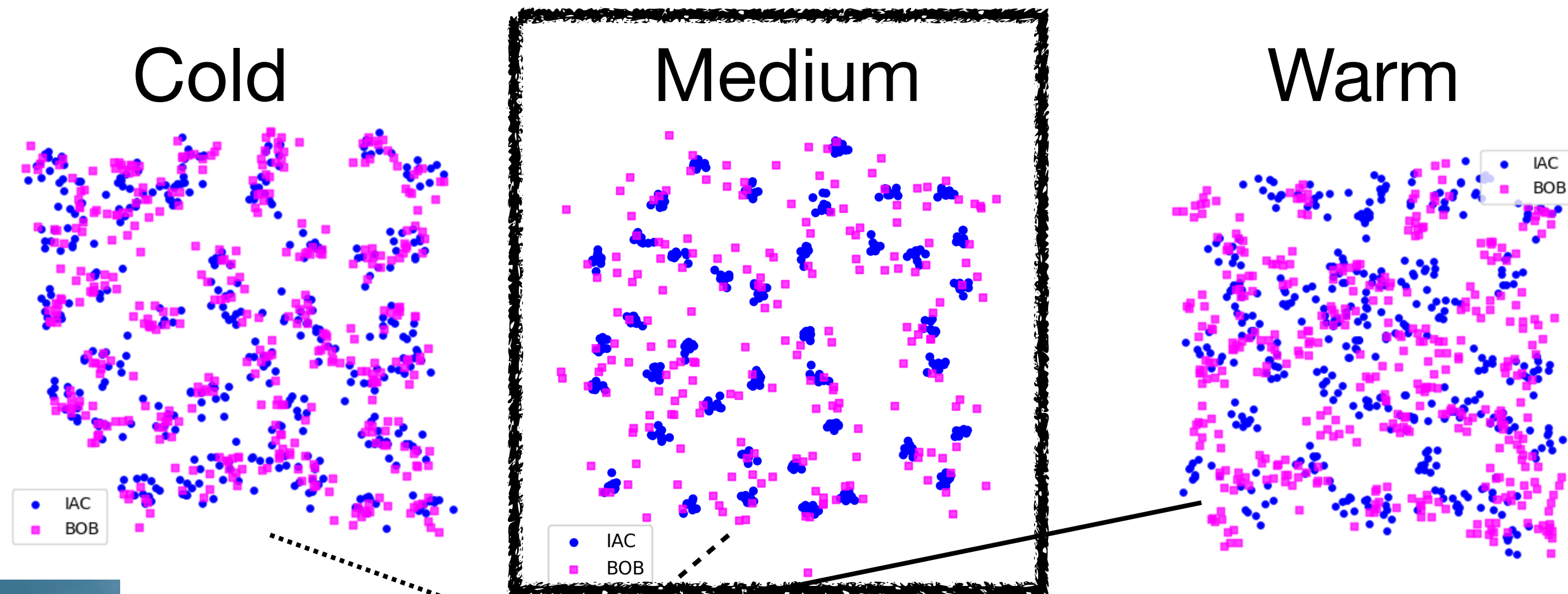
# Results: Mean distance IAC -> BOB



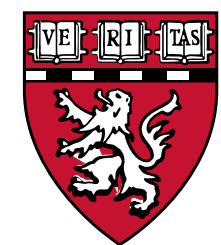




# Results: Mean distance BOB -> IAC







-> Results mean nearest neighbor distance + exercise





# Mean distance to nearest neighbor

- Asymmetric: BOB  $\rightarrow$  IAC  $\neq$  IAC  $\rightarrow$  BOB
- Returns: One number
- Range: Short

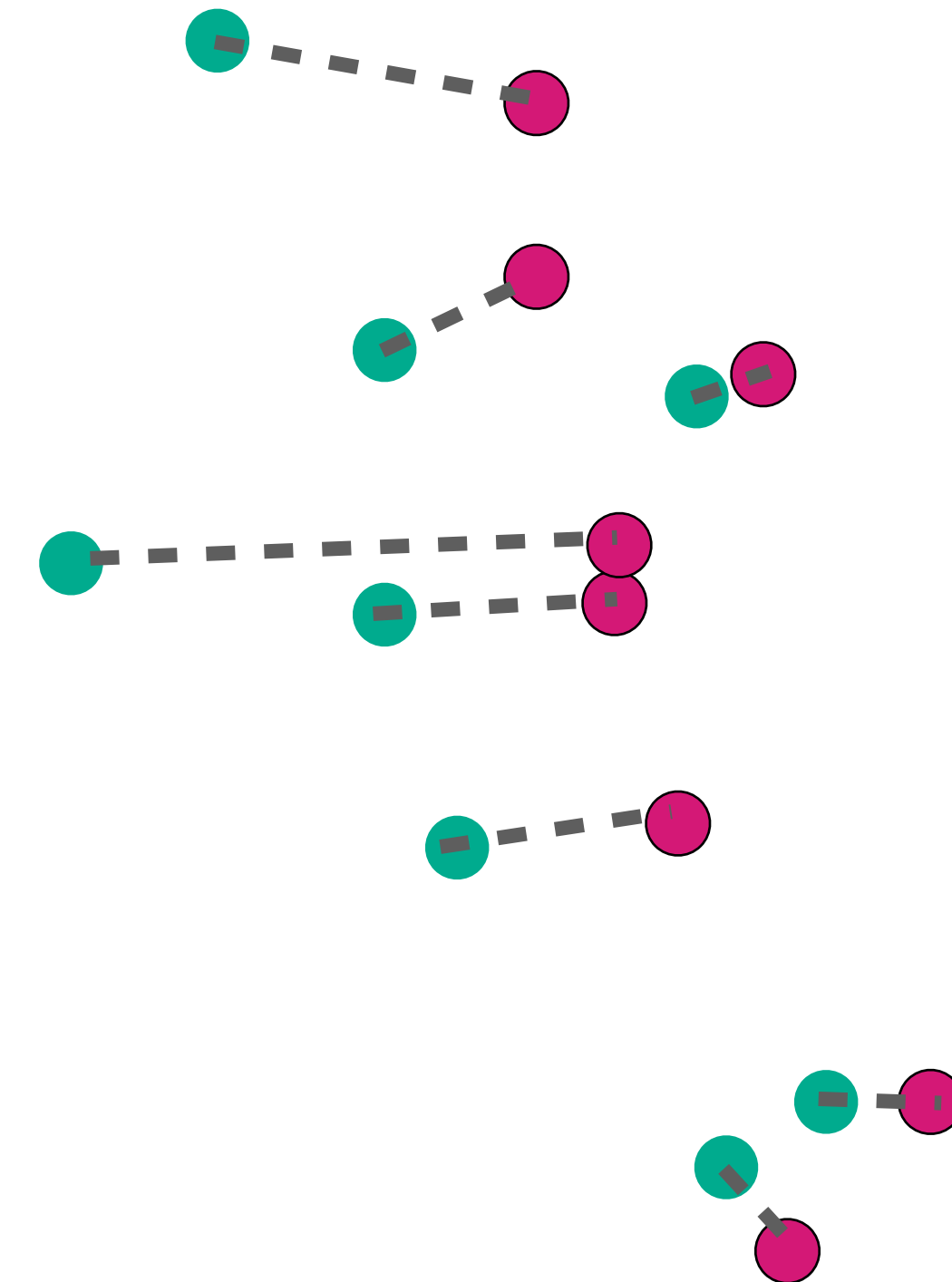






# Beyond the mean distance to nearest neighbor

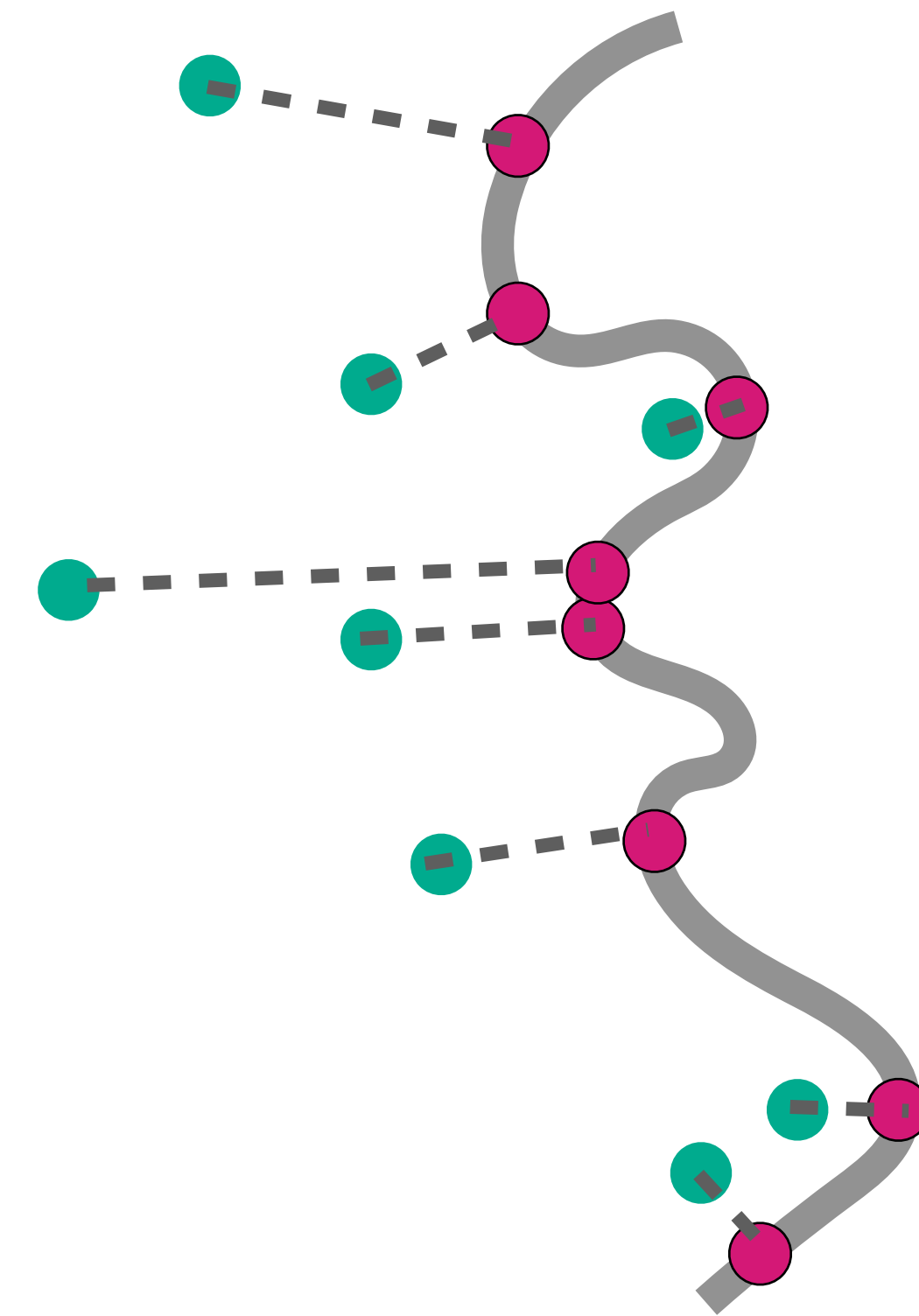
- Similar concepts hold true beyond the realm of just points





# Beyond the mean distance to nearest neighbor

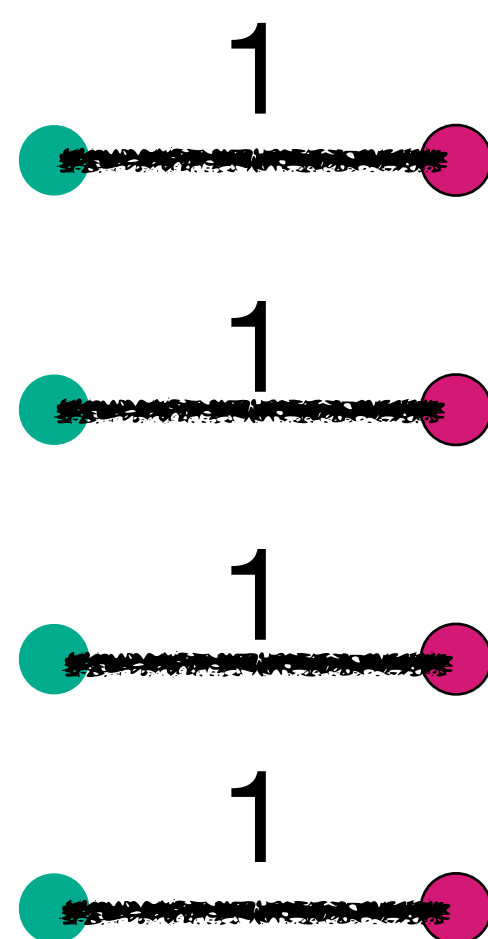
- Similar concepts hold true beyond the realm of just points



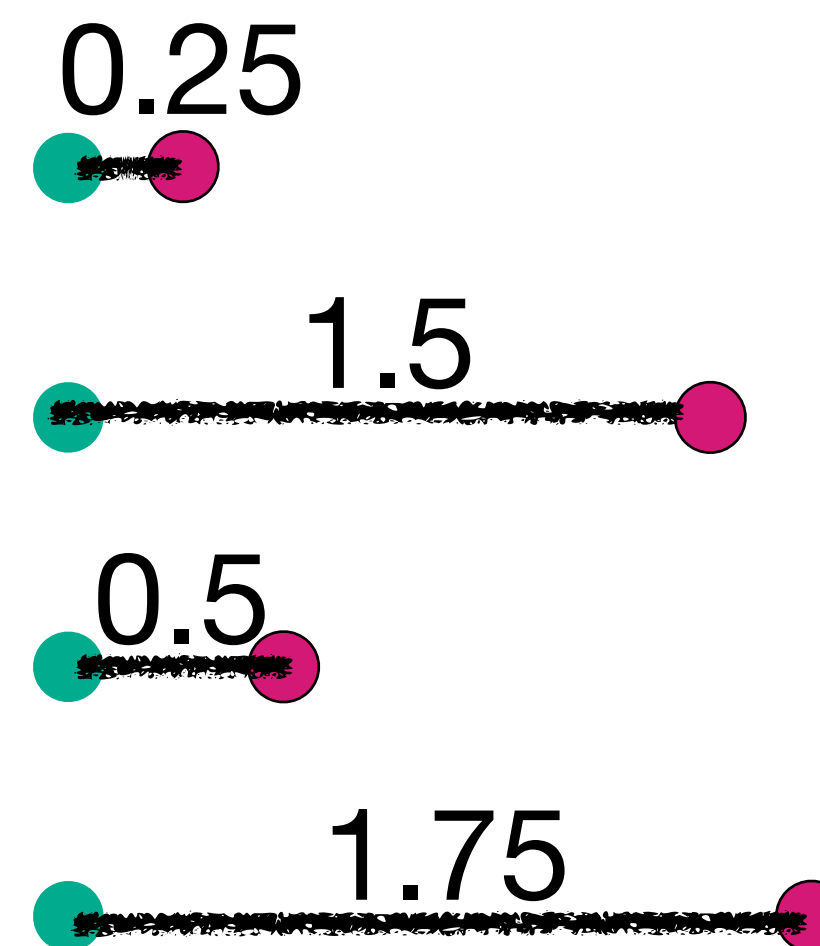




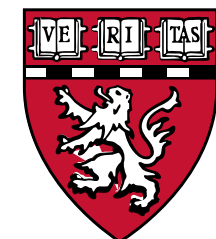
# Nearest neighbor function



Mean dist: 1

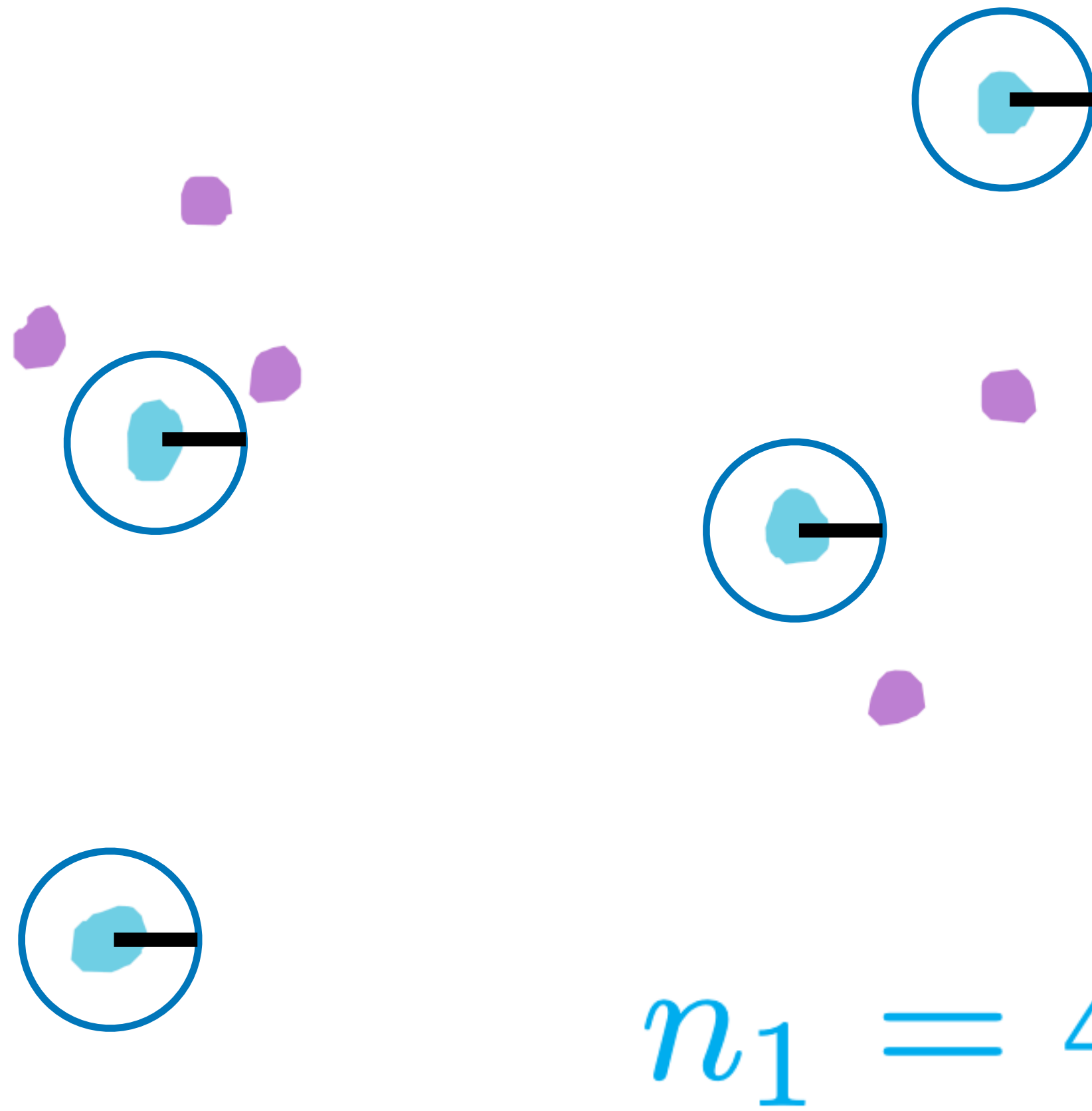


Mean dist: 1

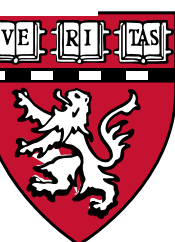
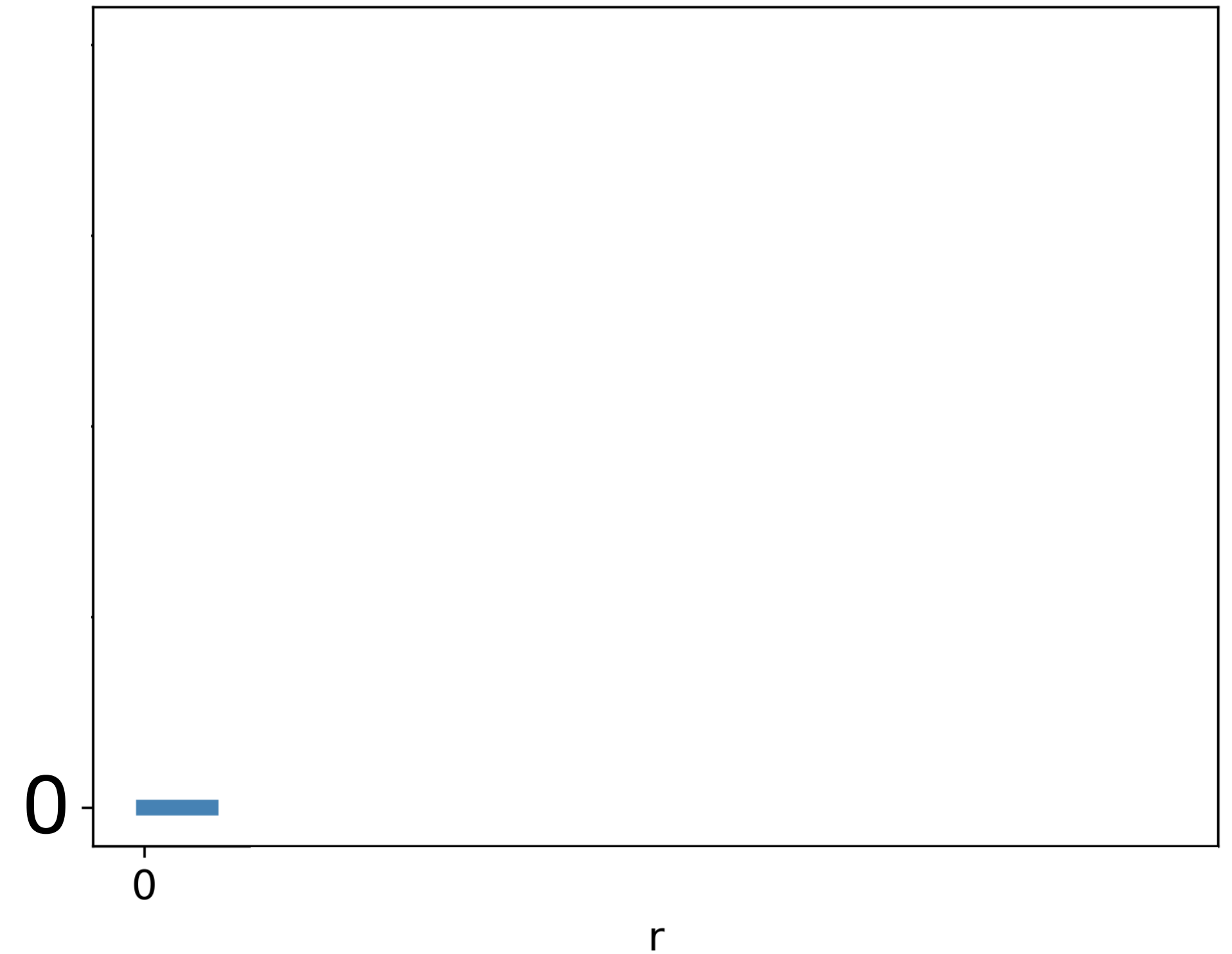




# Nearest neighbor function



$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

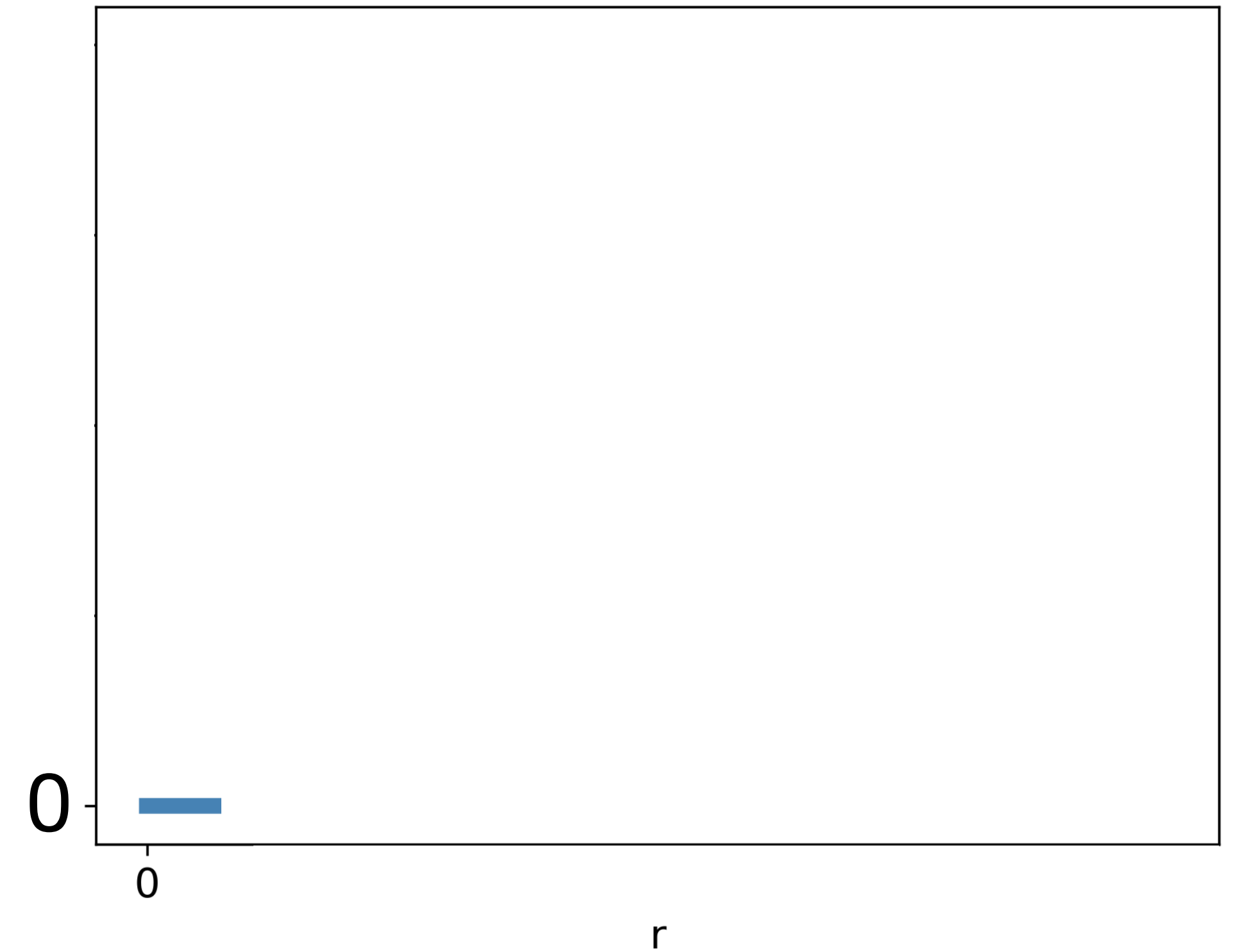
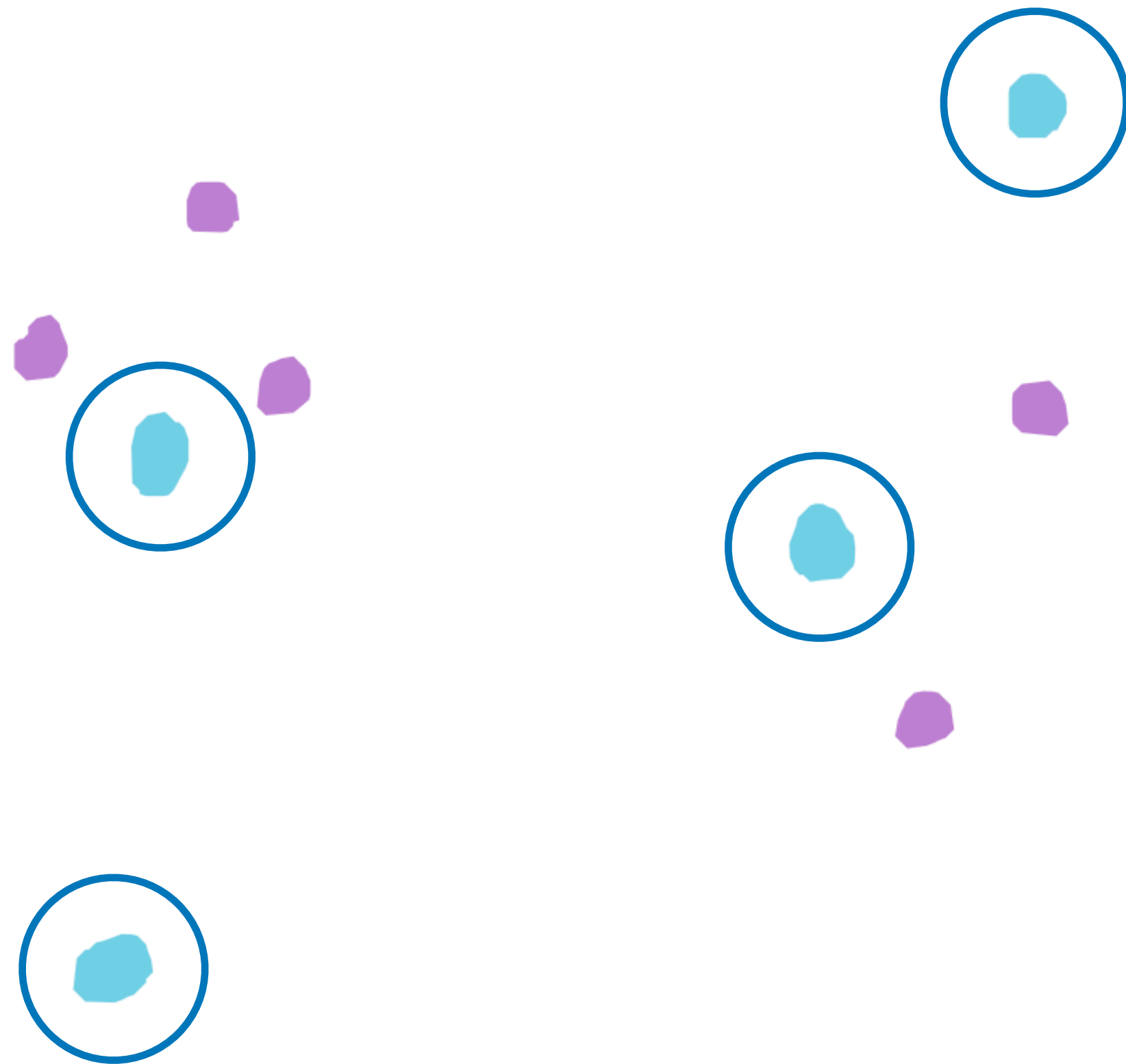






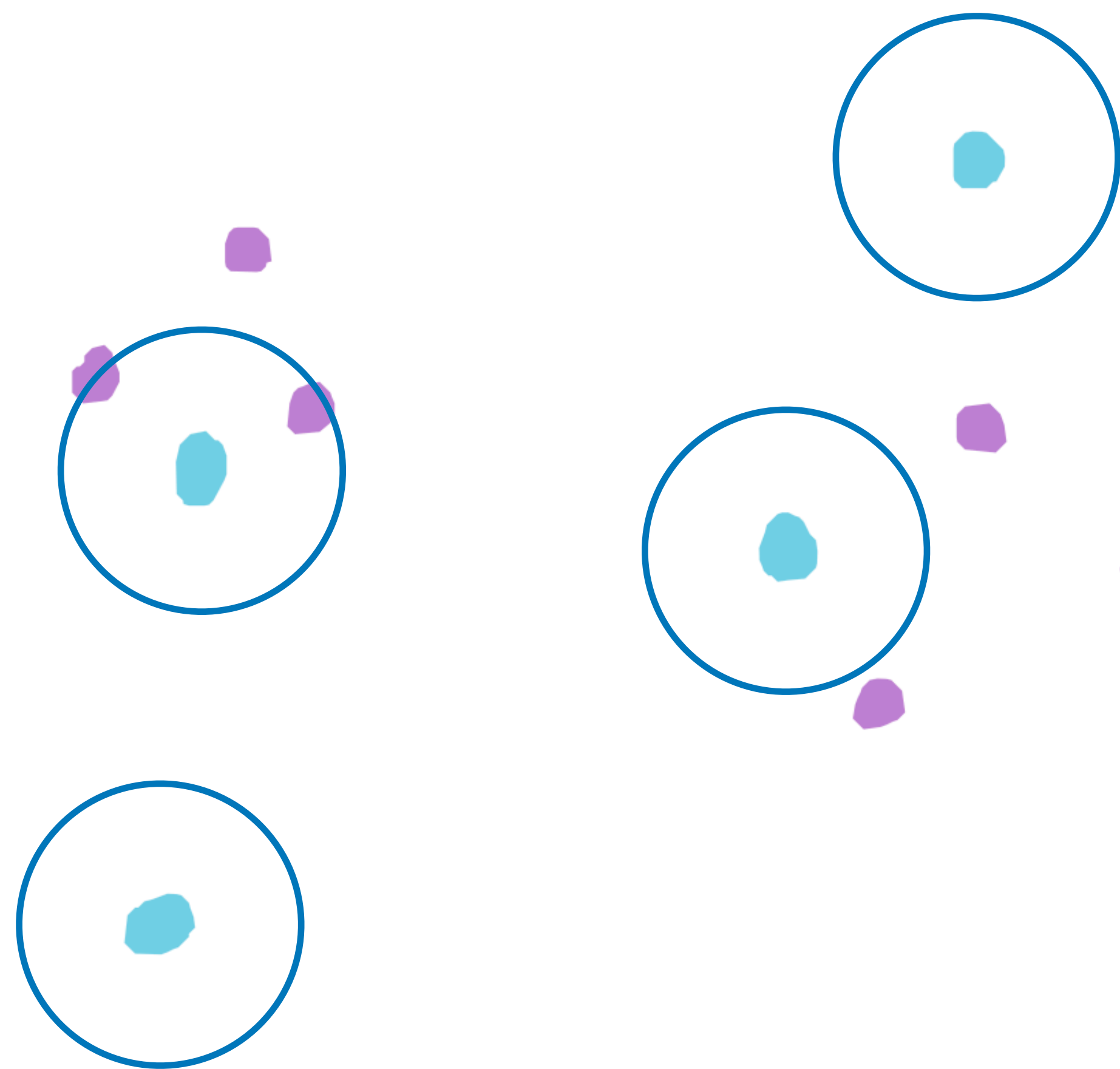
# Nearest neighbor function

$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

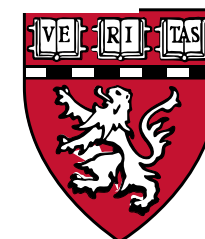
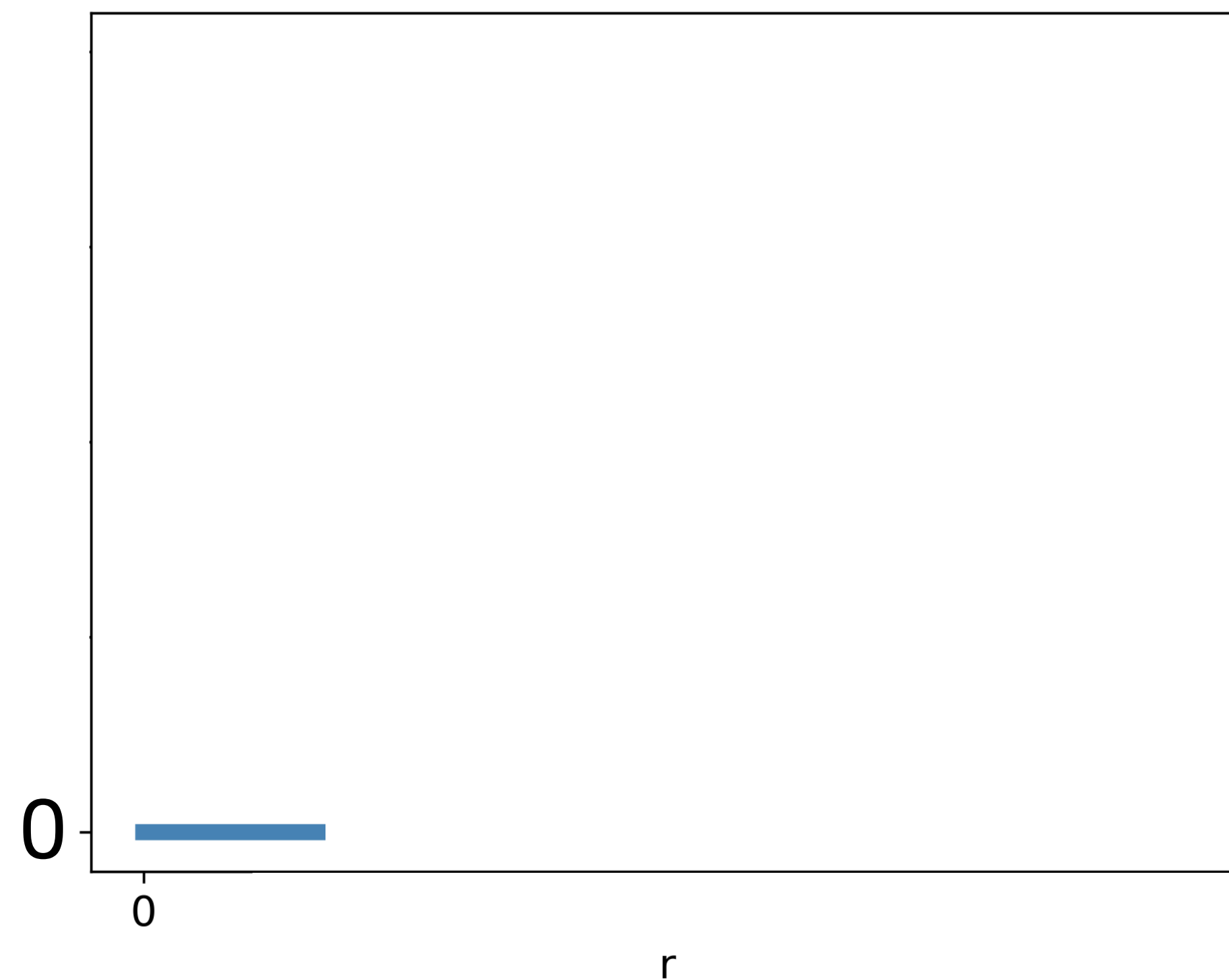




# Nearest neighbor function



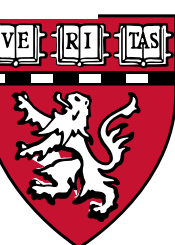
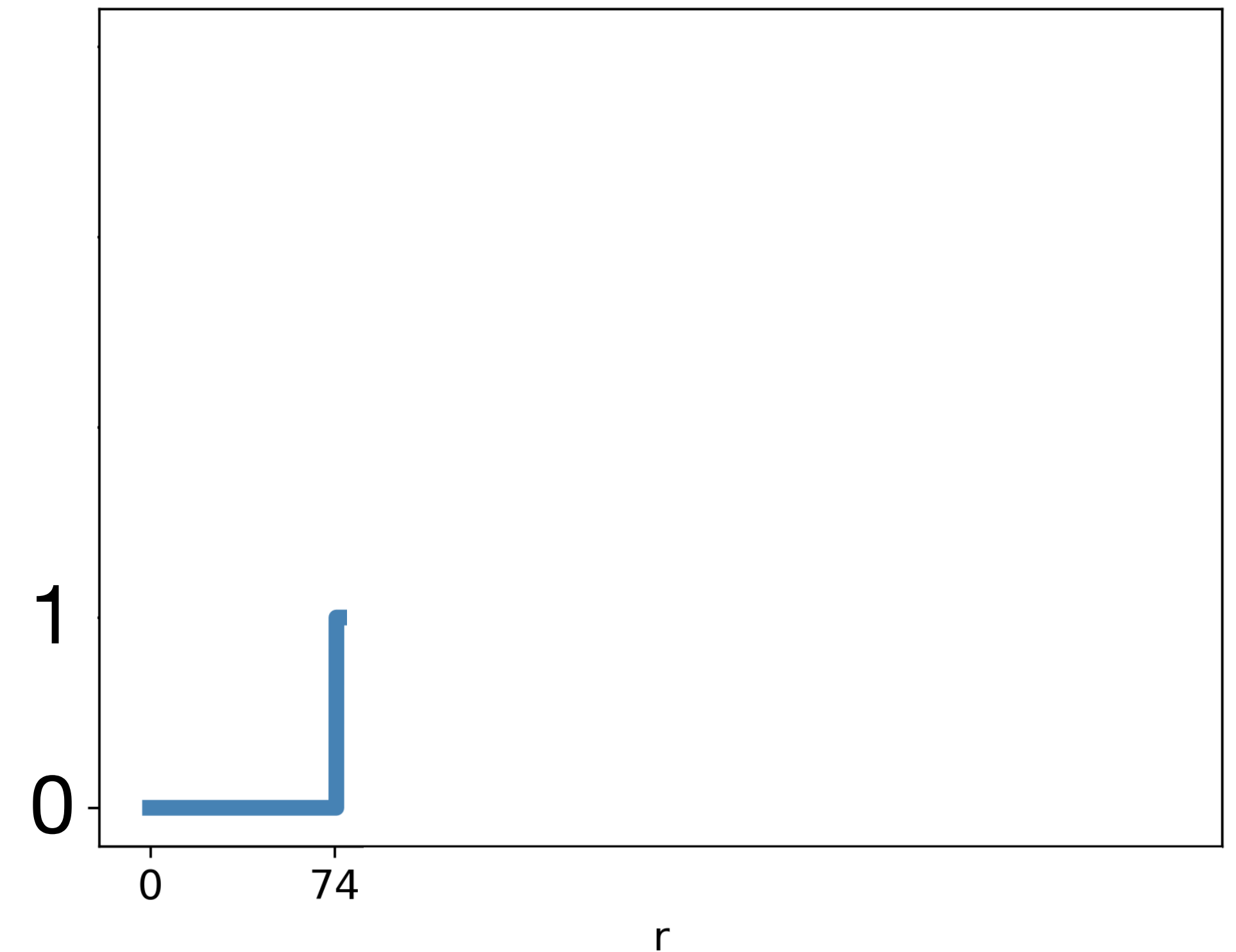
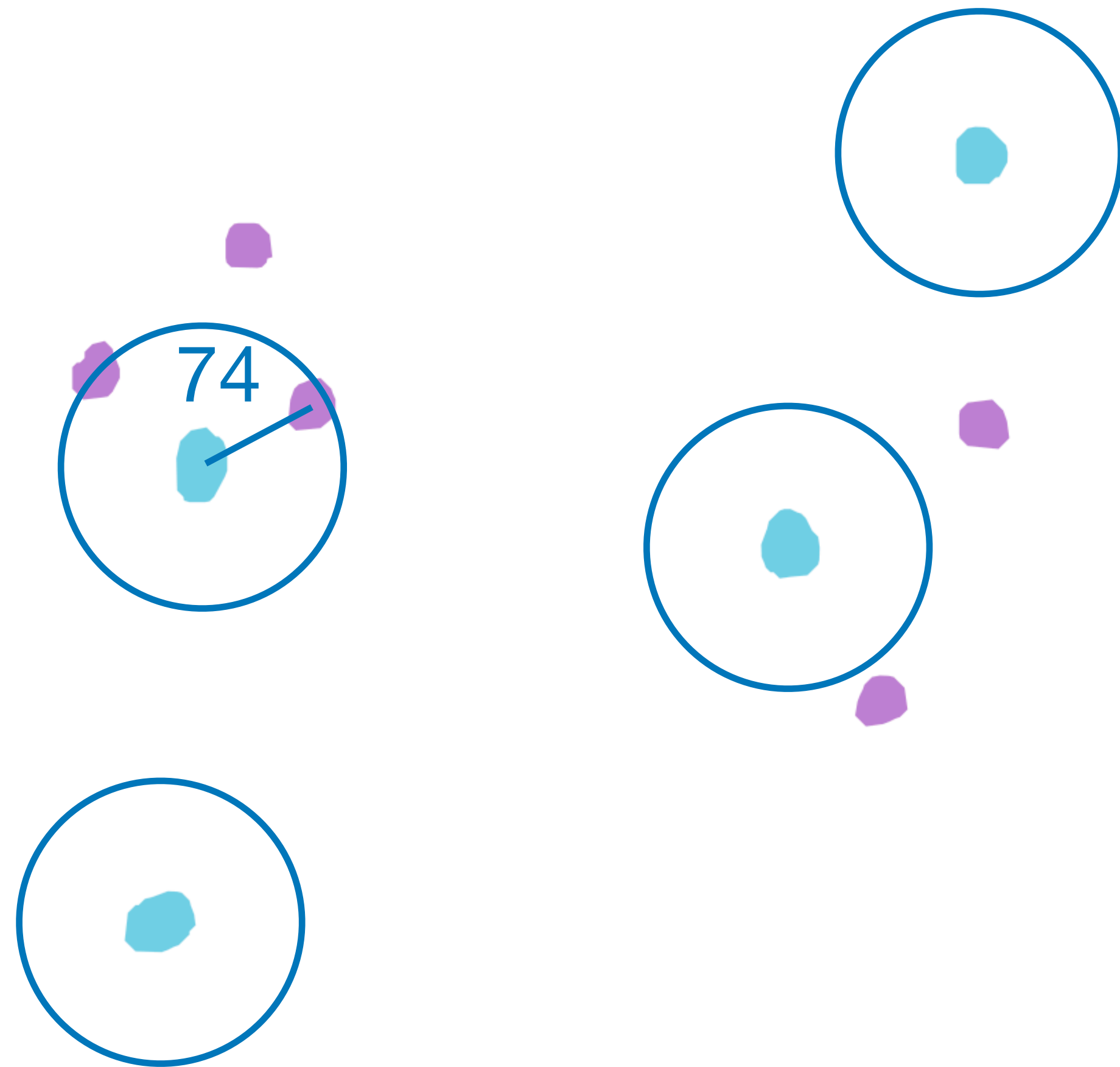
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





# Nearest neighbor function

$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

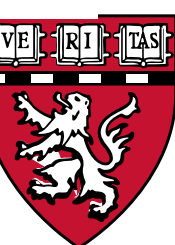
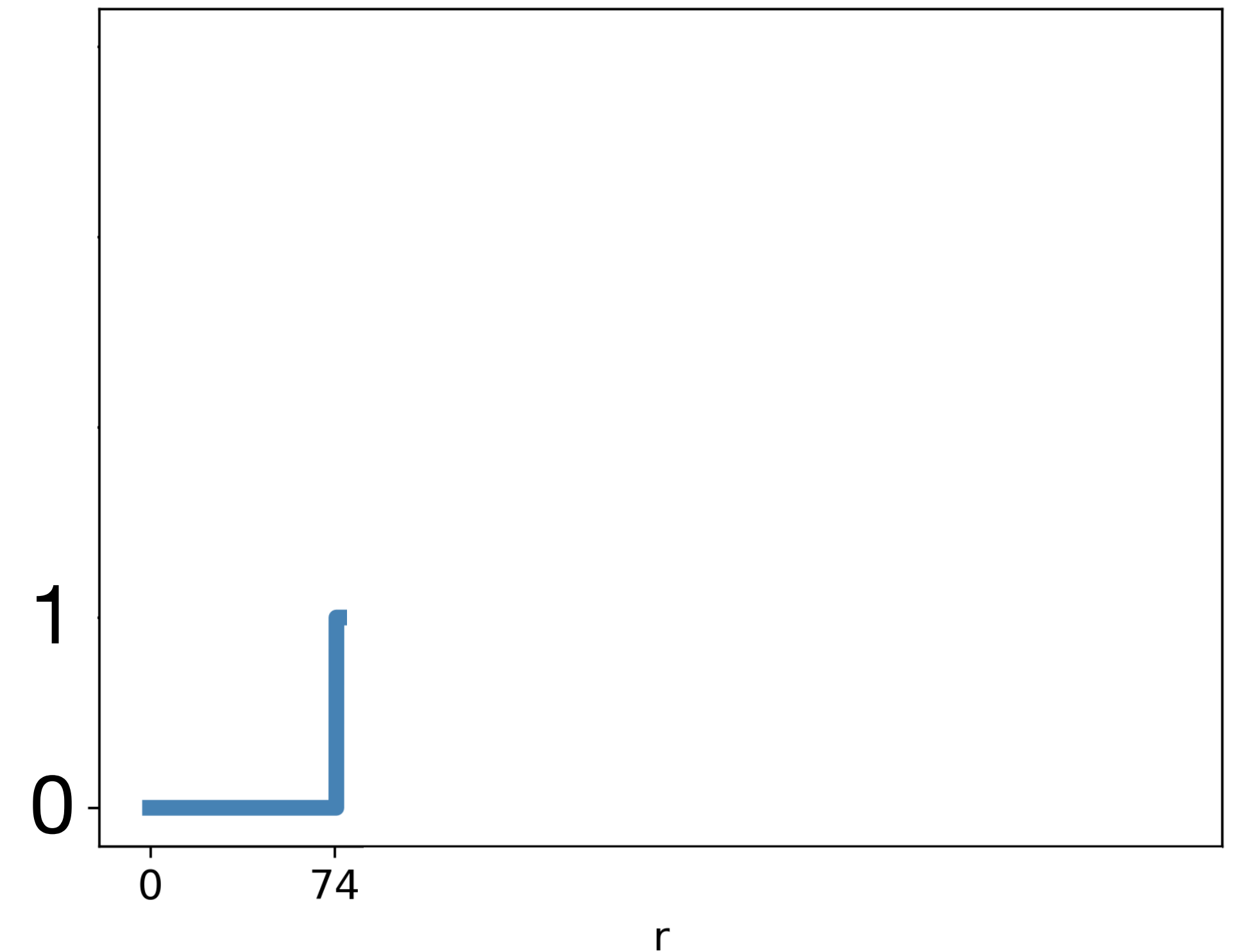
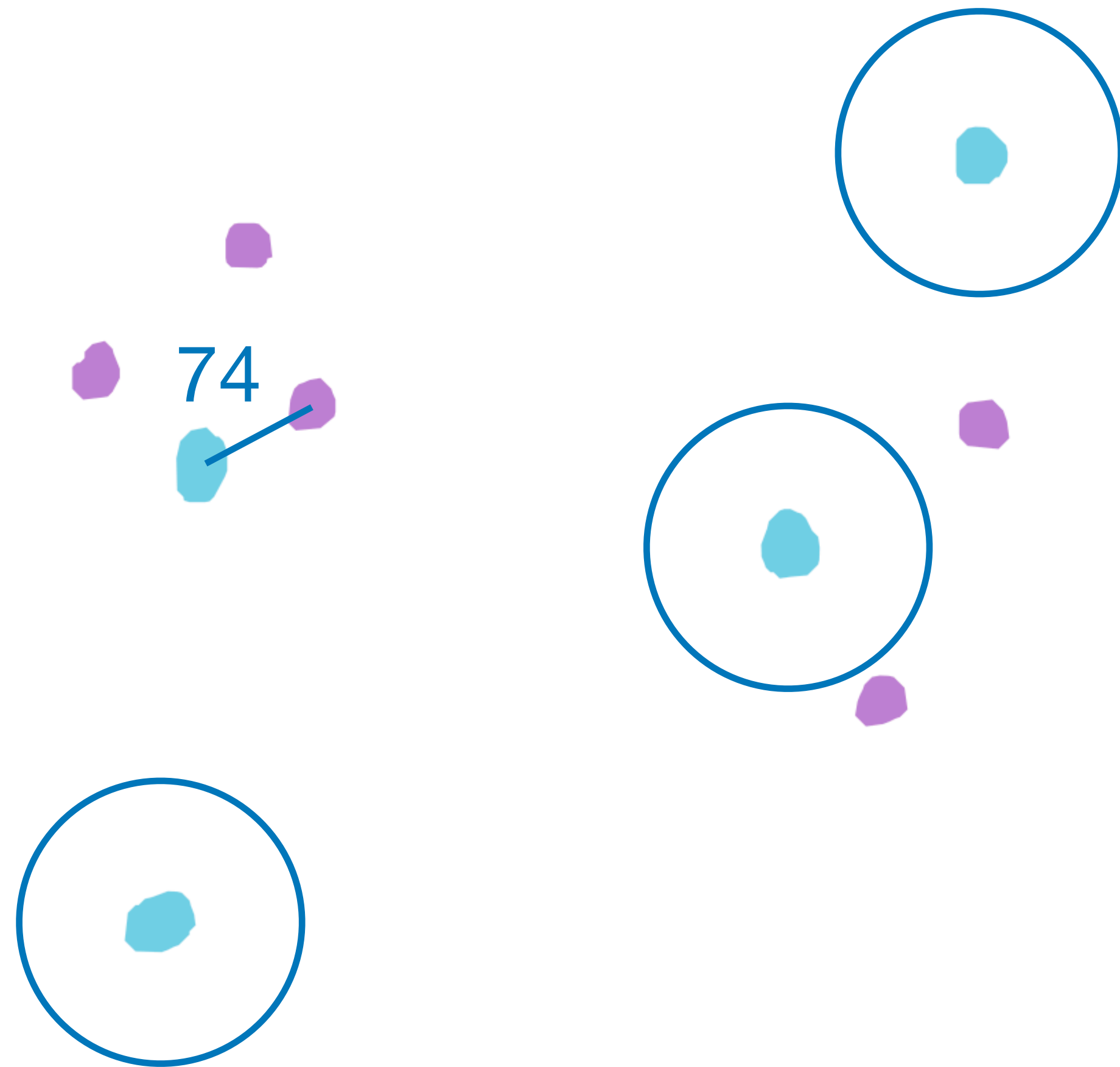






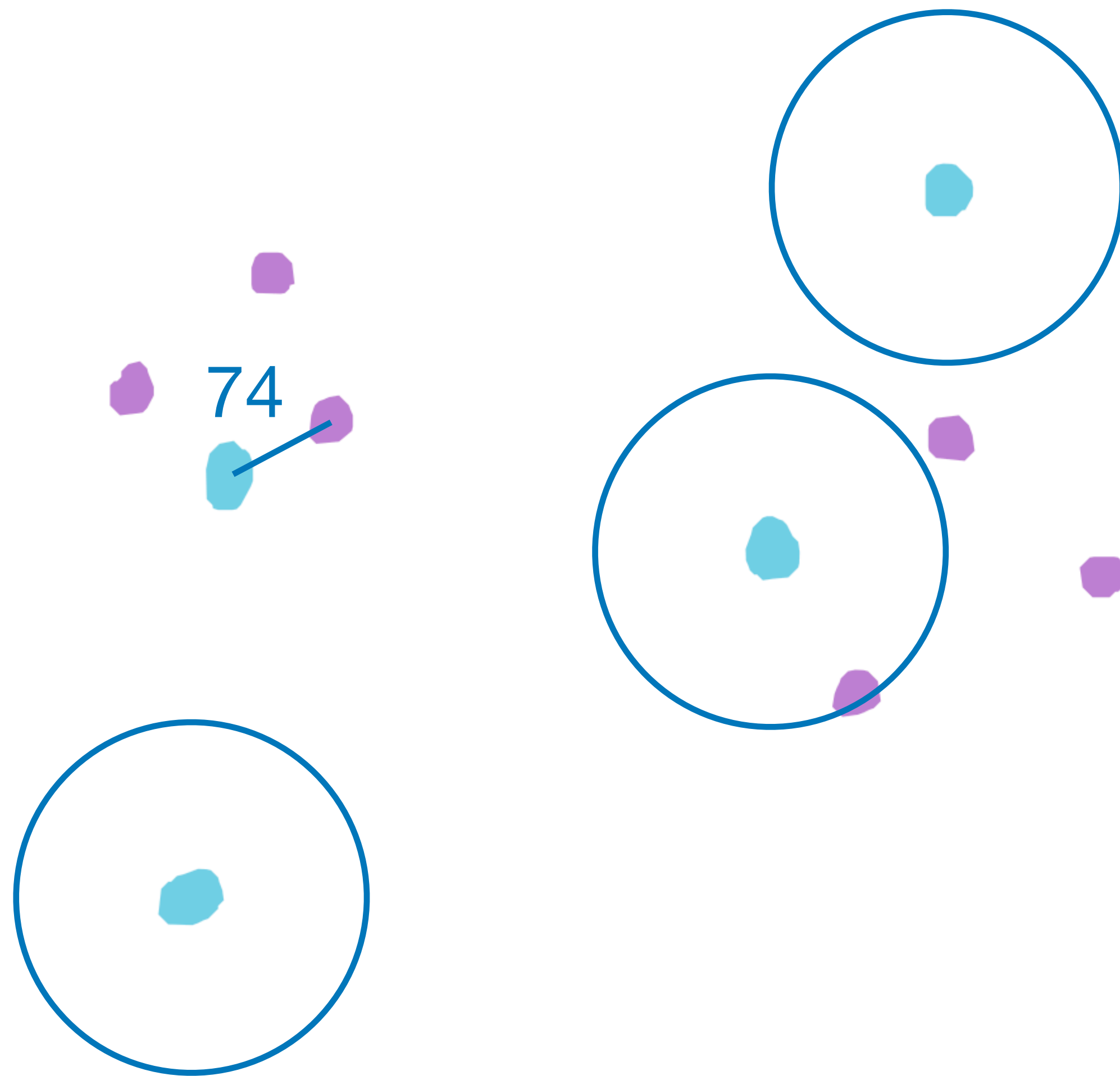
# Nearest neighbor function

$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

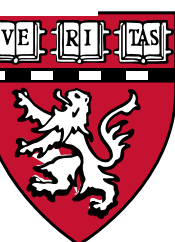
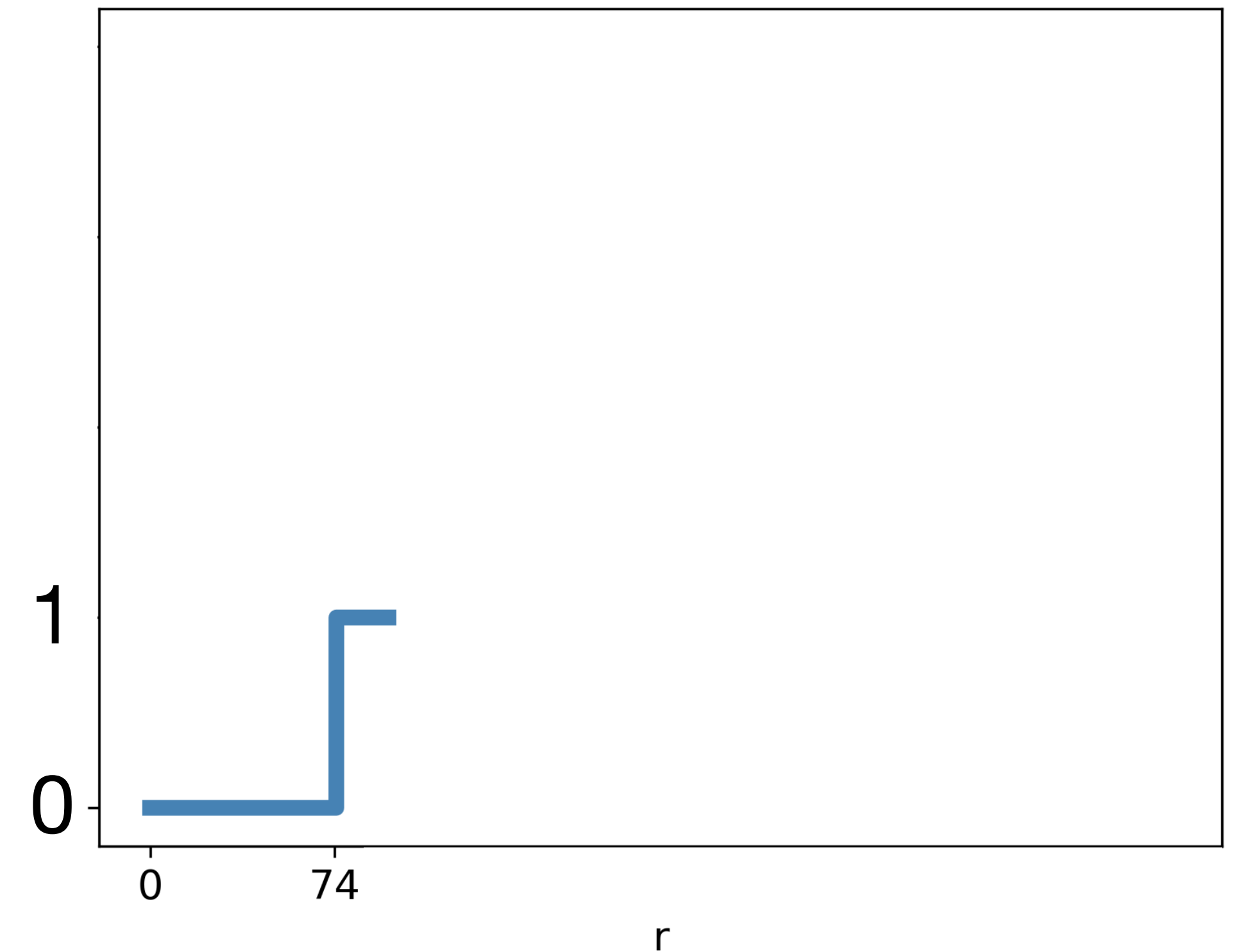




# Nearest neighbor function

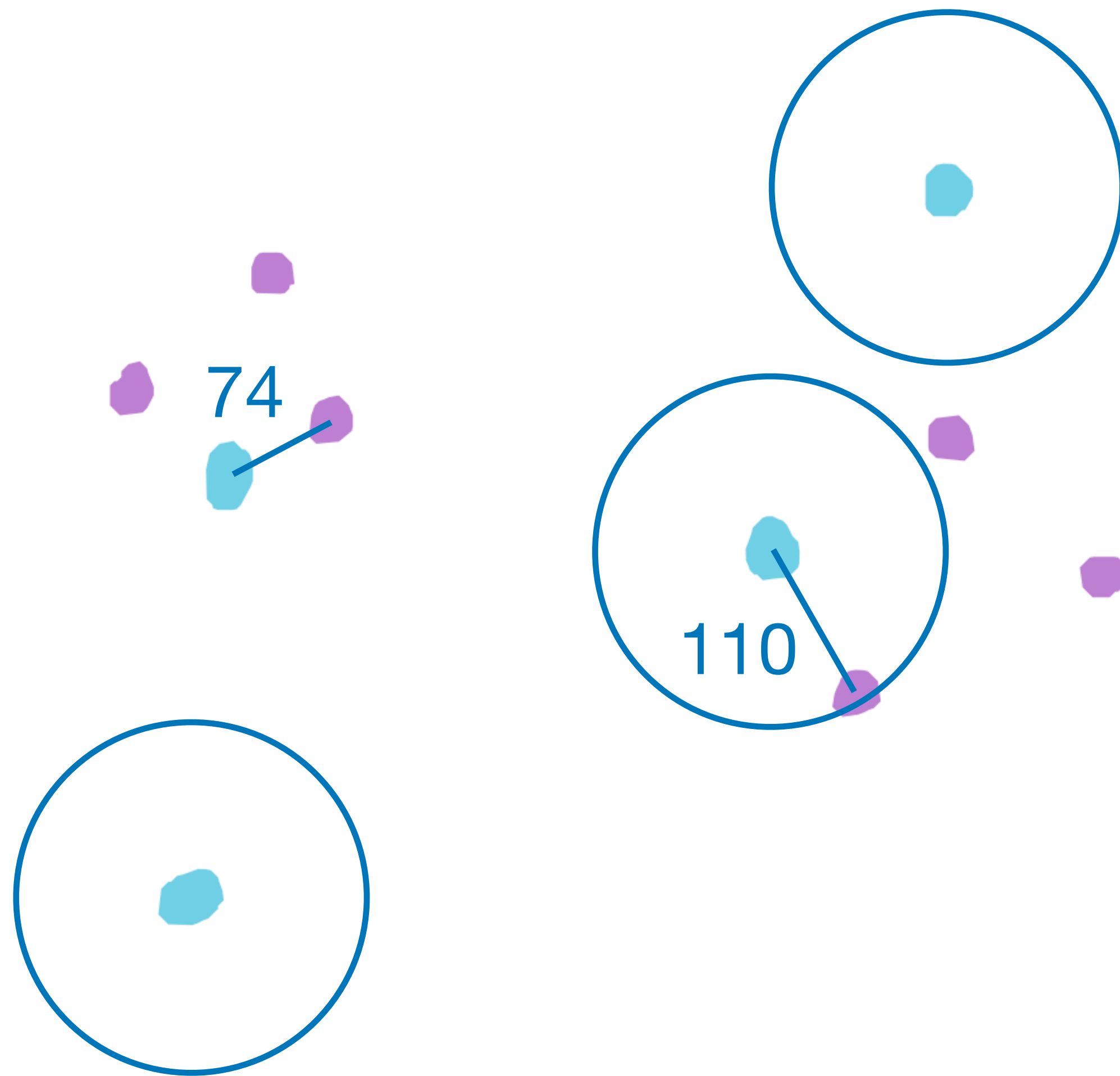


$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

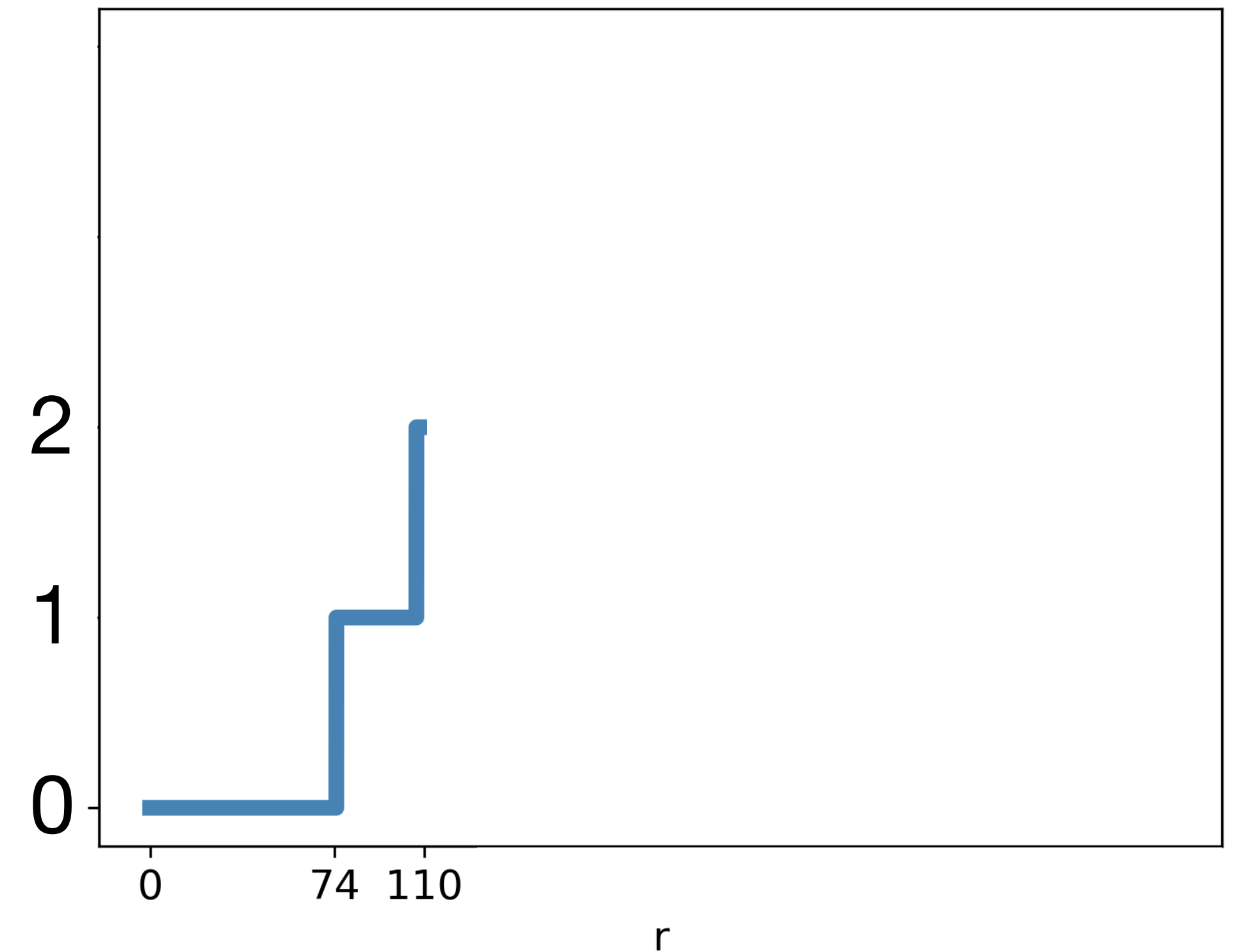




# Nearest neighbor function



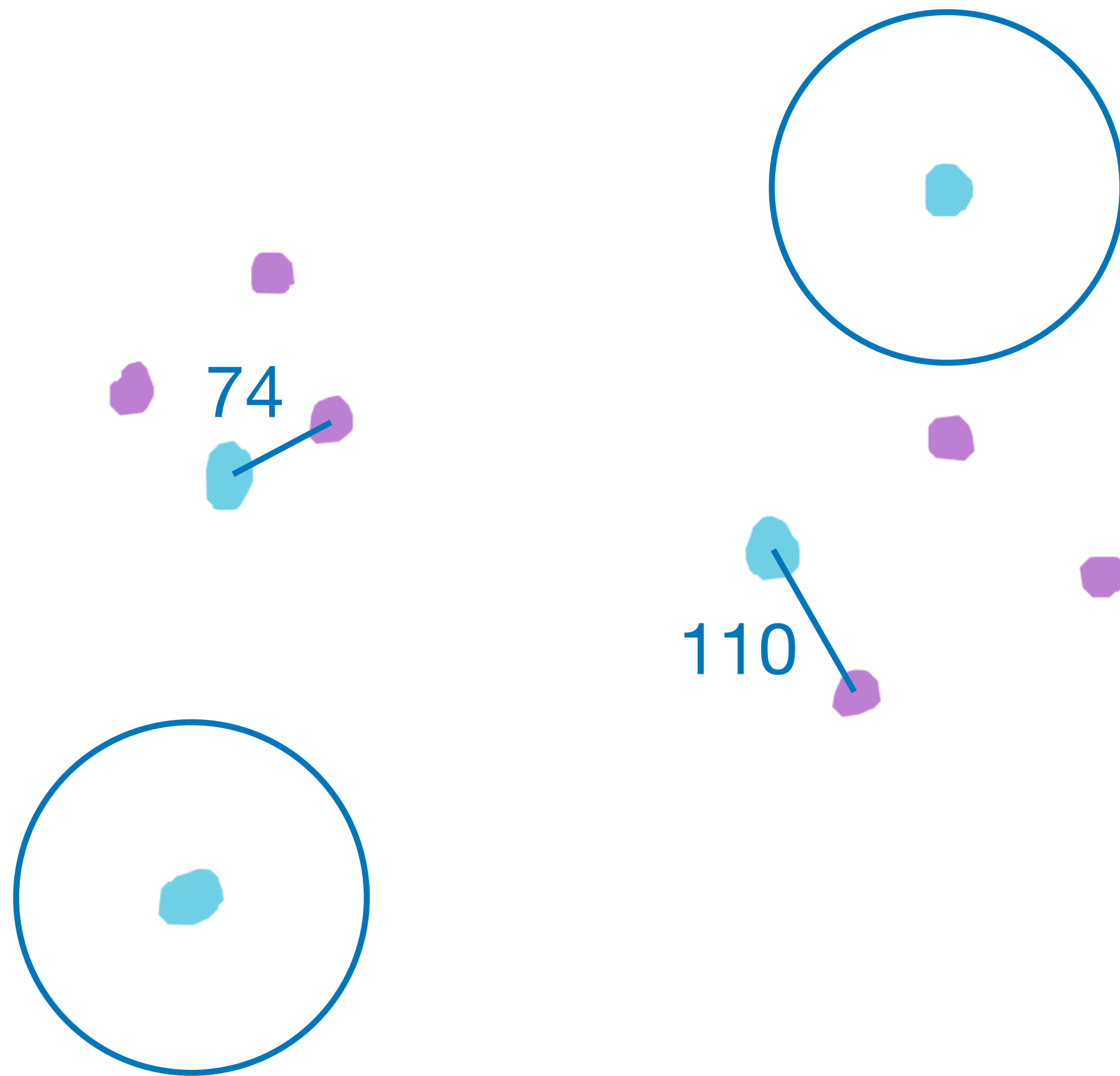
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$



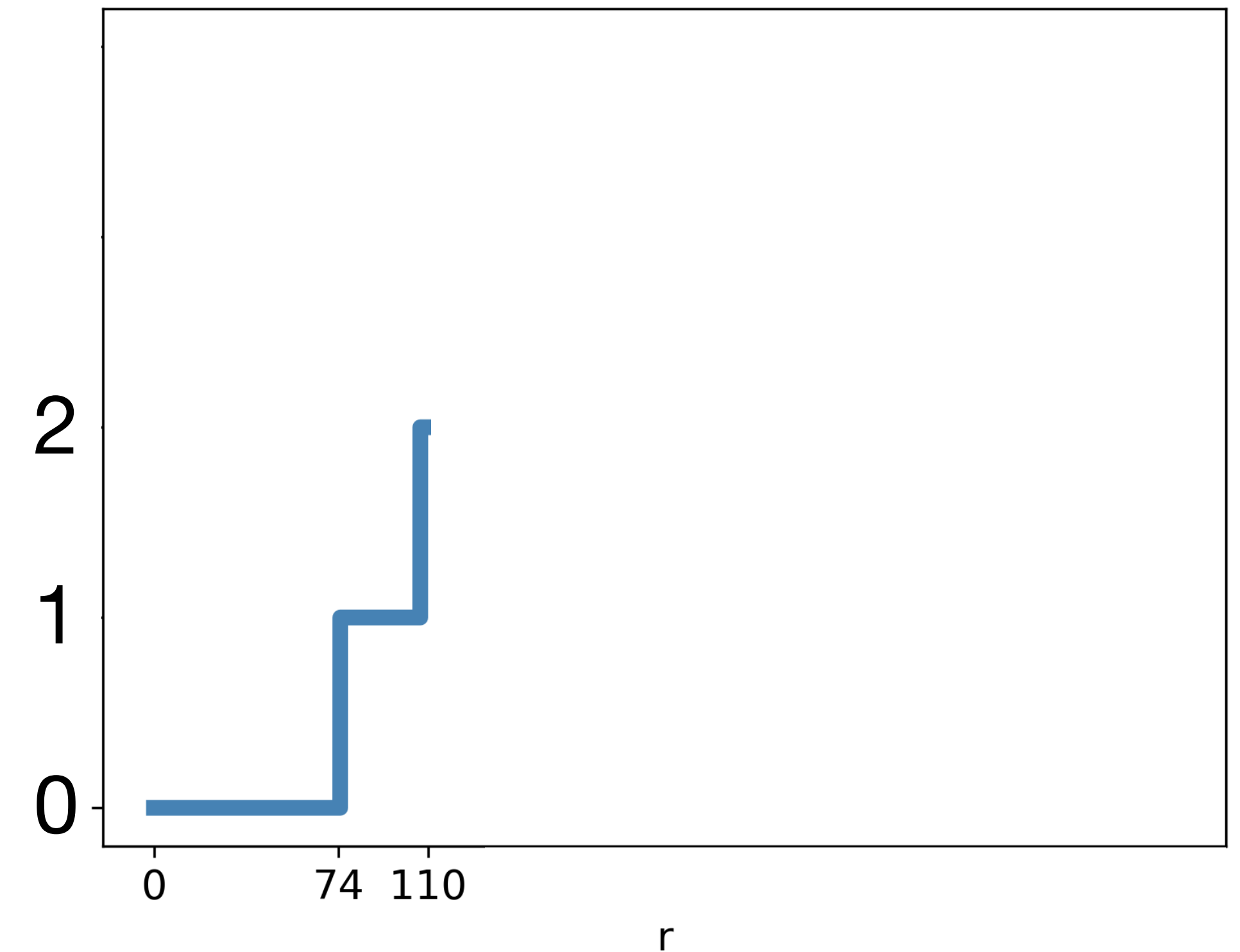




# Nearest neighbor function

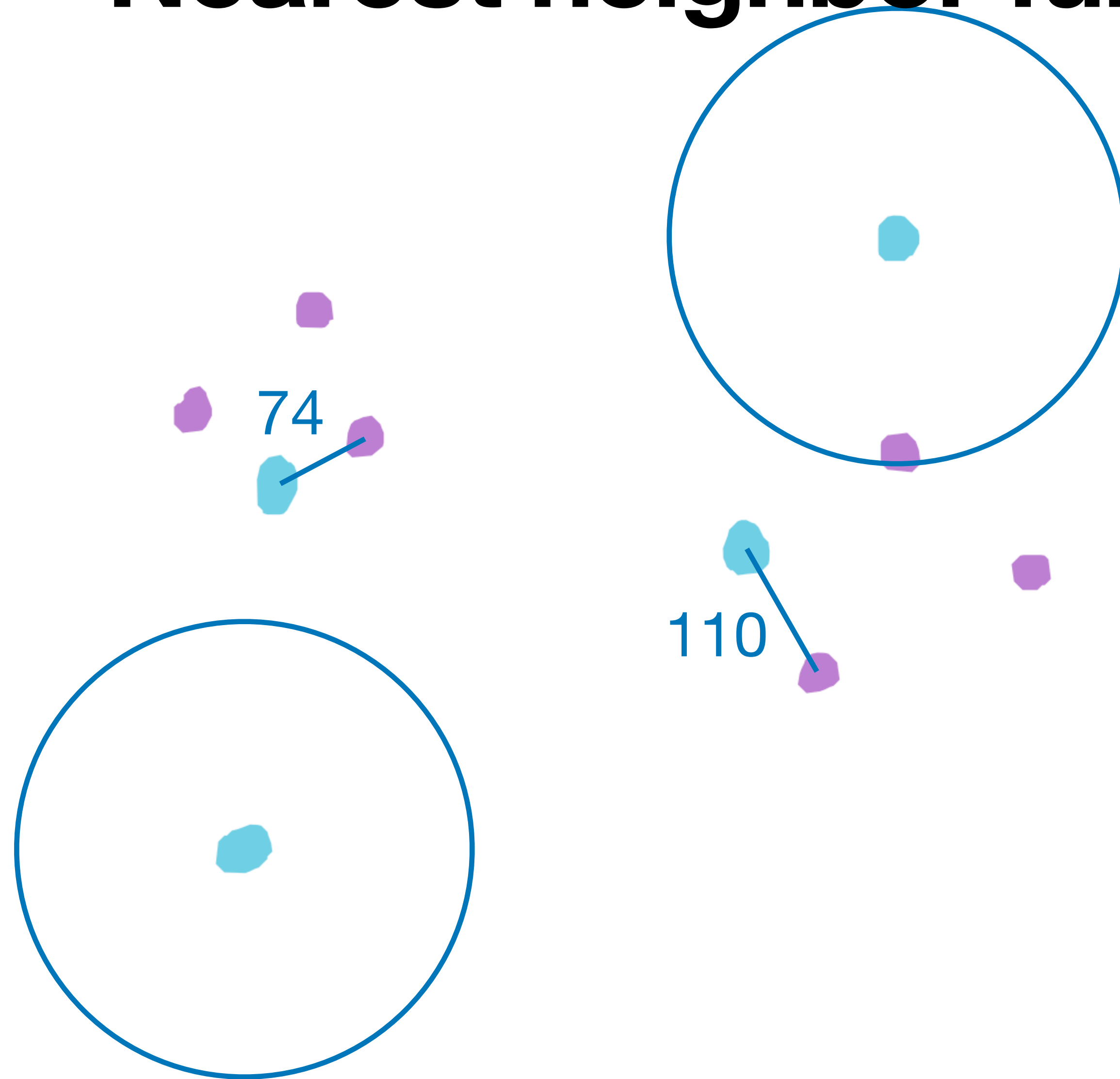


$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

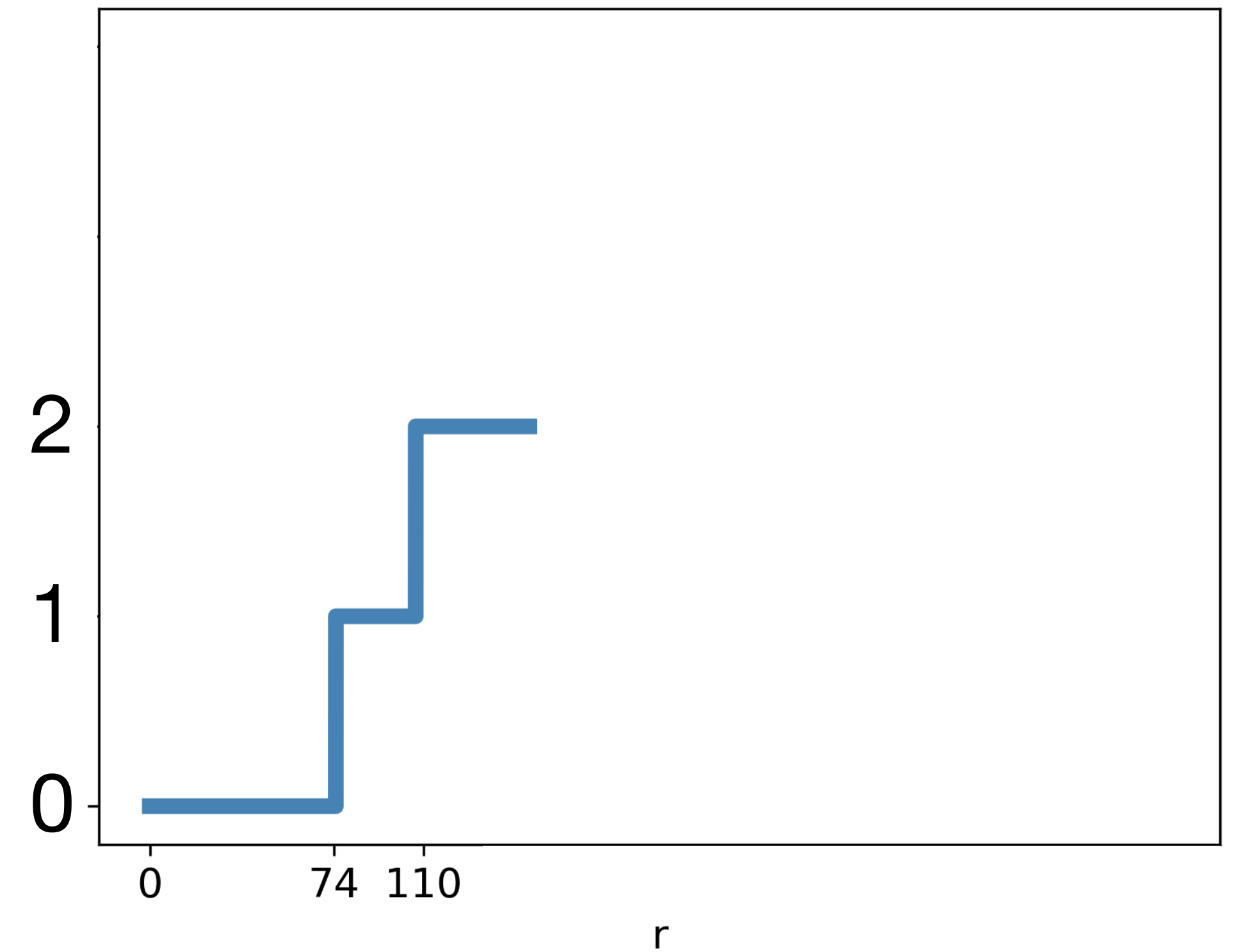




# Nearest neighbor function

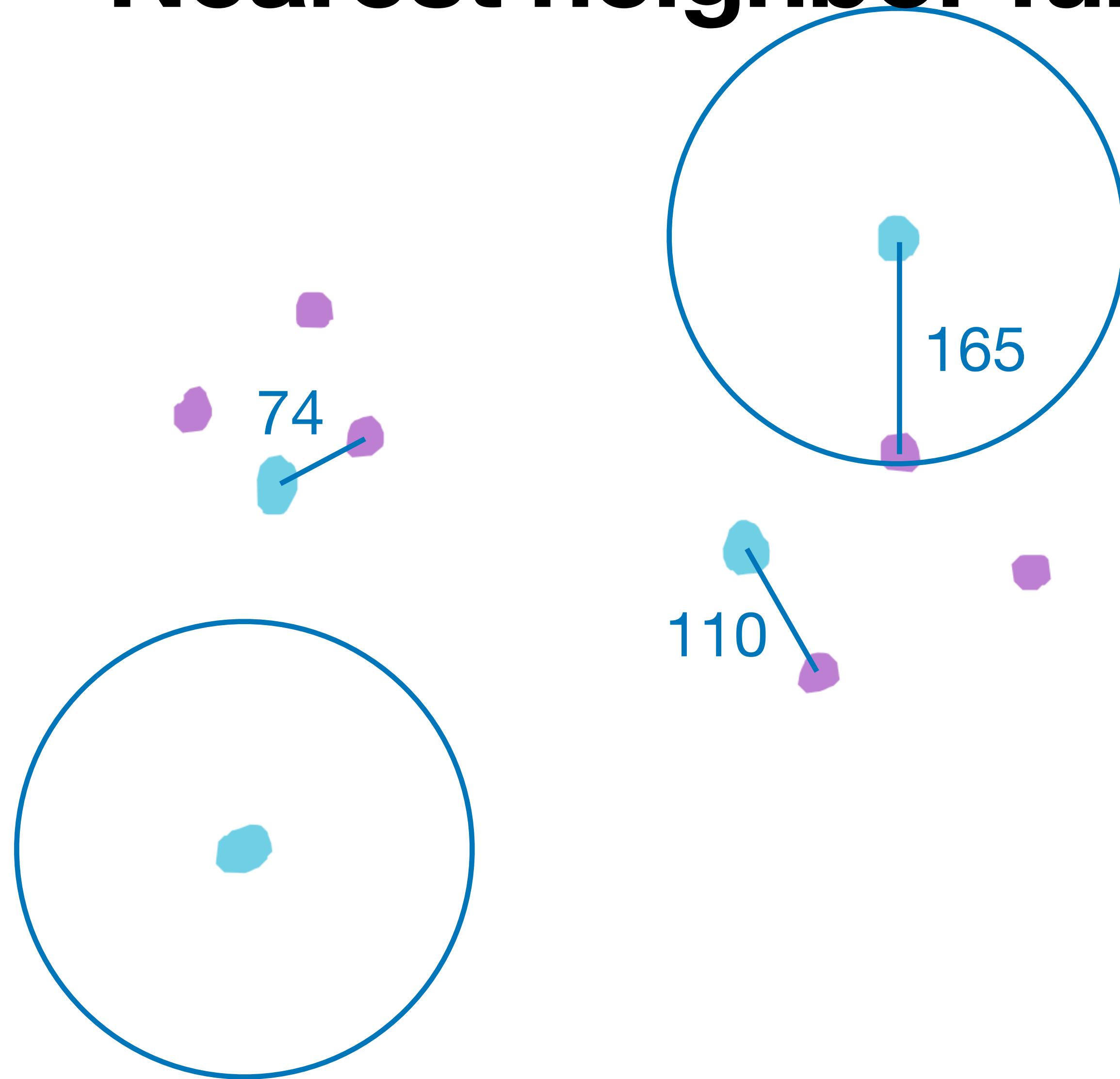


$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

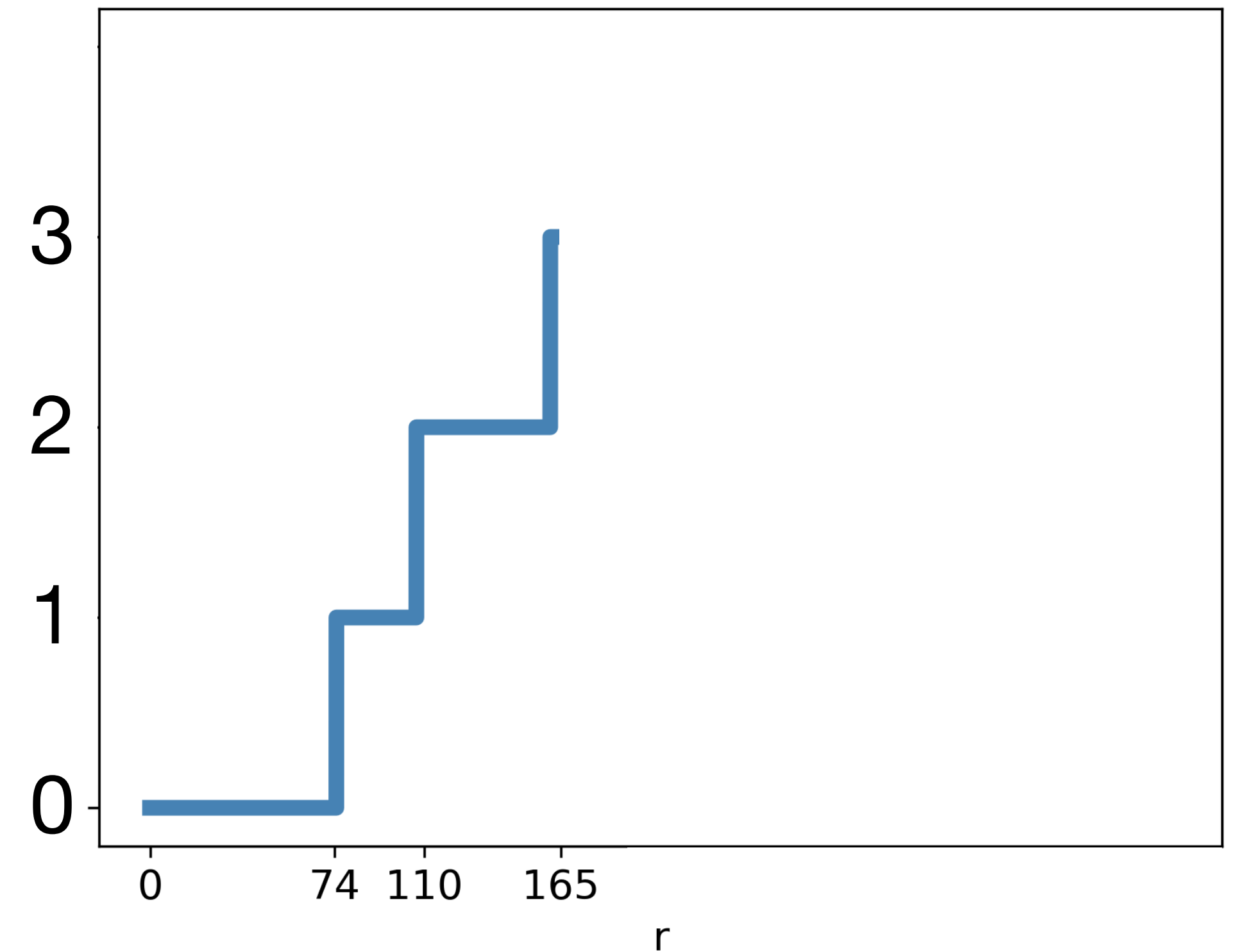




# Nearest neighbor function



$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

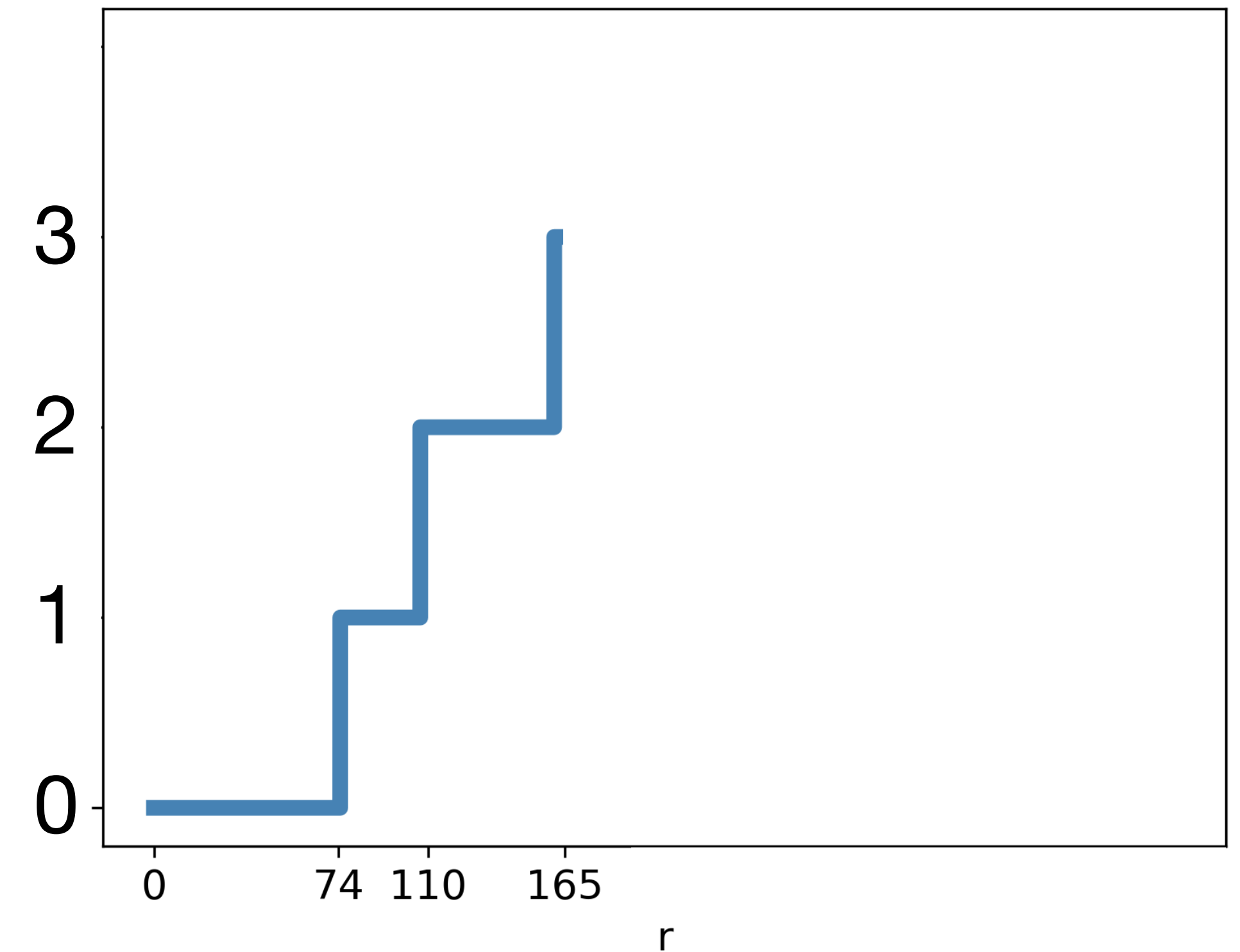
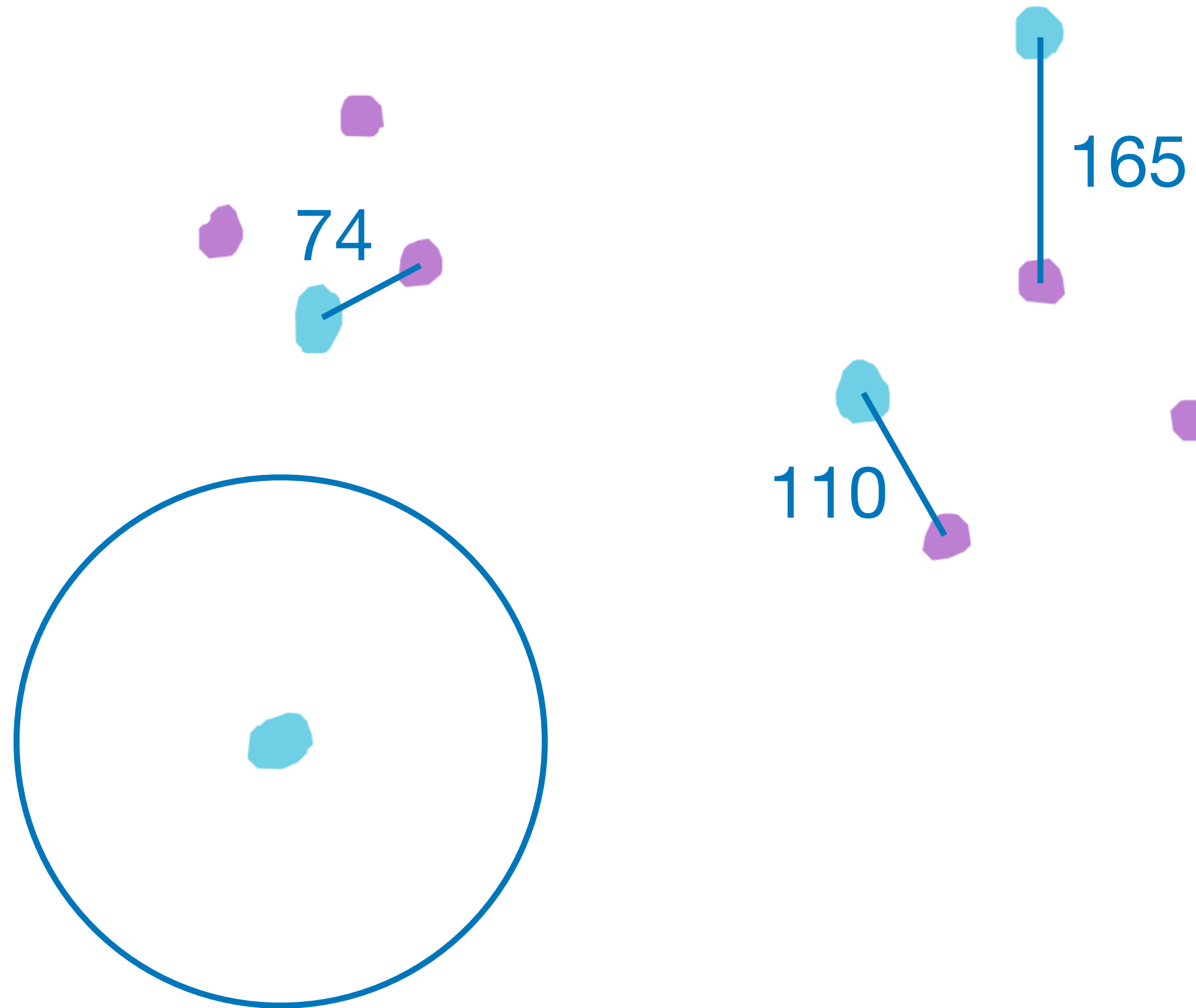






# Nearest neighbor function

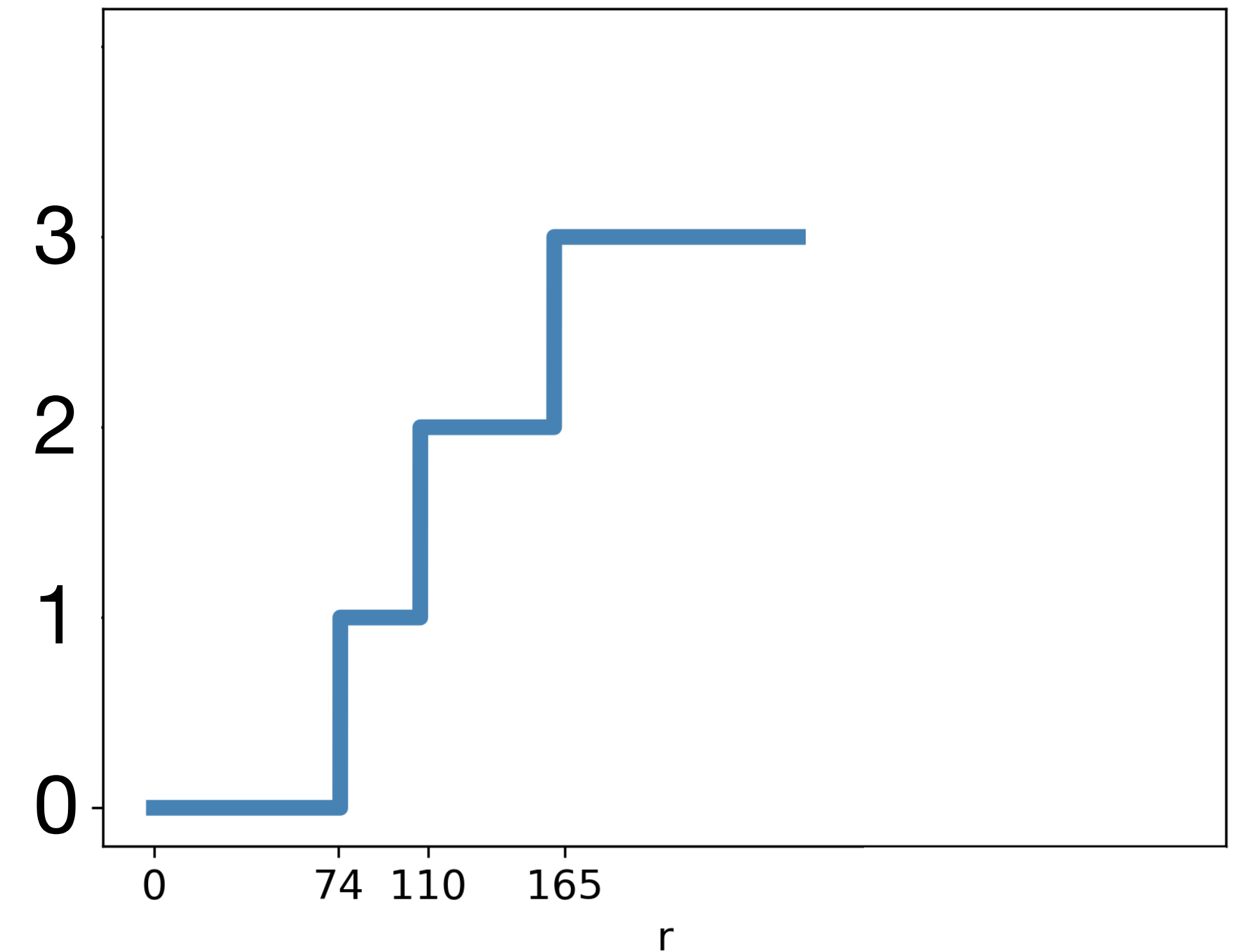
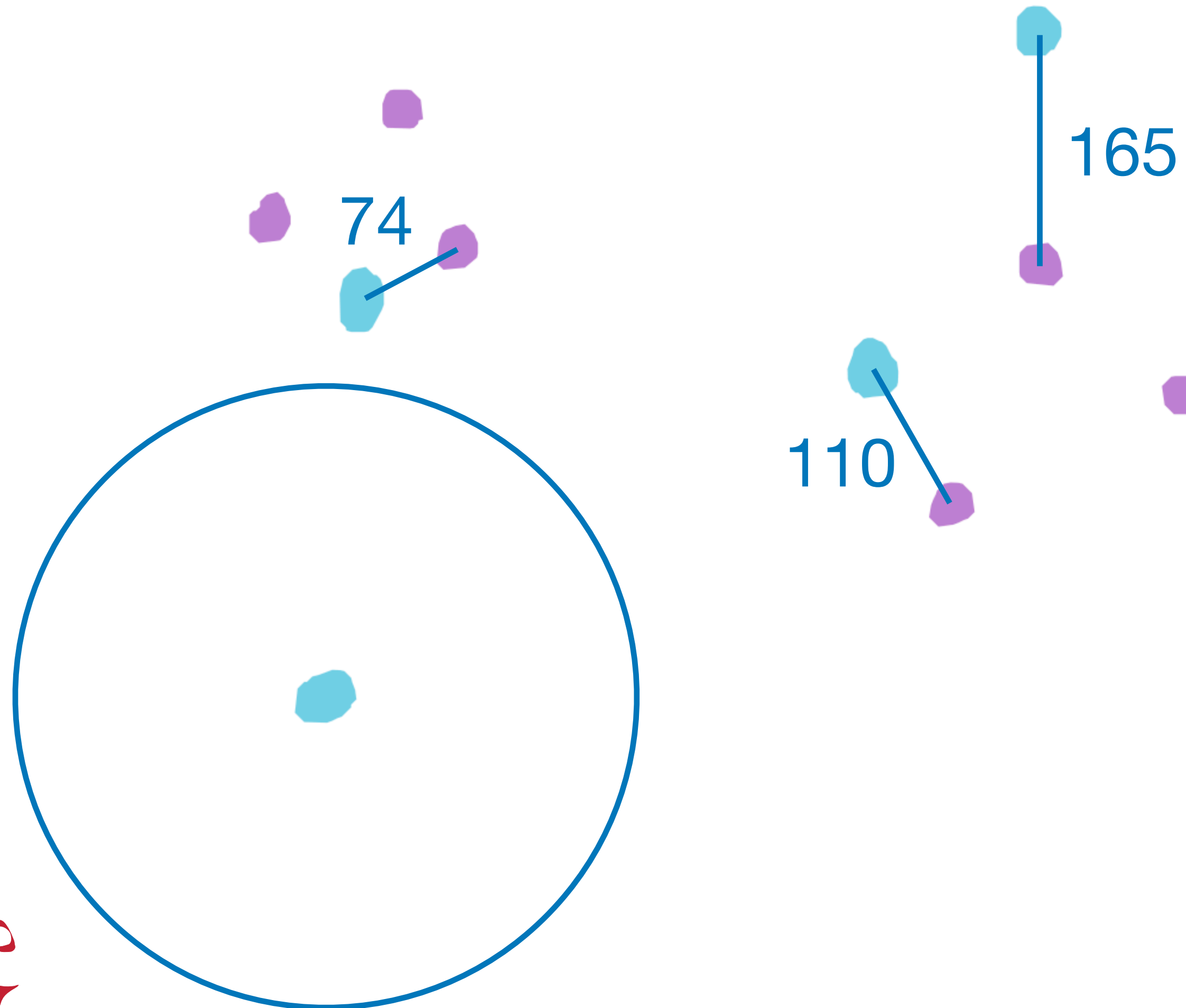
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





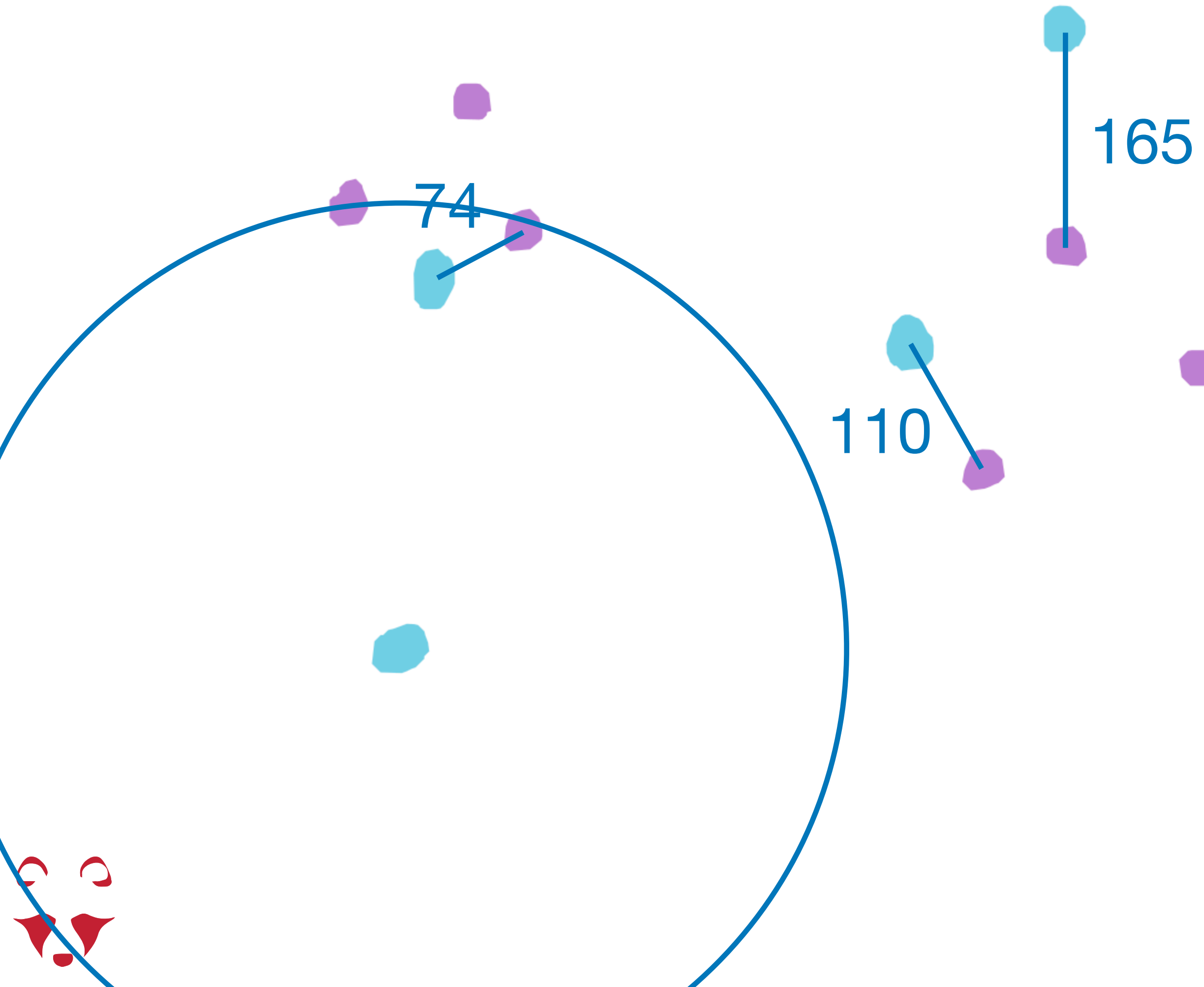
# Nearest neighbor function

$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

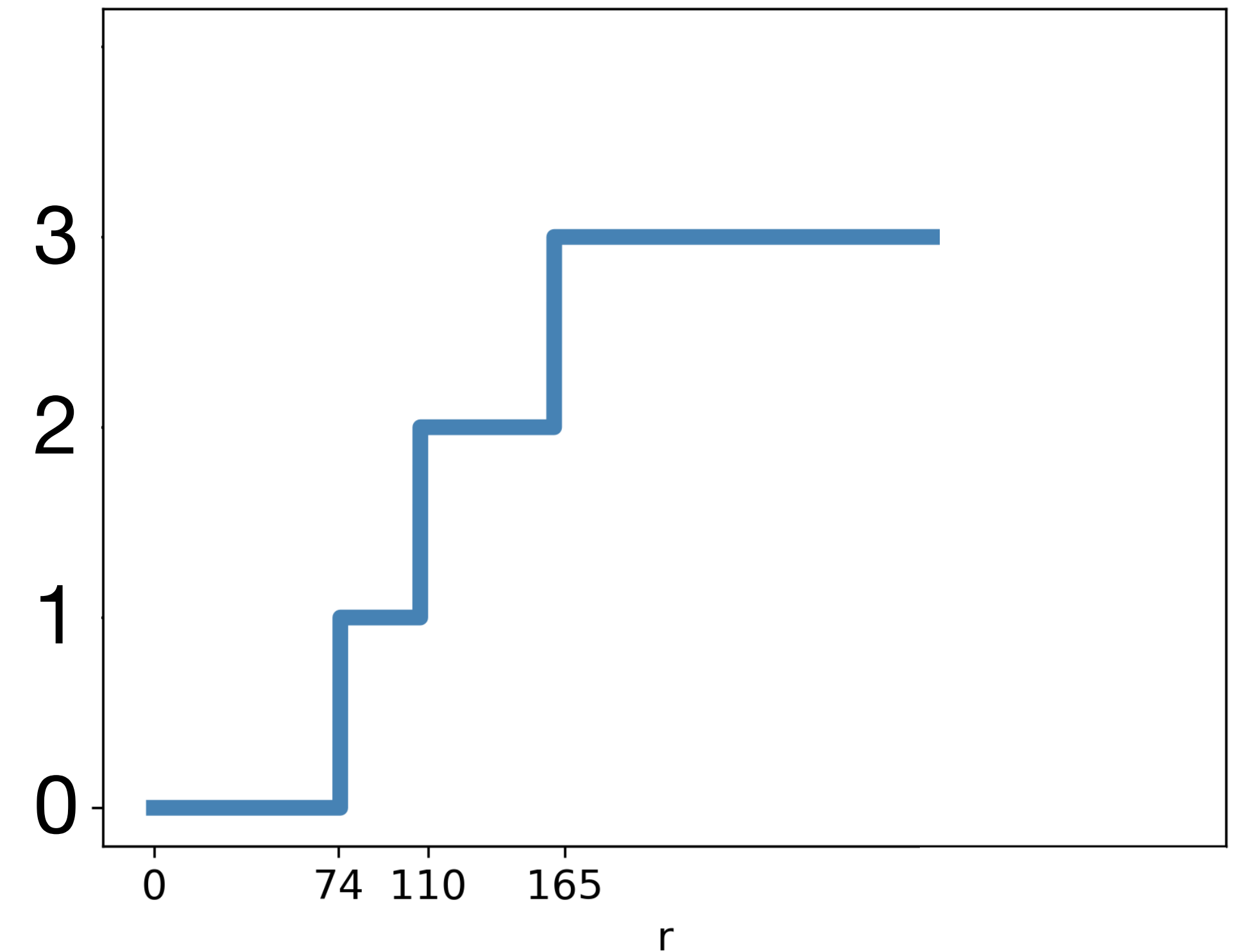




# Nearest neighbor function



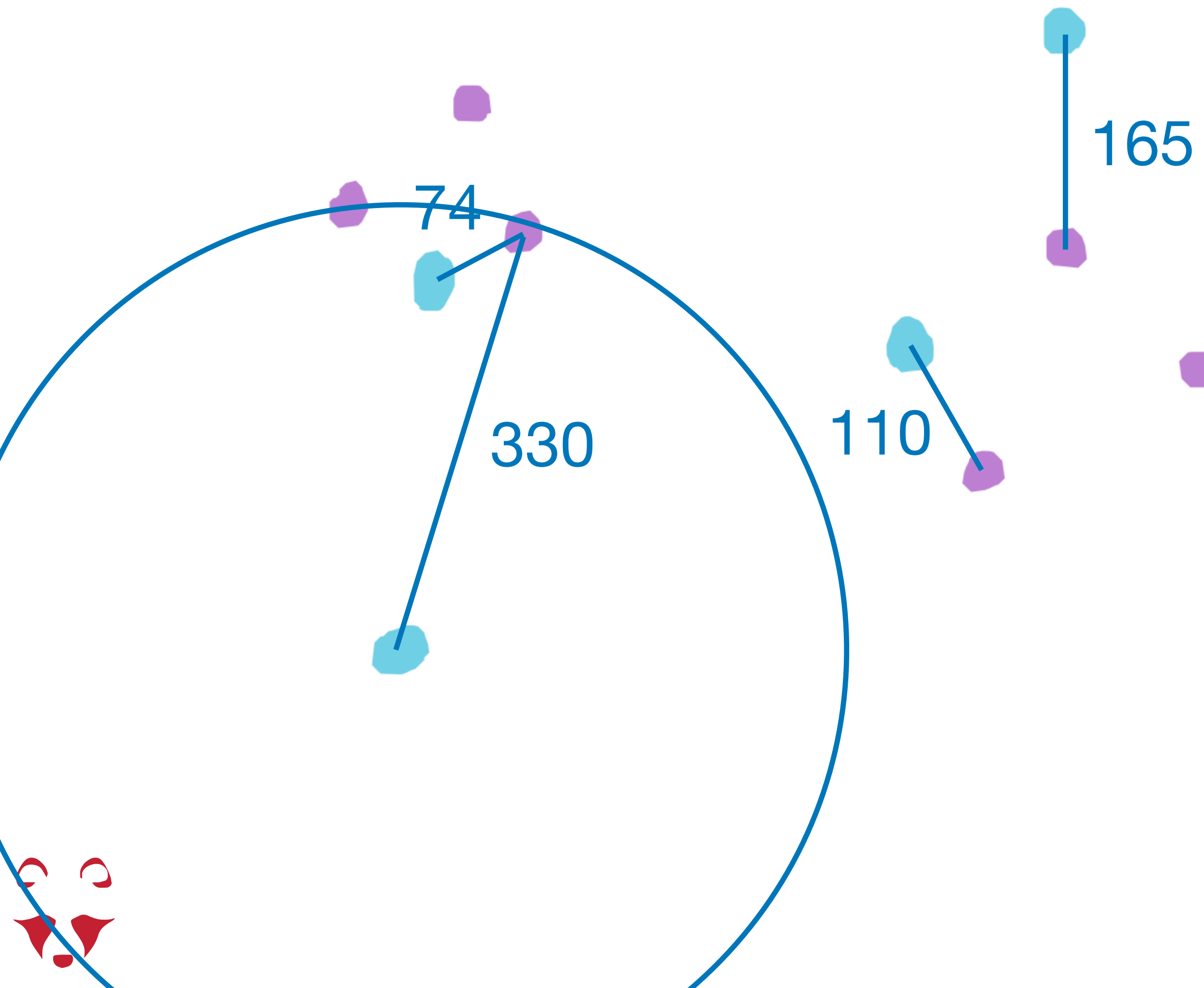
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$



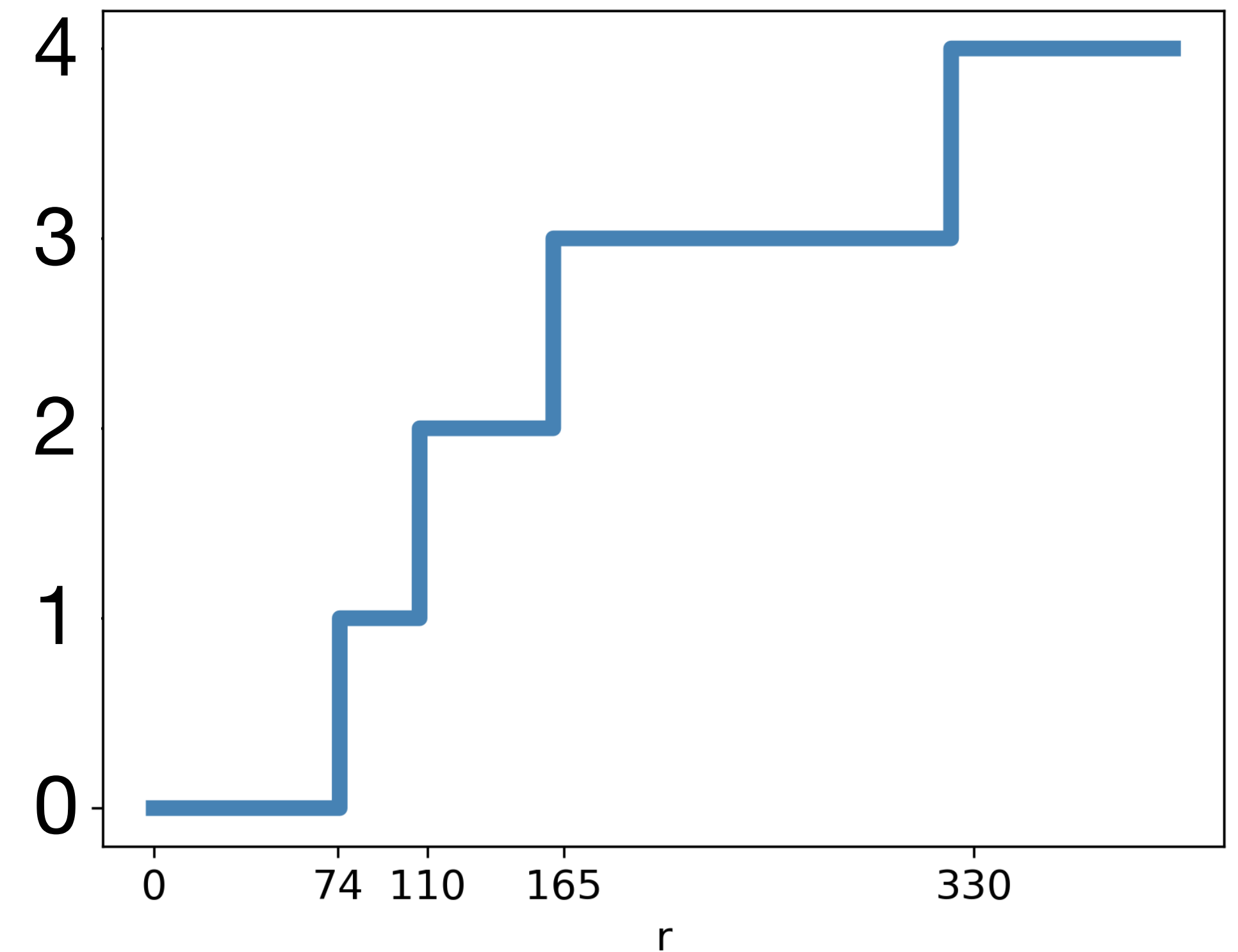




# Nearest neighbor function

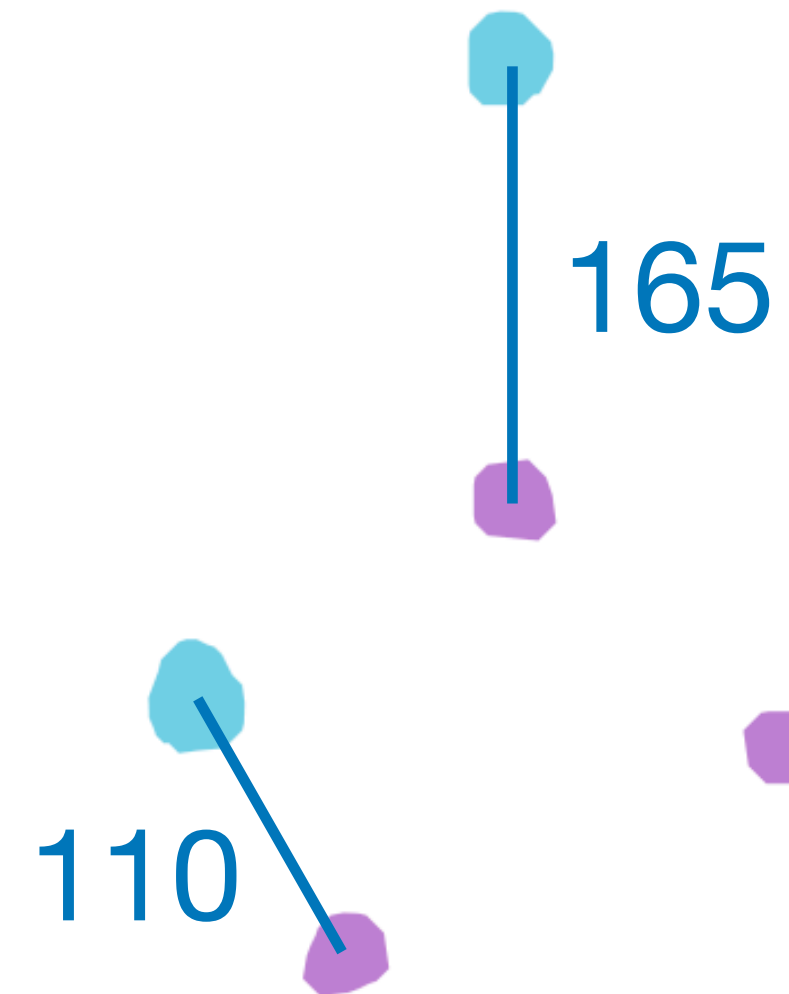
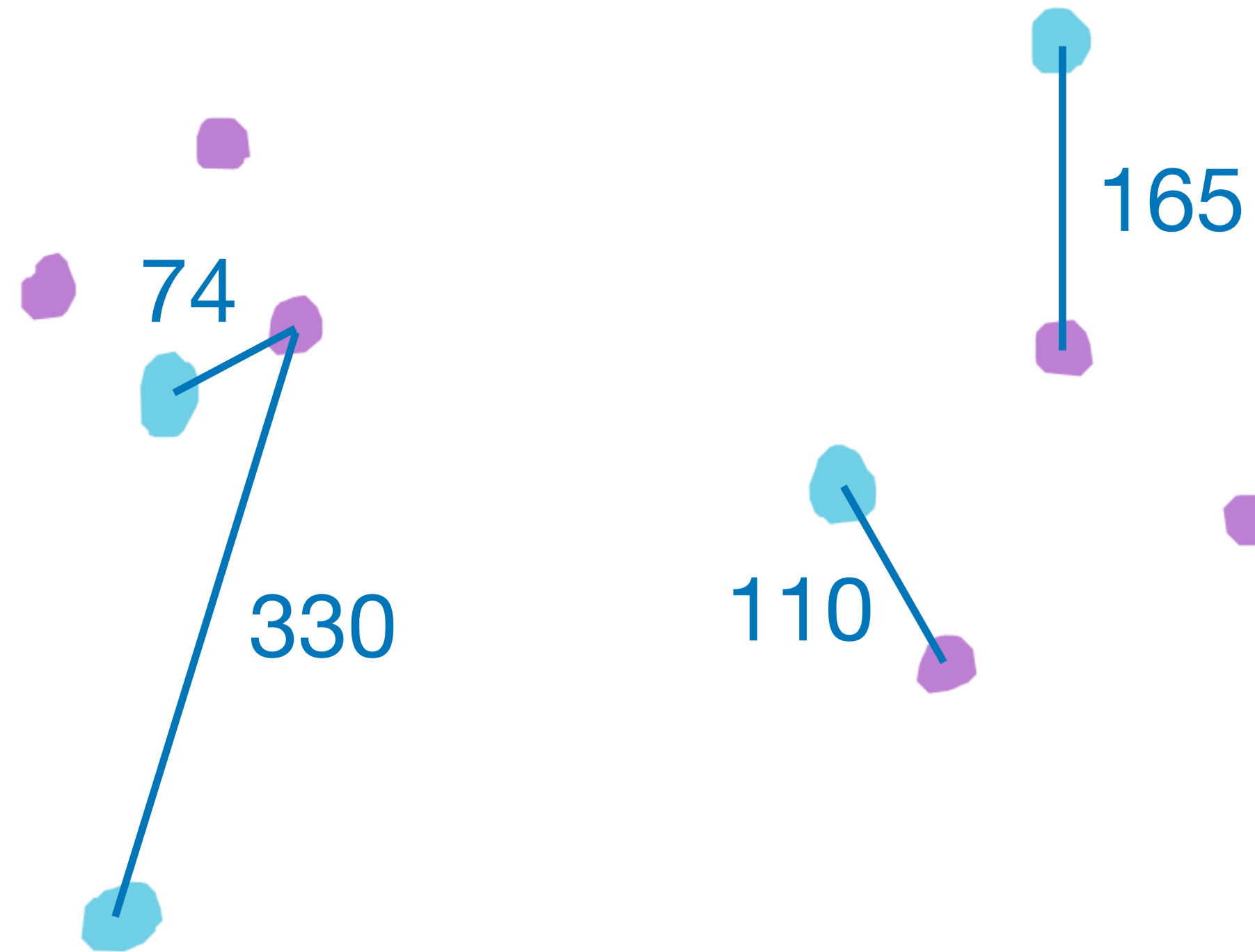


$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

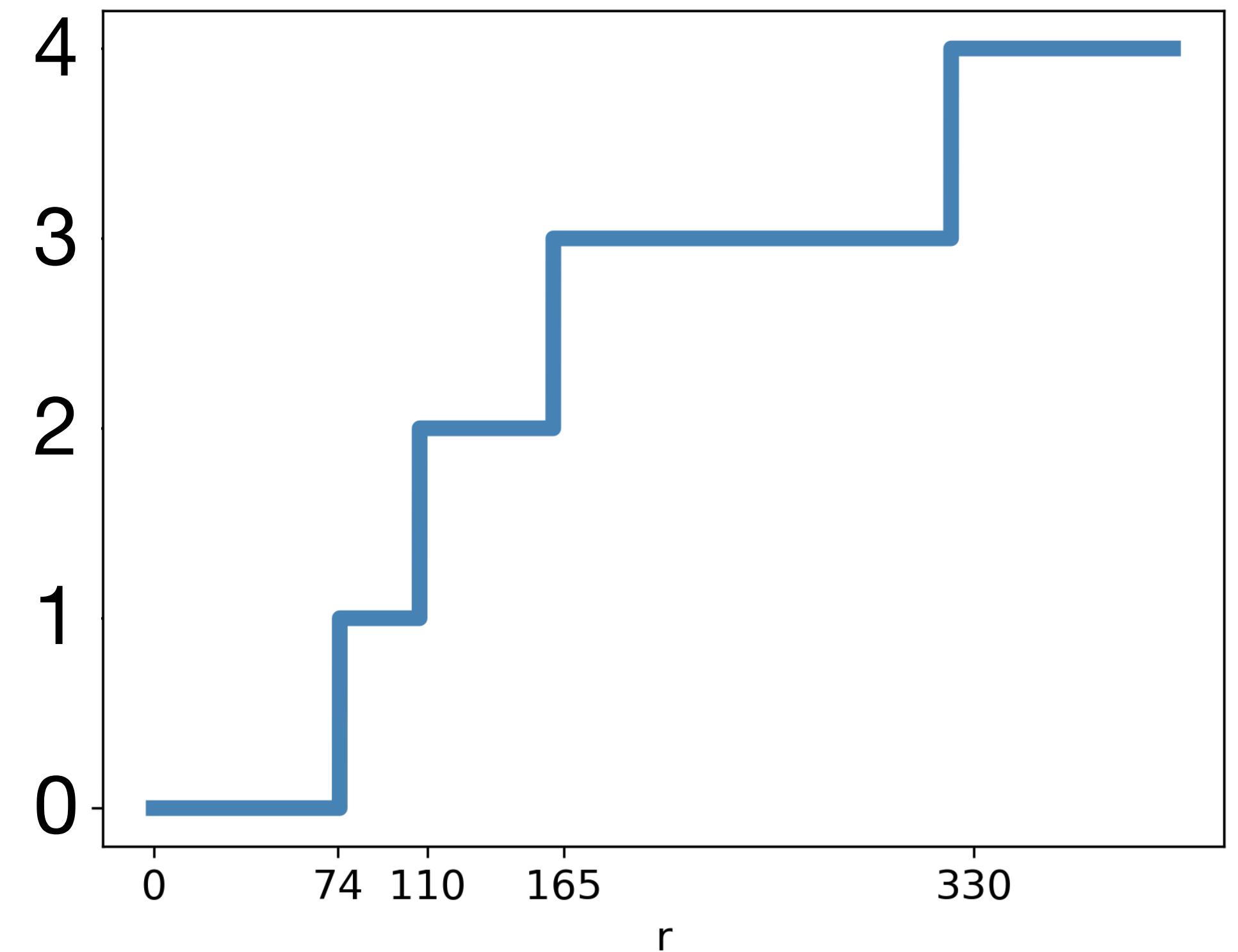




# Nearest neighbor function



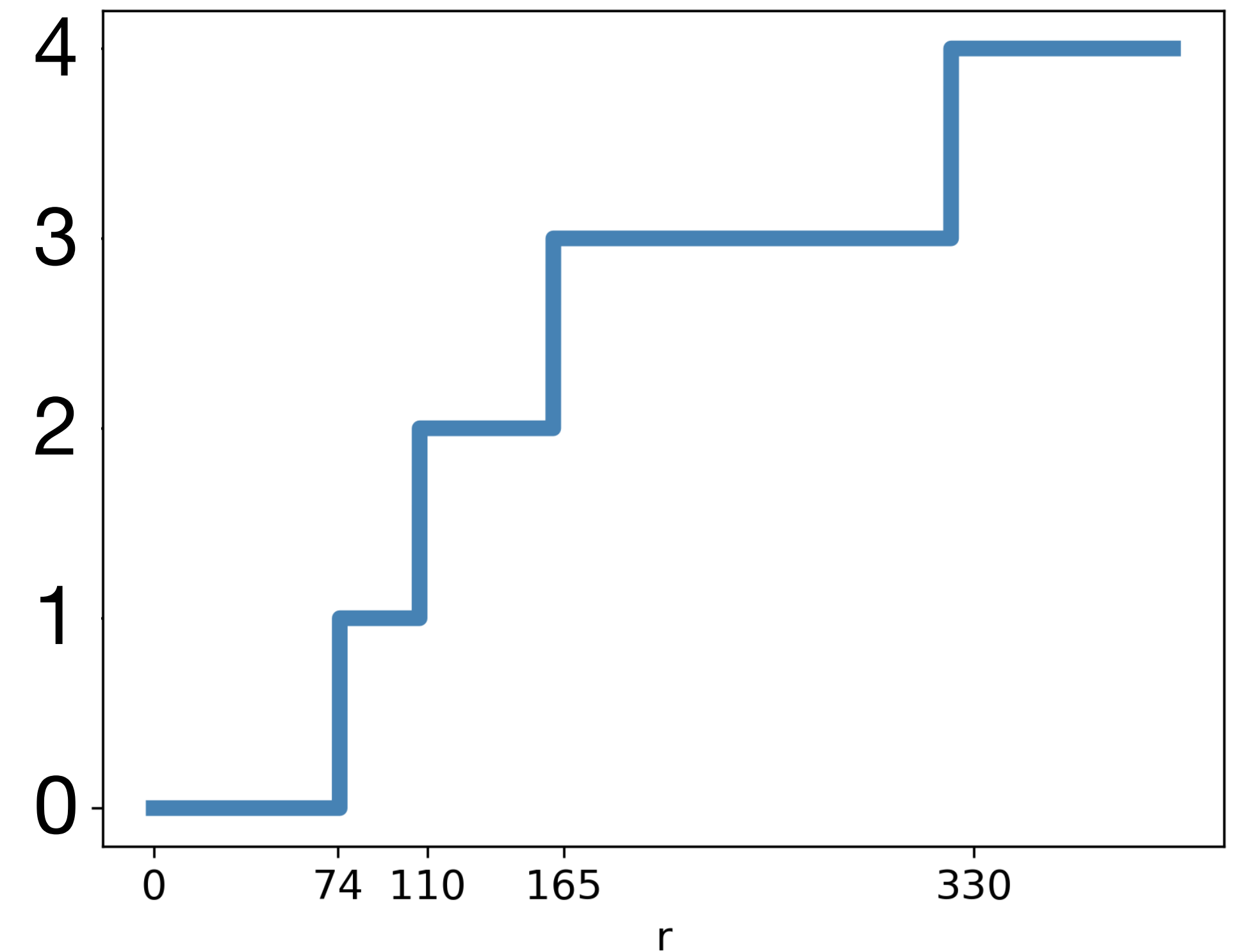
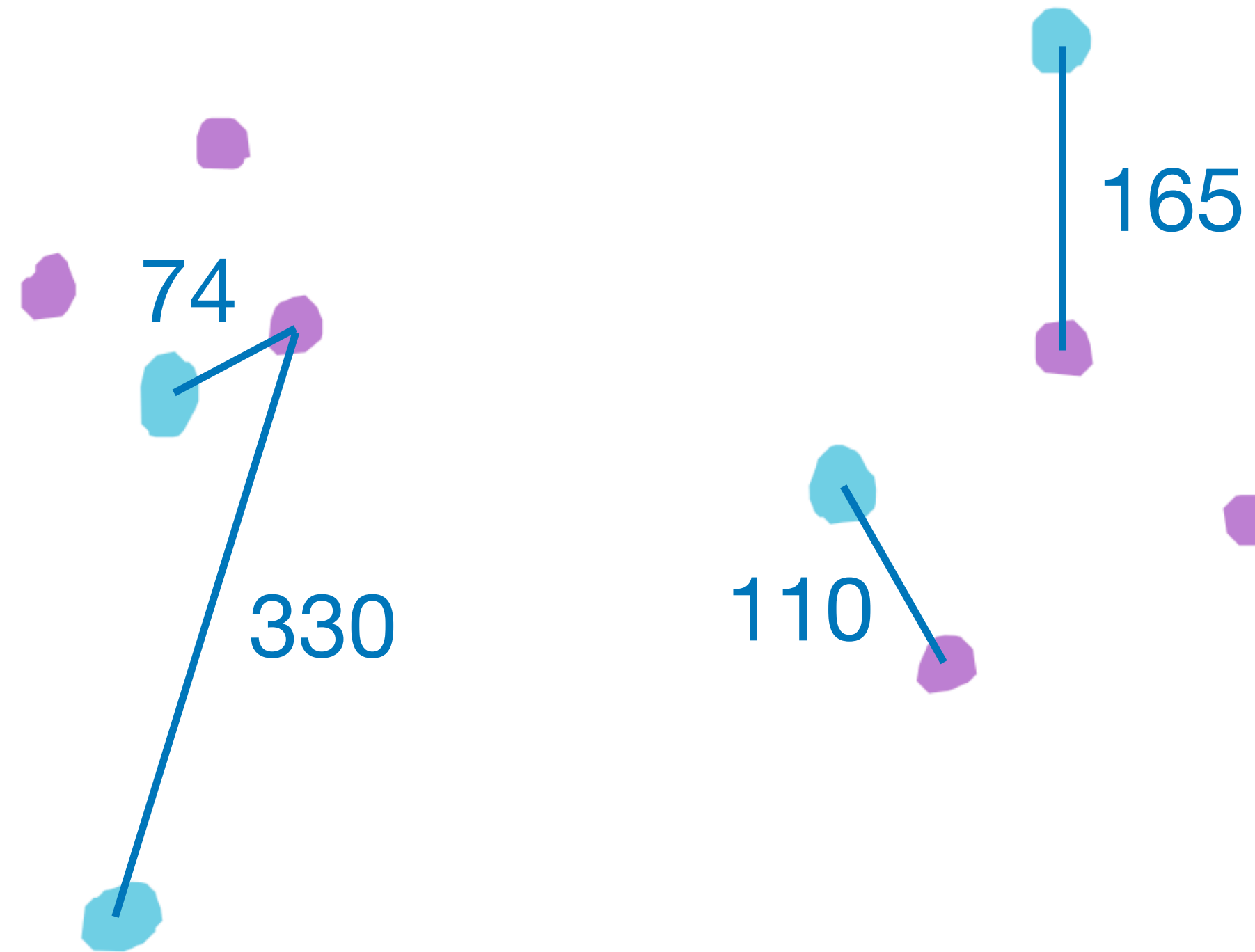
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





# Nearest neighbor function

$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$

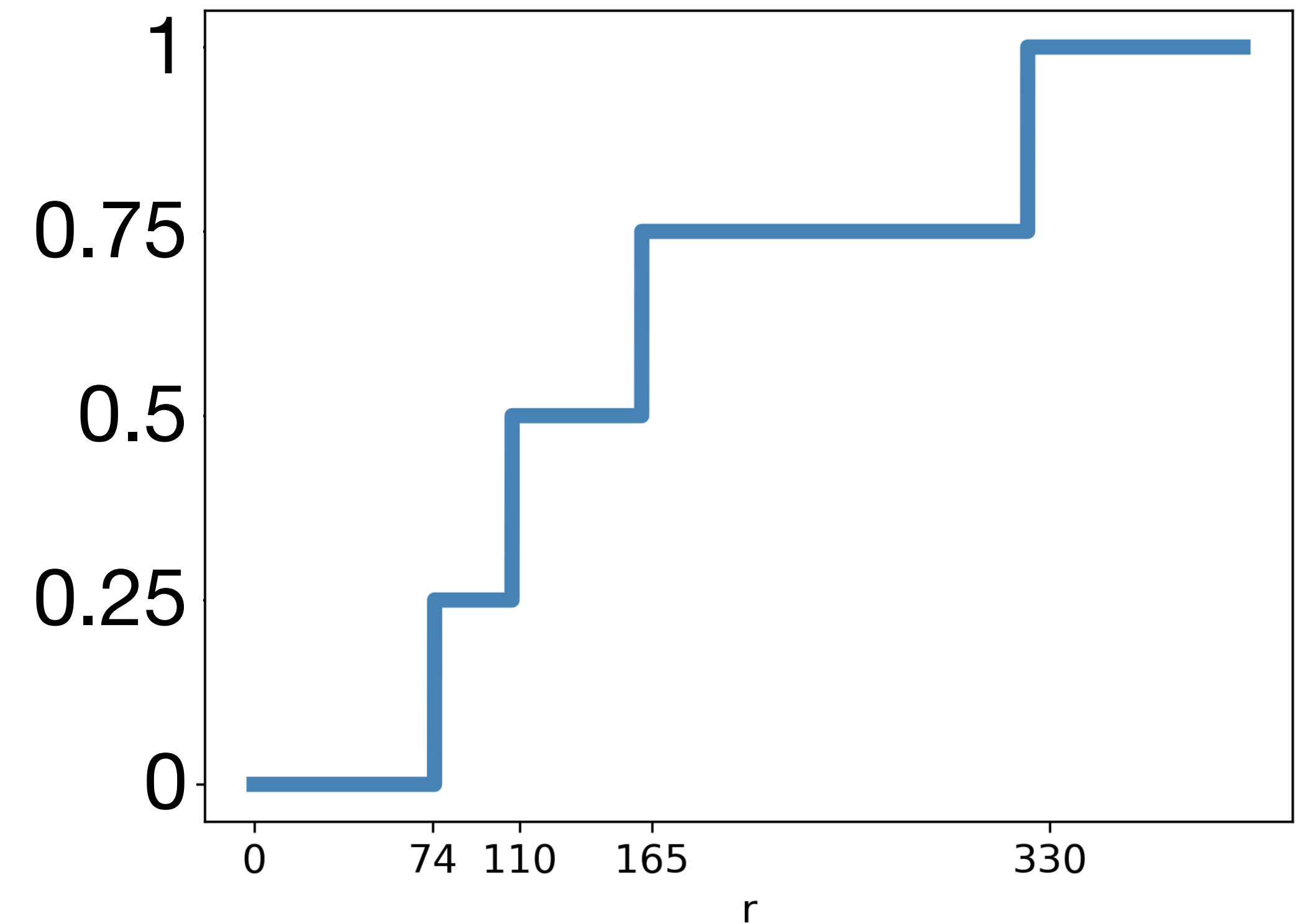
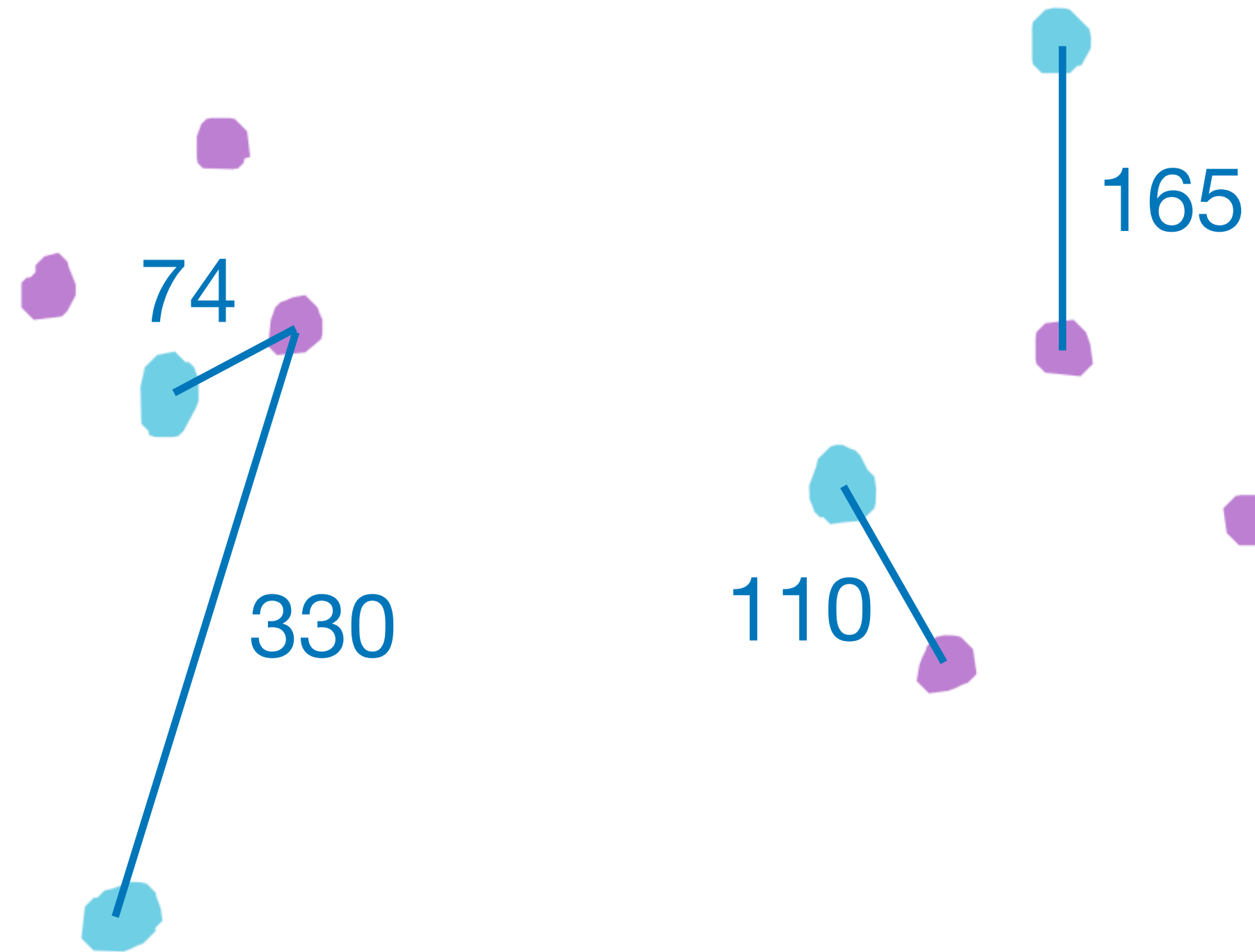






# Nearest neighbor function

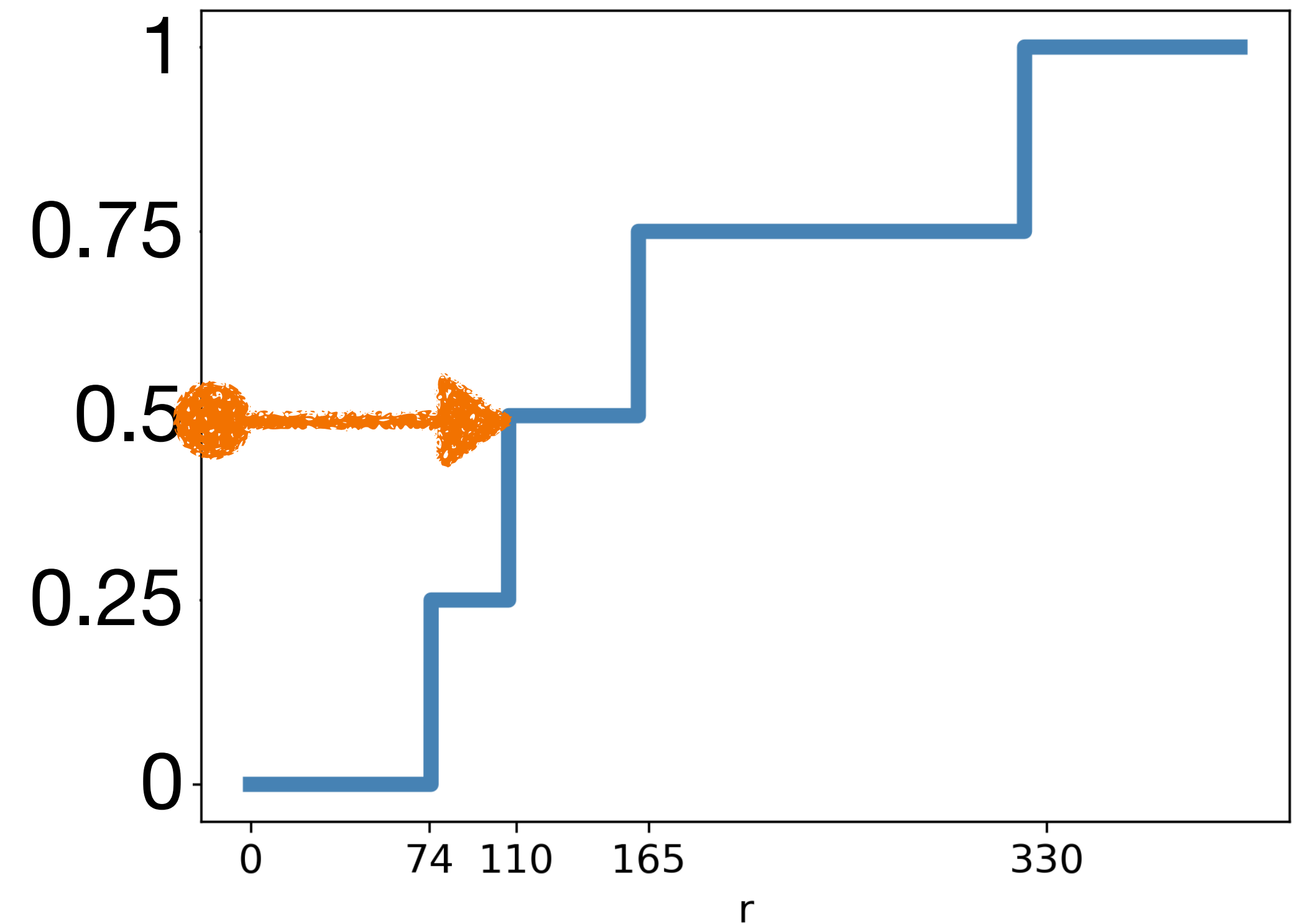
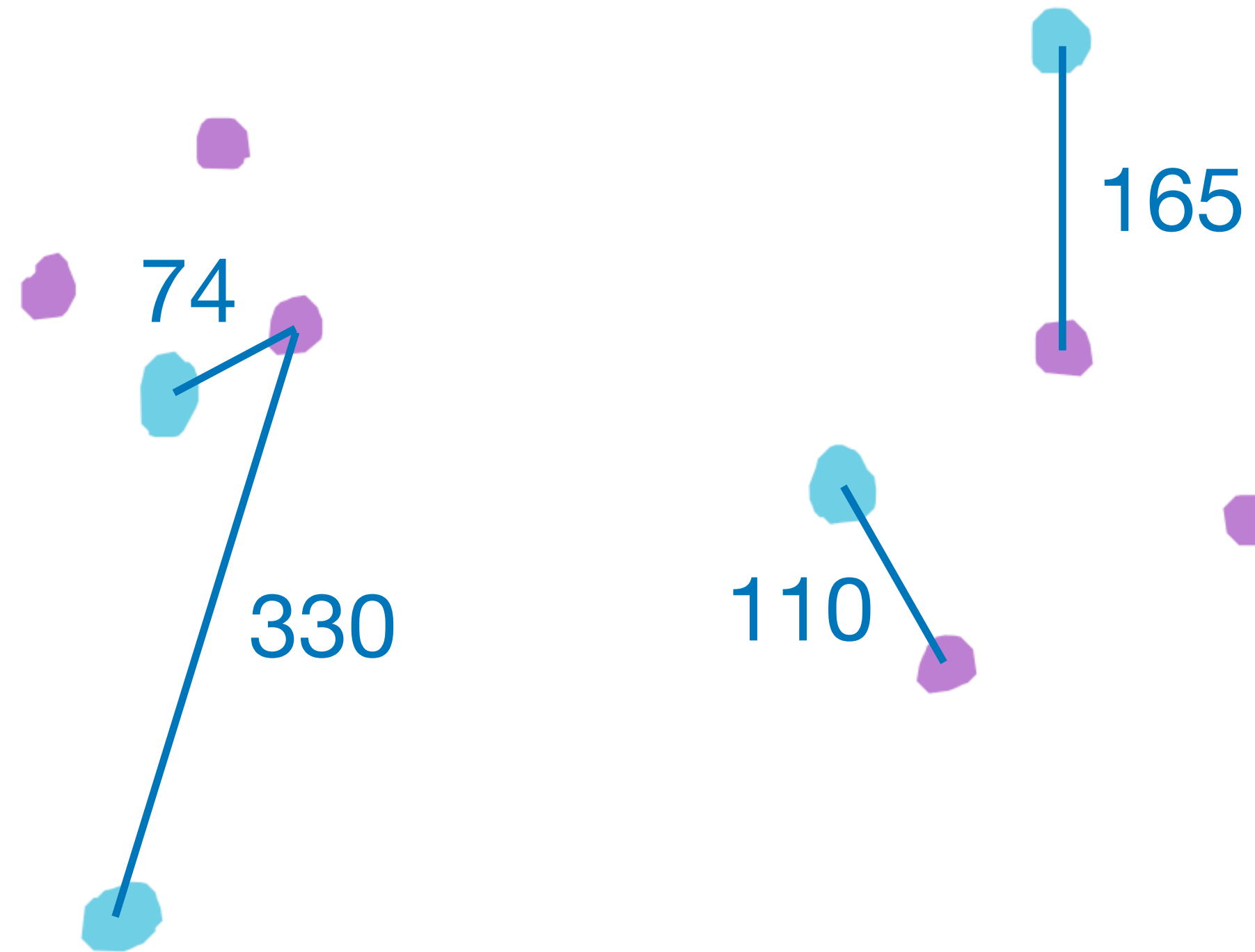
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





# Nearest neighbor function

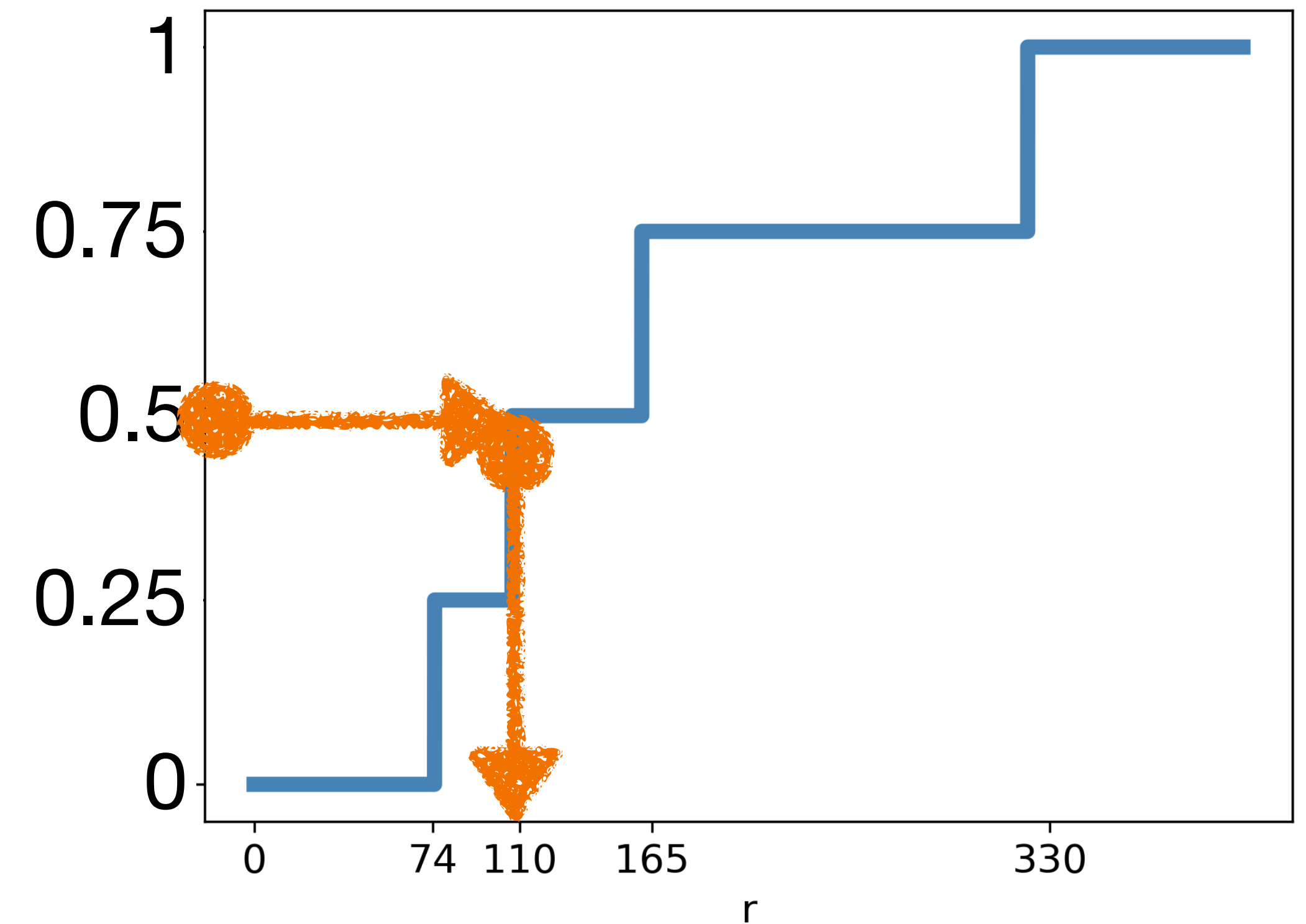
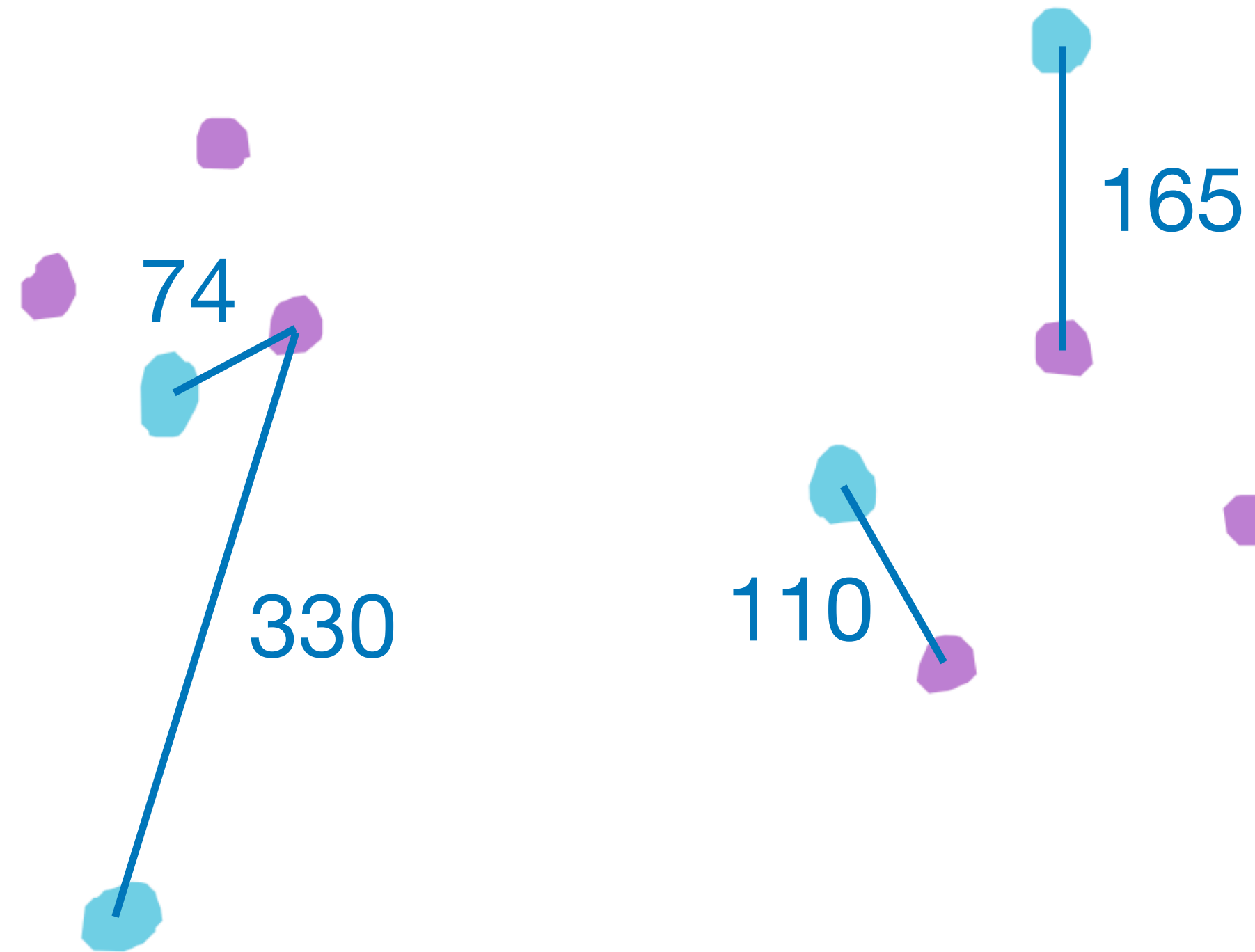
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





# Nearest neighbor function

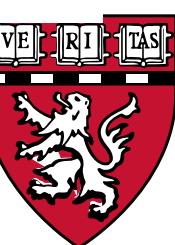
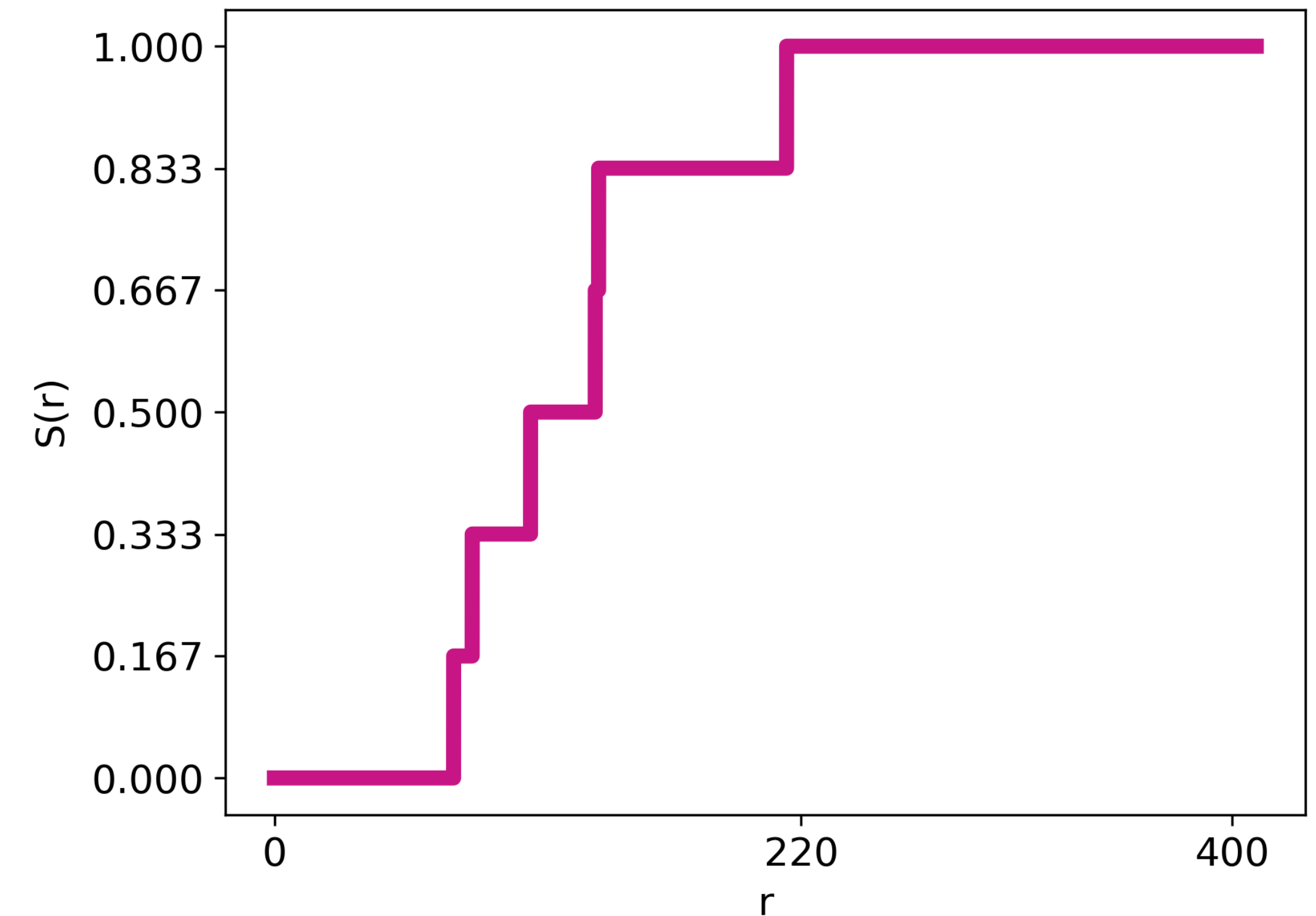
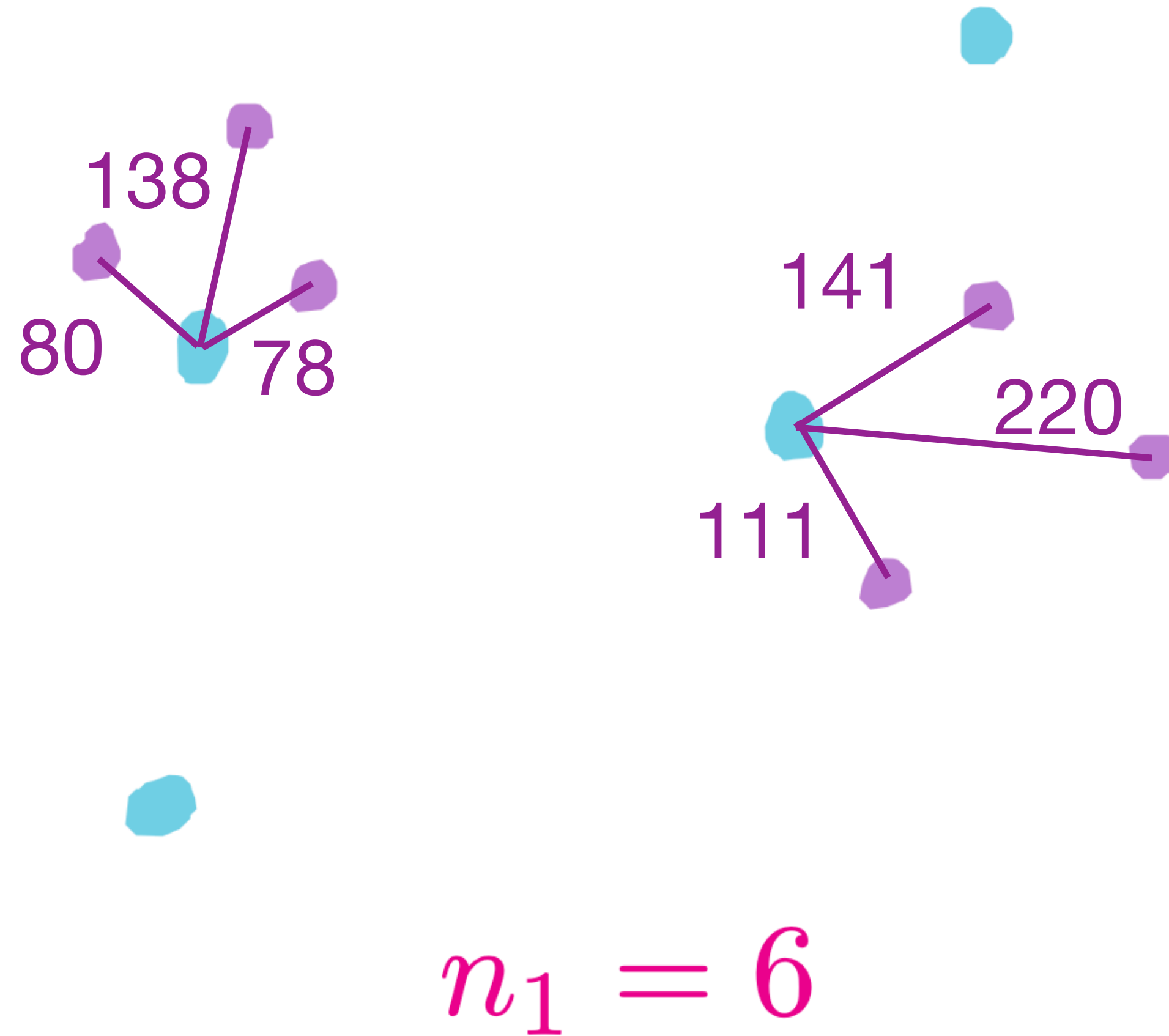
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





# Nearest neighbor function

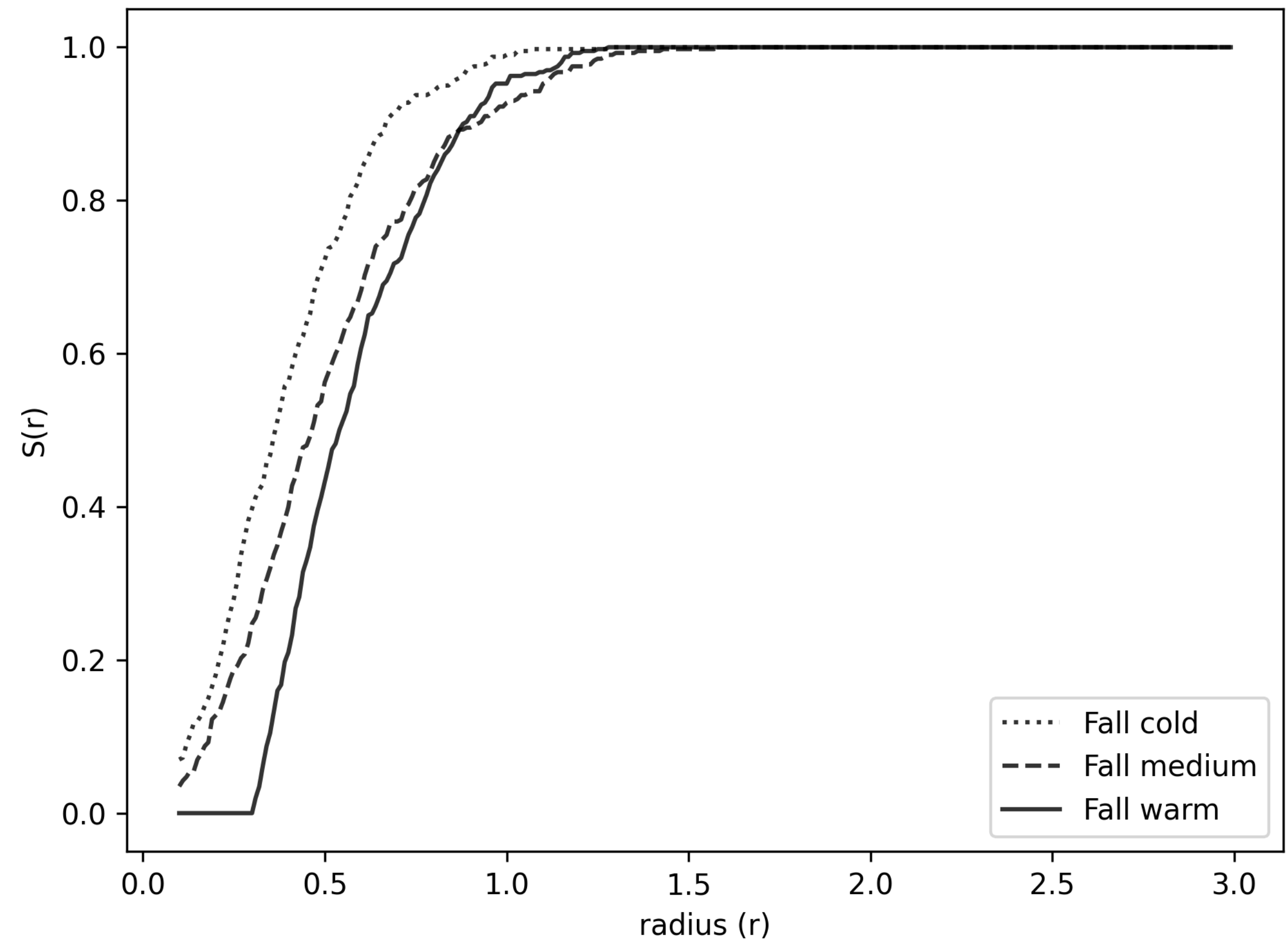
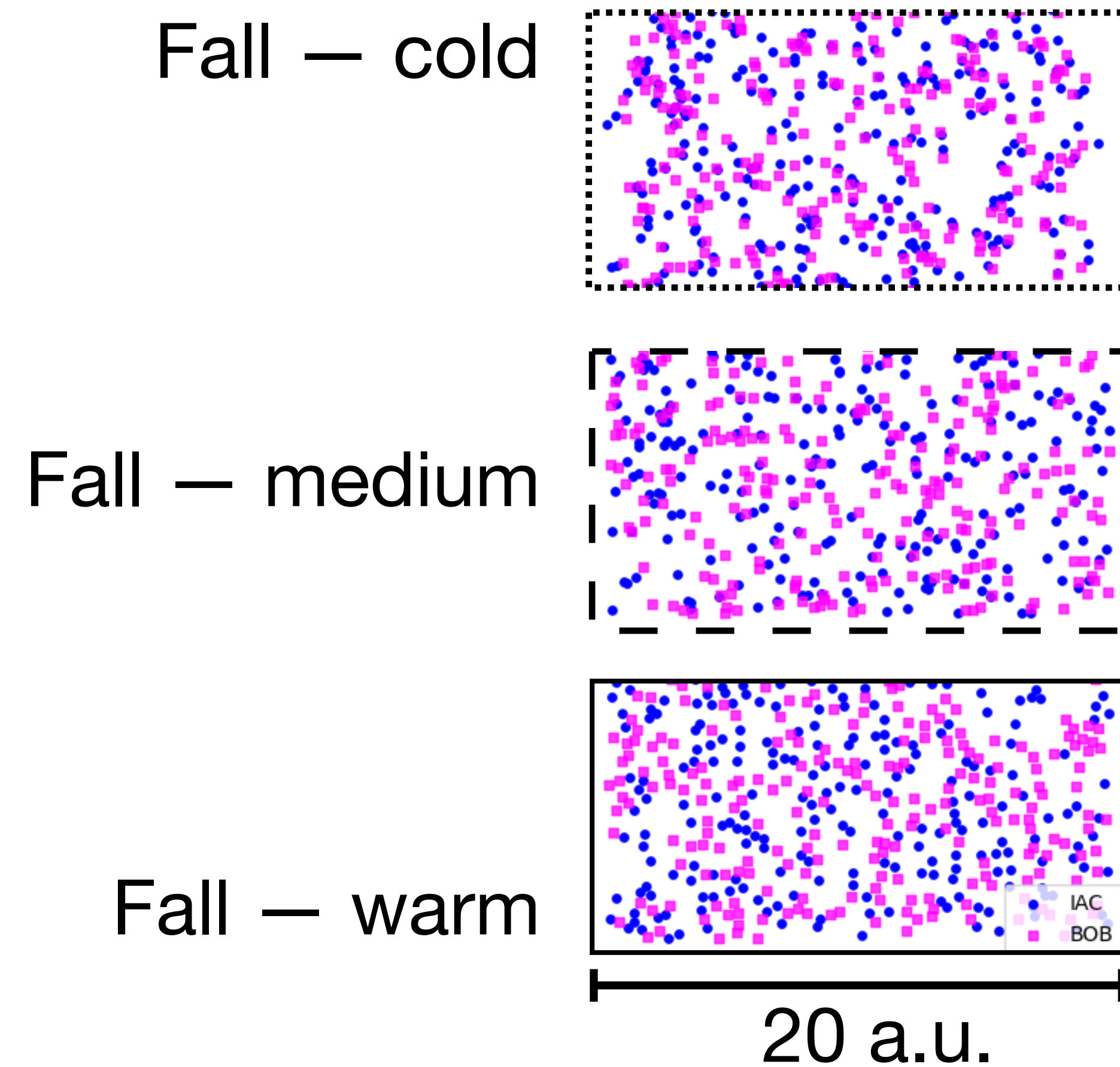
$$S(r) = \frac{1}{n_1} \sum_{i=1}^{n_1} \mathbf{1}(d_i < r)$$





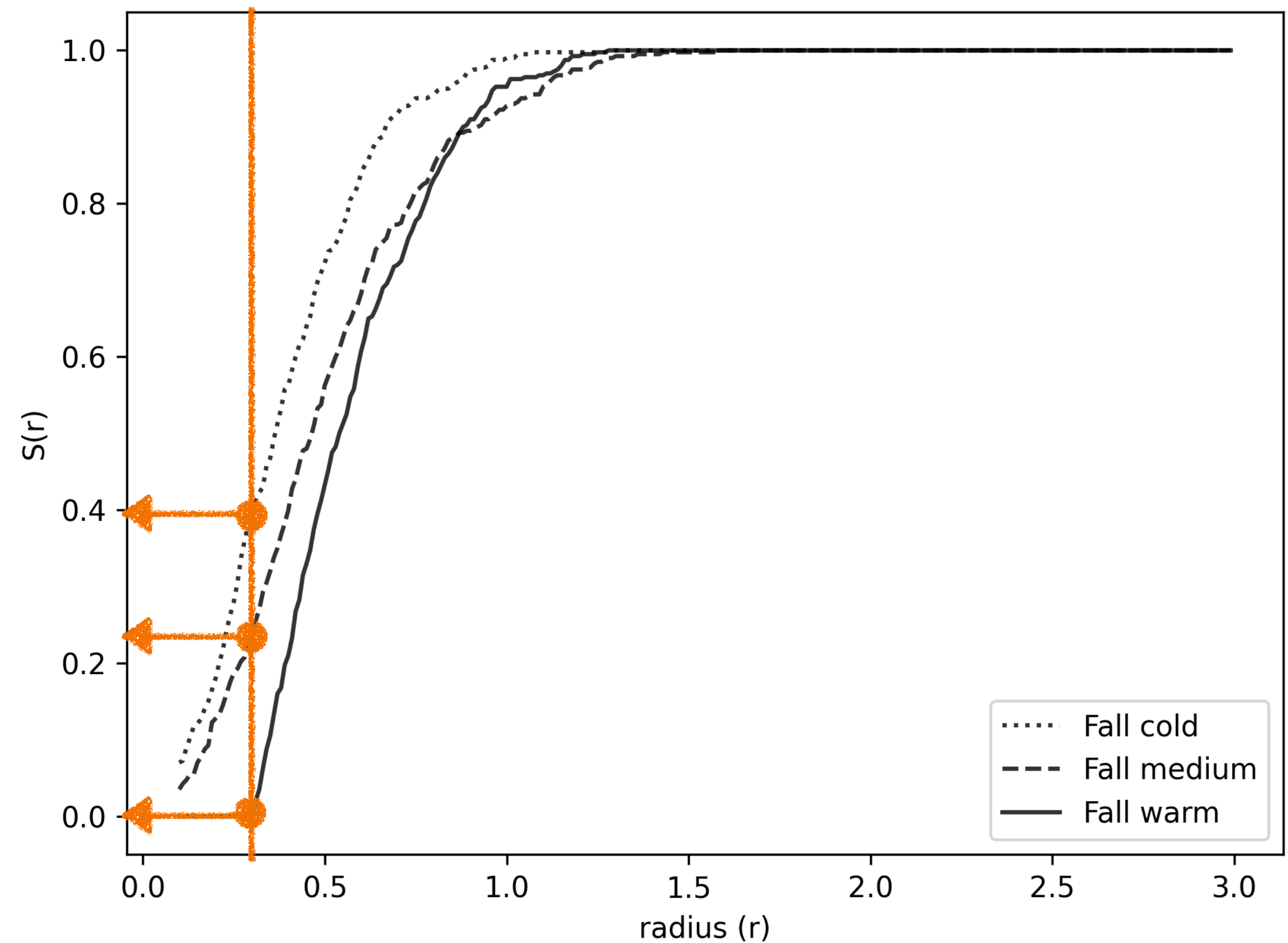
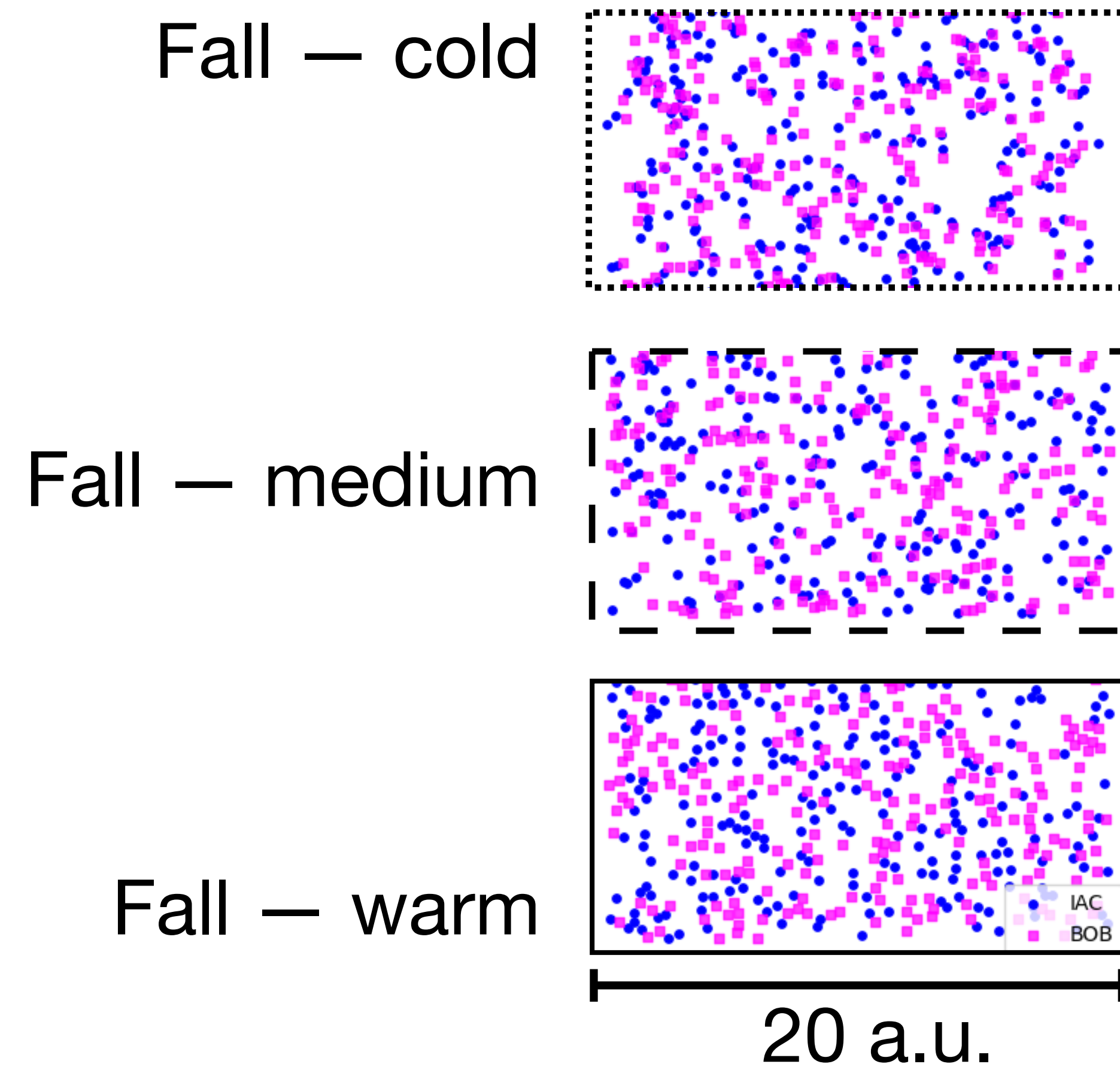


# Results: Nearest neighbor function





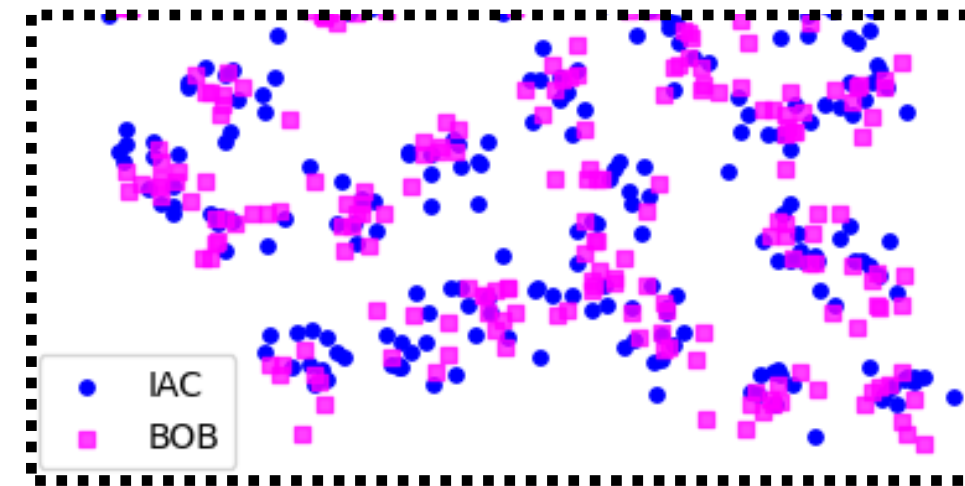
# Results: Nearest neighbor function



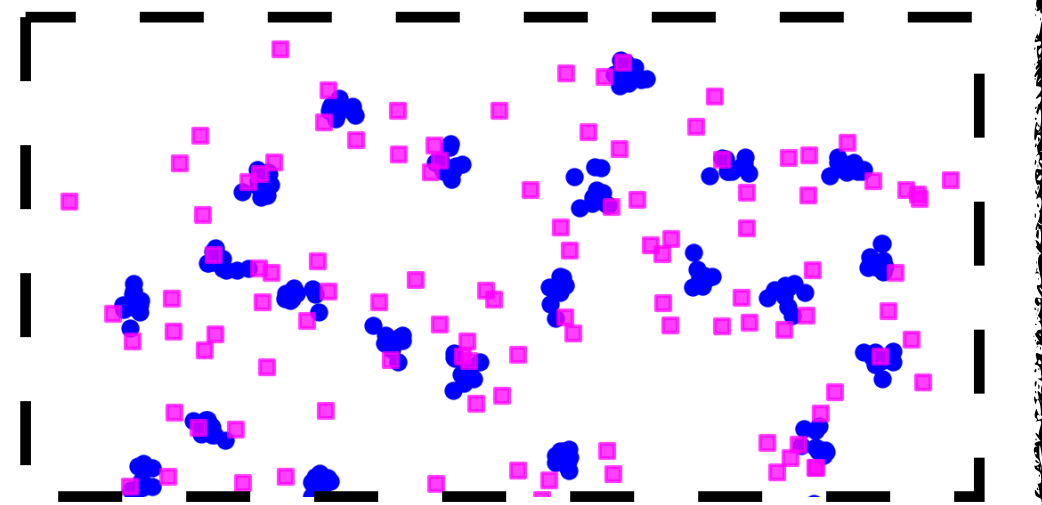


# Results: Nearest neighbor function

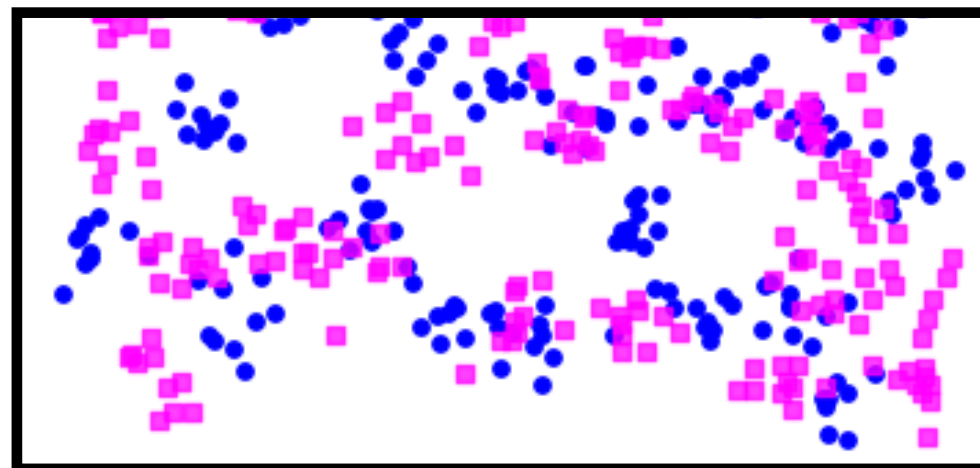
Winter — cold



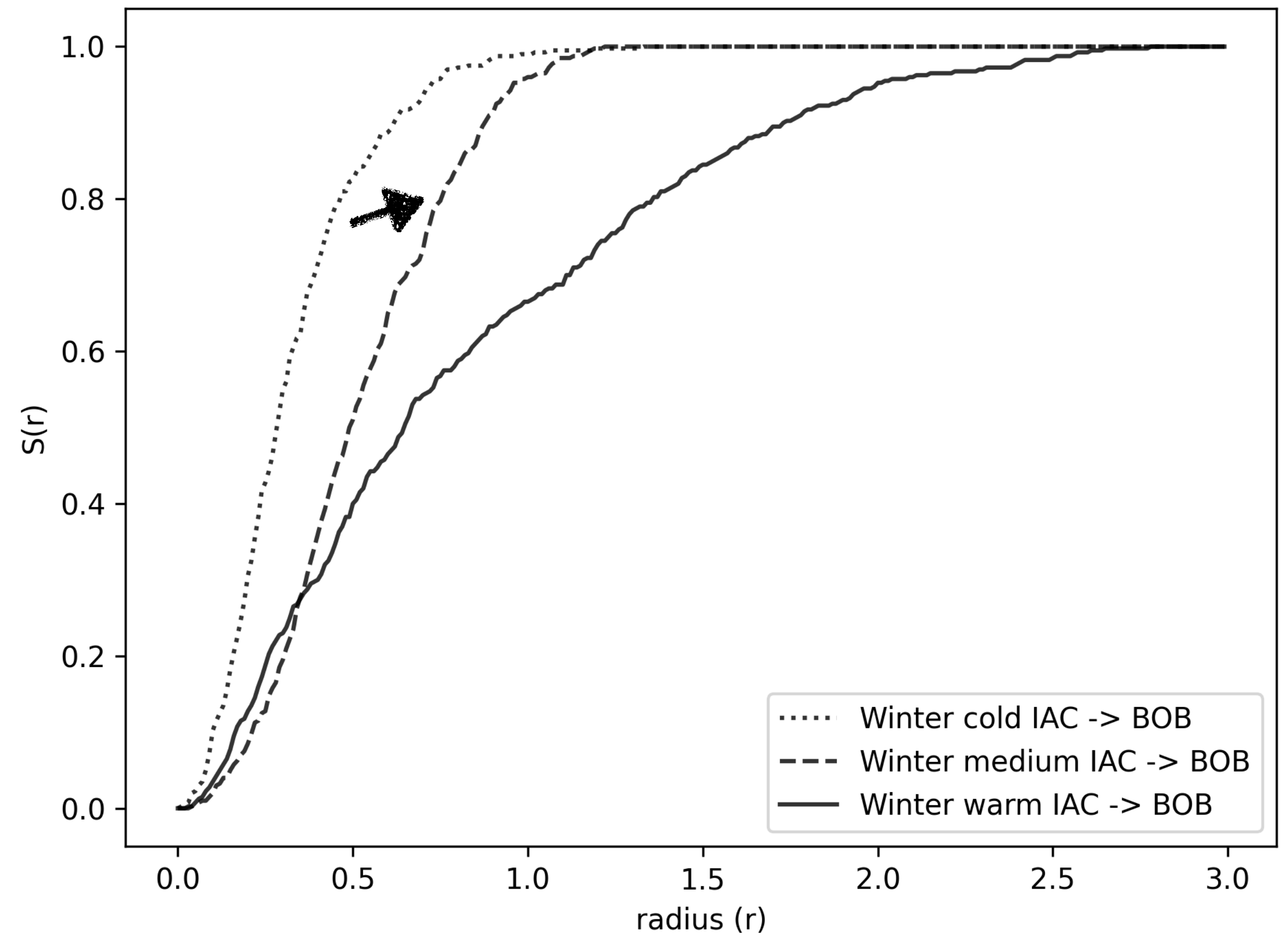
Winter — medium



Winter — warm



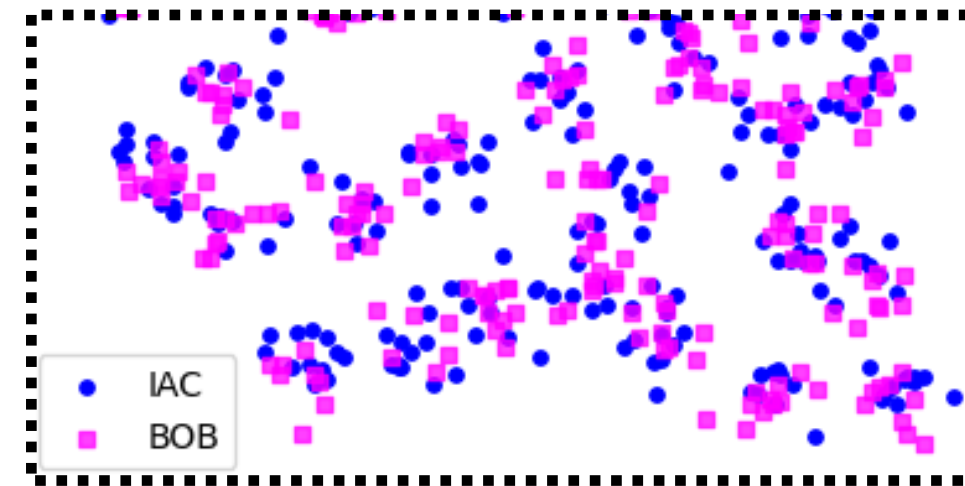
IAC → BOB



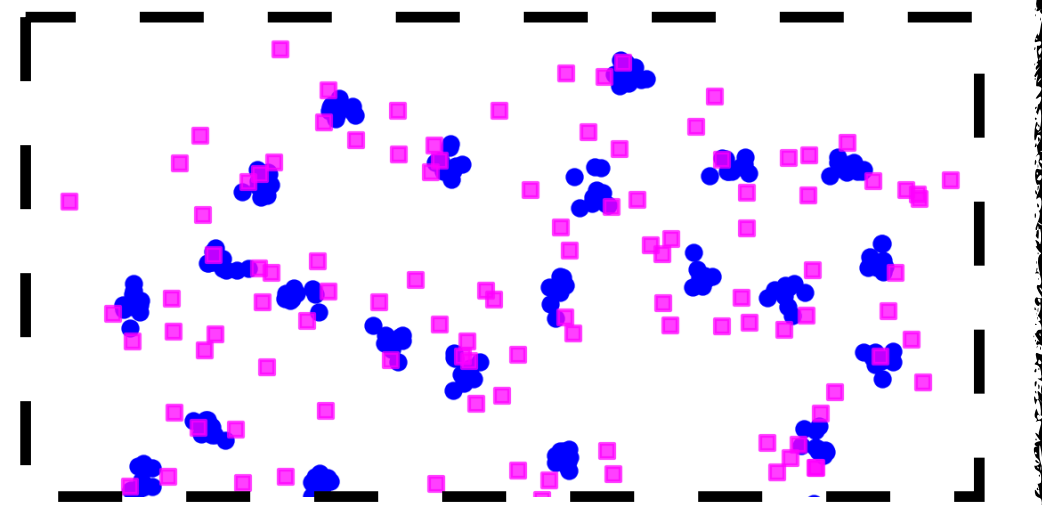


# Results: Nearest neighbor function

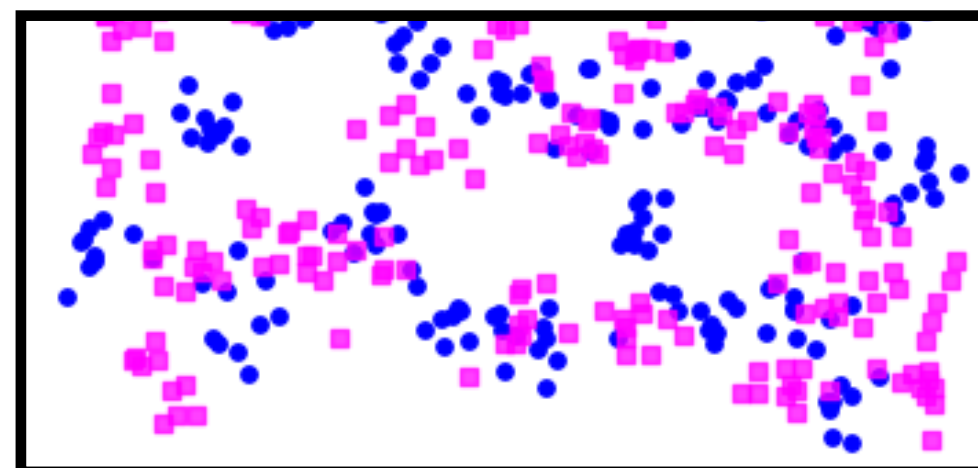
Winter — cold



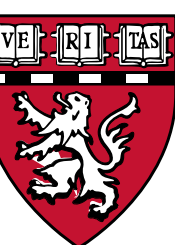
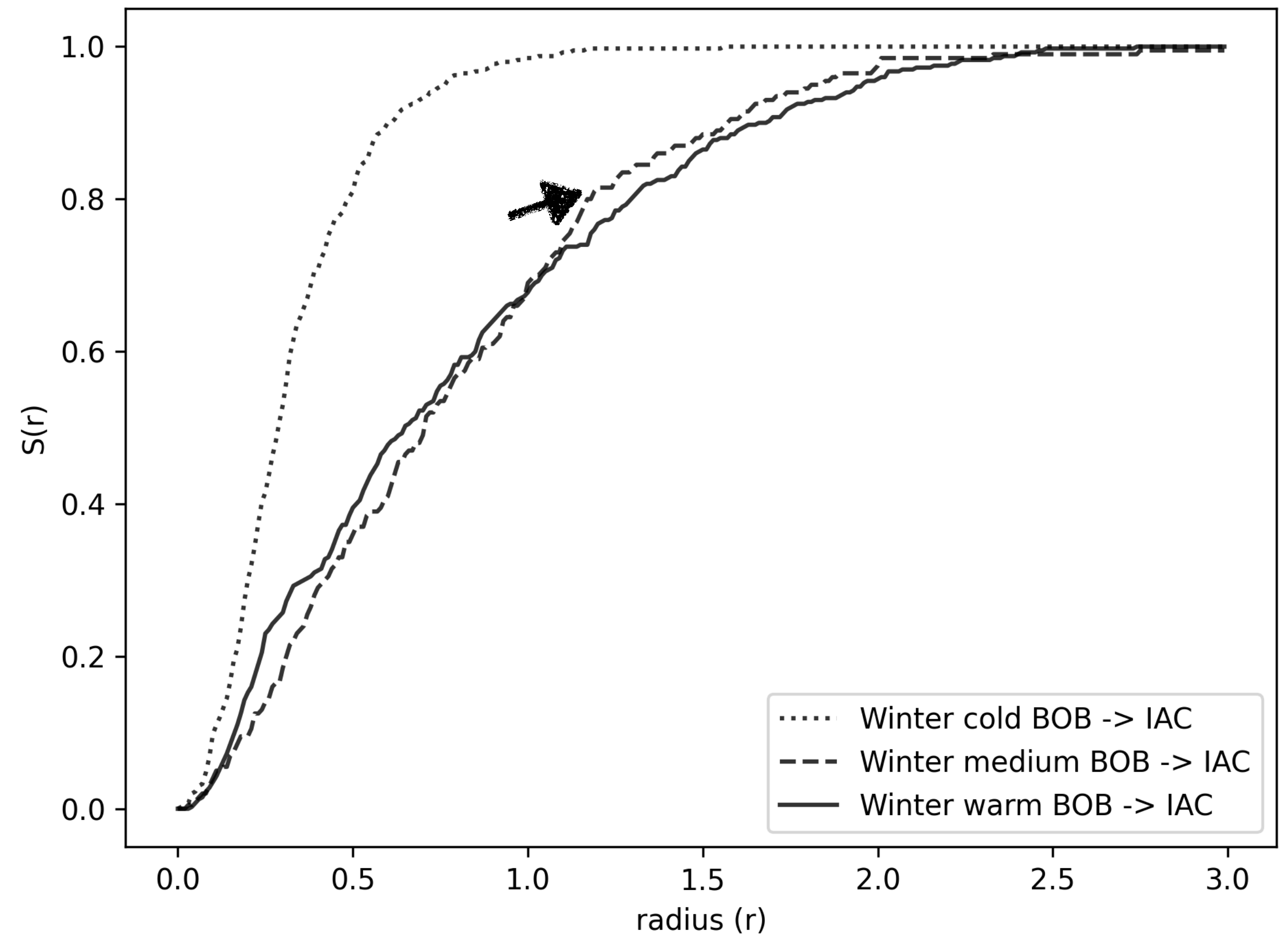
Winter — medium



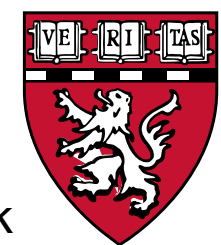
Winter — warm



BOB → IAC







-> Notebook



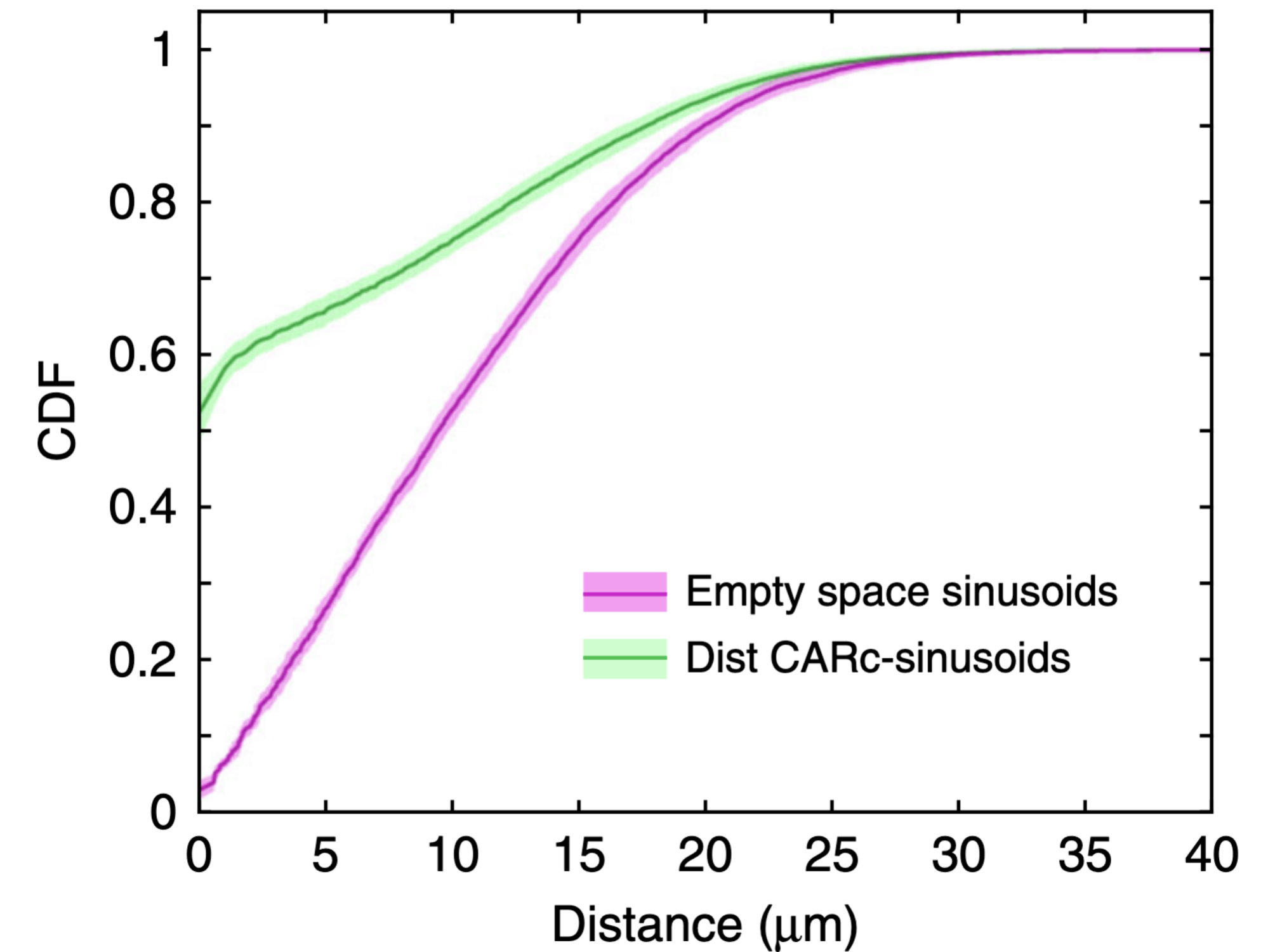
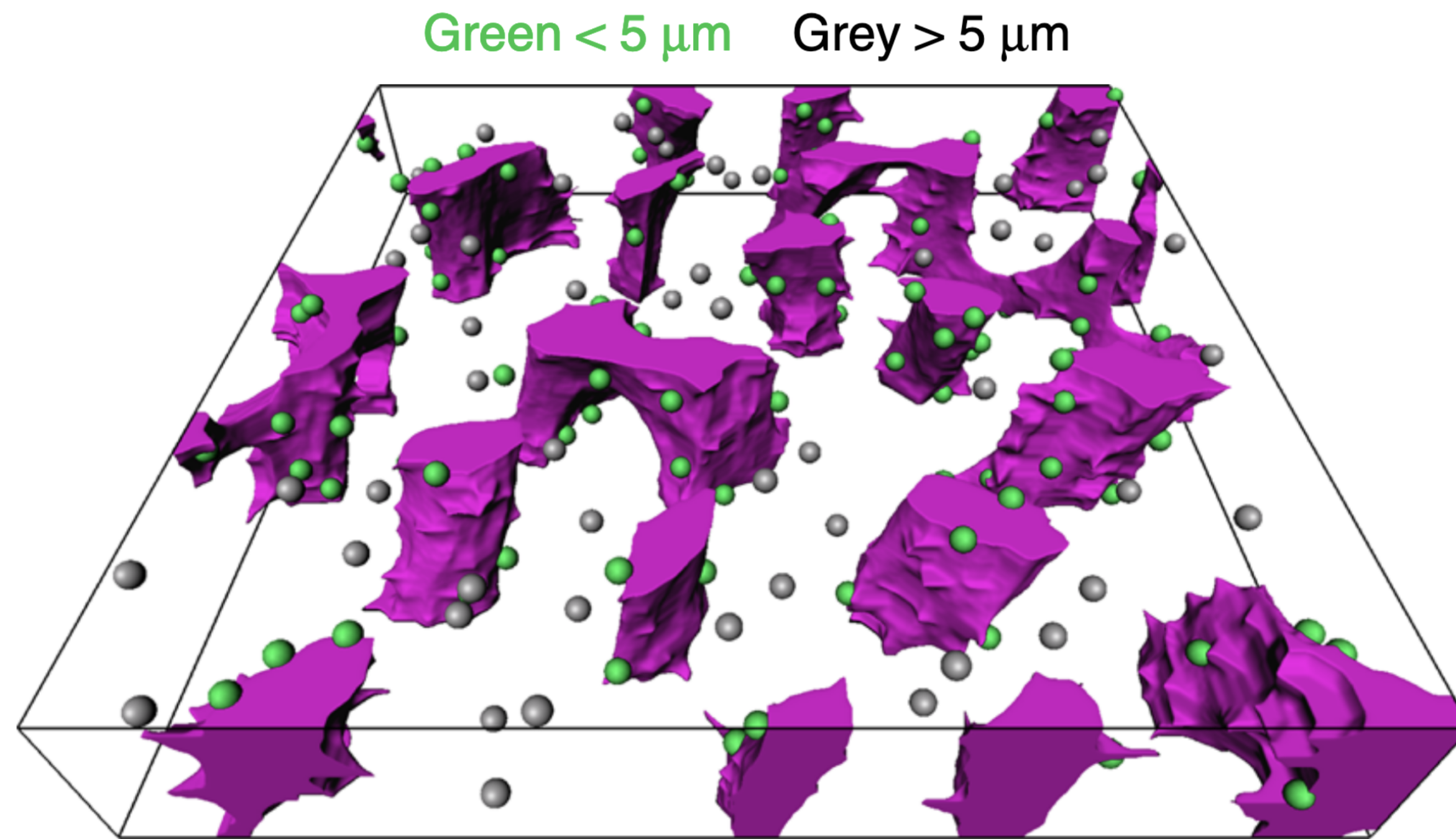


# Nearest neighbor function

- Asymmetric: **BOB**  $\rightarrow$  **IAC**  $\neq$  **IAC**  $\rightarrow$  **BOB**
- Returns: A number for each radius
- Range: Short



# Beyond the nearest neighbor function



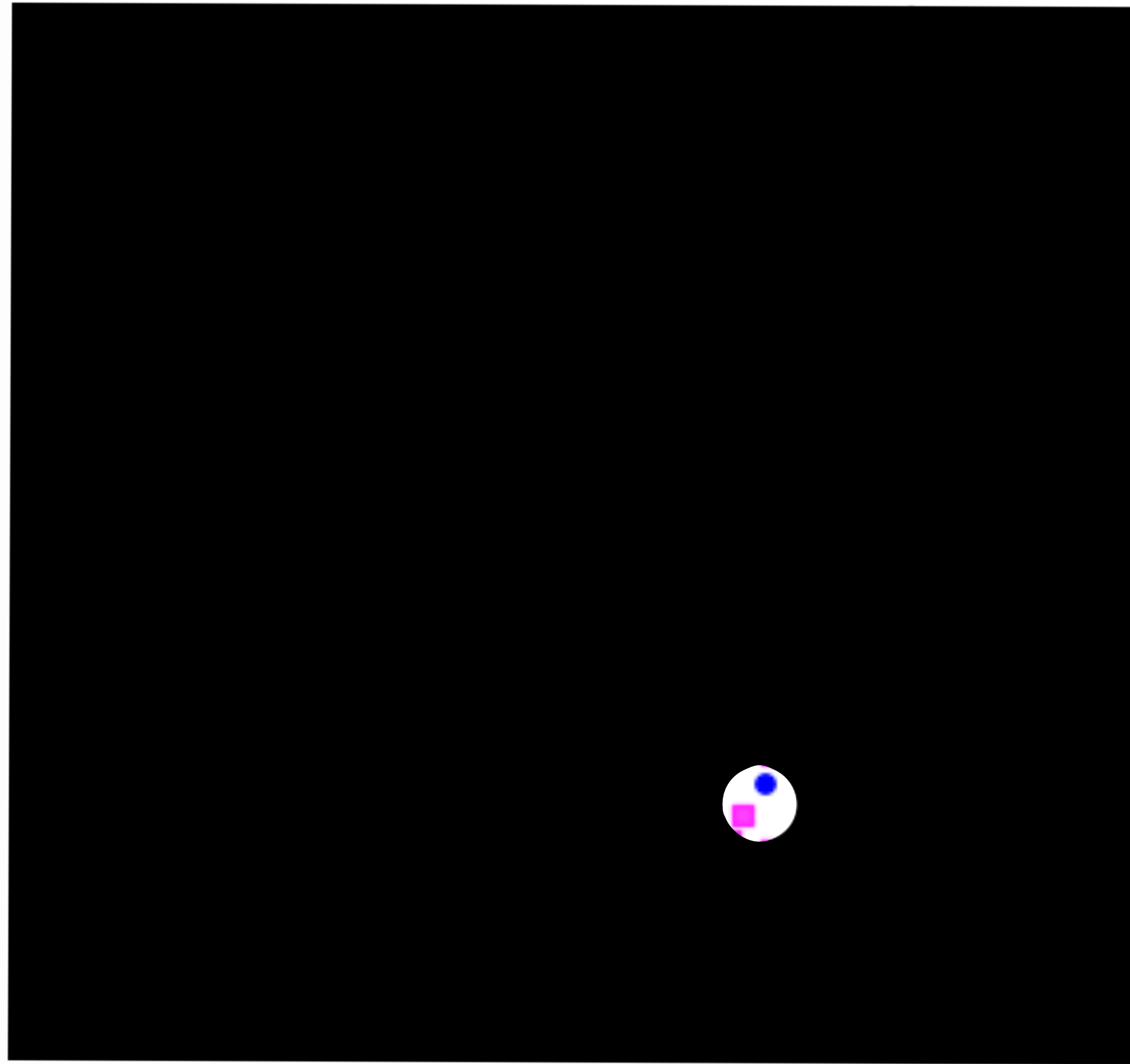
CARcs

Sinusoidal vessel wall





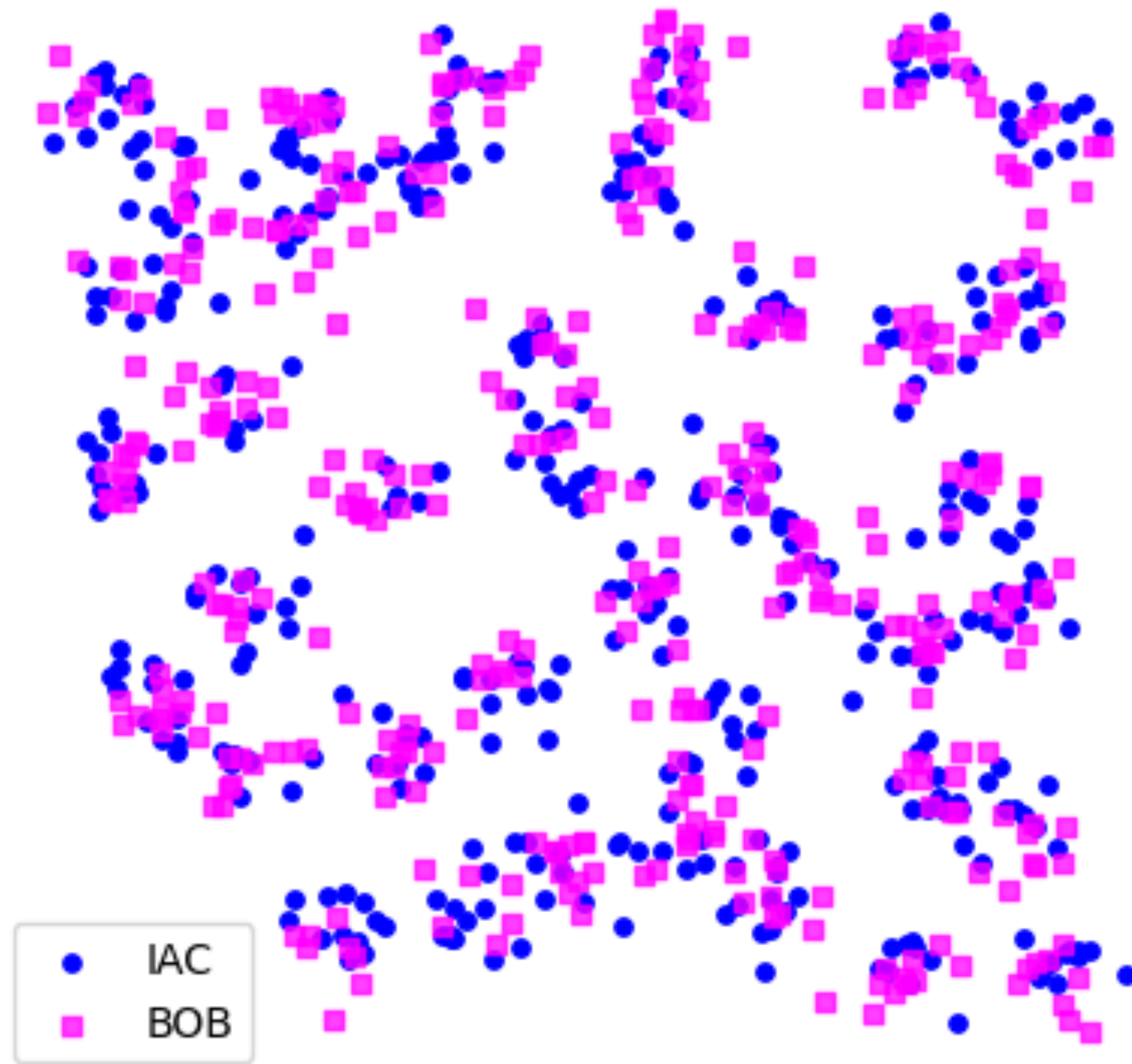
# Ripley's K function







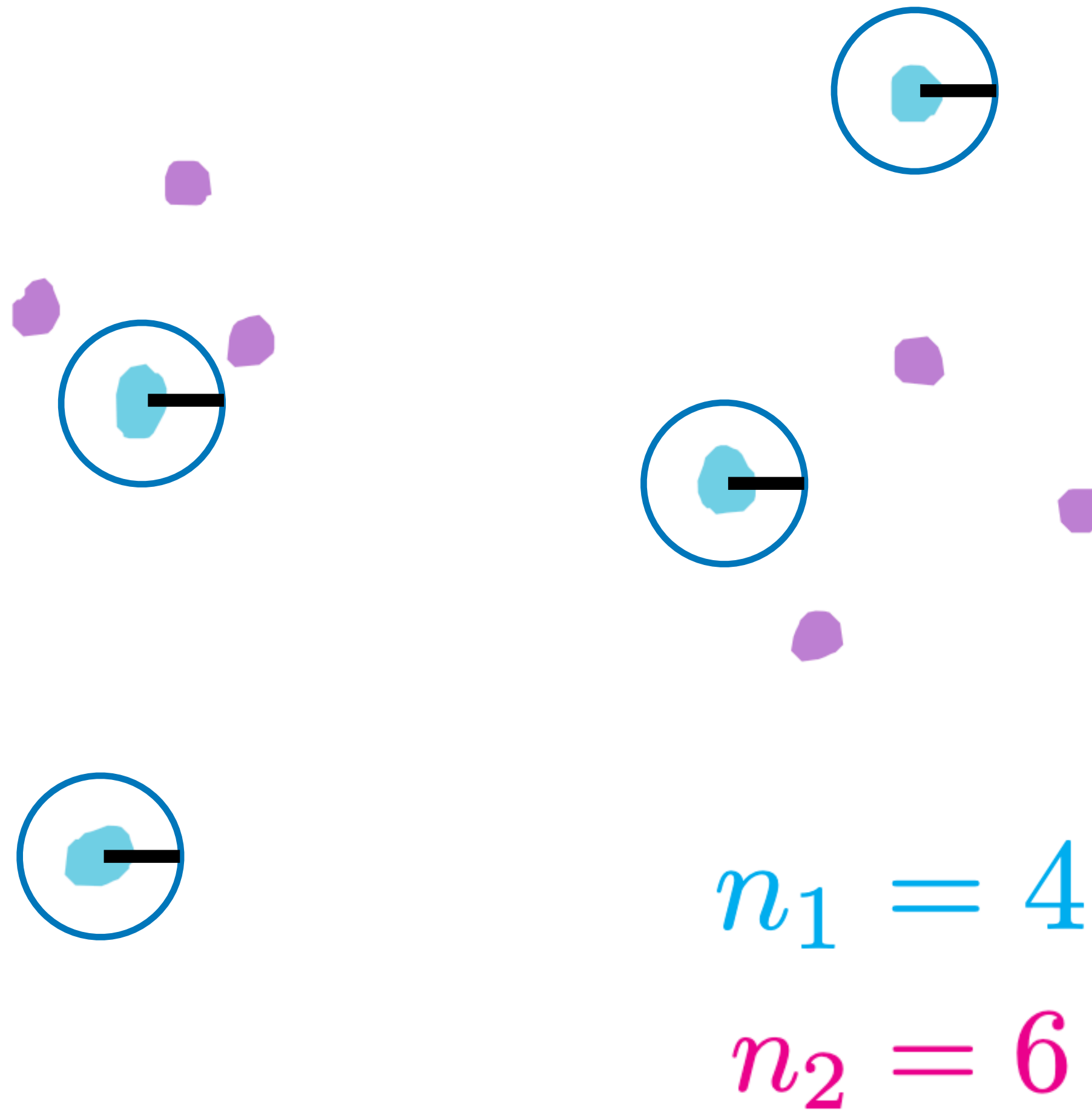
# Ripley's K function



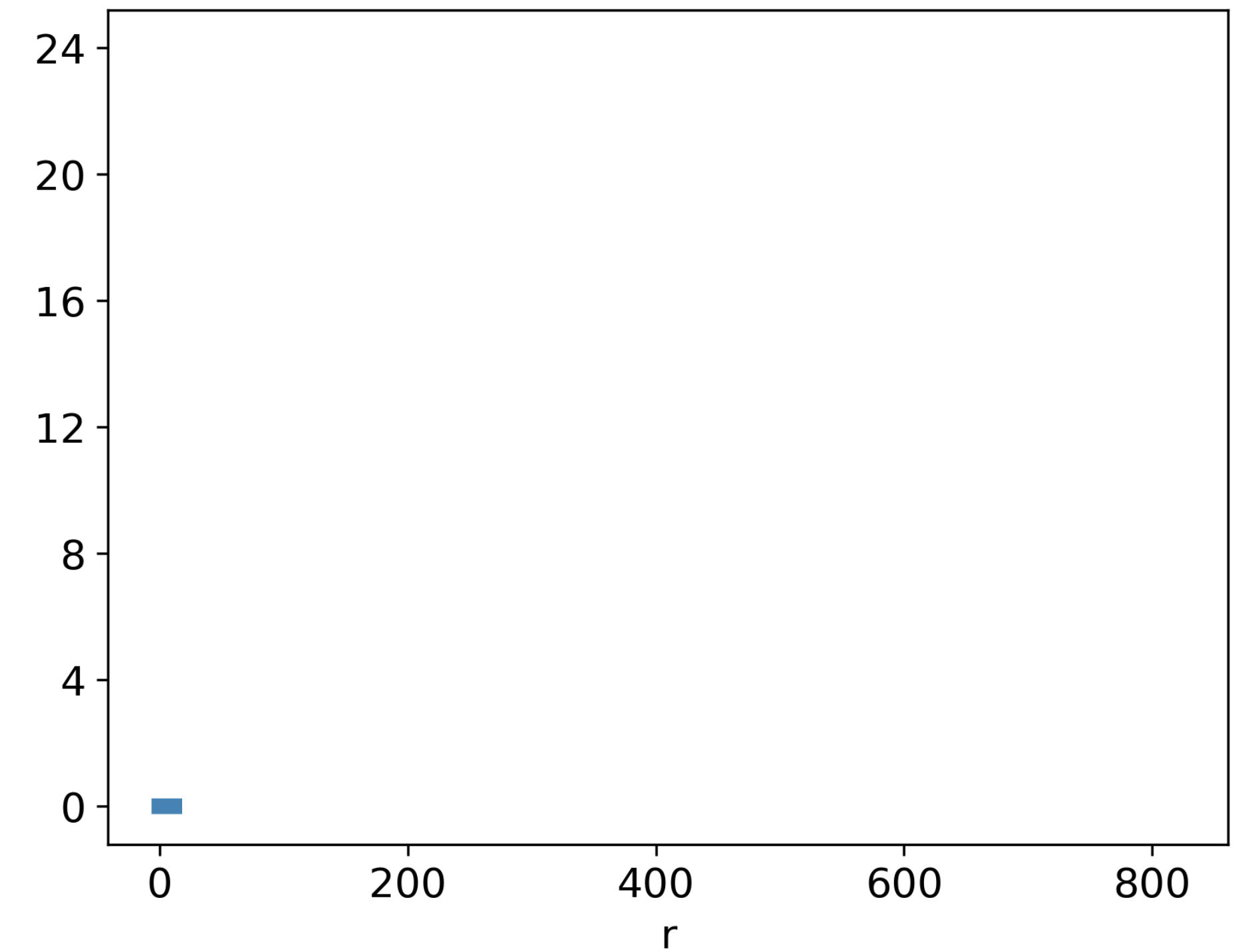




# Ripley's K function

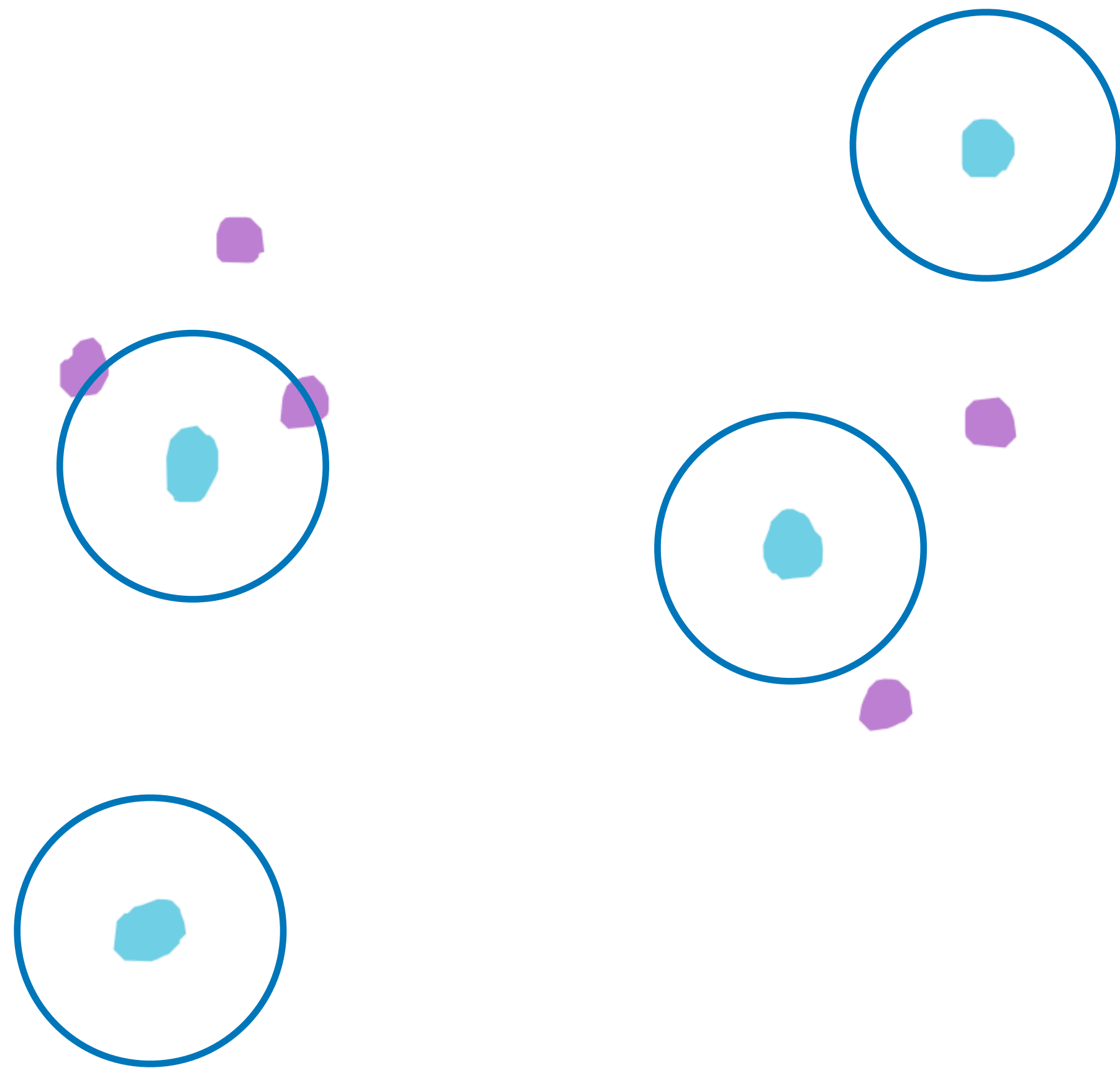


$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

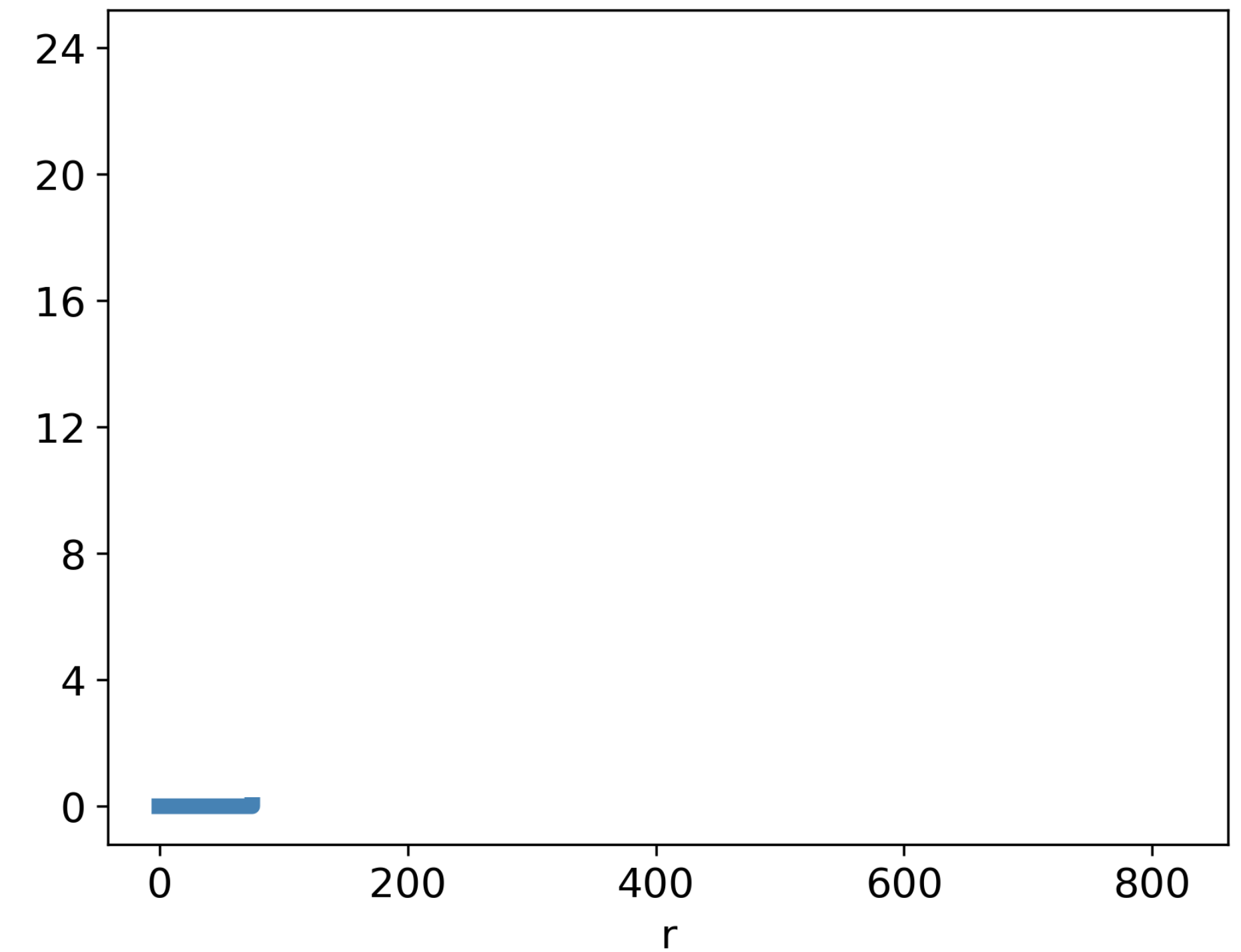




# Ripley's K function

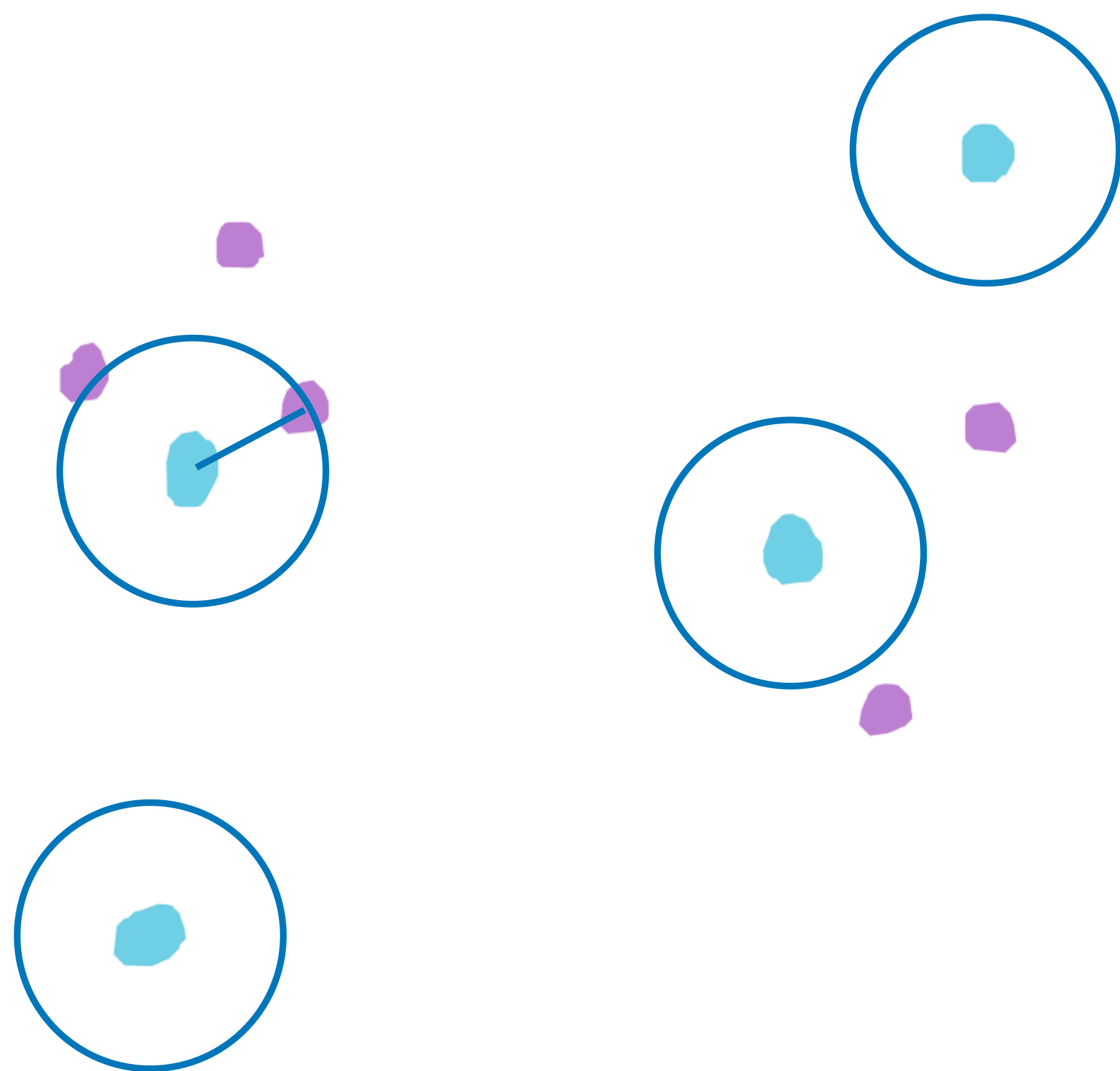


$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

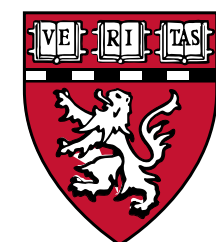
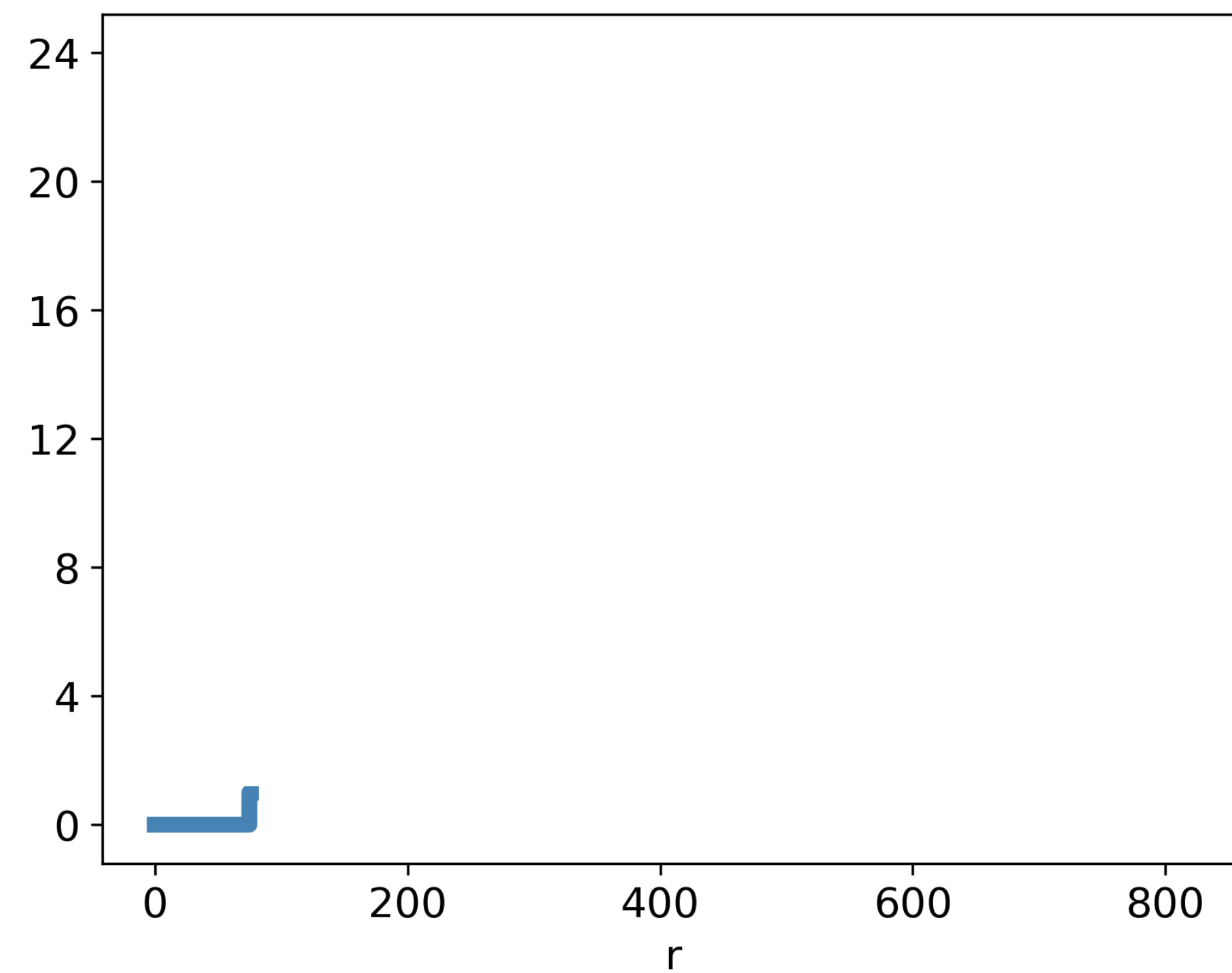




# Ripley's K function



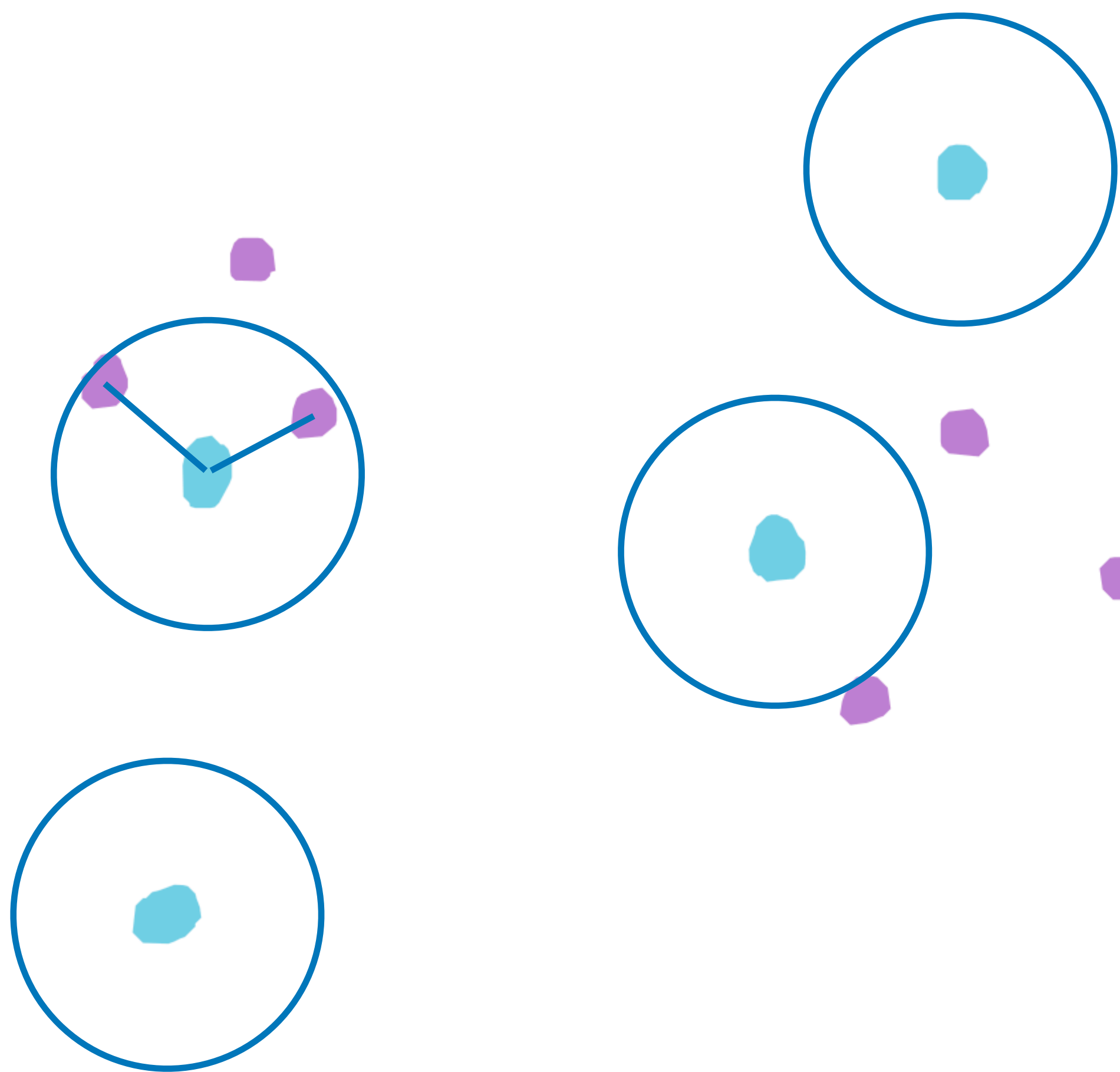
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



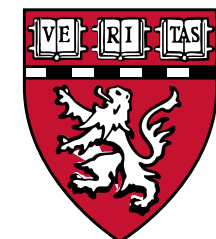
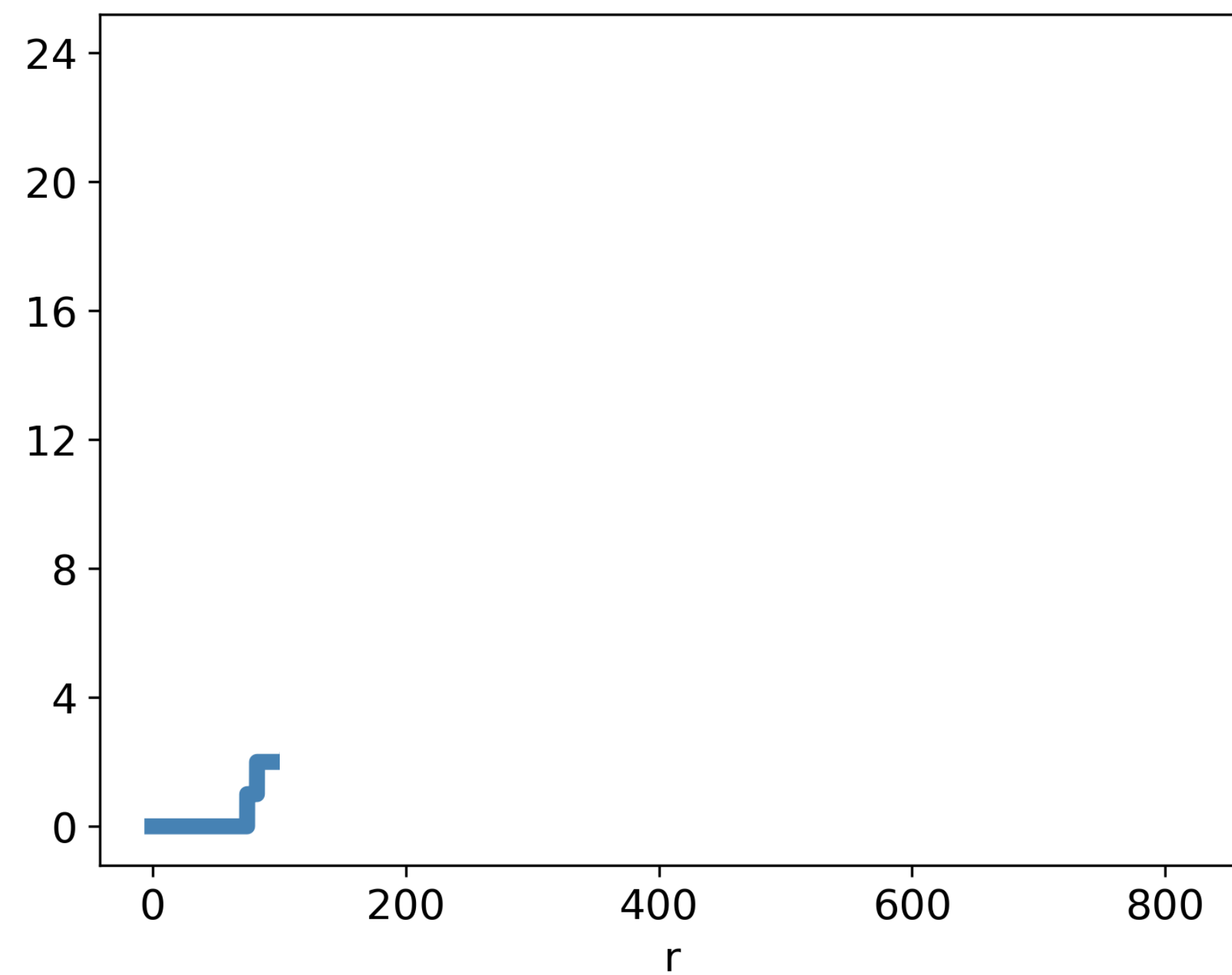




# Ripley's K function

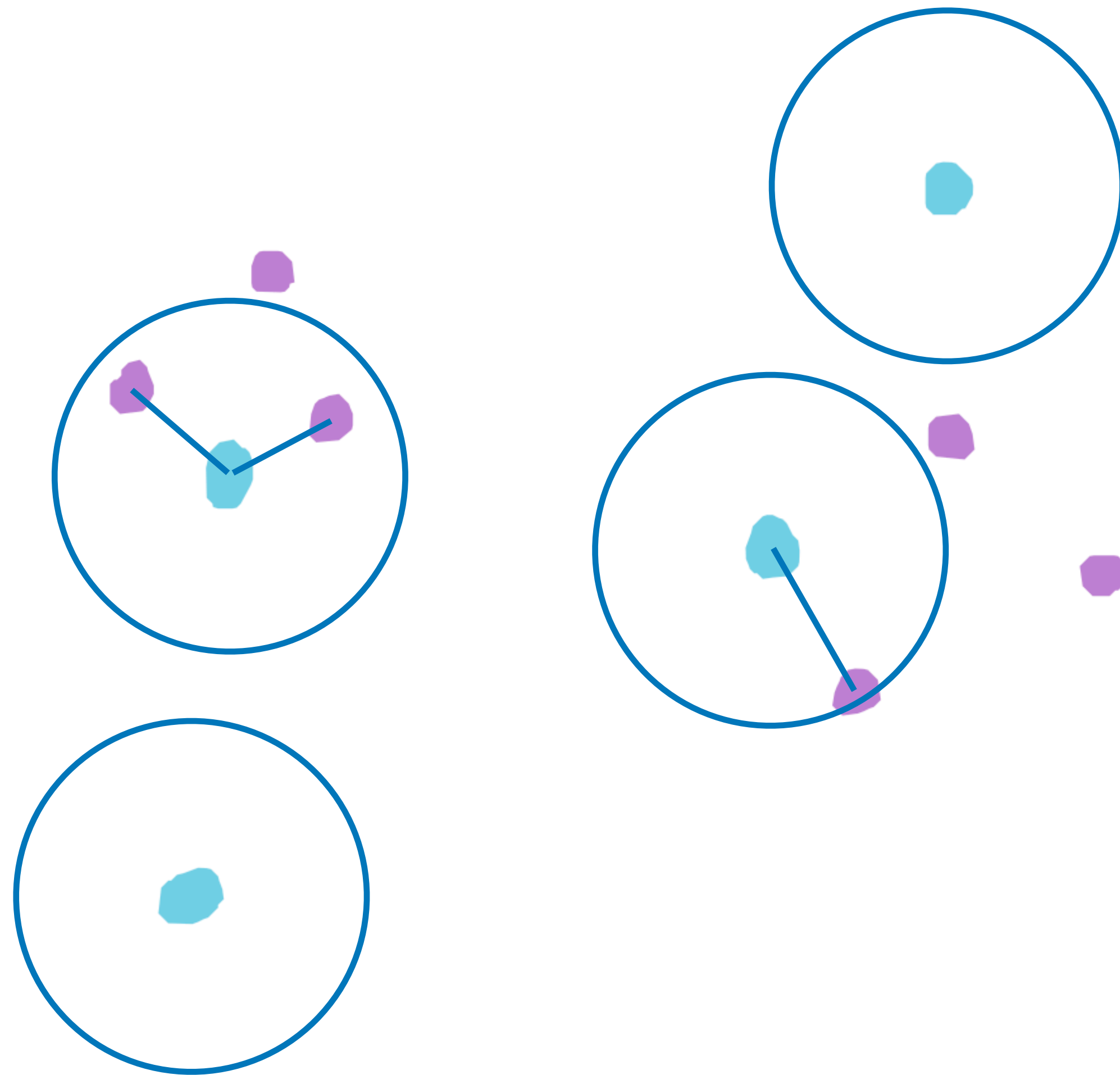


$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

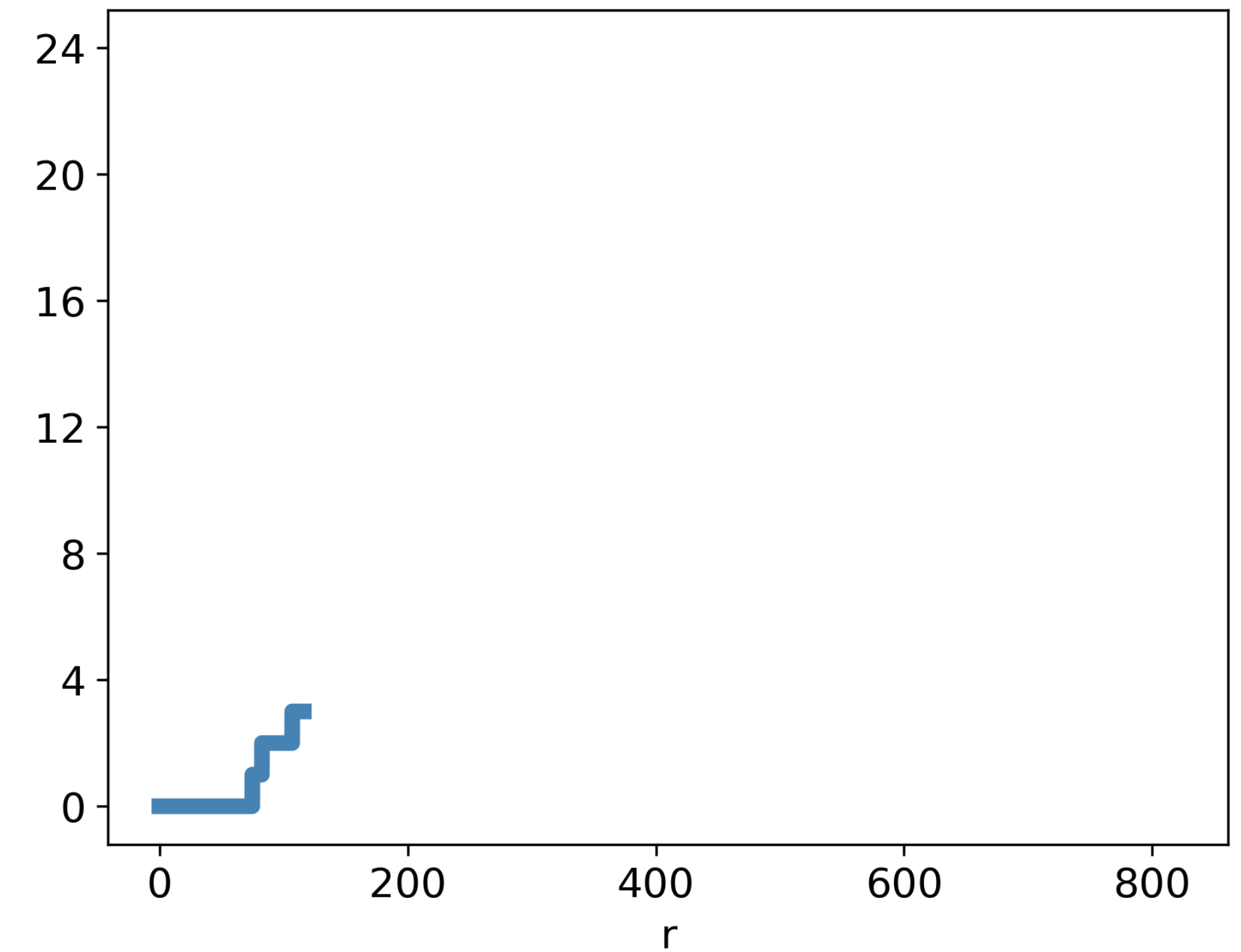




# Ripley's K function

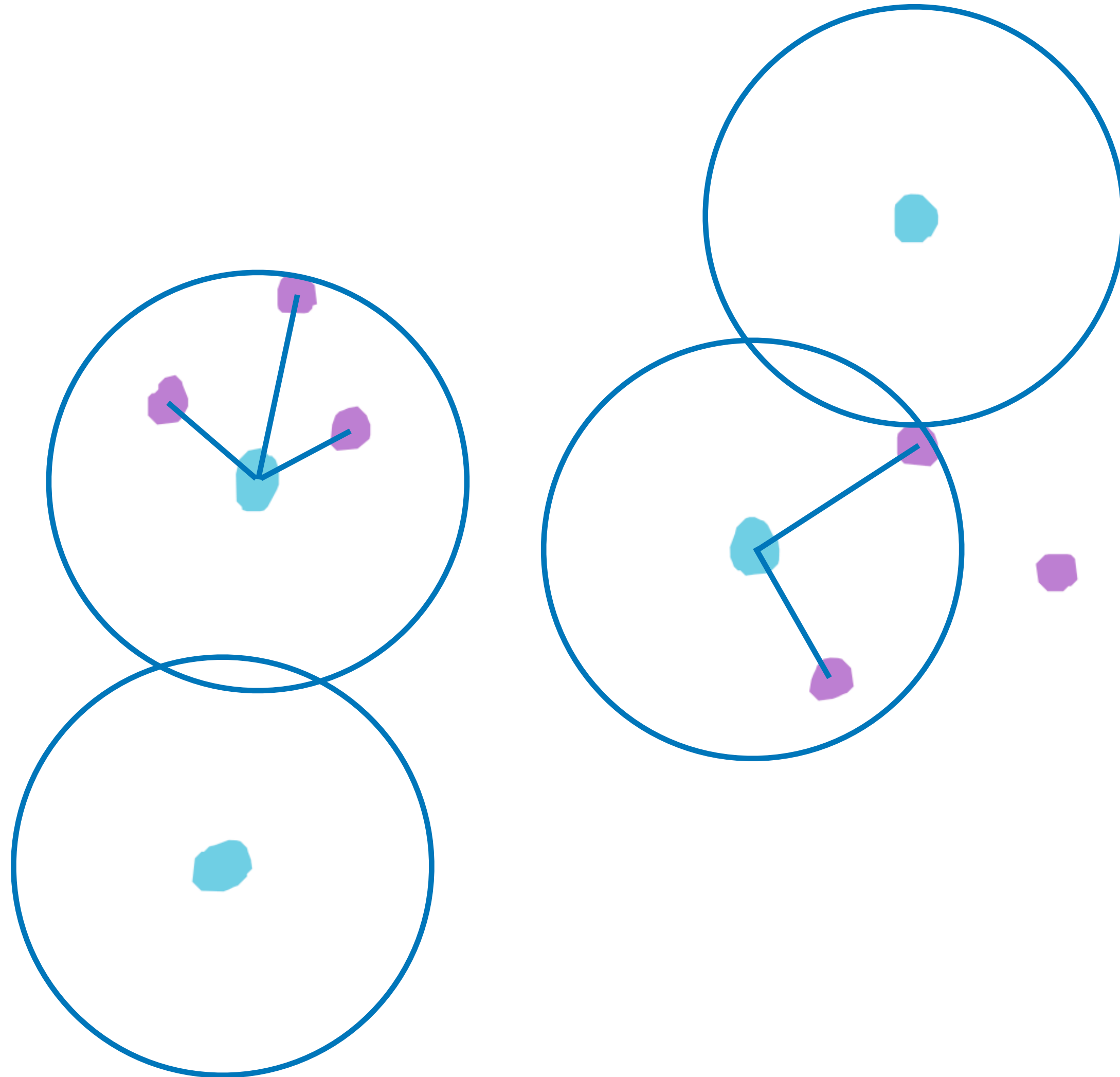


$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

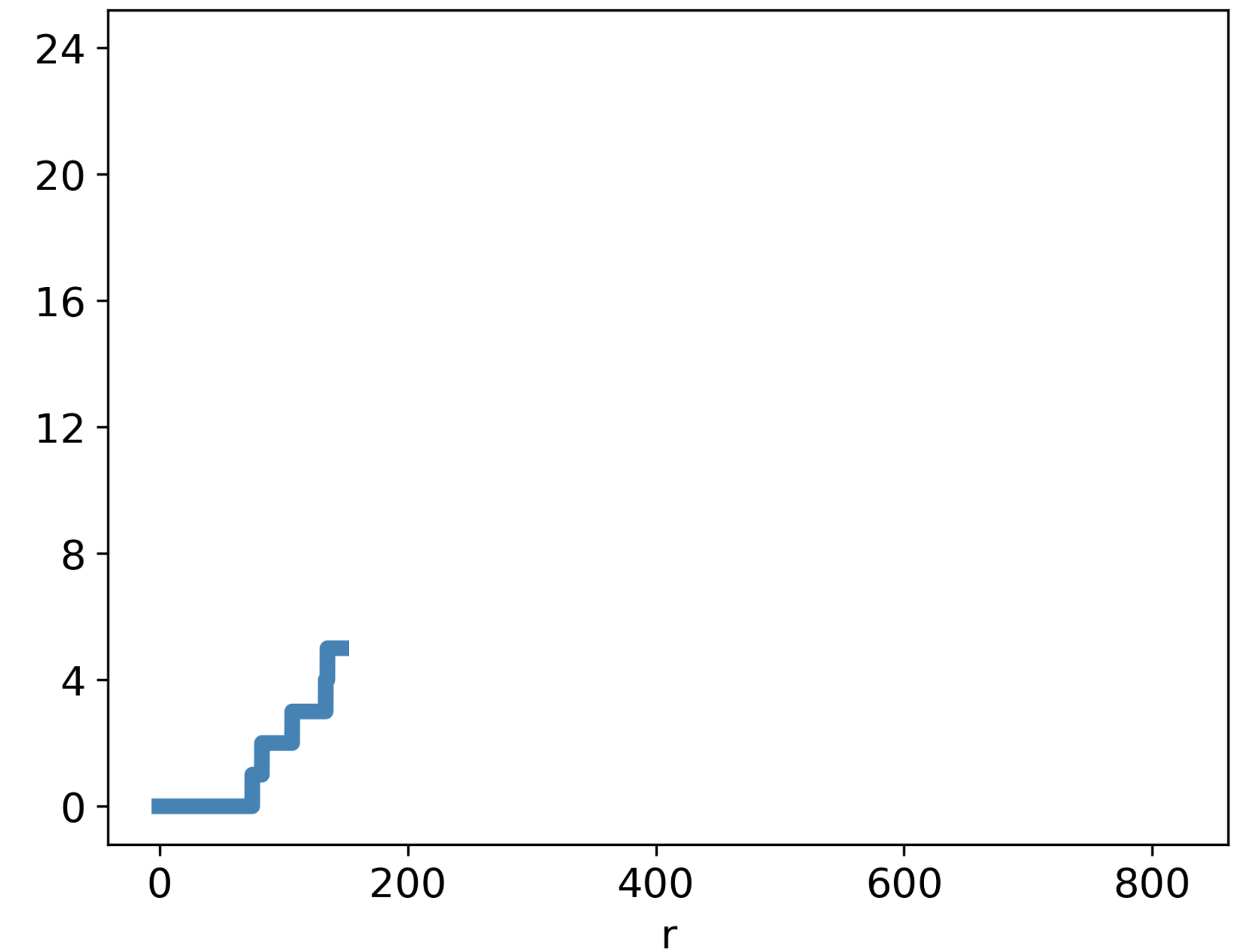




# Ripley's K function



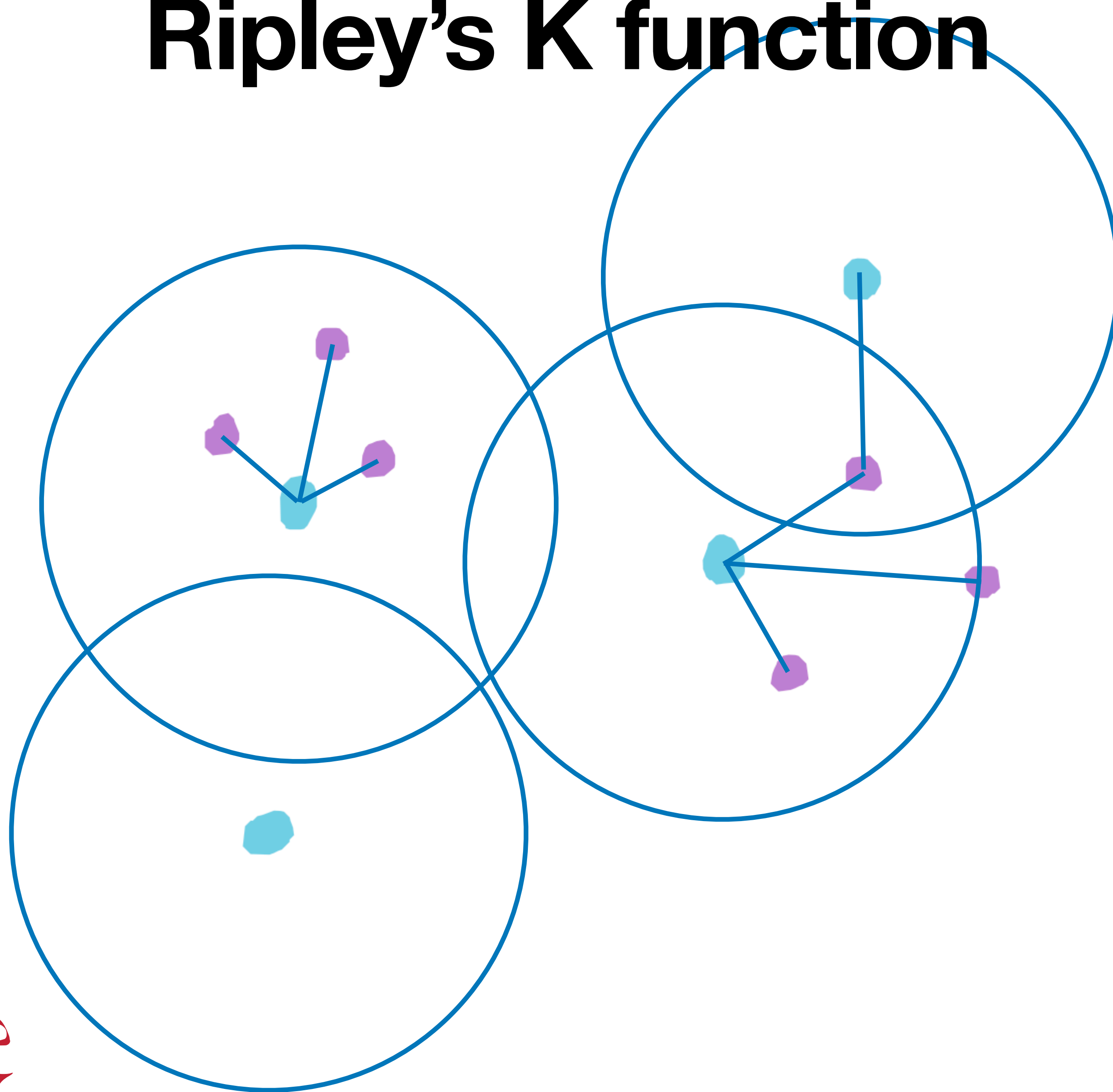
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



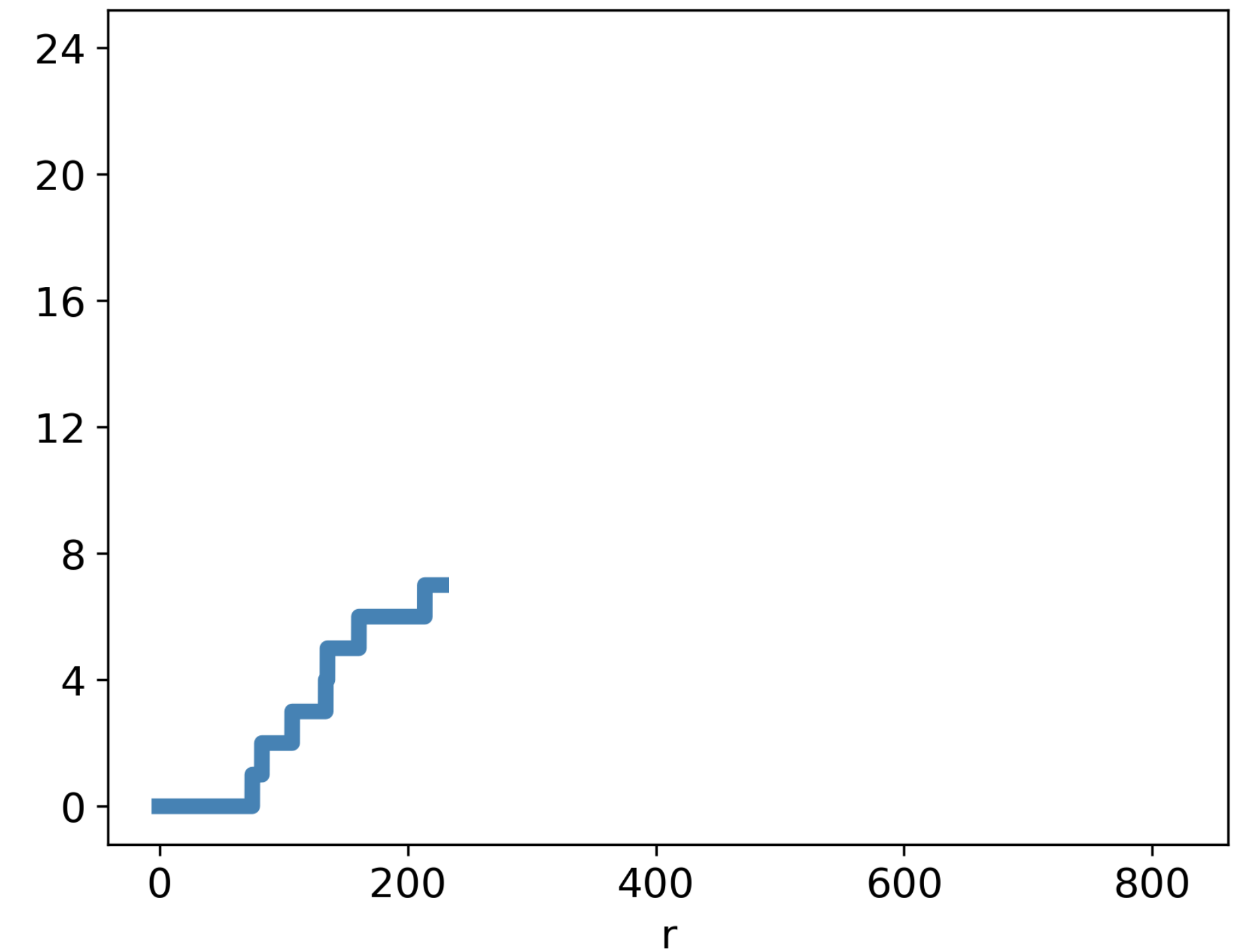




# Ripley's K function



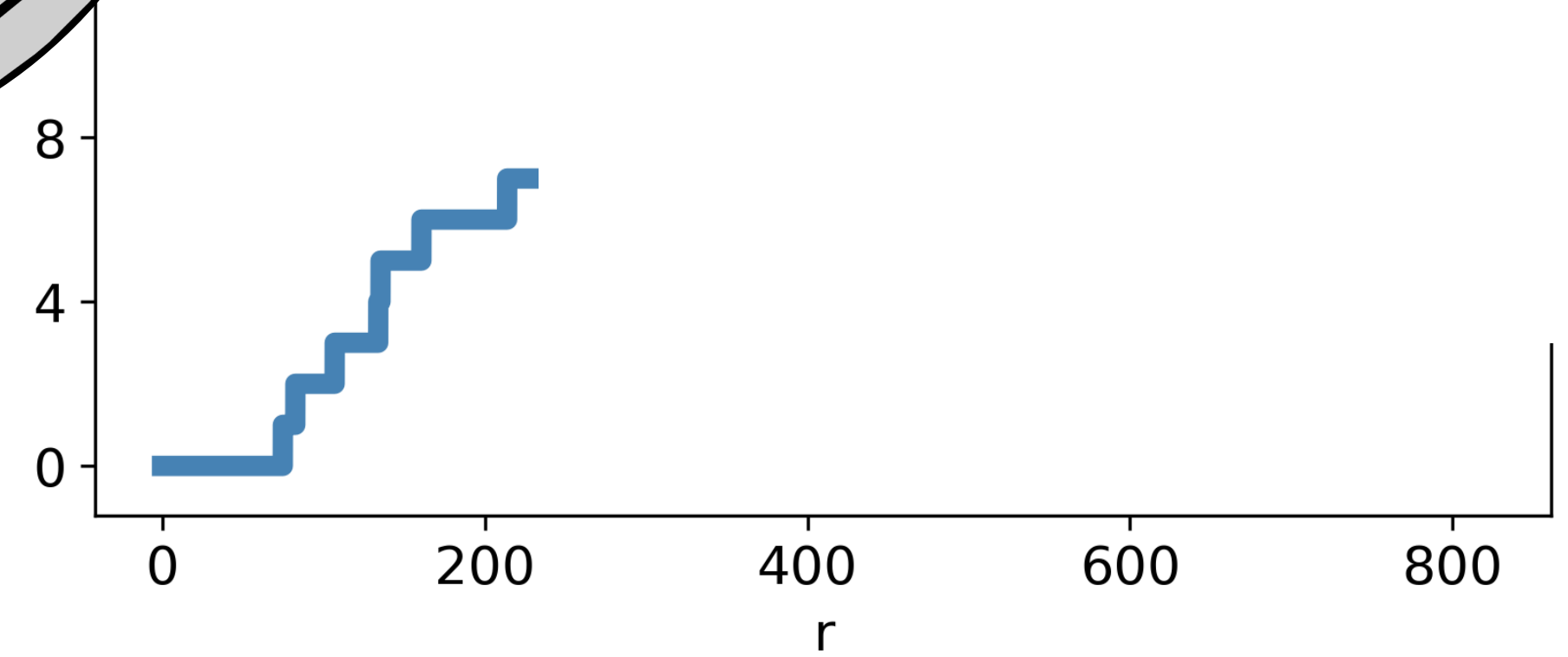
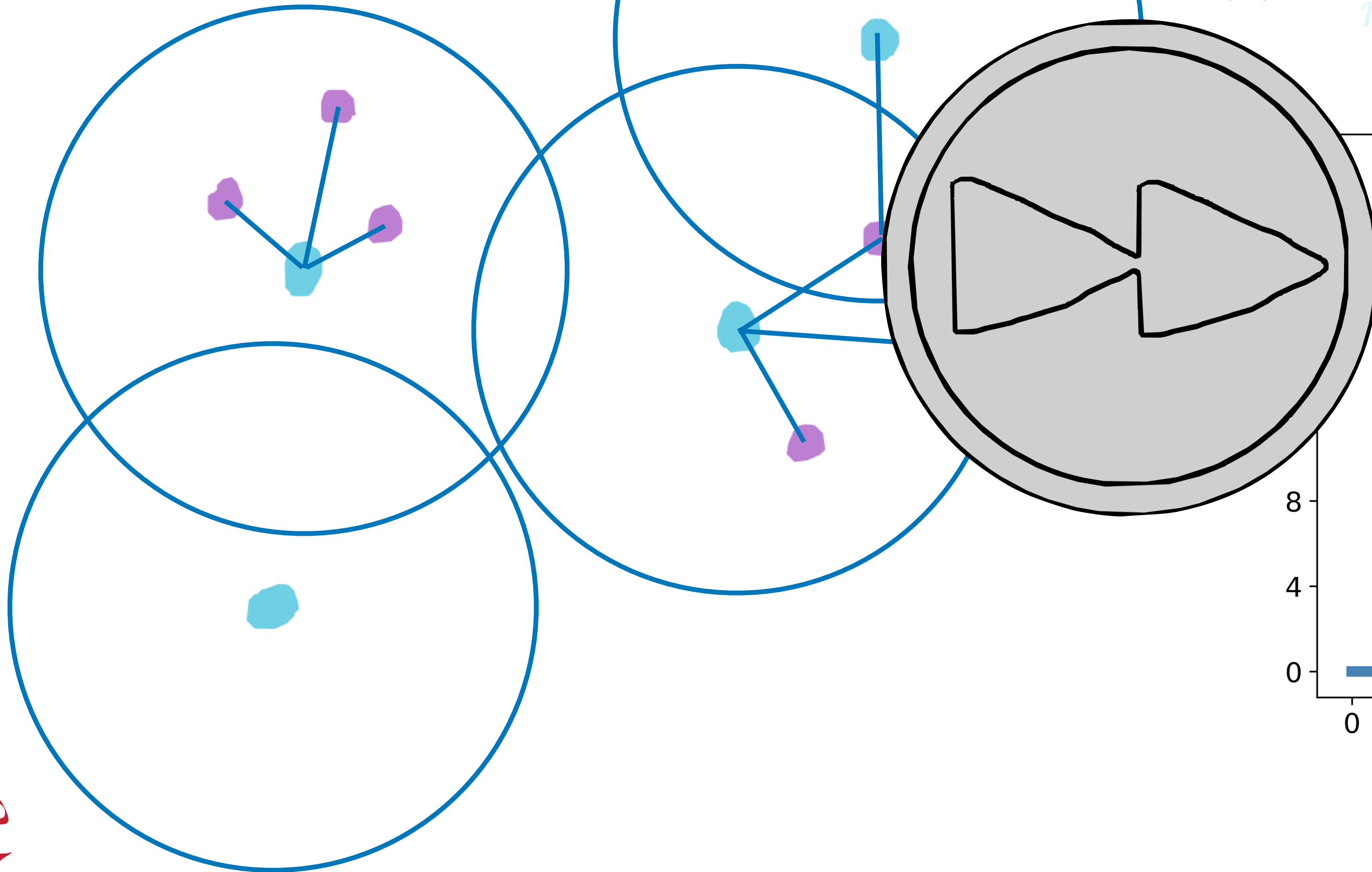
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$





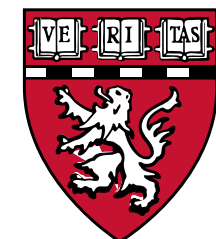
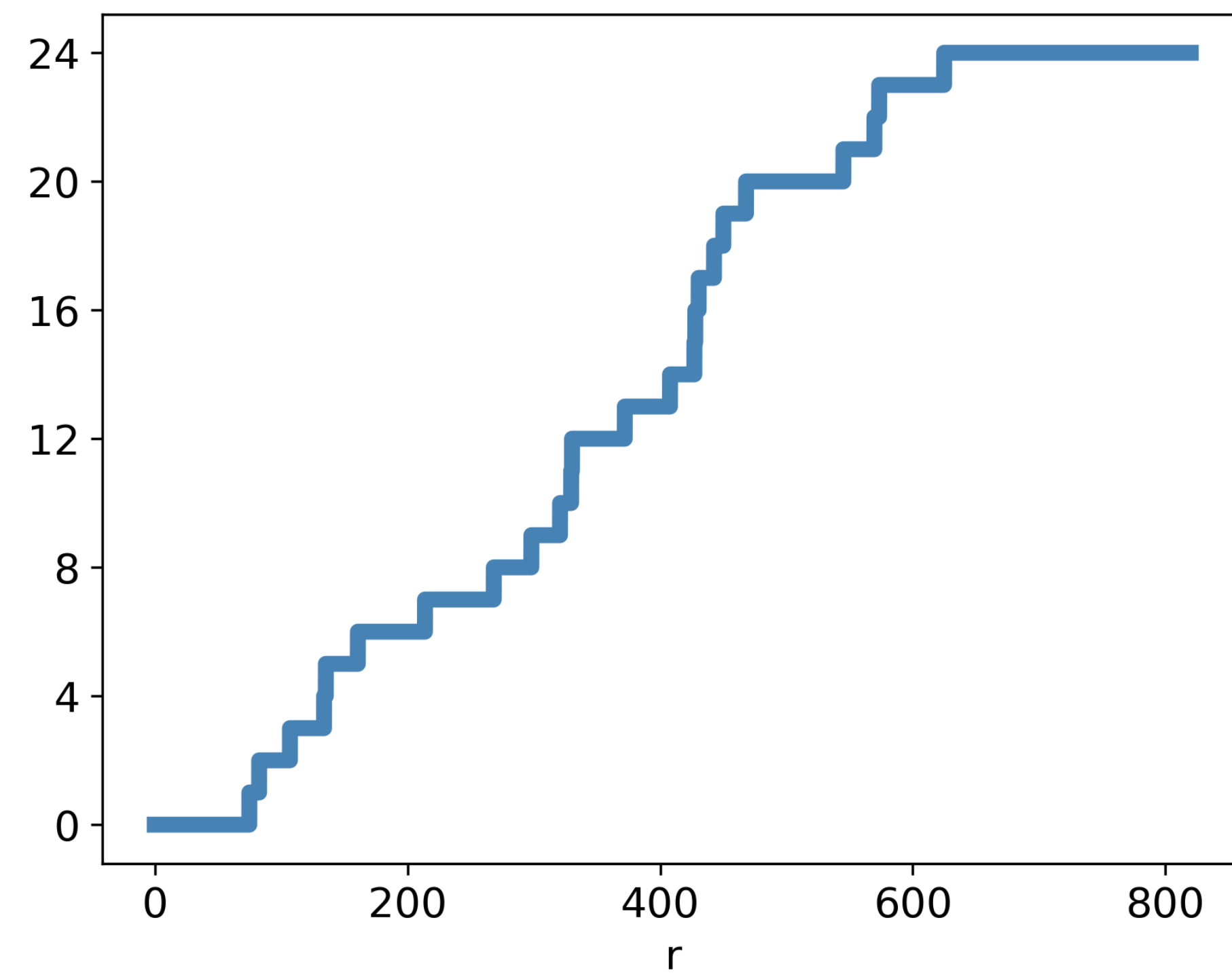
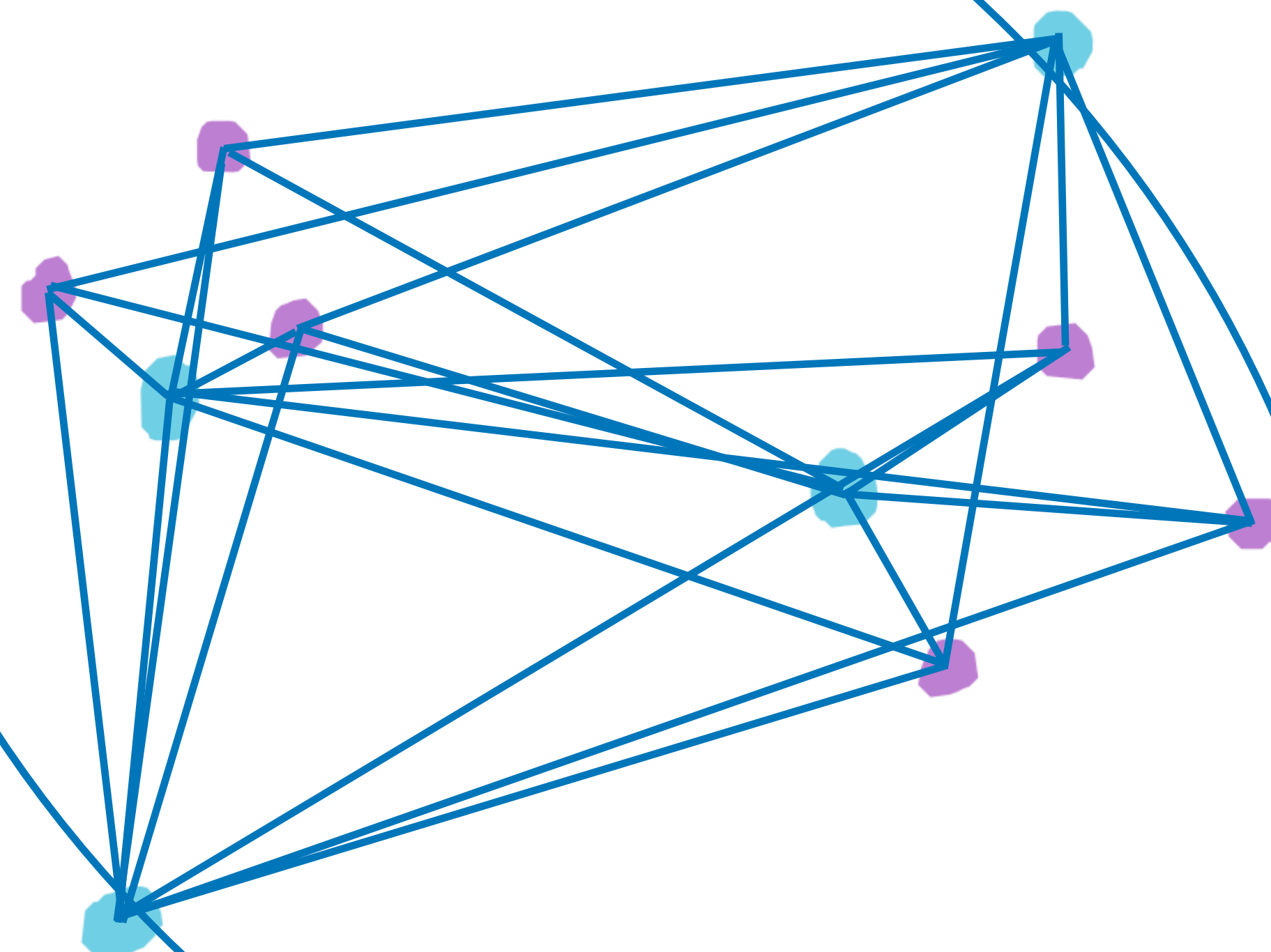
# Ripley's K function

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$





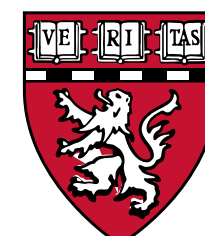
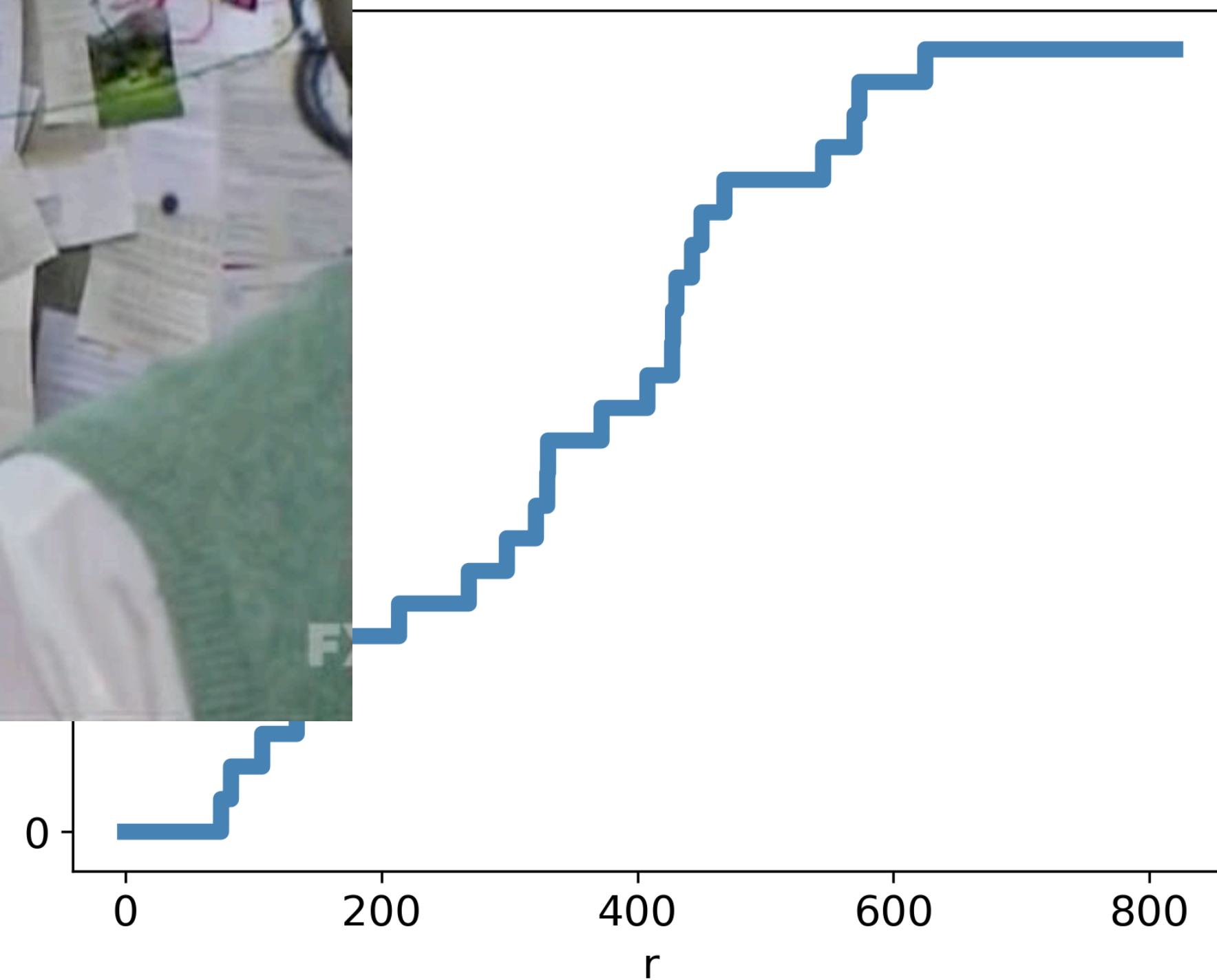
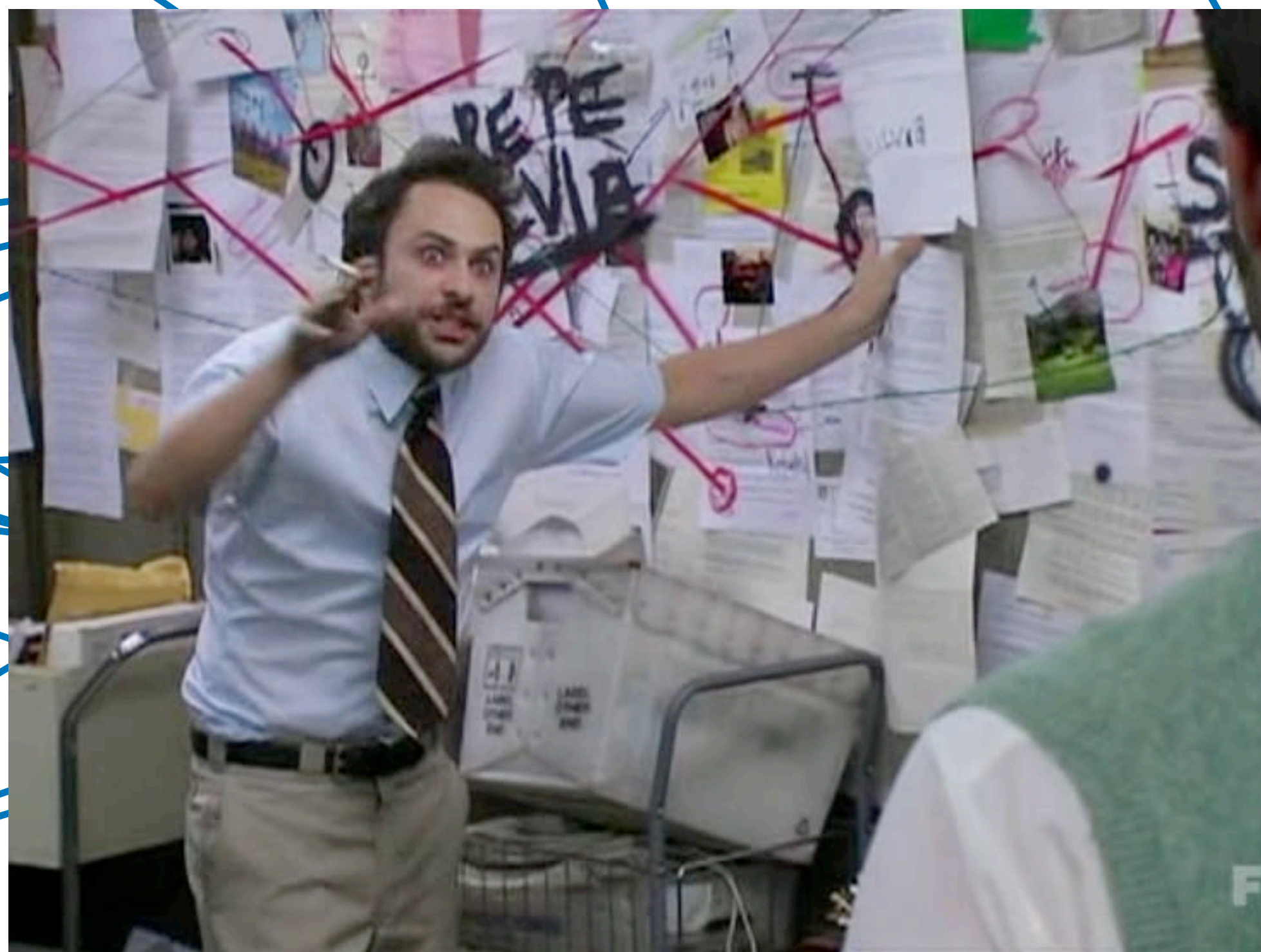
# Ripley's K function





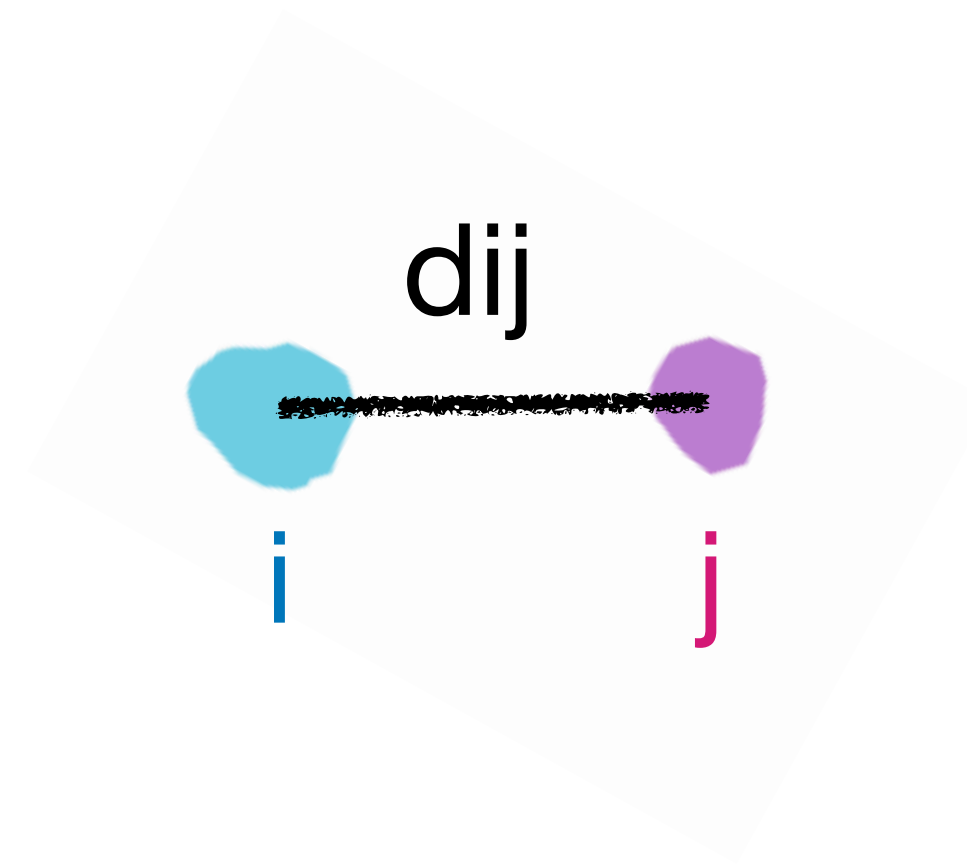
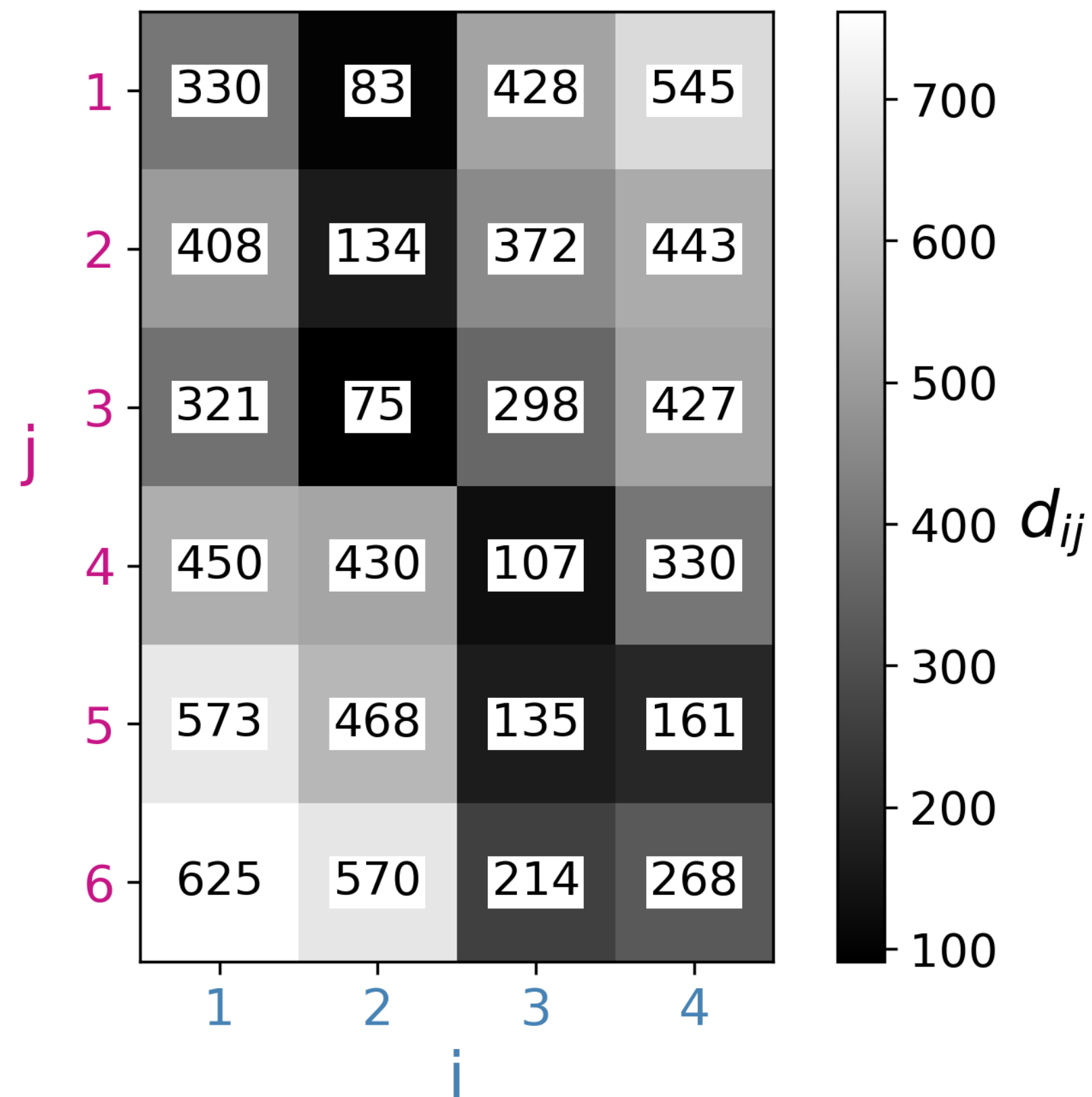


# Ripley's K function

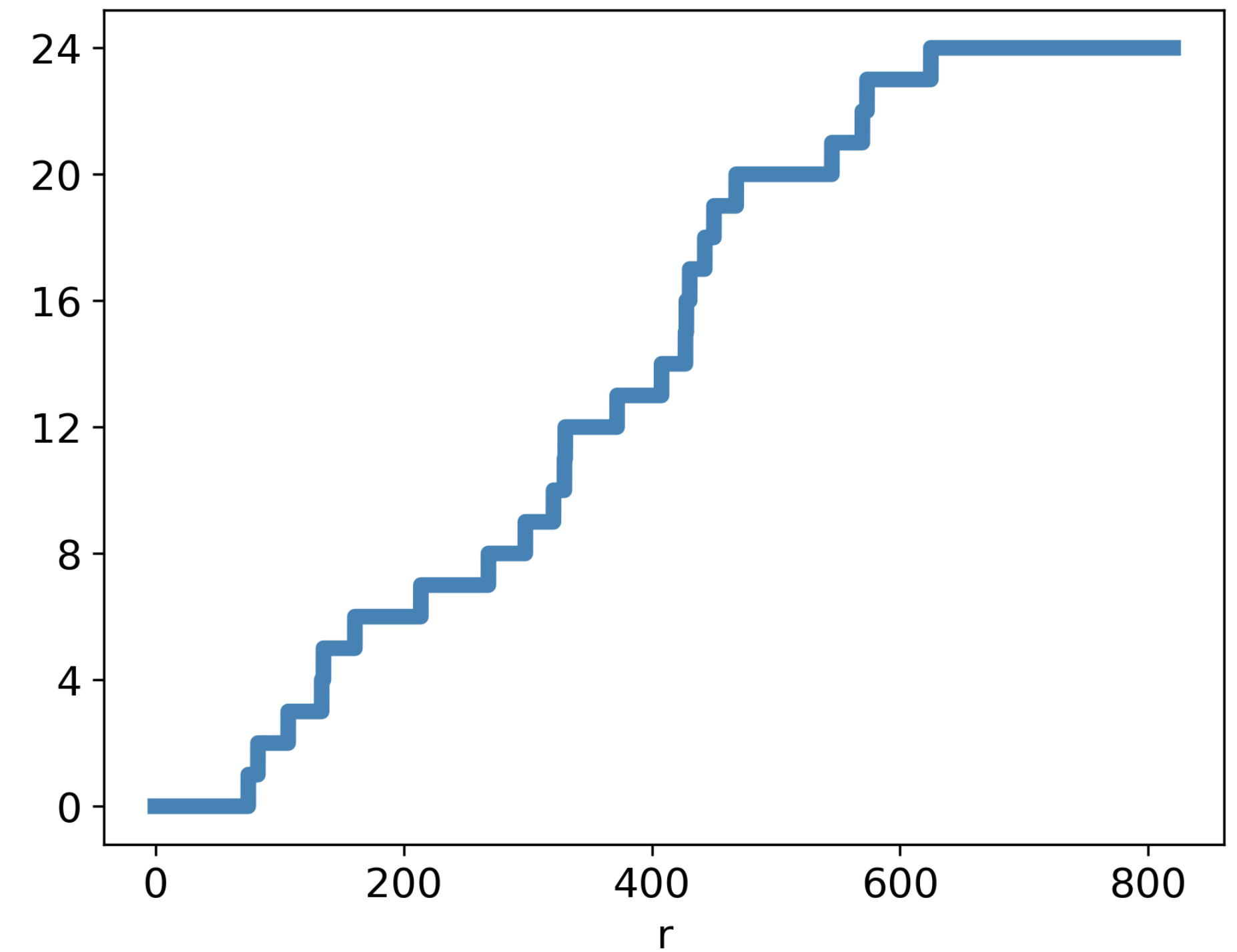




# Ripley's K function



$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

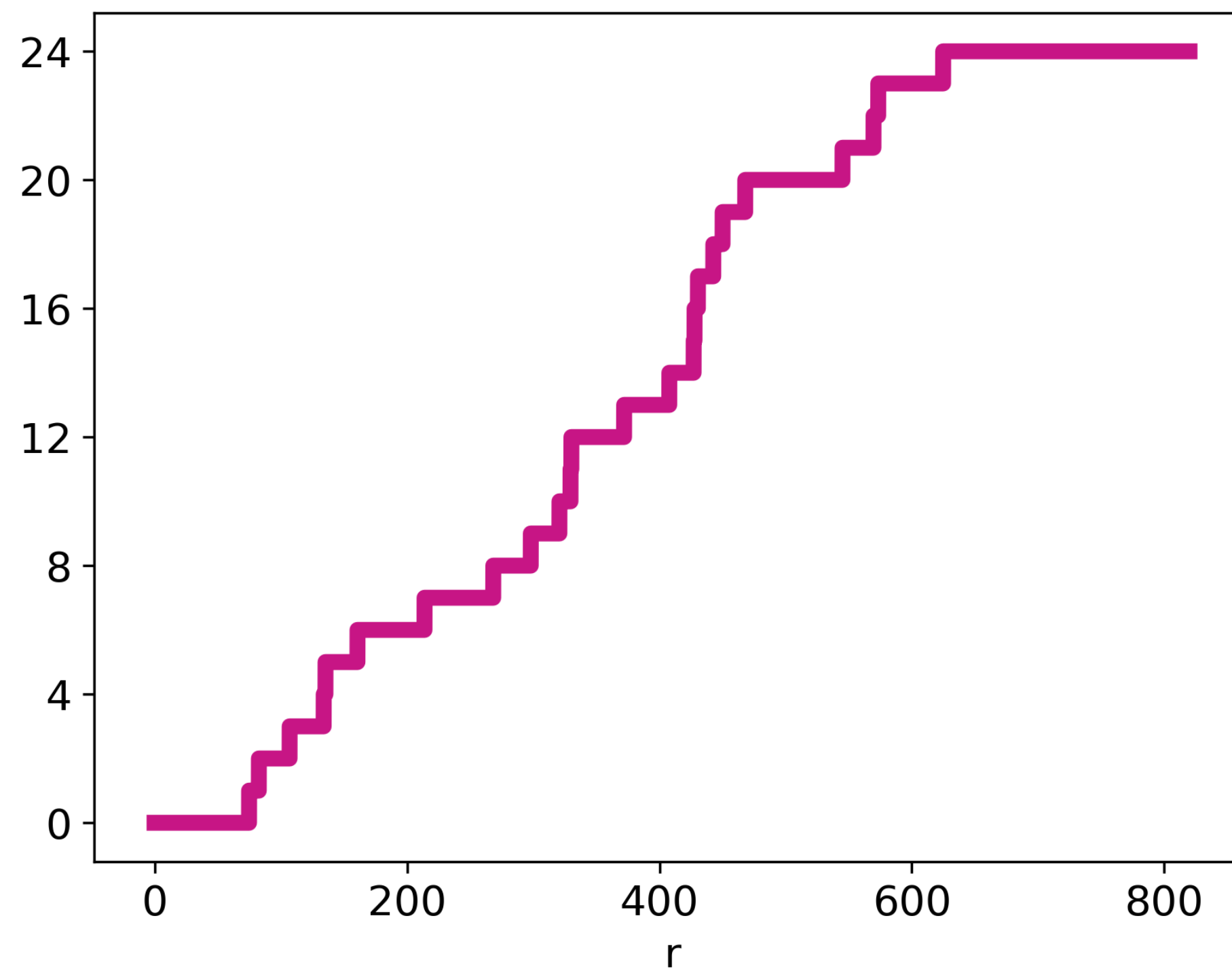




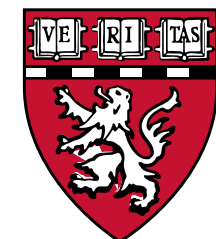
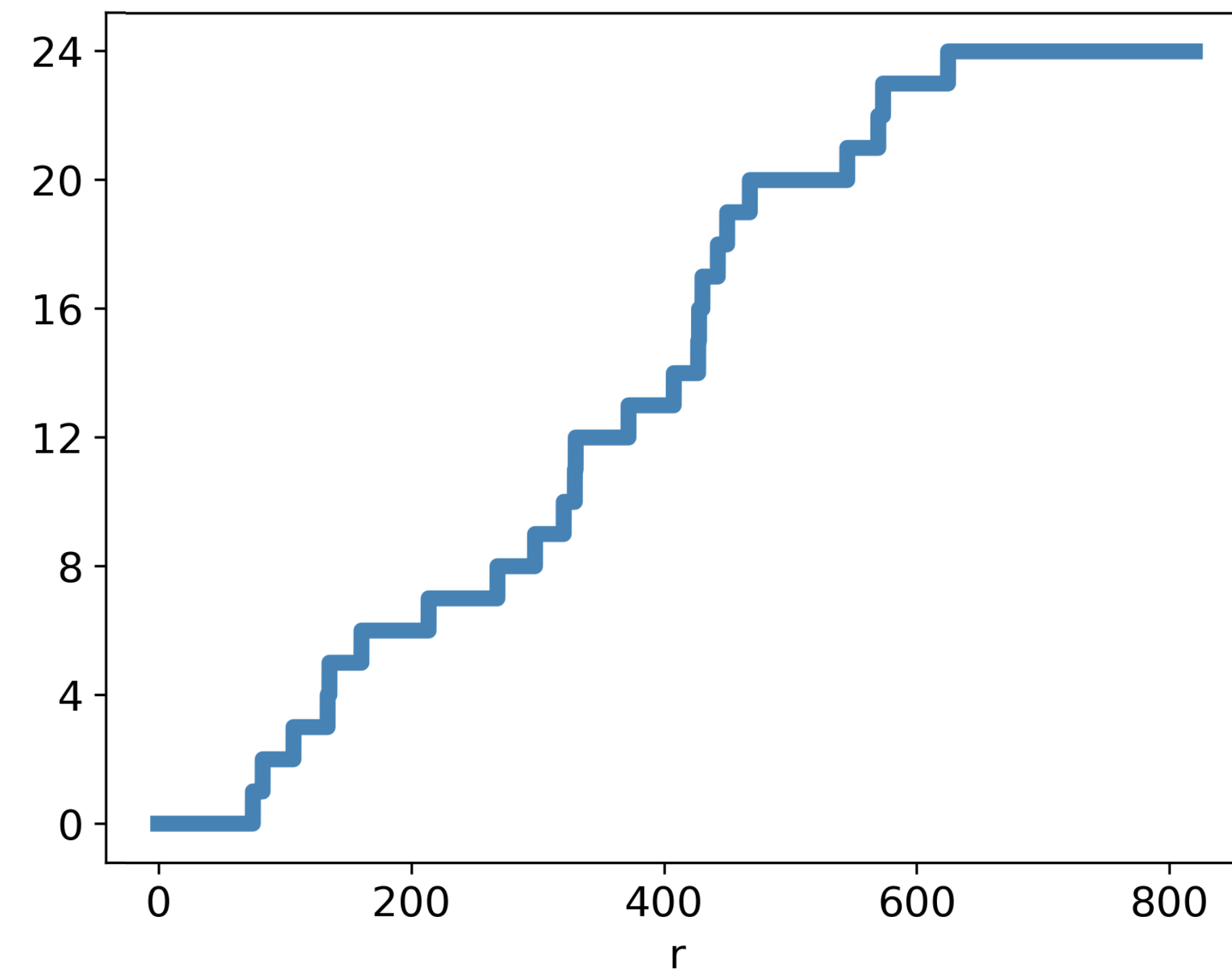
# Ripley's K function

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



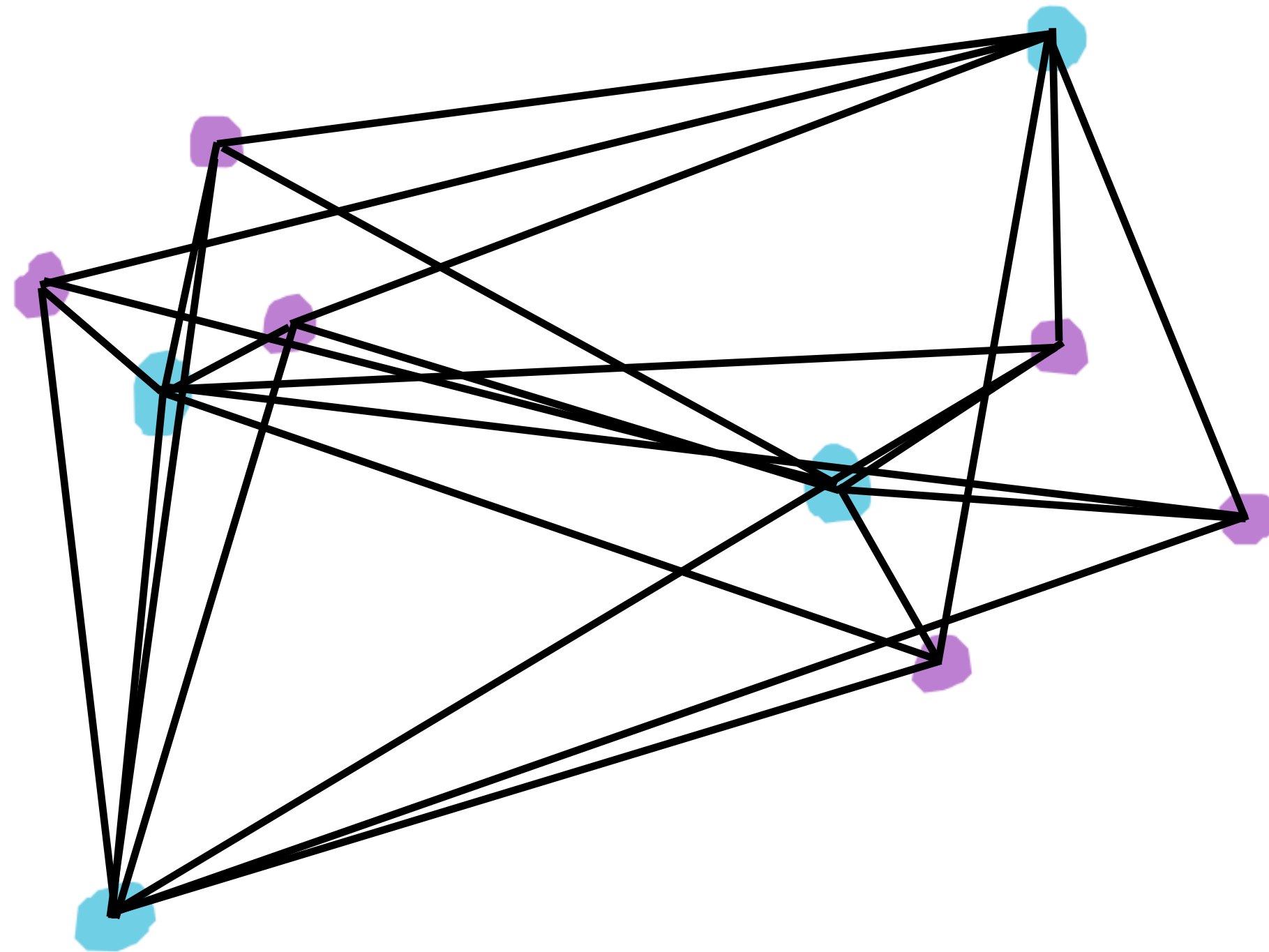
=



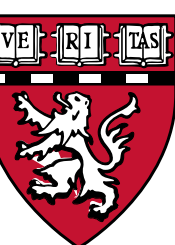
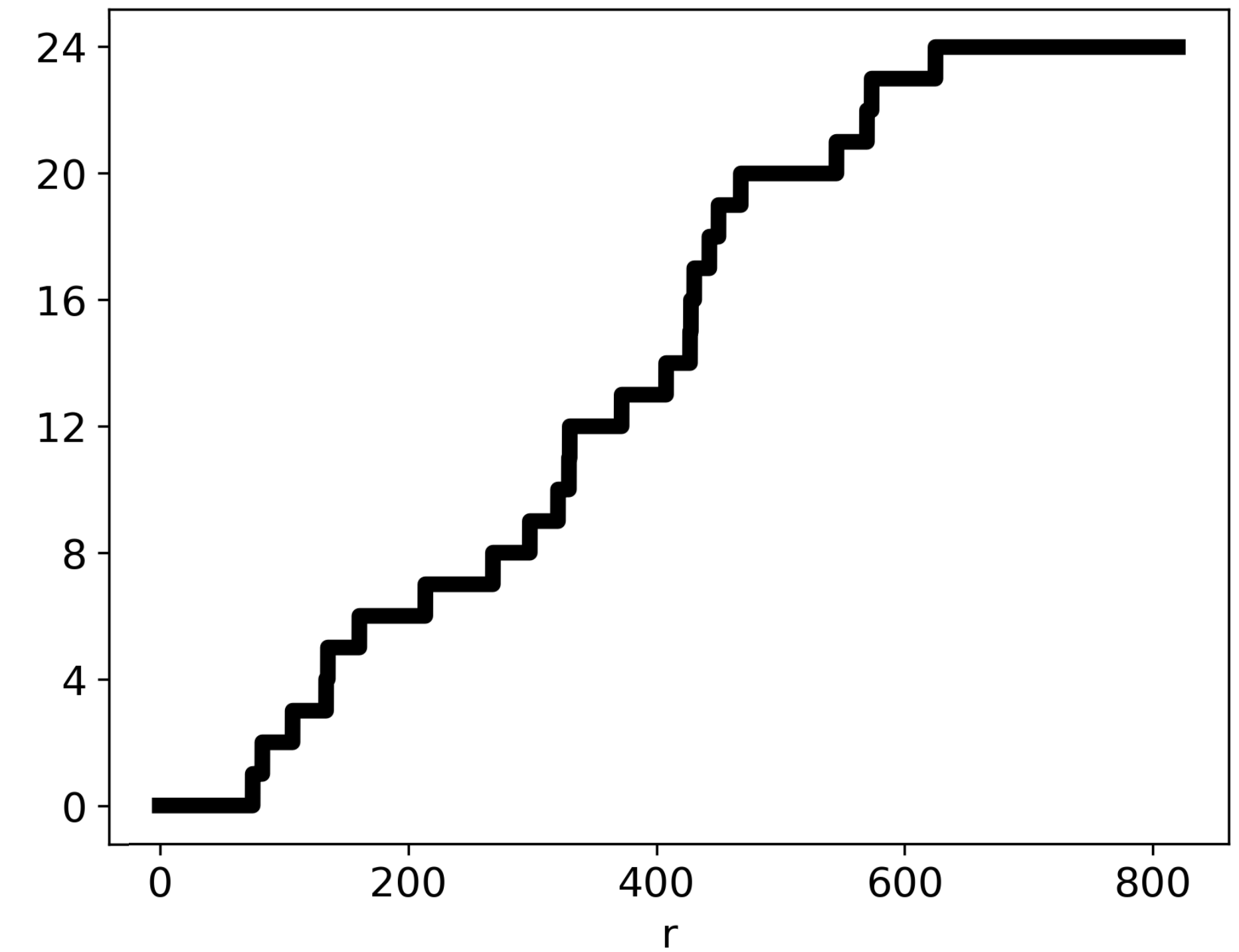




# Ripley's K function



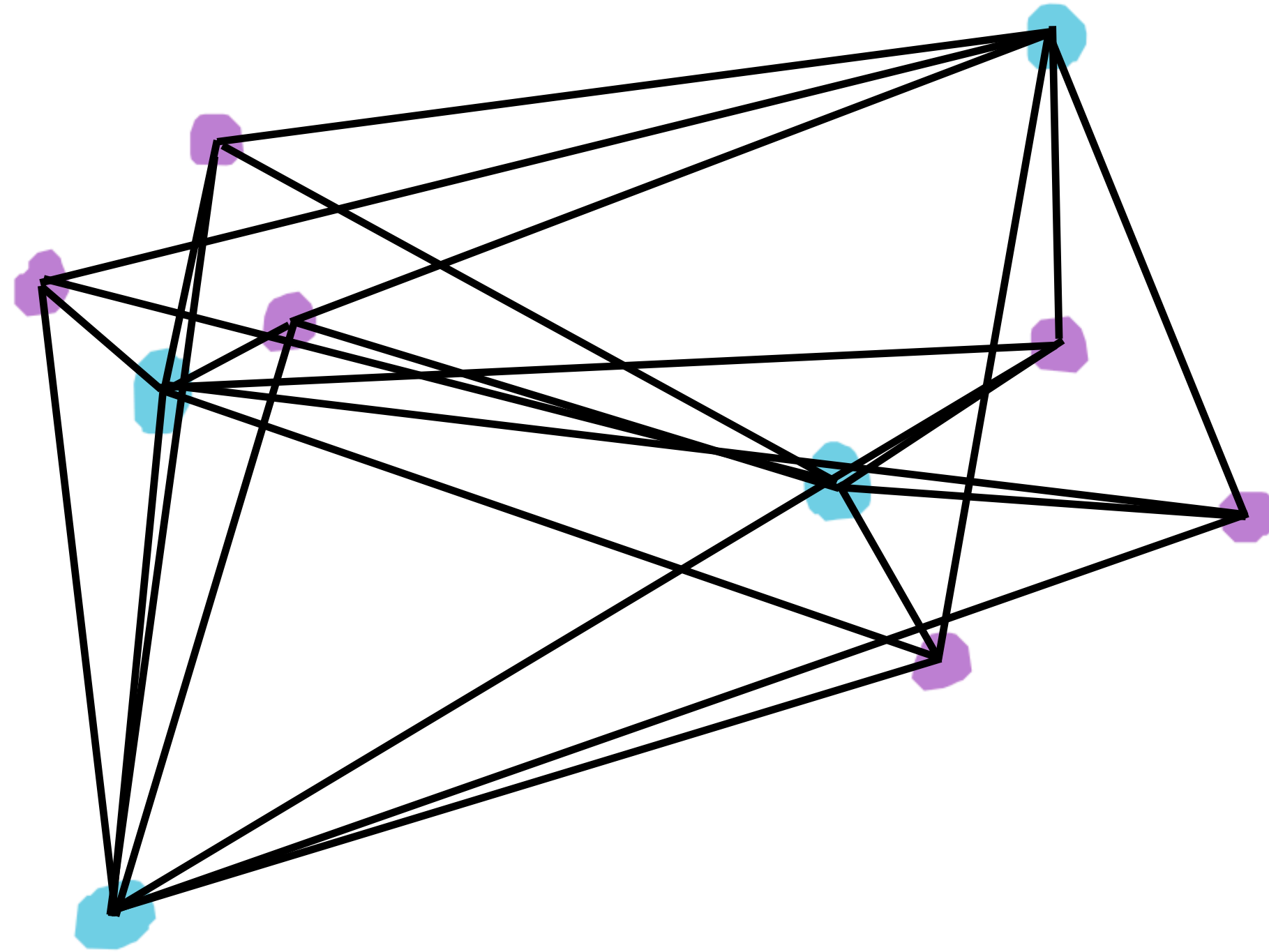
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



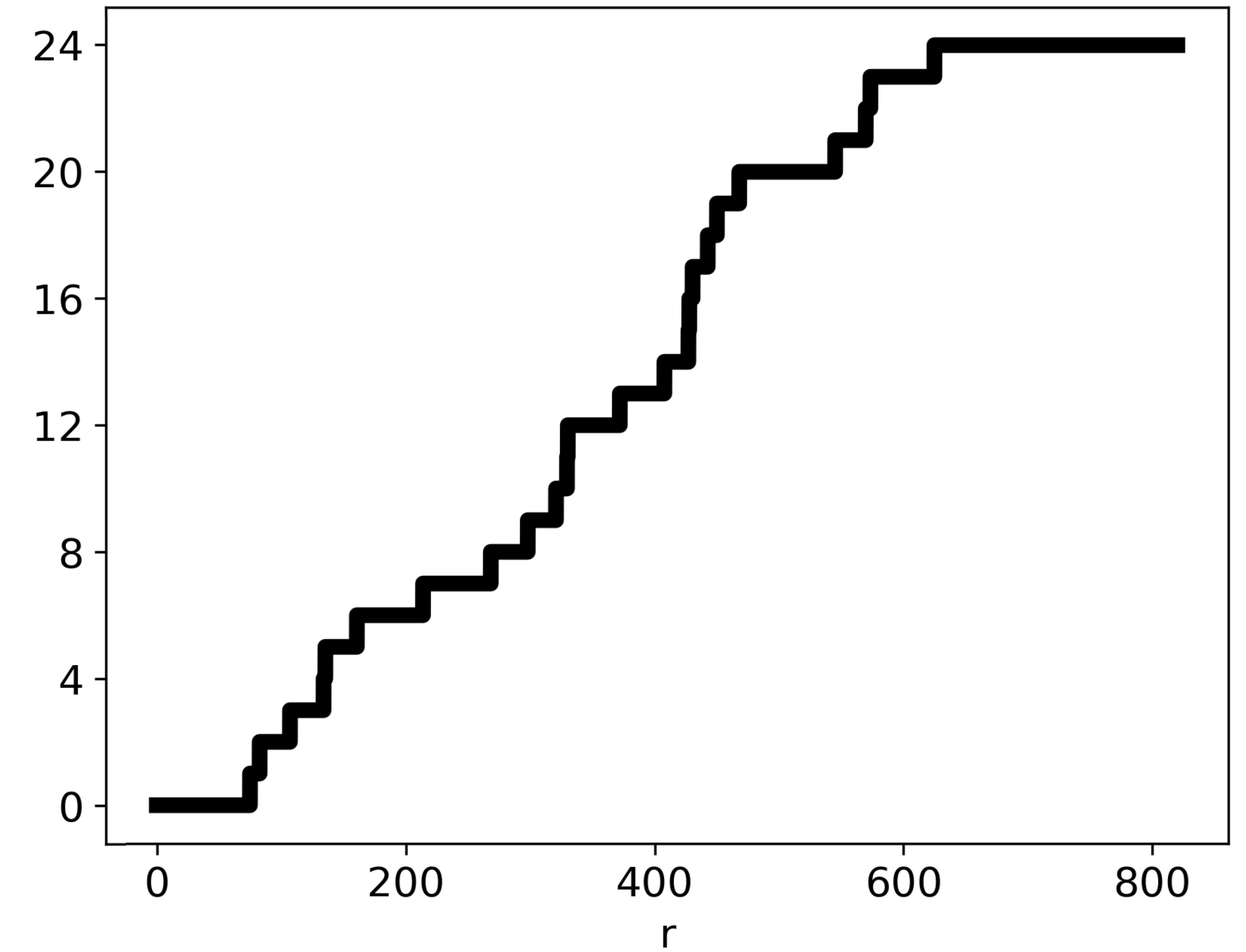




# Ripley's K function

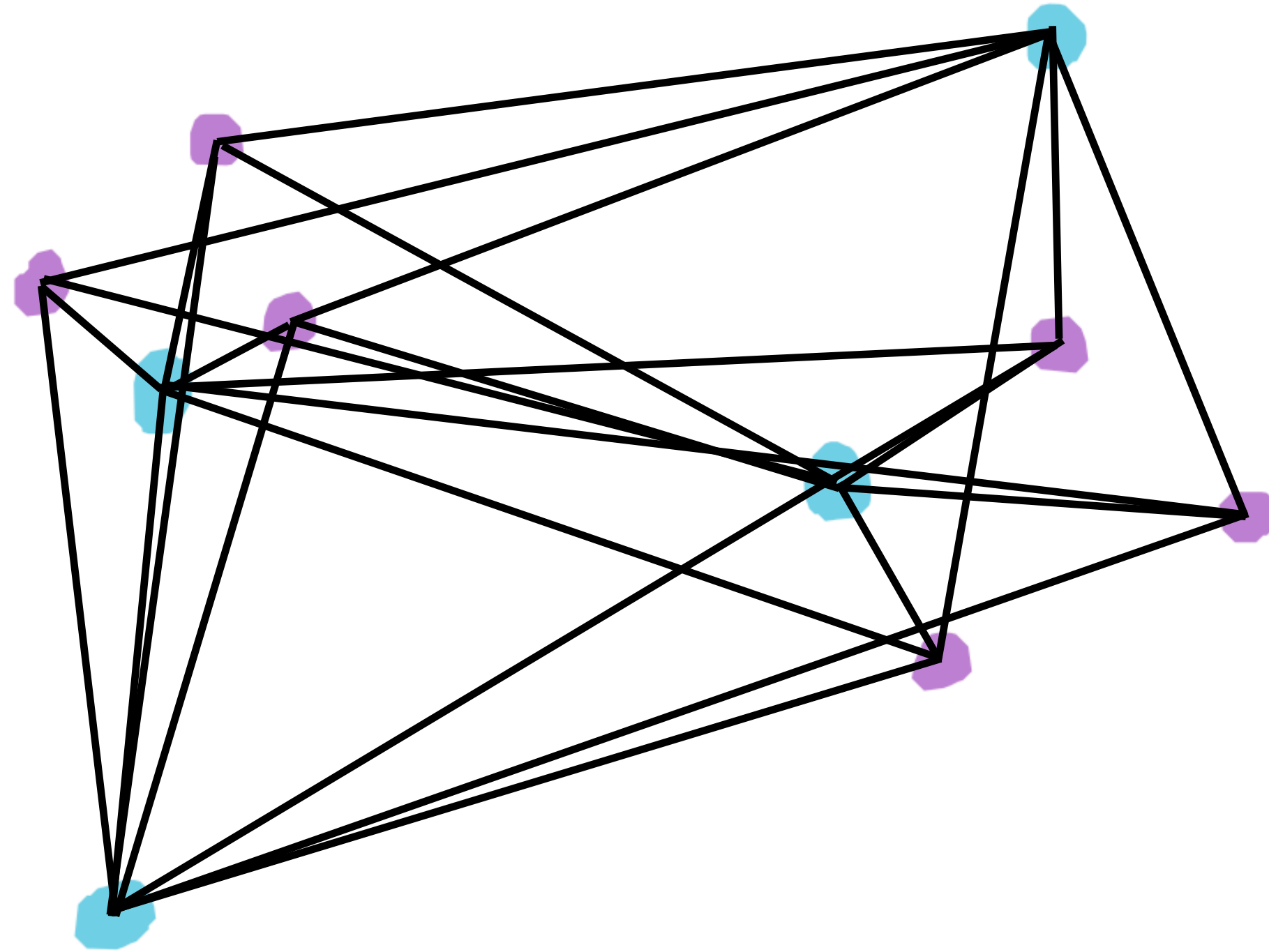


$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



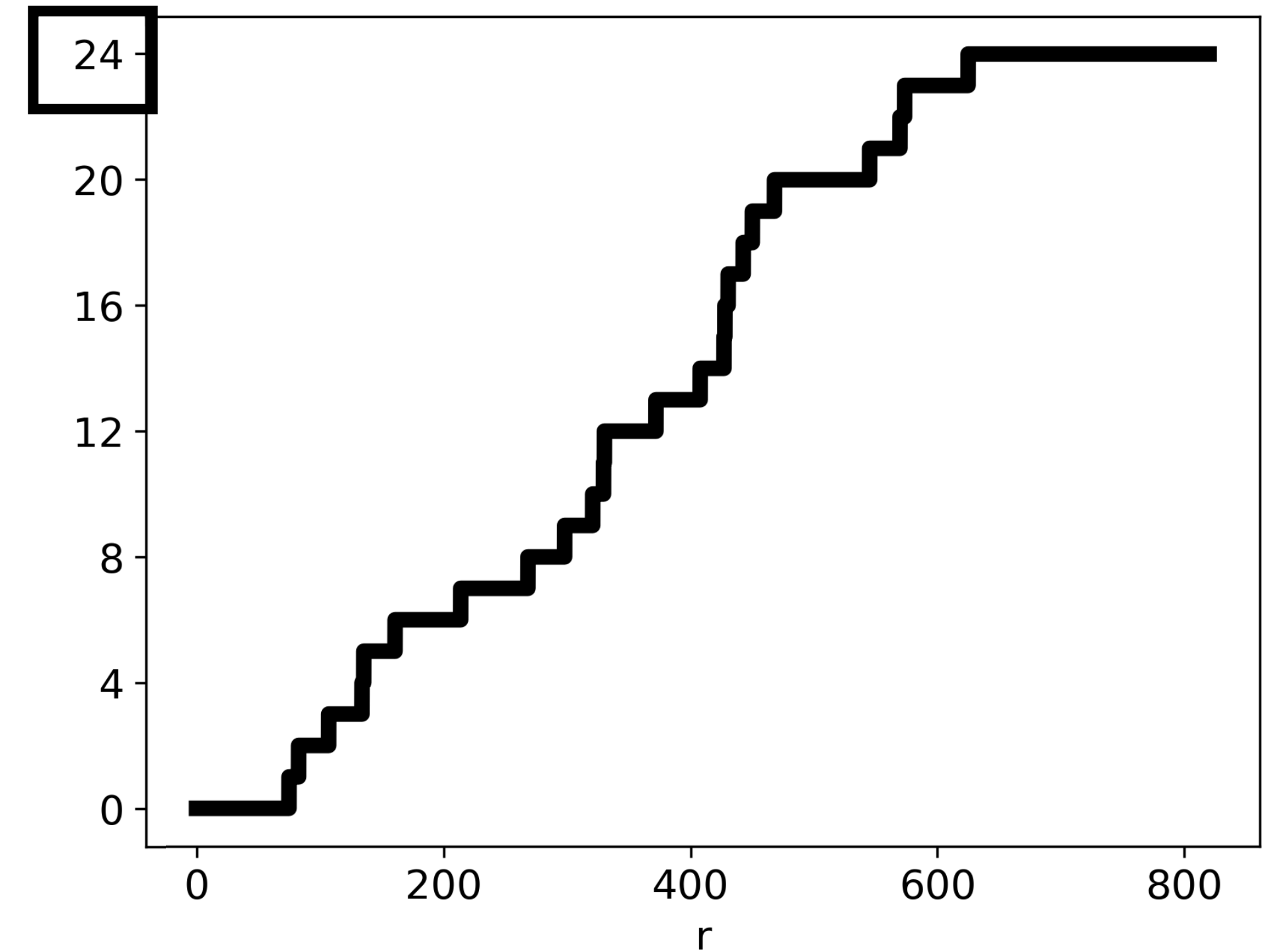


# Ripley's K function



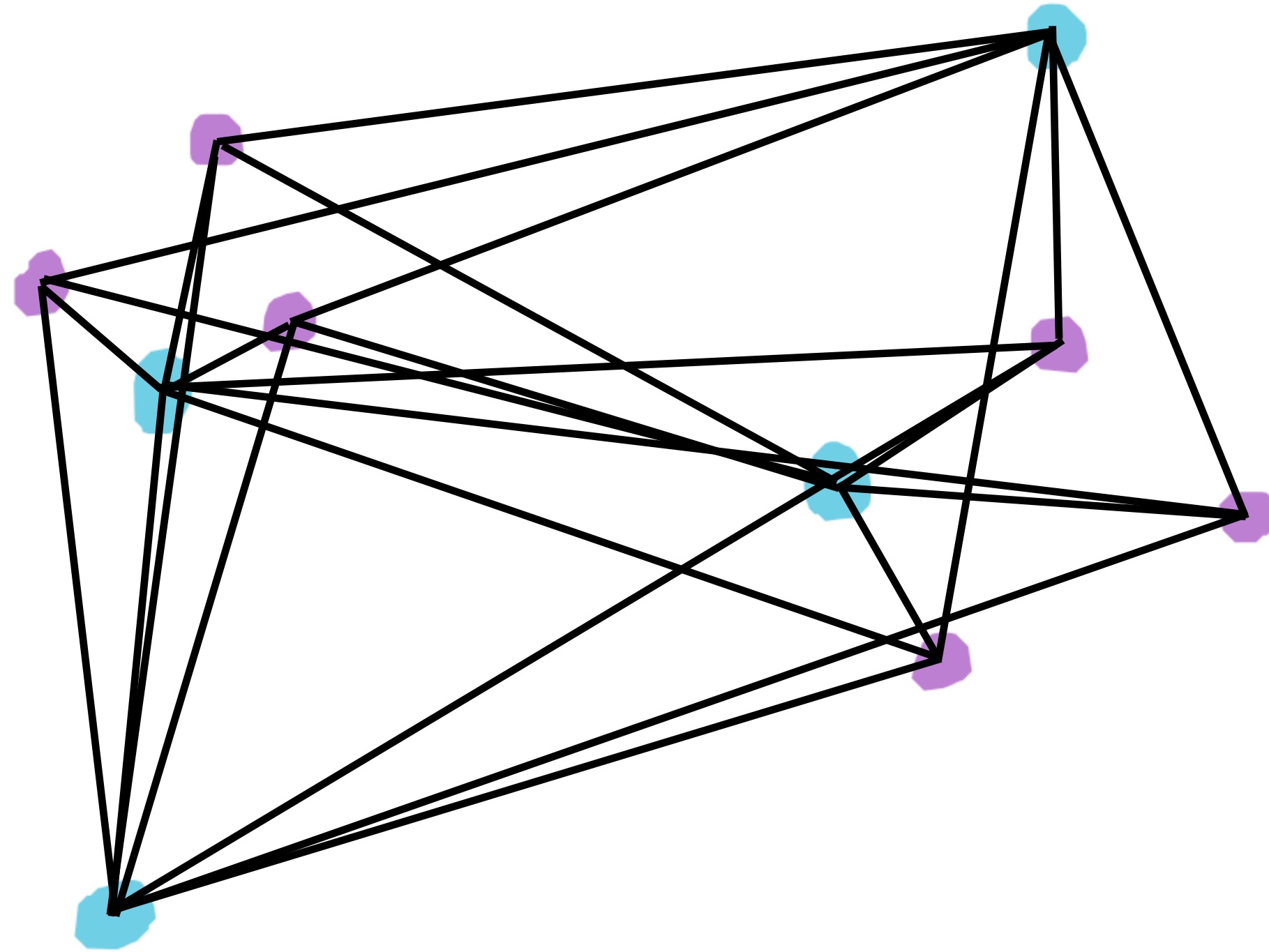
$$n_1 n_2 = n \text{ connections} = 24$$

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



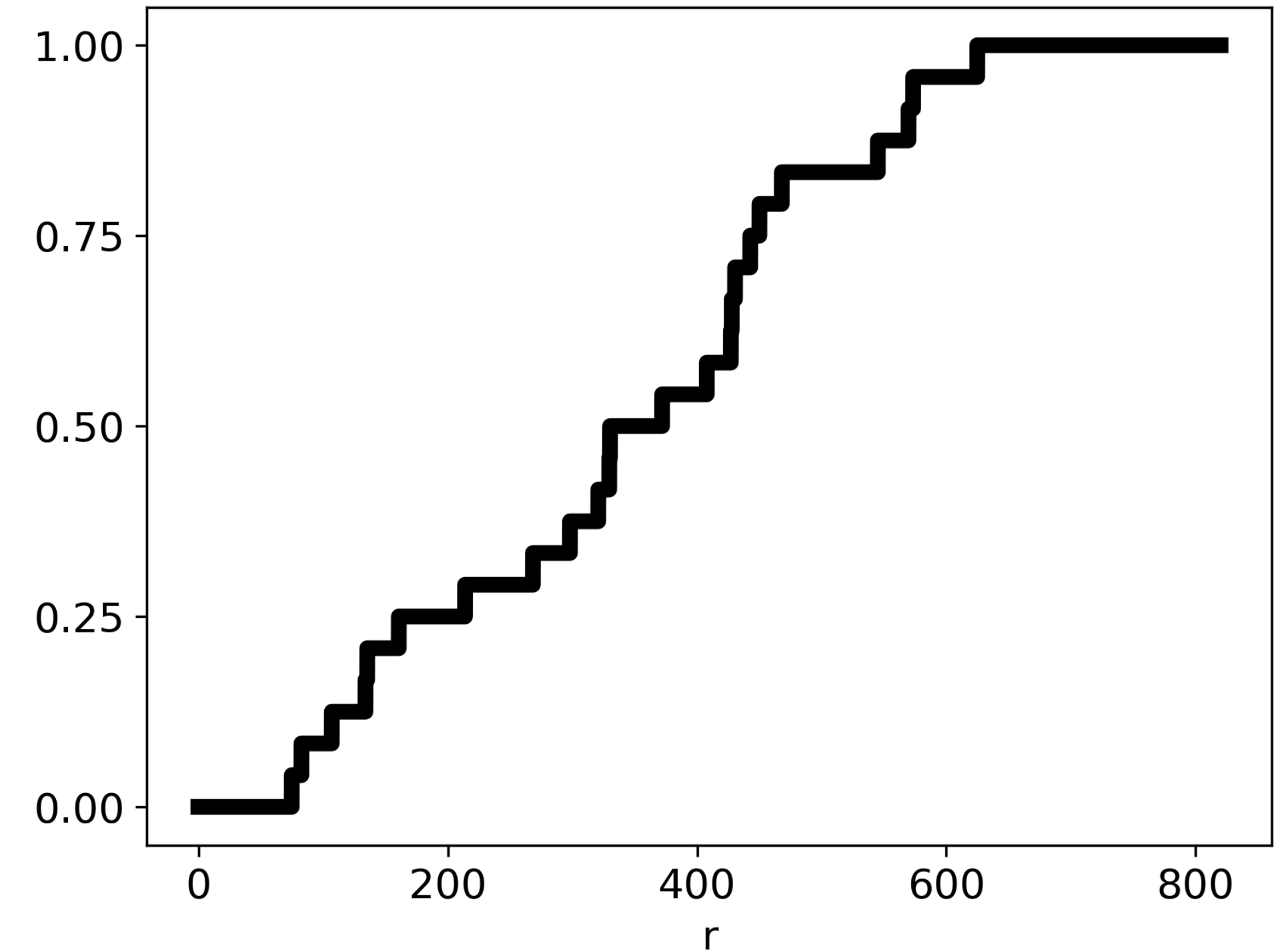


# Ripley's K function



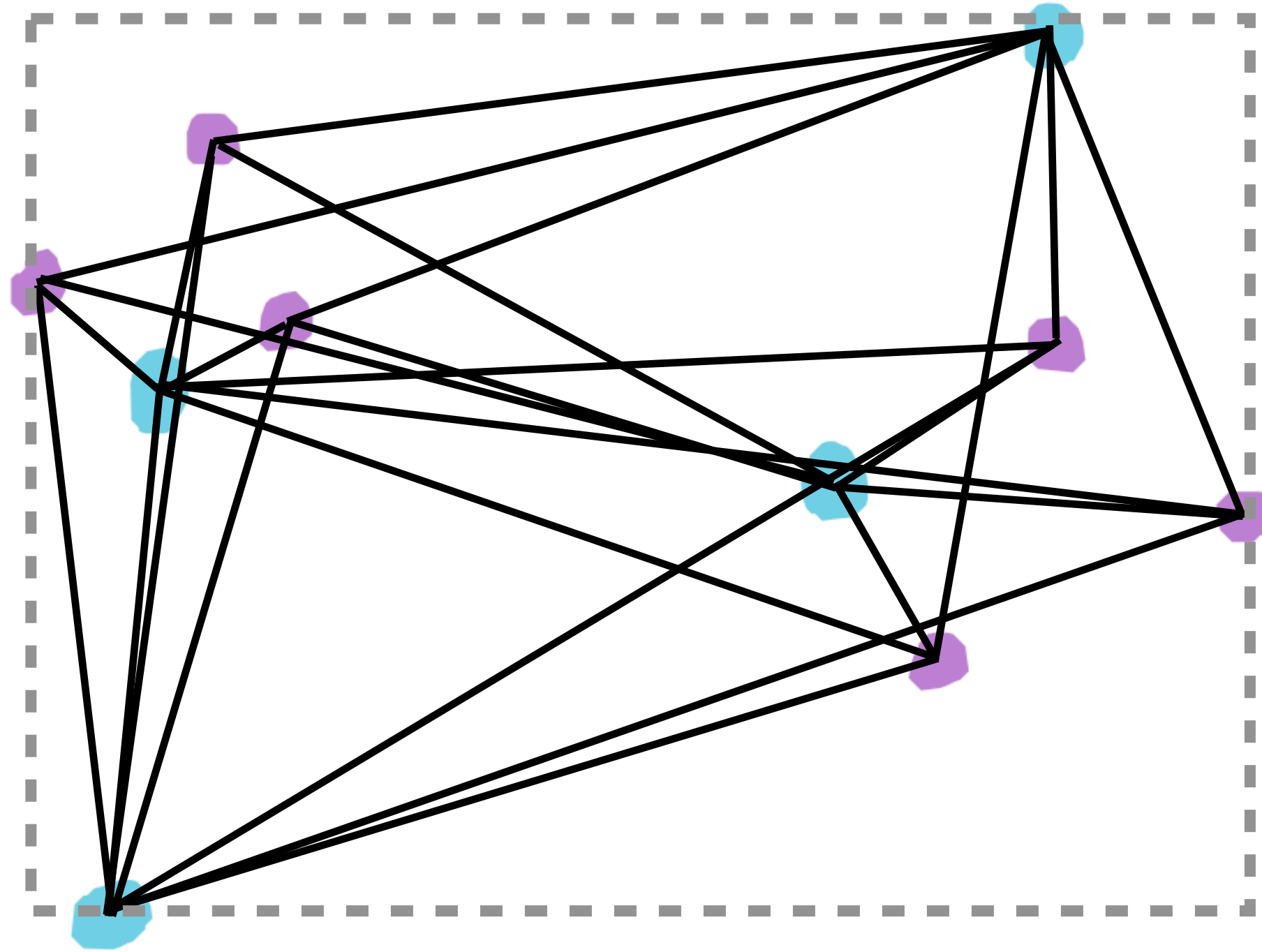
$$n_1 n_2 = \text{n connections} = 24$$

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



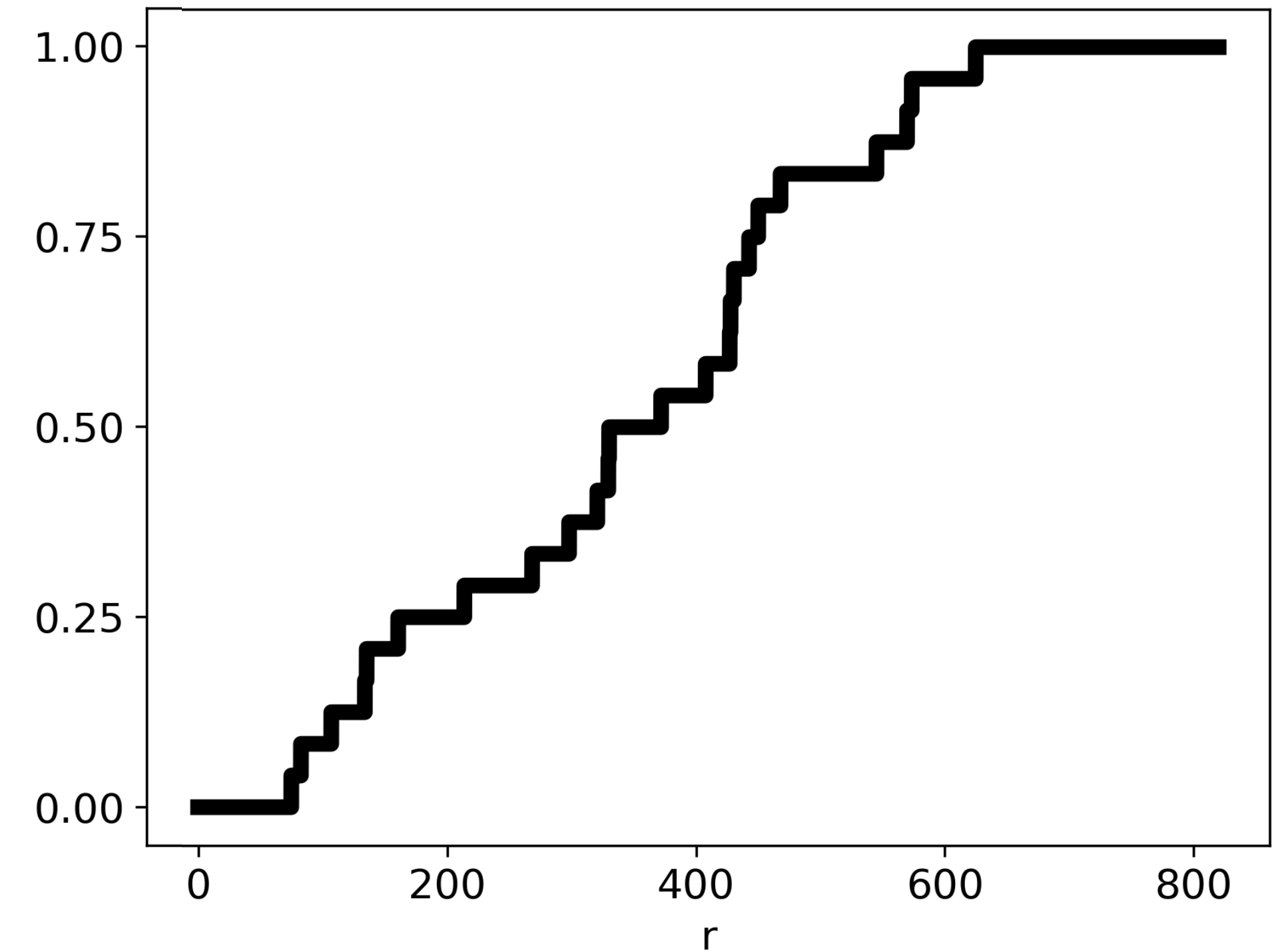


# Ripley's K function



$|\Omega| = \text{Area of FOV}$

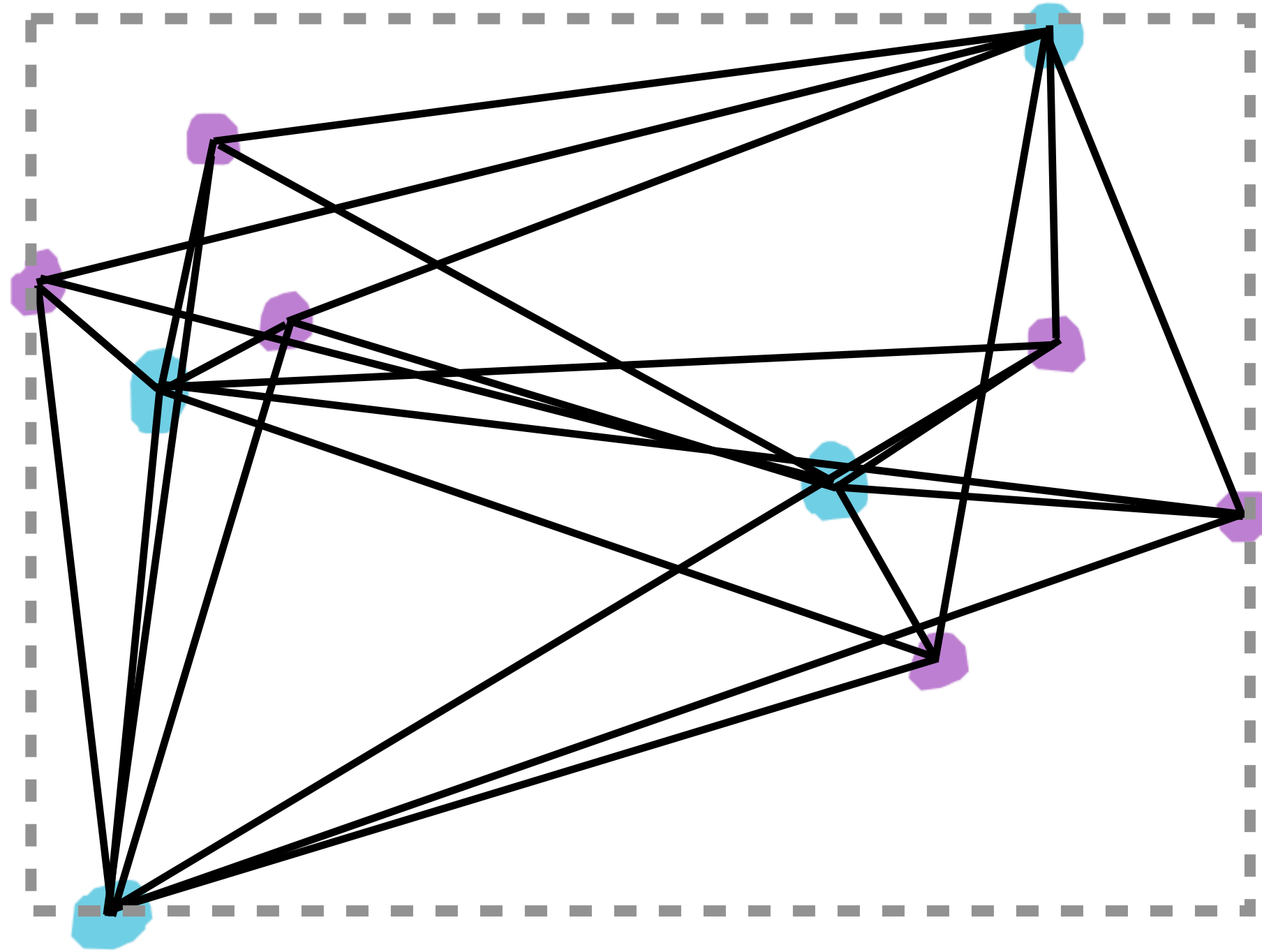
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$





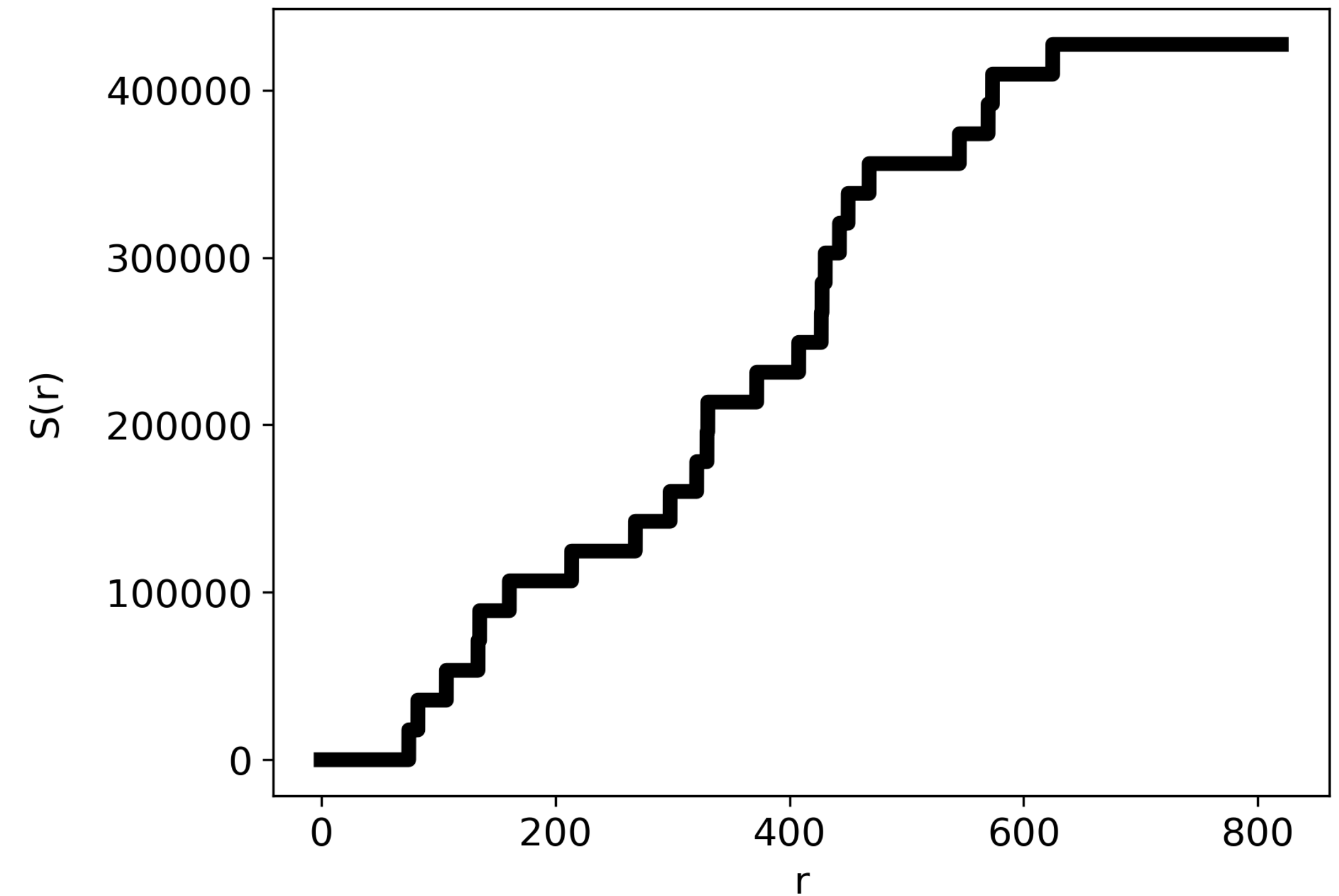


# Ripley's K function



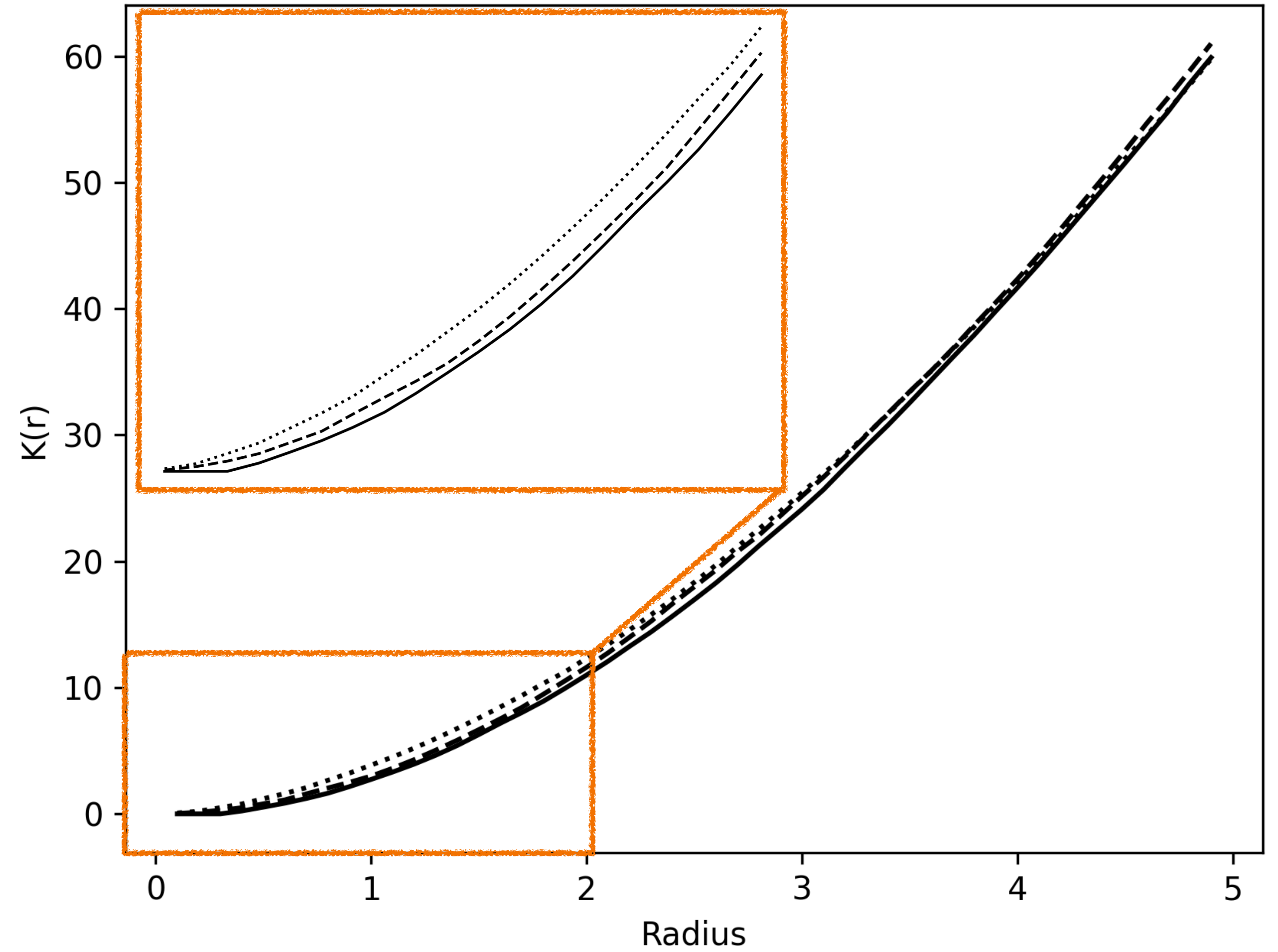
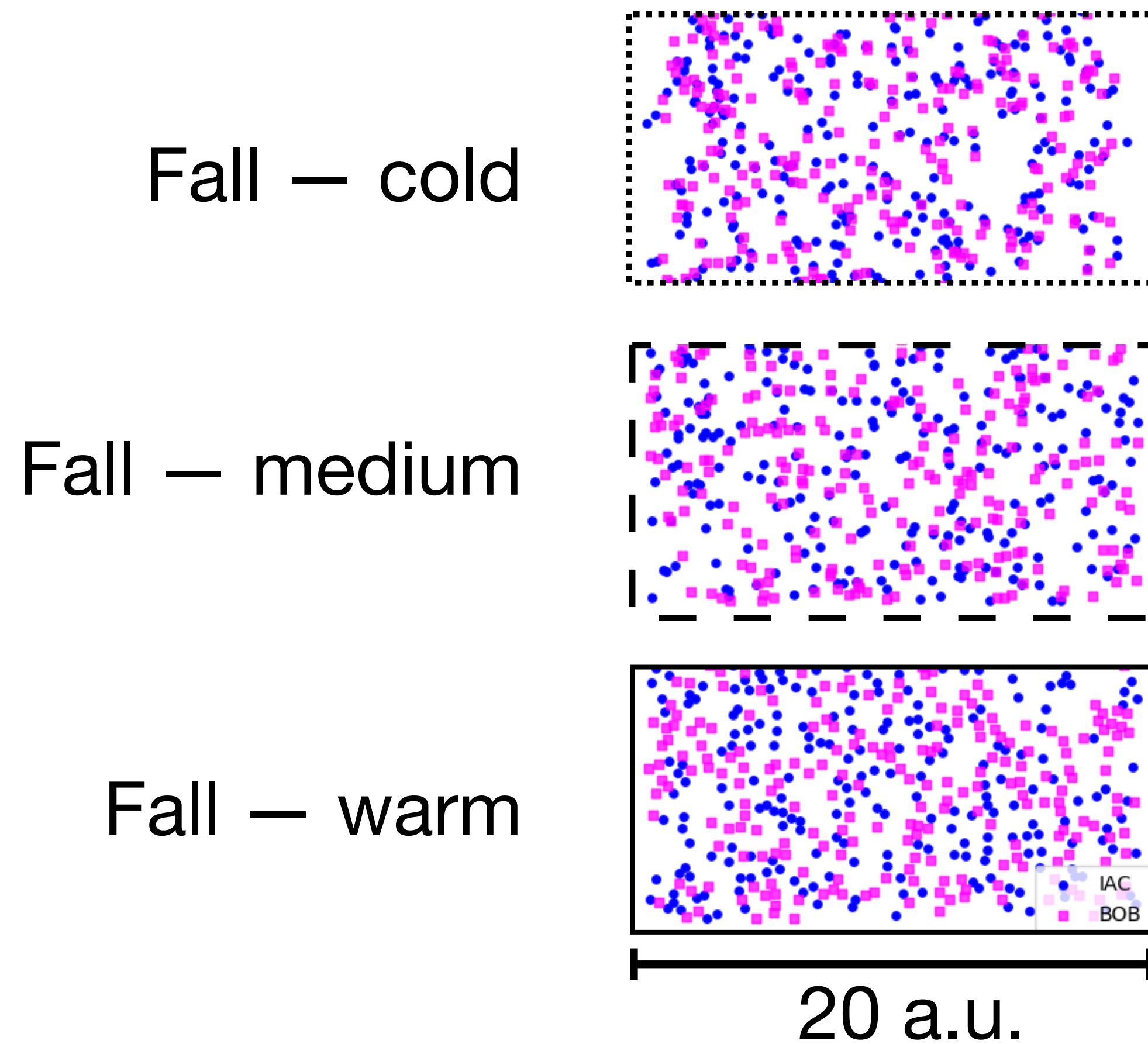
$|\Omega| = \text{Area of FOV}$

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$





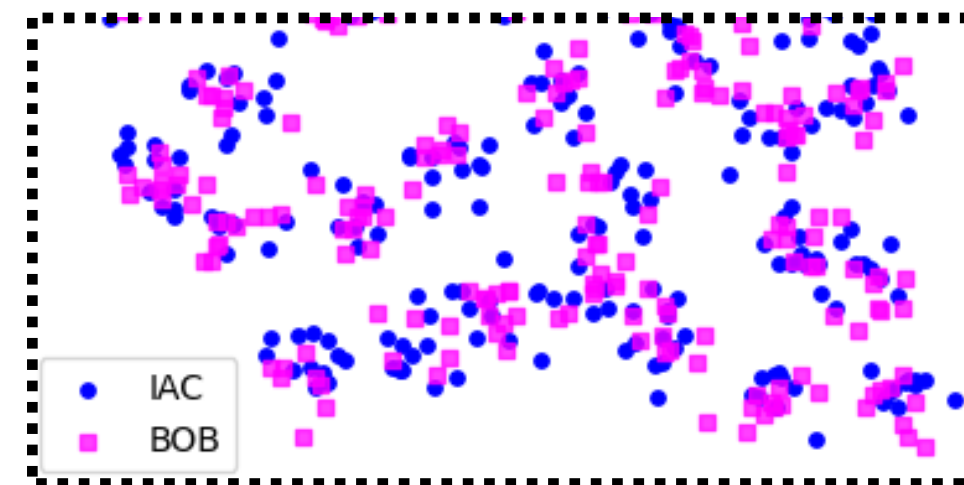
# Results: Ripley's K function



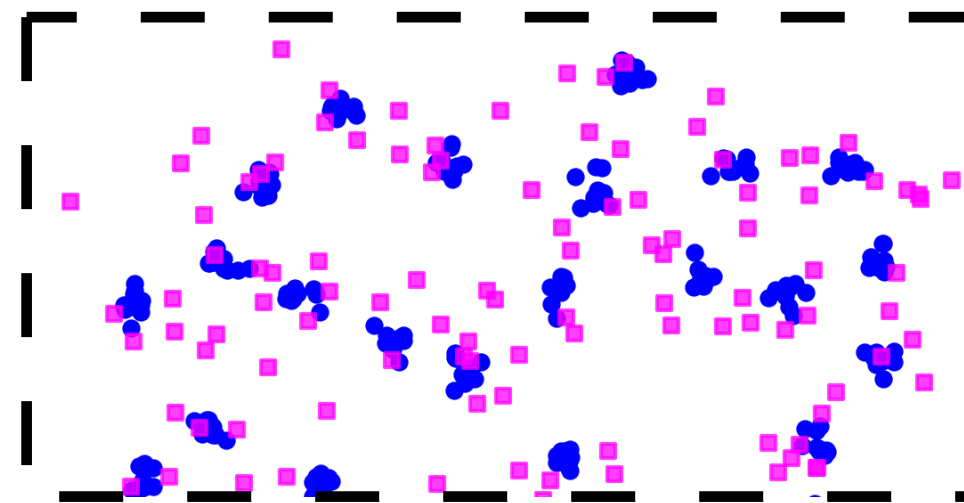


# Results: Ripley's K function

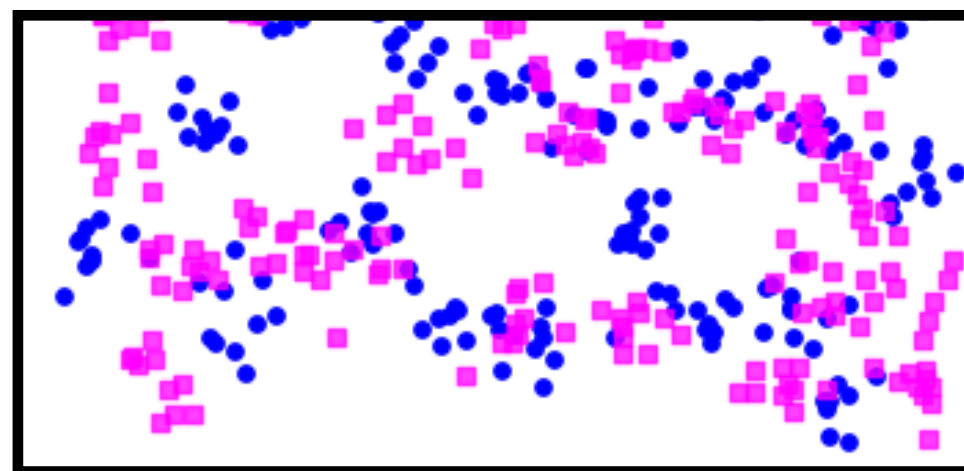
Winter — cold



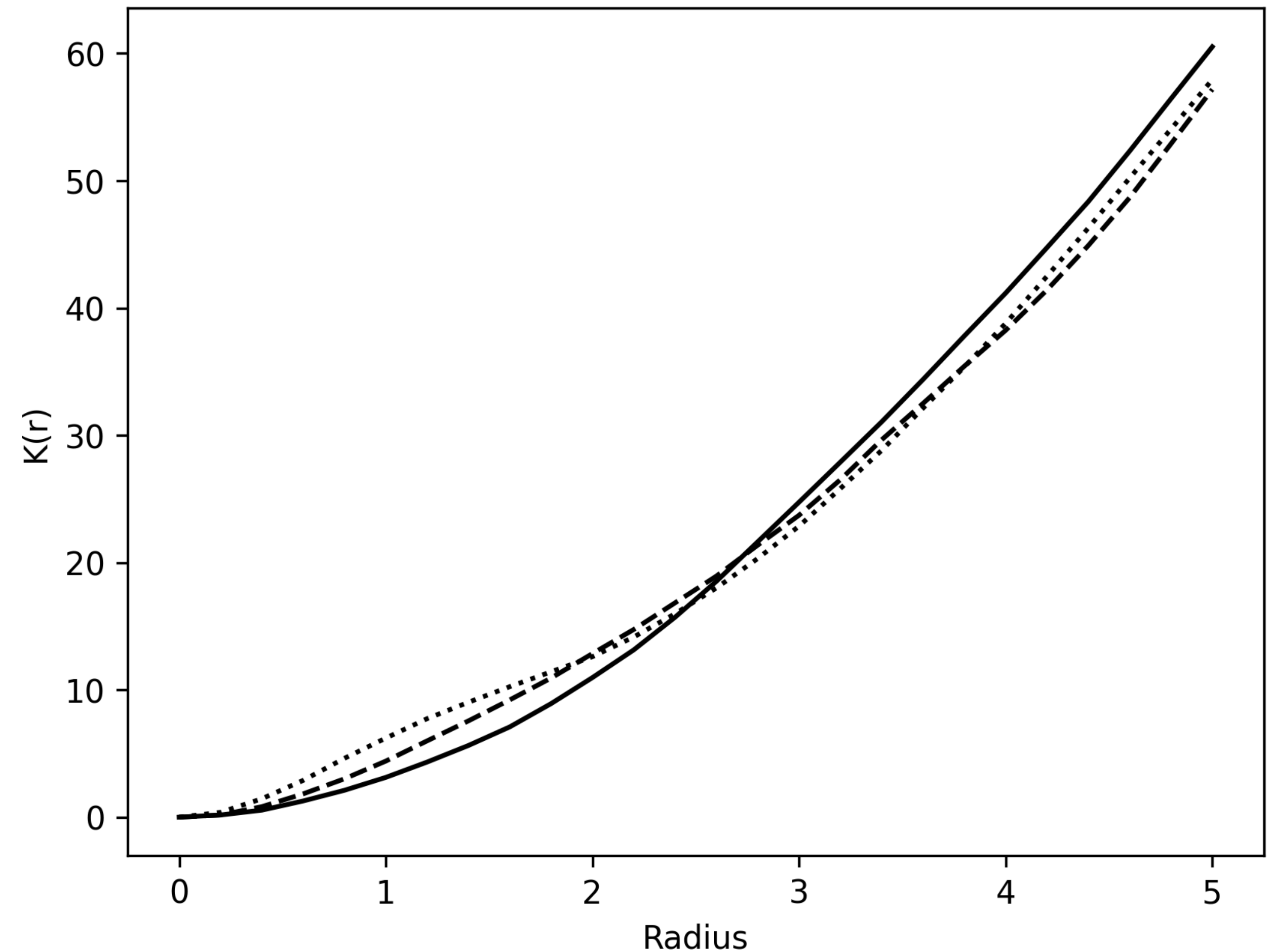
Winter — medium



Winter — warm



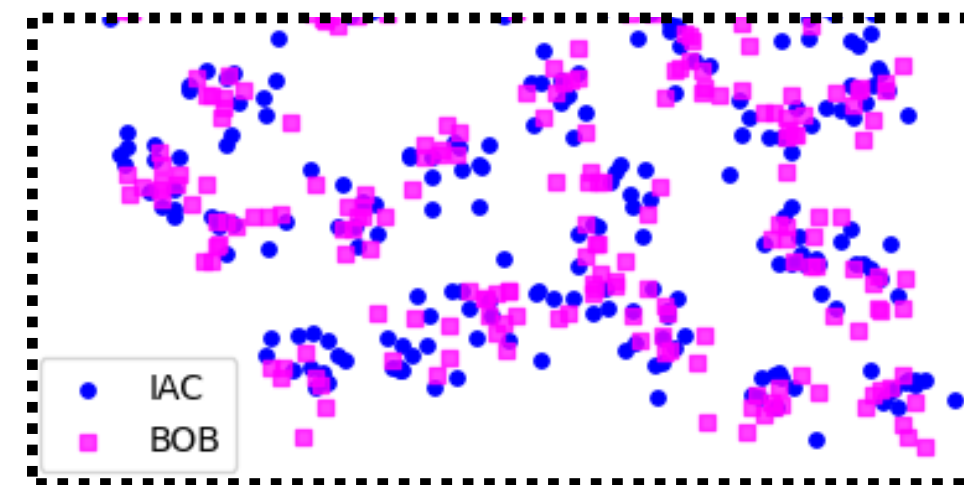
20 a.u.



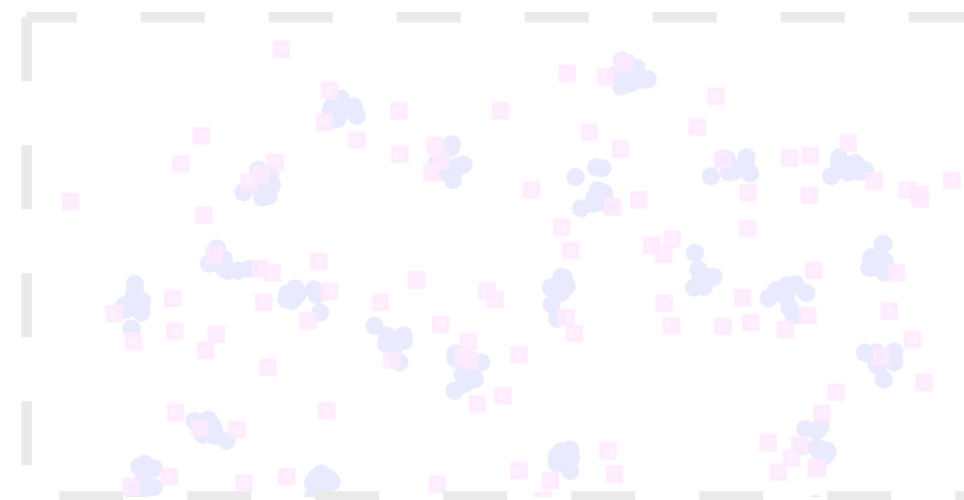


# Results: Ripley's K function

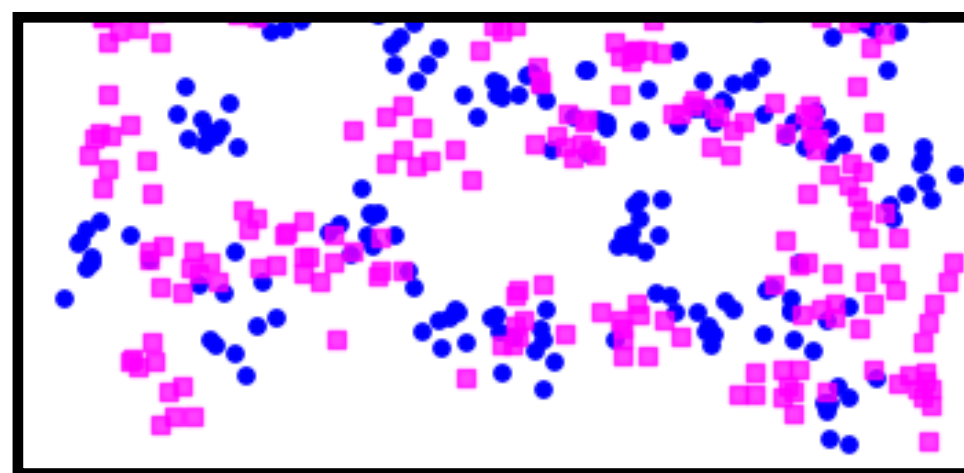
Winter — cold



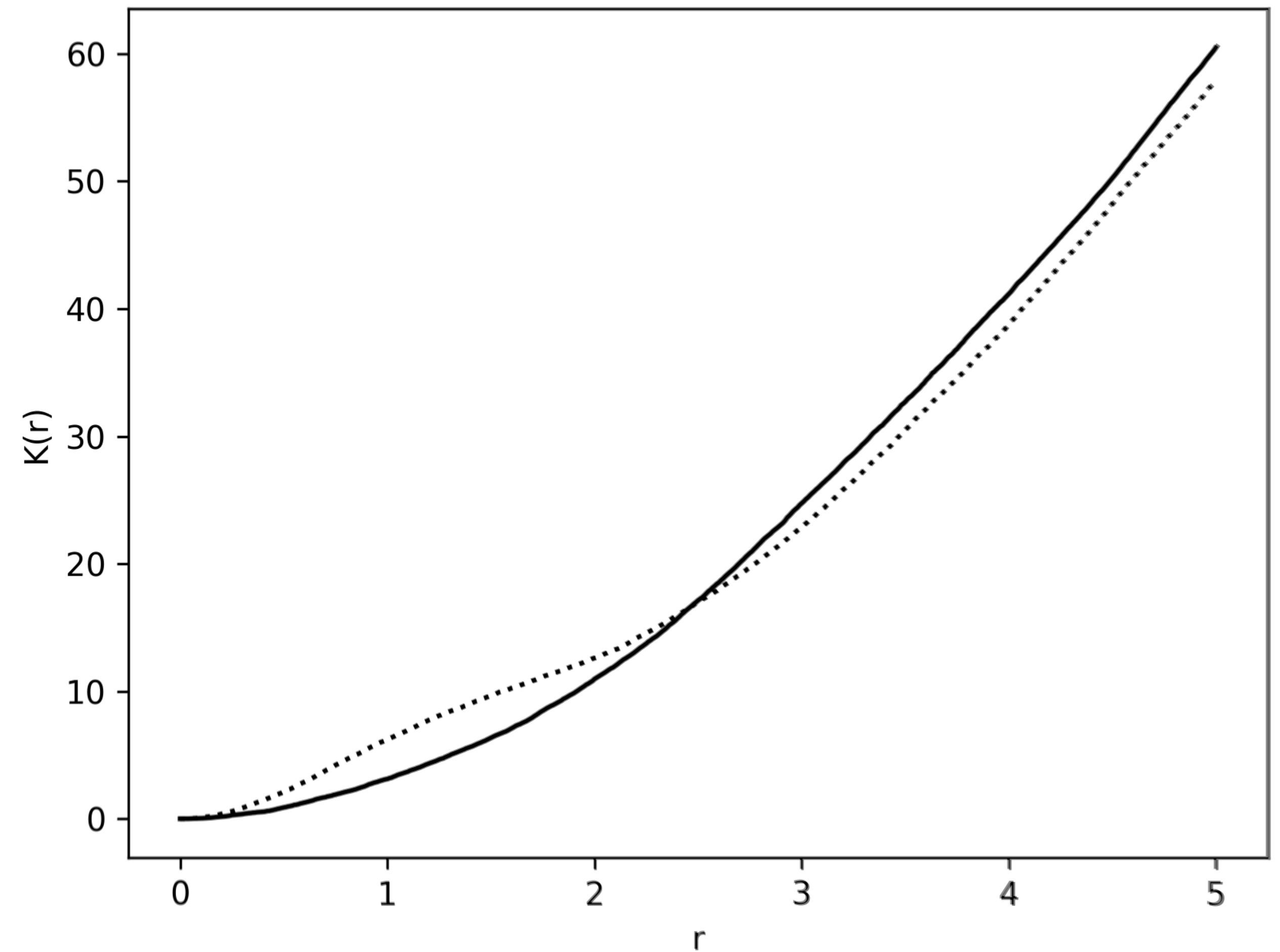
Winter — medium



Winter — warm



20 a.u.

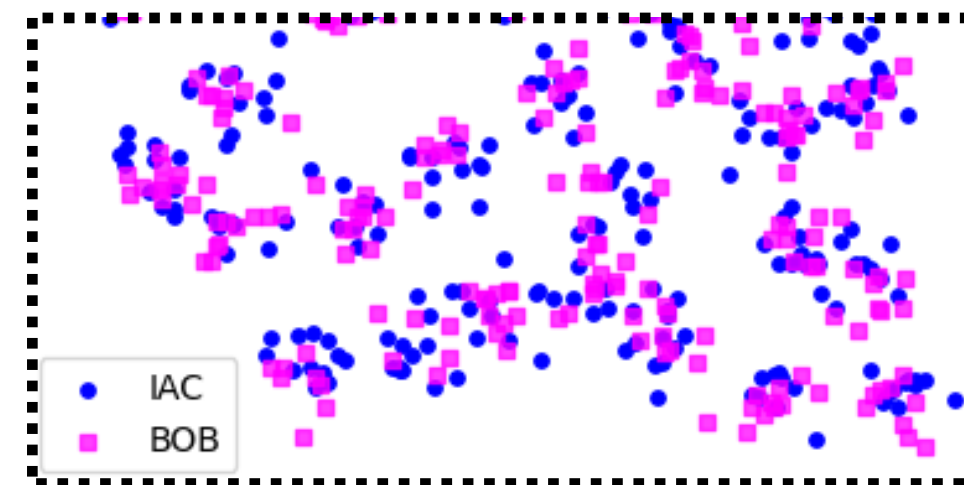




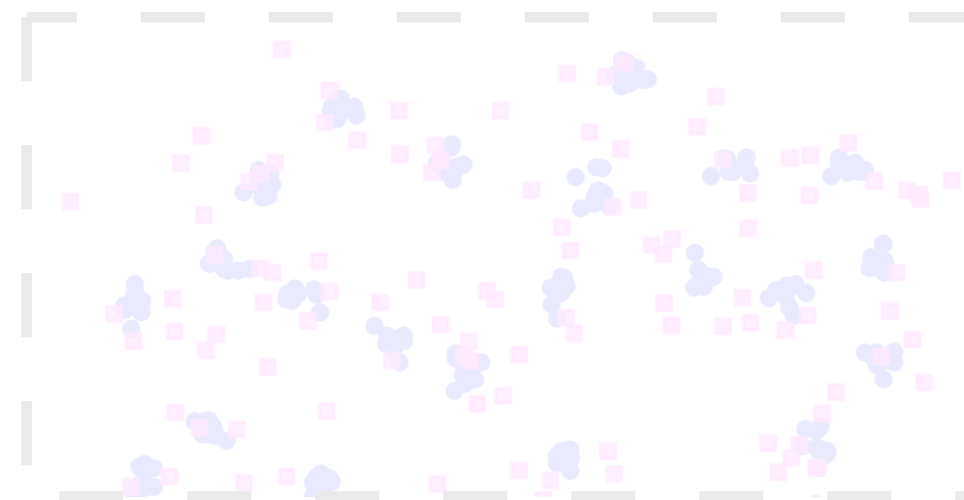


# Results: Ripley's K function

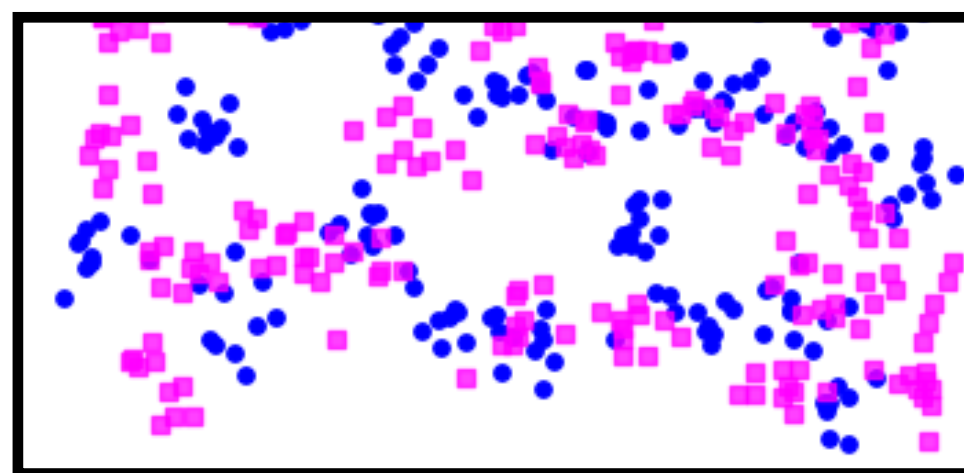
Winter — cold



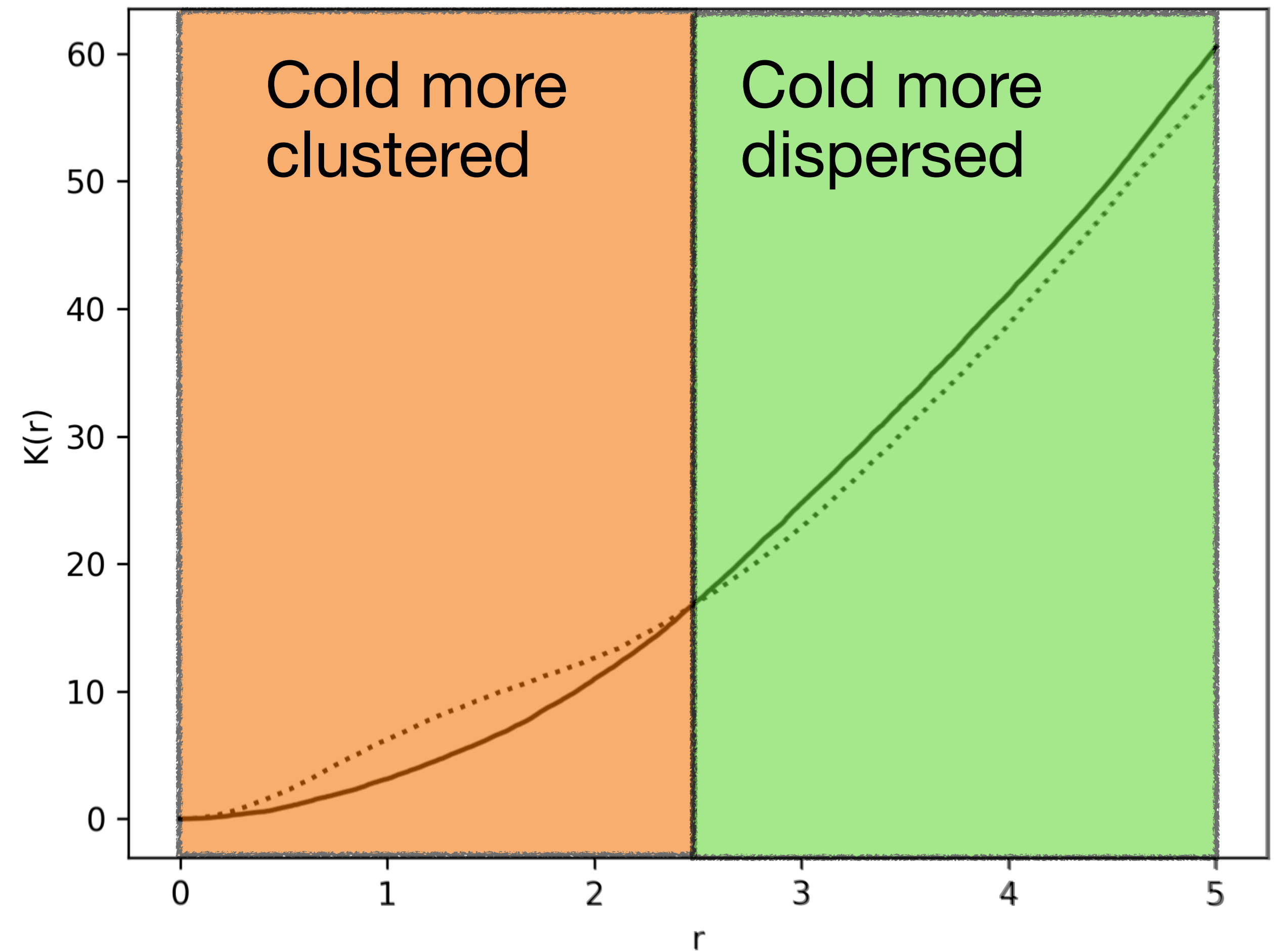
Winter — medium

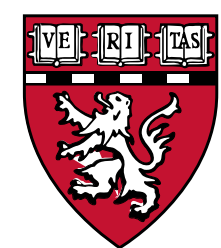


Winter — warm



20 a.u.



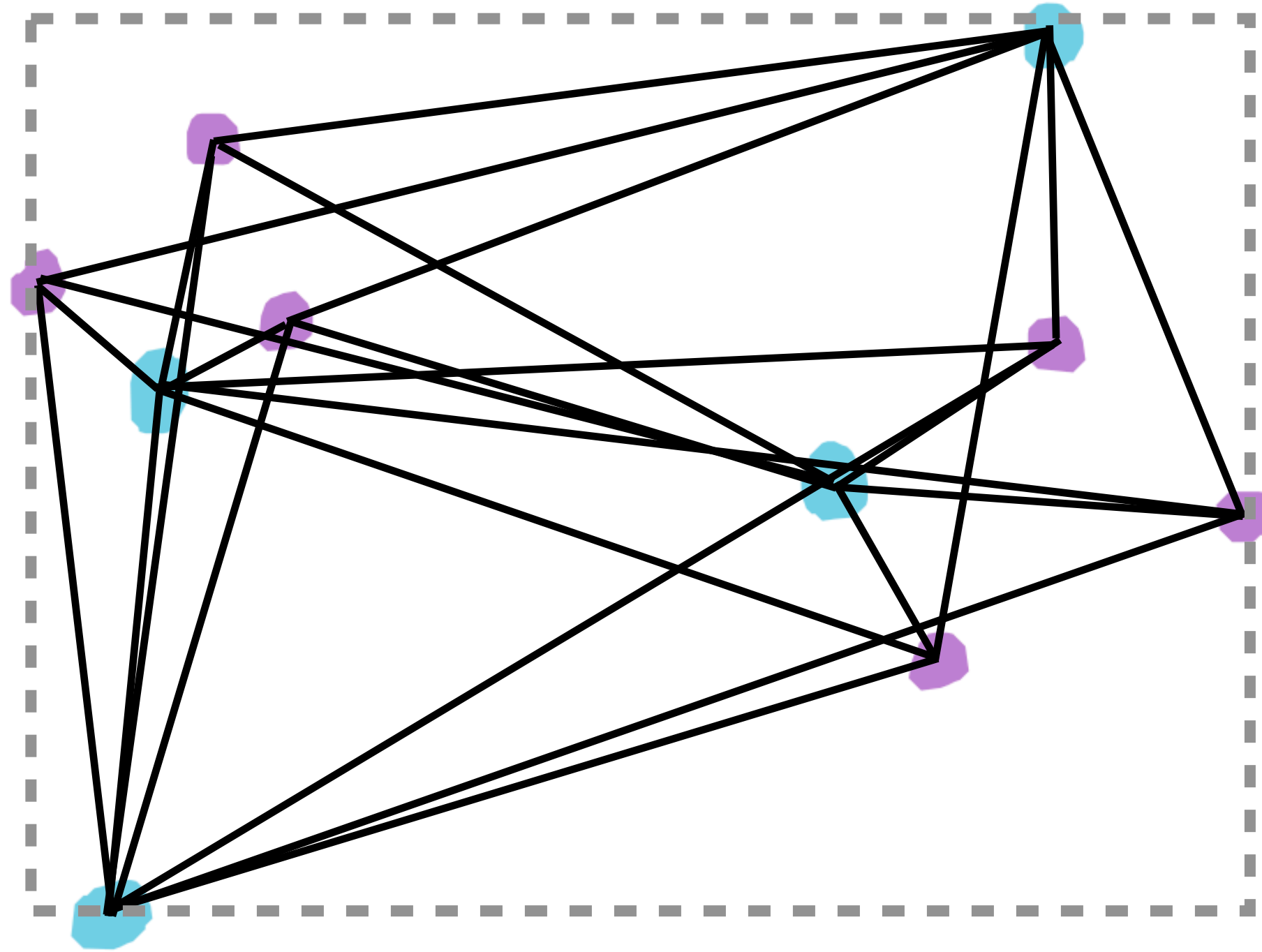


-> 4. Ripley's K function



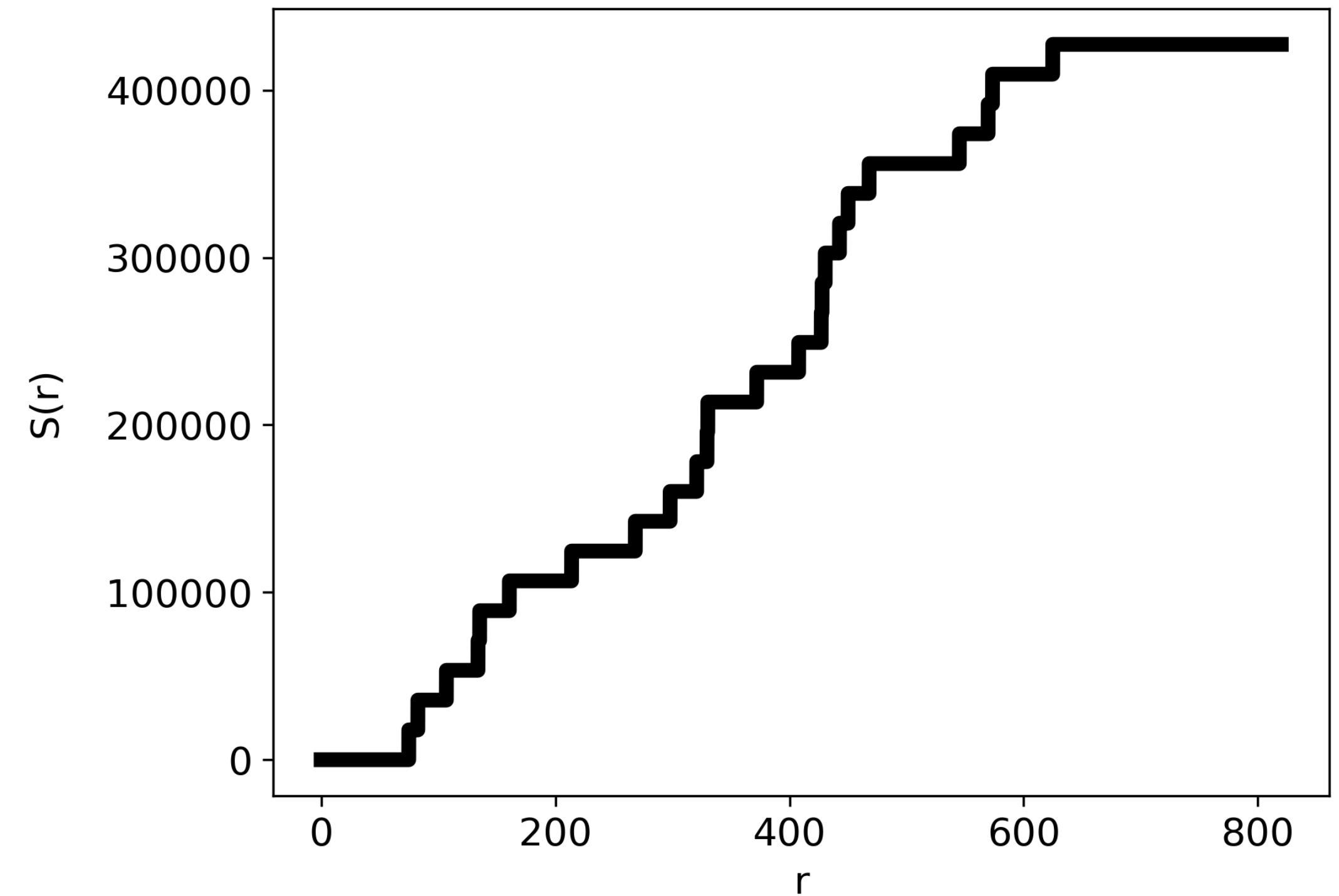


# Ripley's K function



$|\Omega| = \text{Area of FOV}$

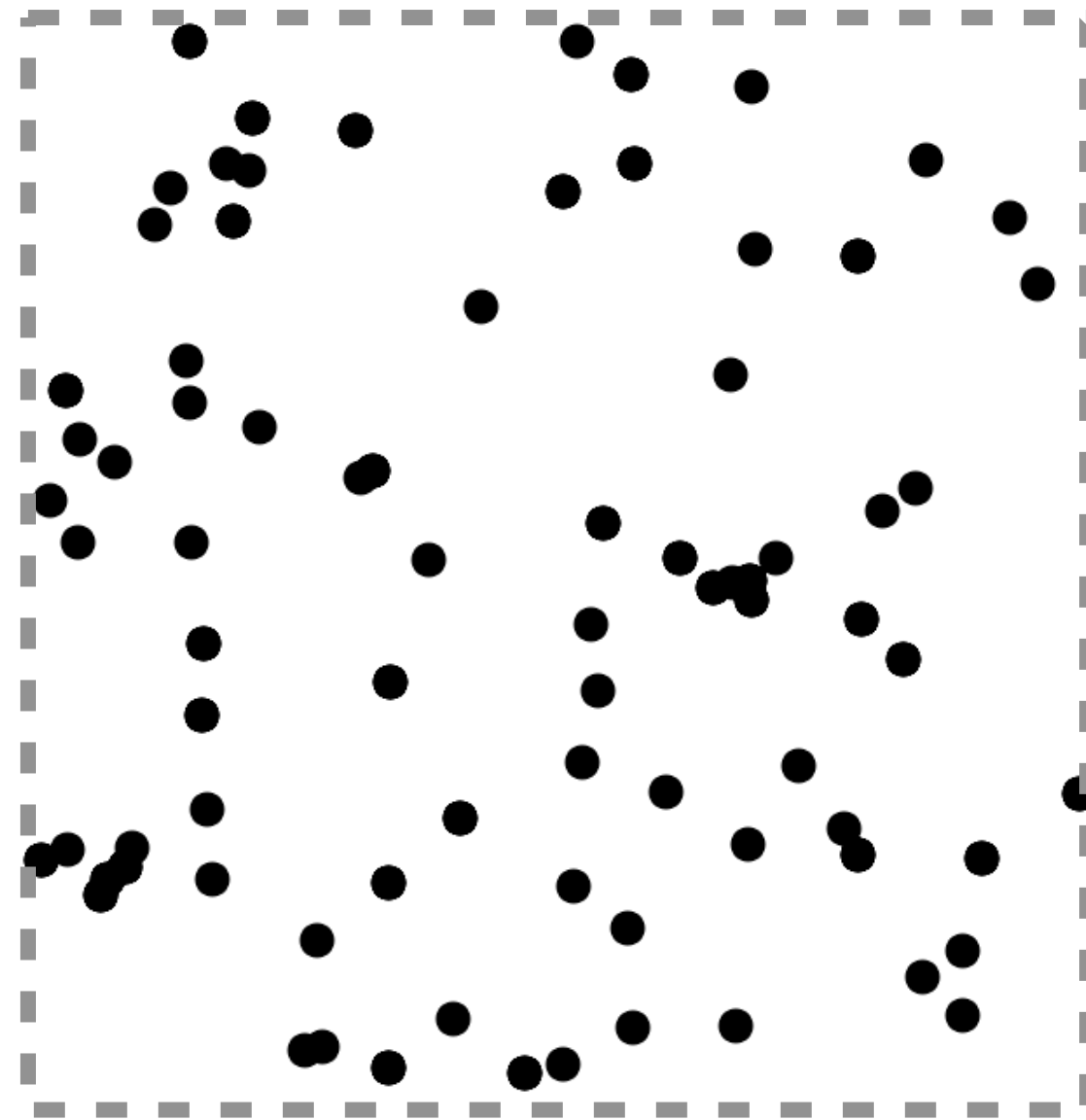
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$





# Ripley's K function

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



$$b(i, j, r) = \frac{|c(i, d_{ij})|}{|c(i, d_{ij}) \cap \Omega|}$$

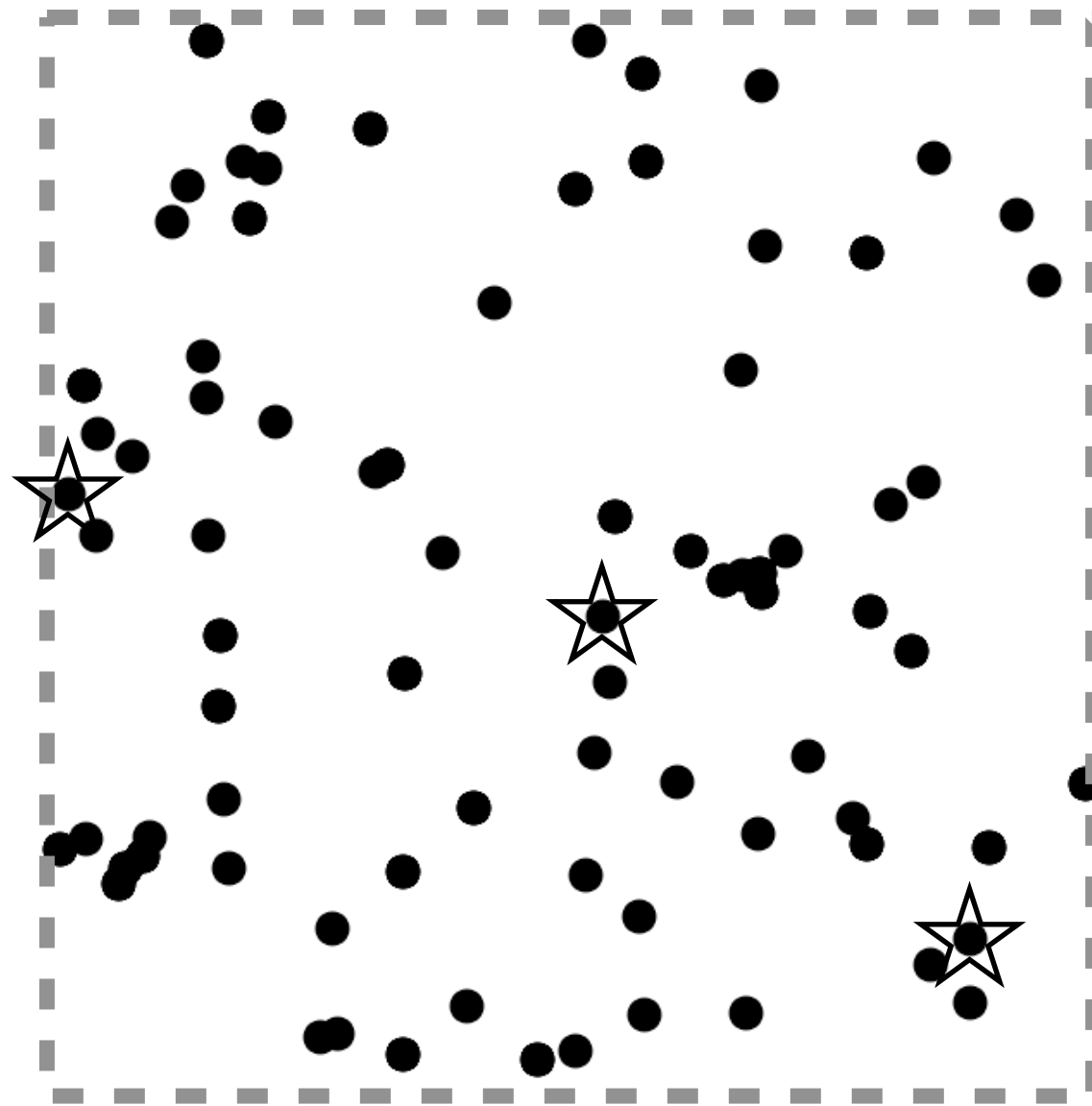






# Ripley's K function

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



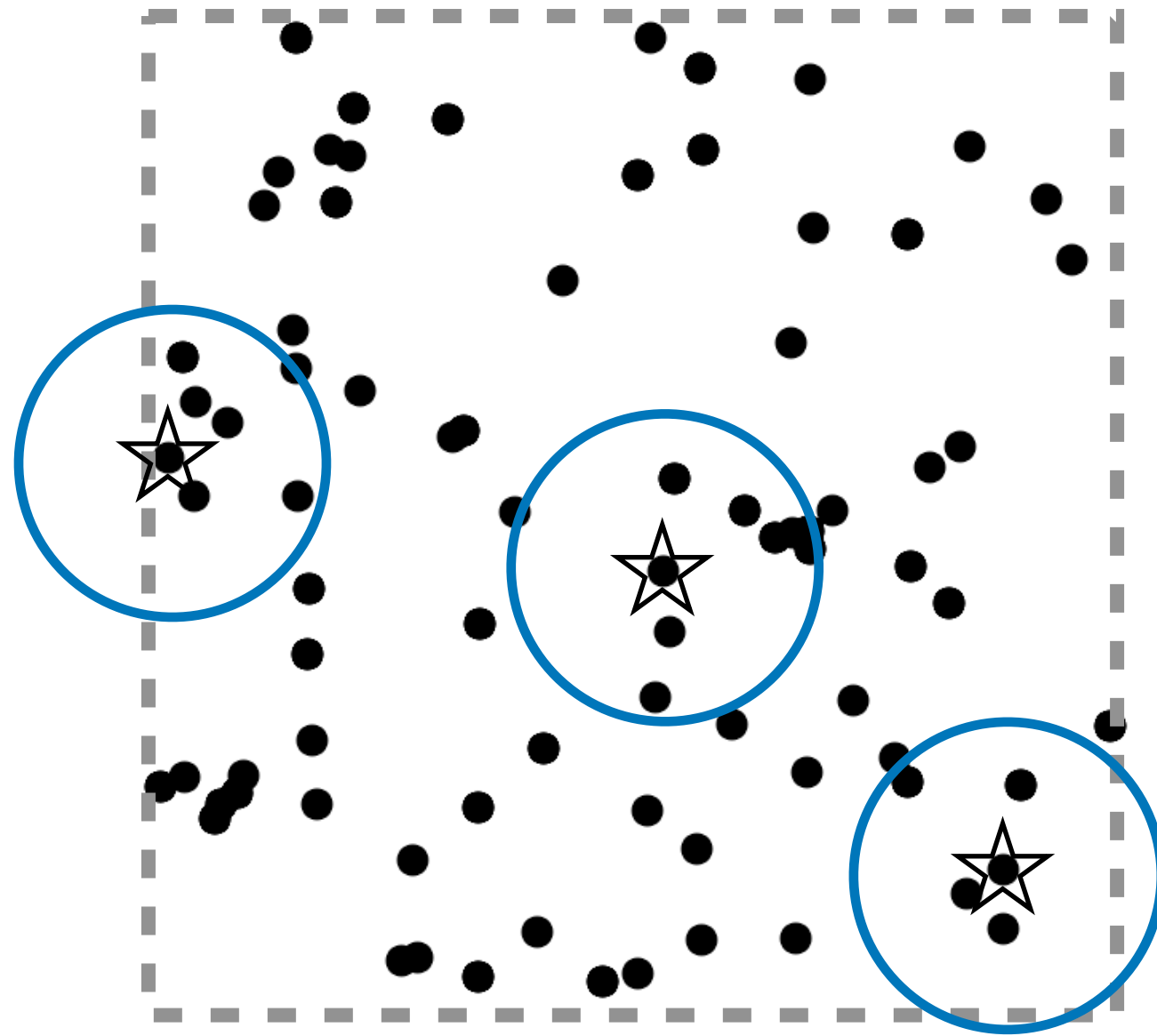
$$b(i, j, r) = \frac{|c(i, d_{ij})|}{|c(i, d_{ij}) \cap \Omega|}$$





# Ripley's K function

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$



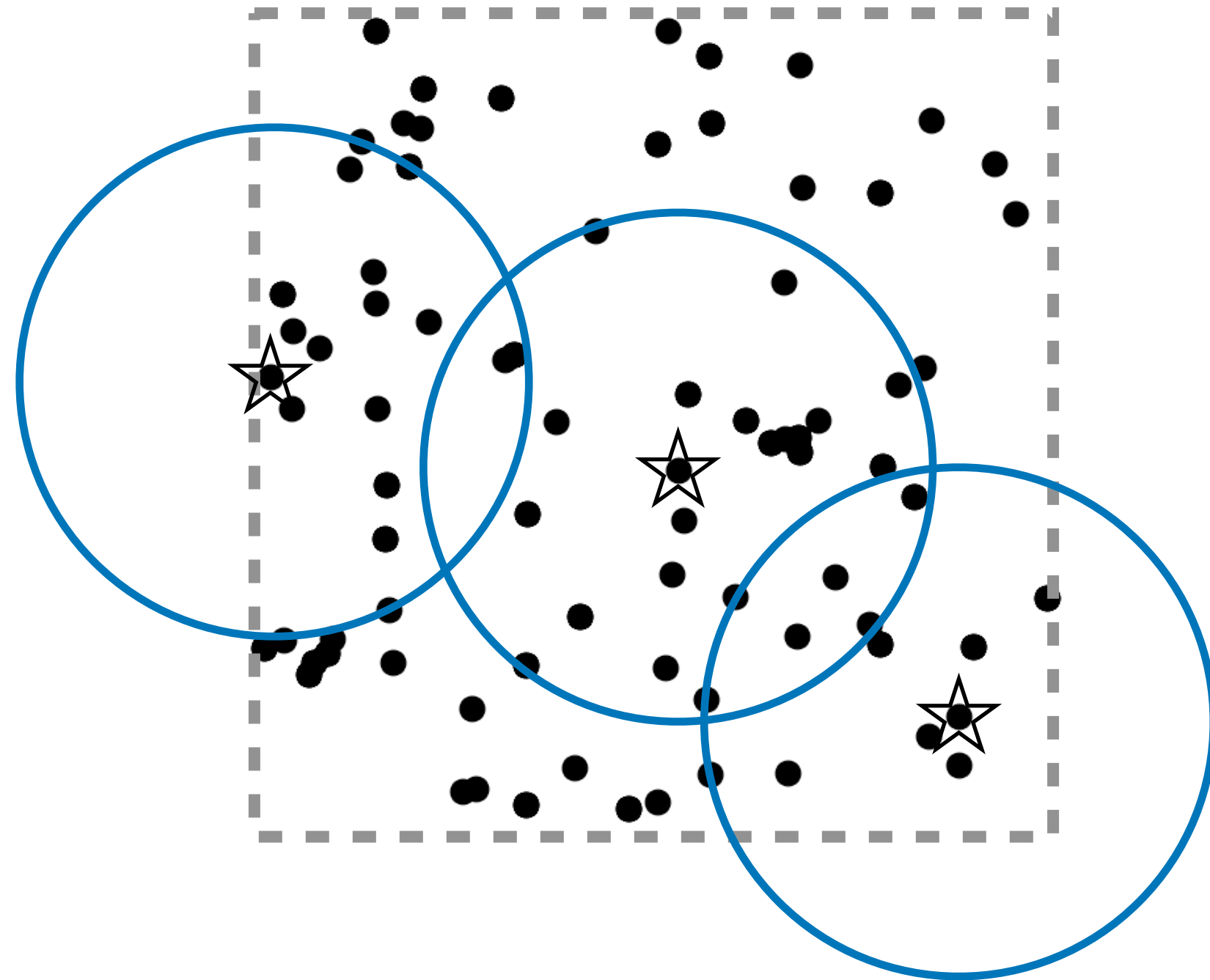
$$b(i, j, r) = \frac{|c(i, d_{ij})|}{|c(i, d_{ij}) \cap \Omega|}$$





# Ripley's K function

$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

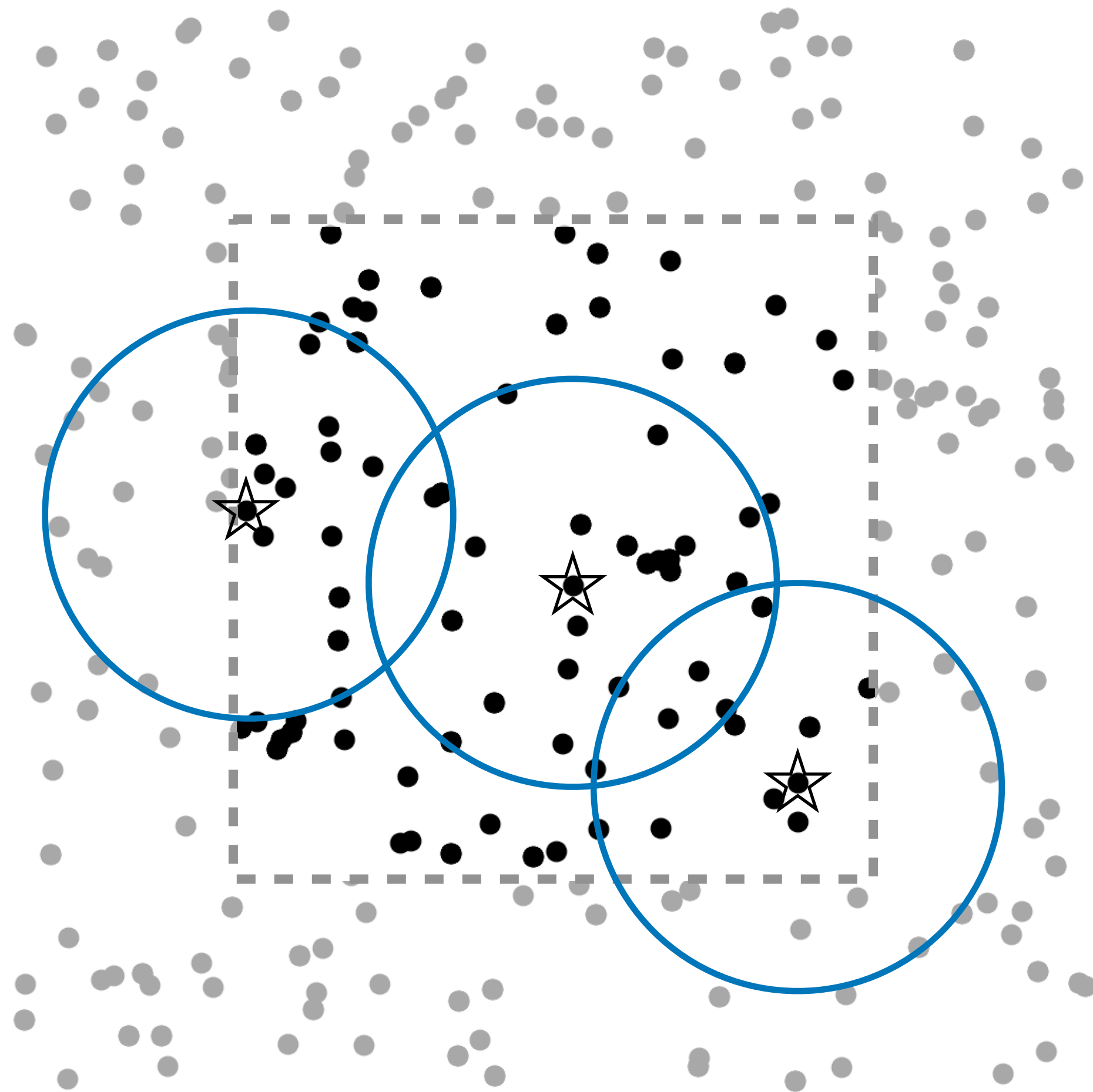


$$b(i, j, r) = \frac{|c(i, d_{ij})|}{|c(i, d_{ij}) \cap \Omega|}$$



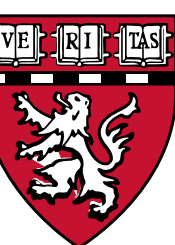


# Ripley's K function



$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

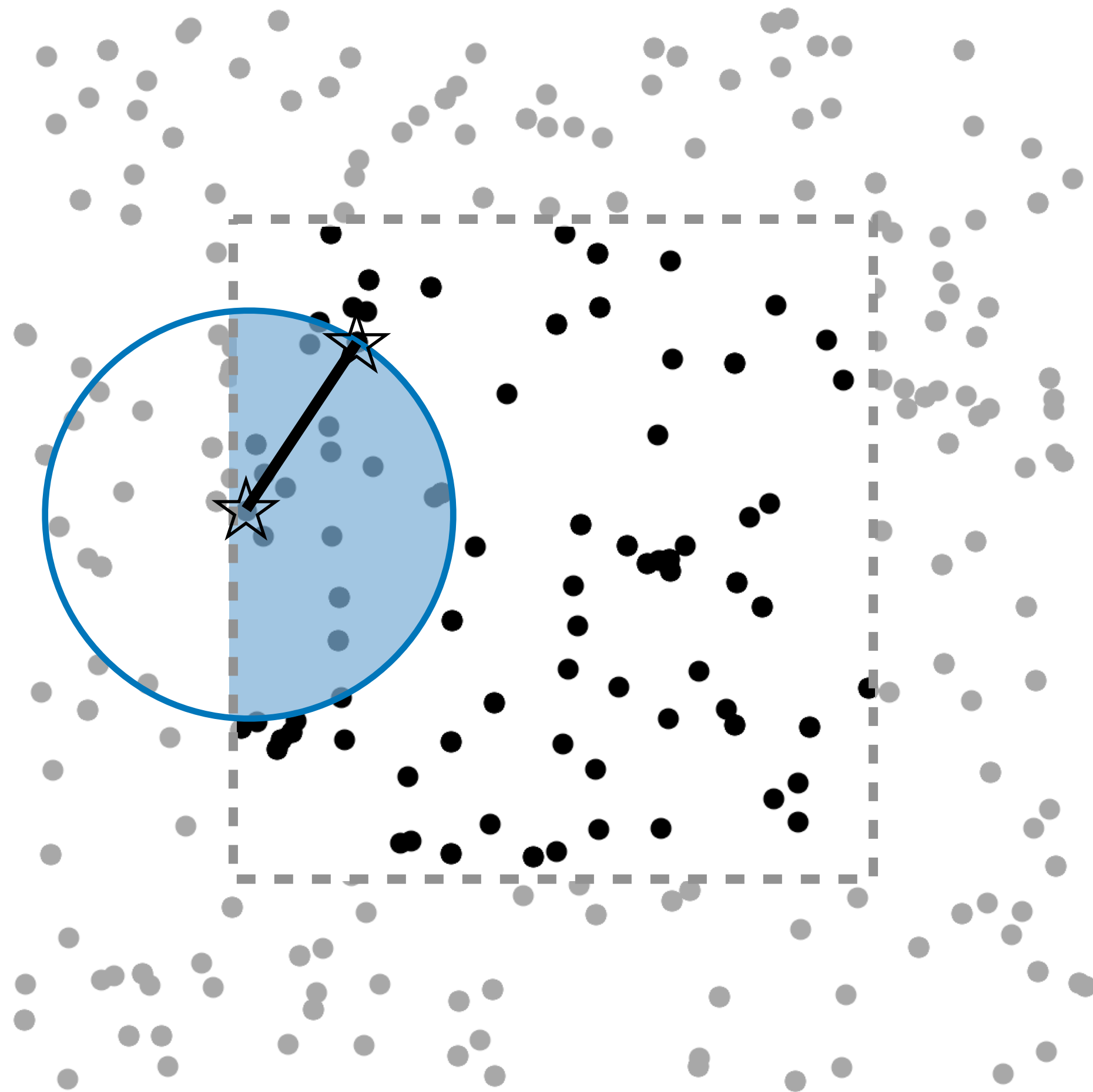
$$b(i, j, r) = \frac{|c(i, d_{ij})|}{|c(i, d_{ij}) \cap \Omega|}$$





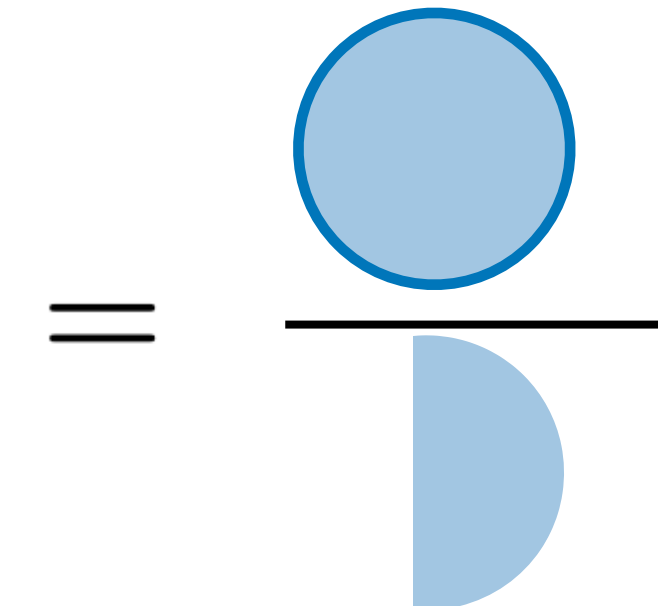


# Ripley's K function



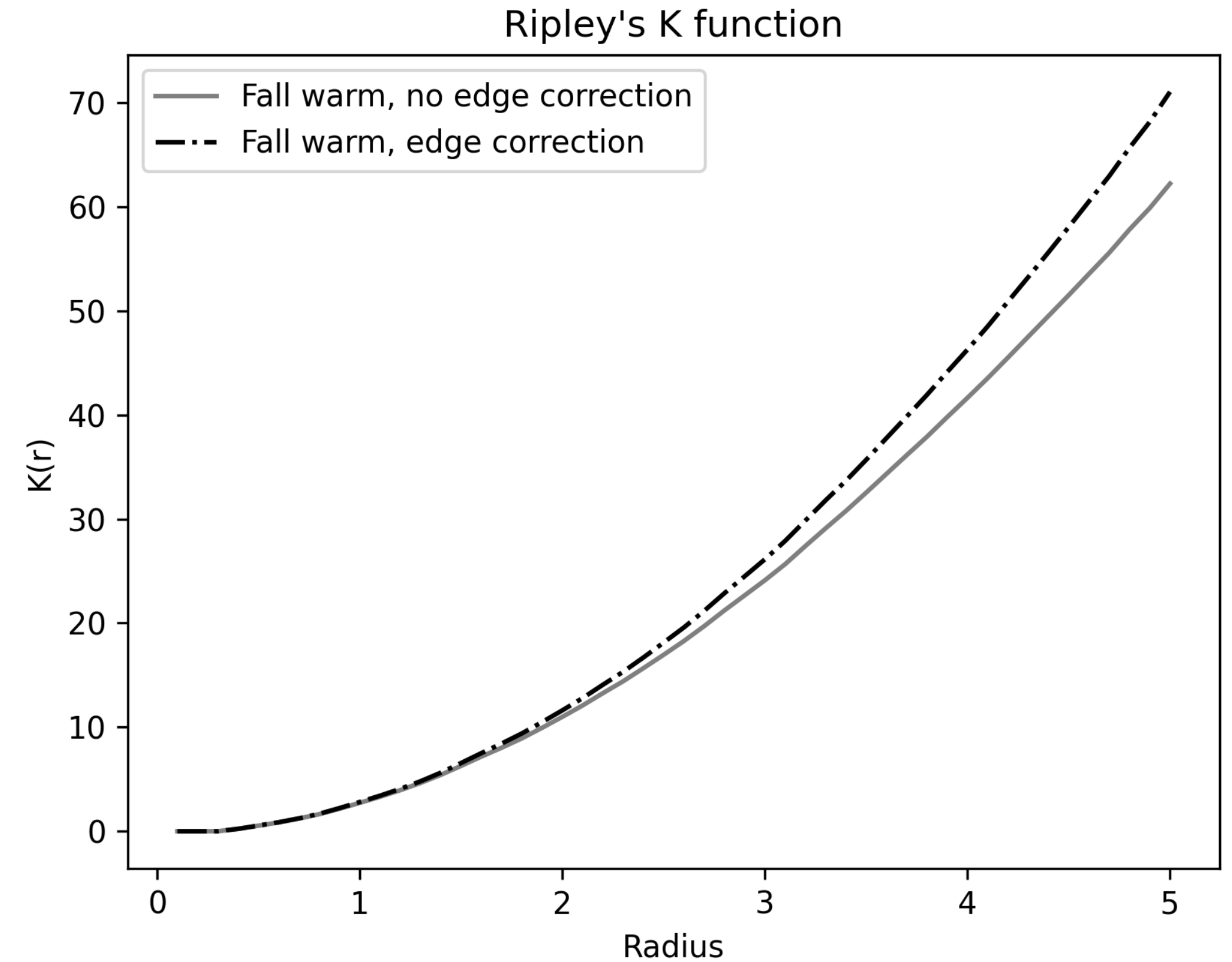
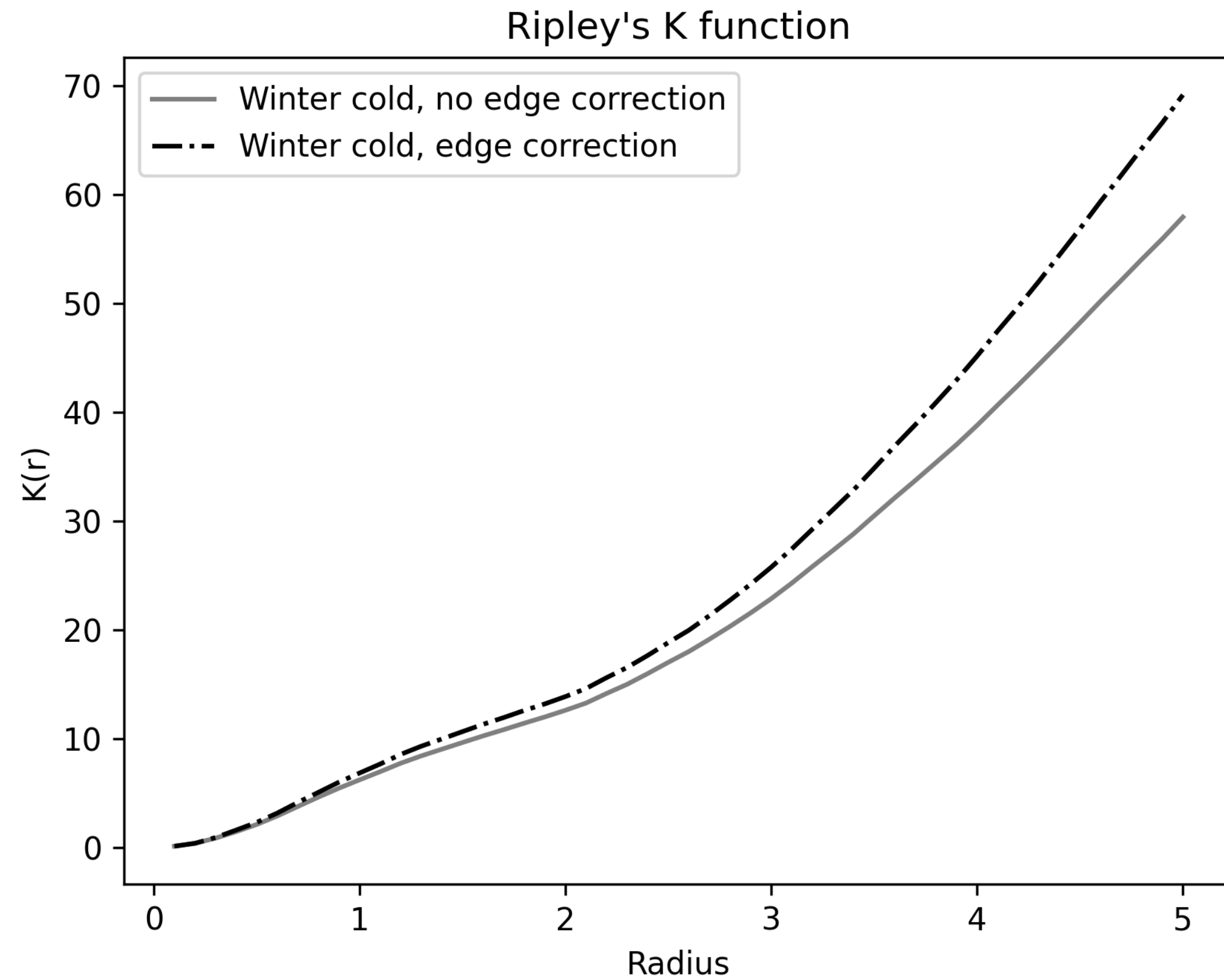
$$S(r) = \frac{|\Omega|}{n_1 n_2} \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \mathbf{1}(d_{ij} < r) b(i, j, r)$$

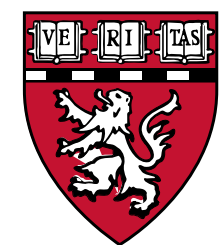
$$b(i, j, r) = \frac{|c(i, d_{ij})|}{|c(i, d_{ij}) \cap \Omega|}$$





# Ripley's K function





-> Code





# Ripley's K function

- Symmetric: **BOB**  $\rightarrow$  **IAC** = **IAC**  $\rightarrow$  **BOB**
- Returns: A number for each radius
- Range: Long

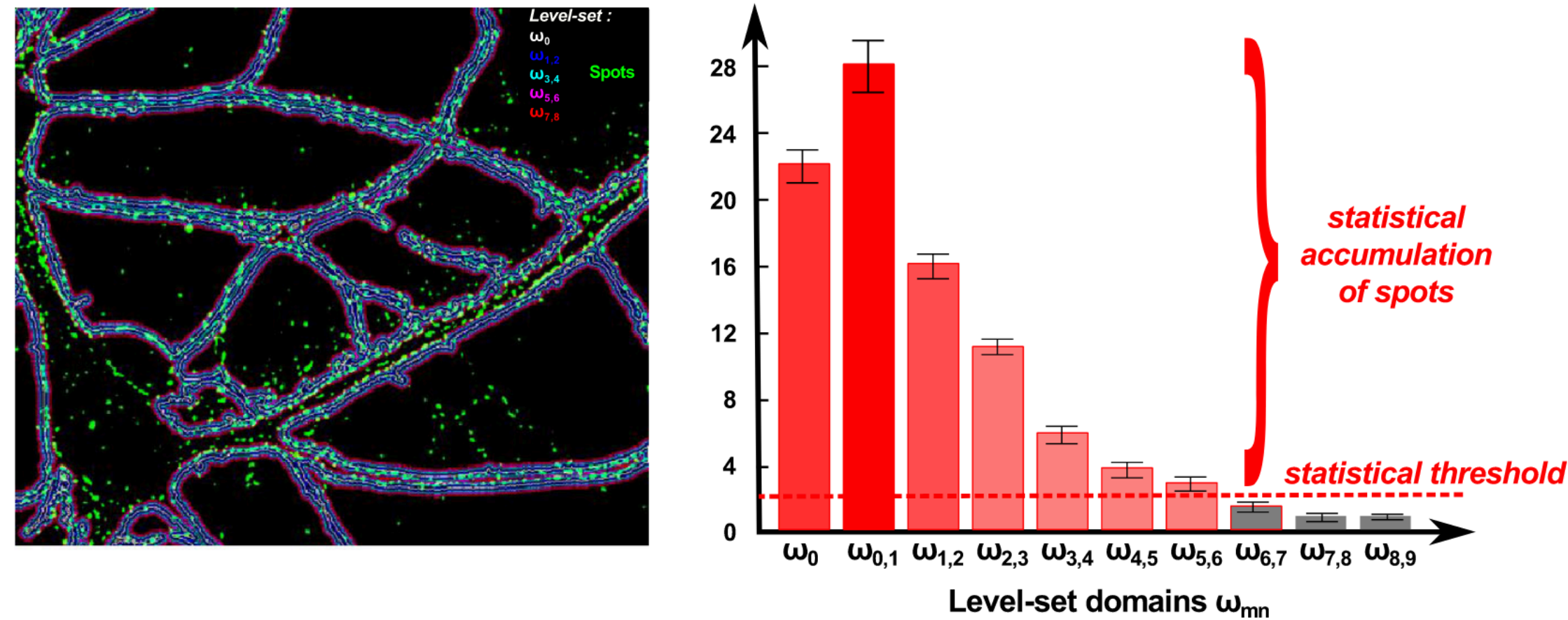






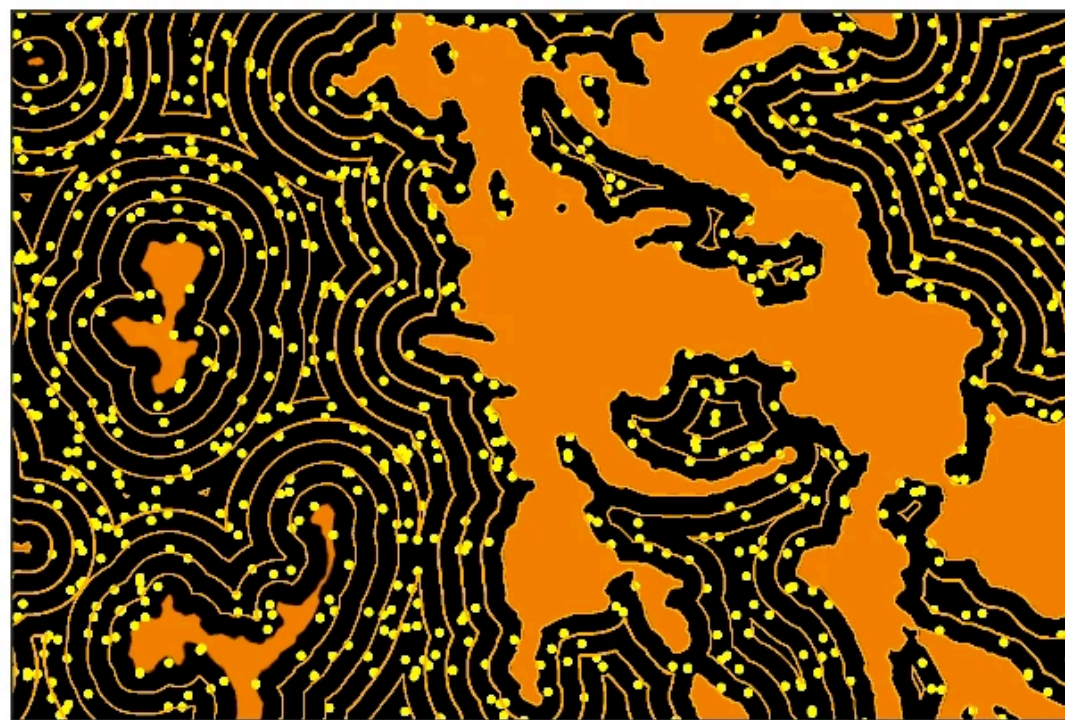
# Beyond Ripley's K function

(b)

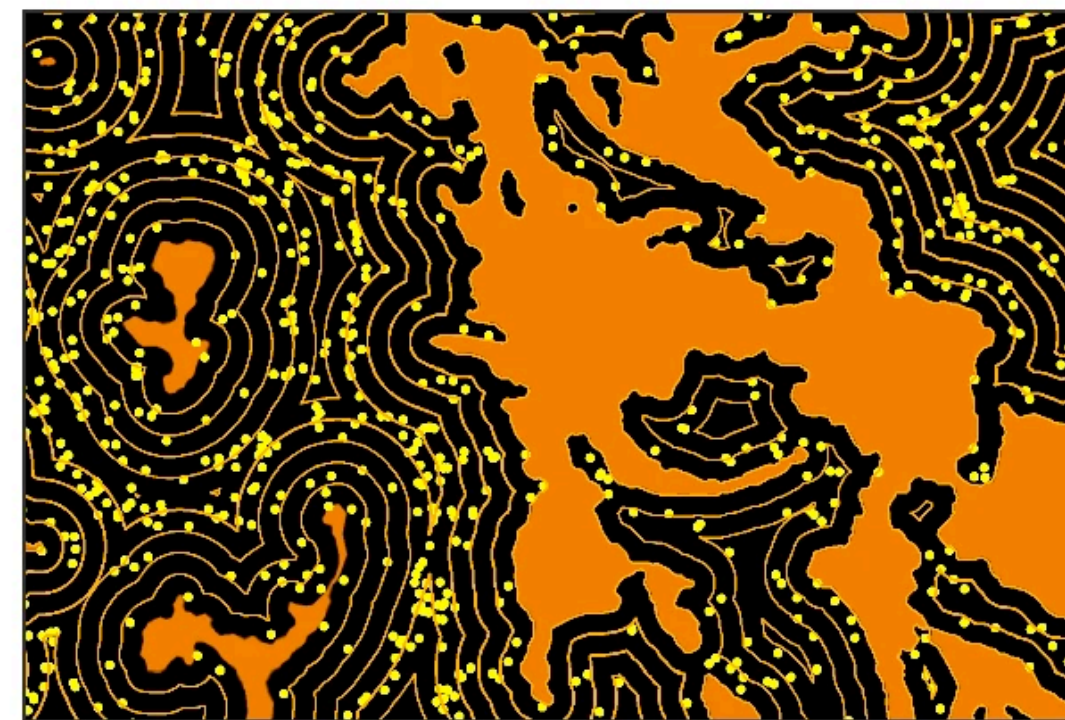


S. Mukherjee, C. Gonzalez-Gomez, L. Danglot, T. Lagache and J. -C. Olivo-Marin, "Generalizing the Statistical Analysis of Objects' Spatial Coupling in Bioimaging," in *IEEE Signal Processing Letters*, vol. 27, pp. 1085-1089, 2020, doi: 10.1109/LSP.2020.3003821.

b



c

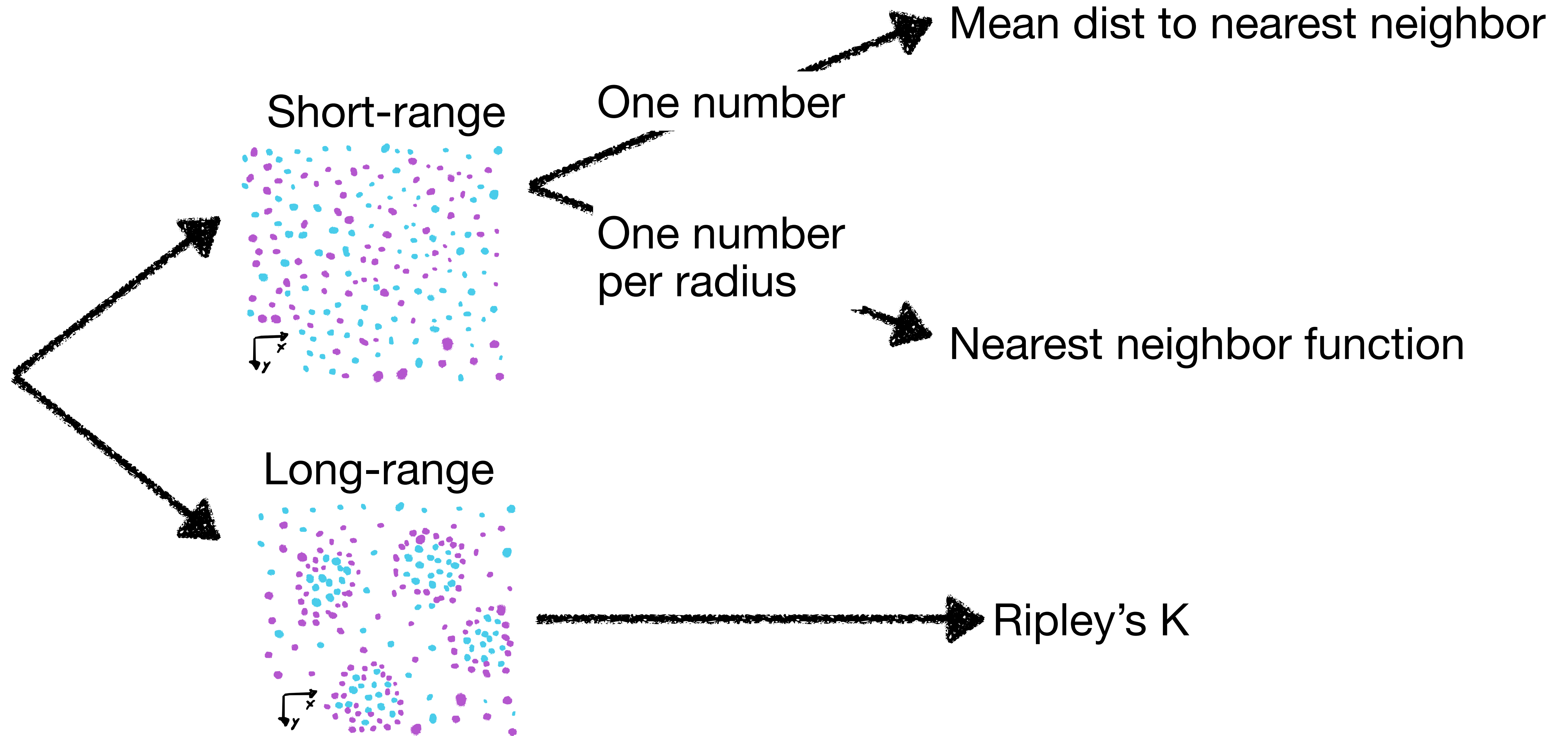


Benimam, M.M., Meas-Yedid, V., Mukherjee, S. *et al.* Statistical analysis of spatial patterns in tumor microenvironment images. *Nat Commun* **16**, 3090 (2025). <https://doi.org/10.1038/s41467-025-57943-y>





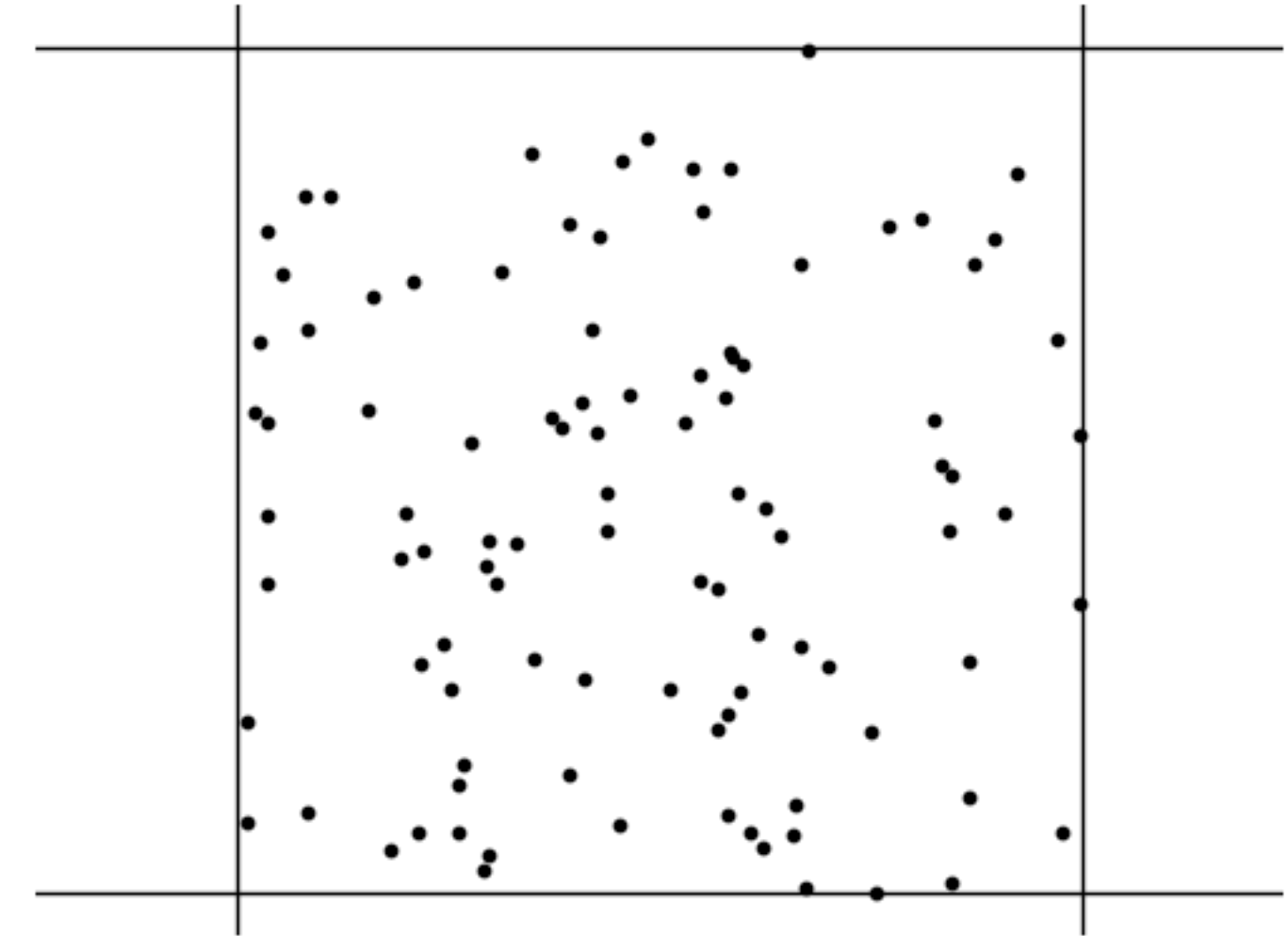
# Summary





# Validation — the null distribution

- How are proteins distributed that
  - Don't interact with each other
  - Or their surrounding

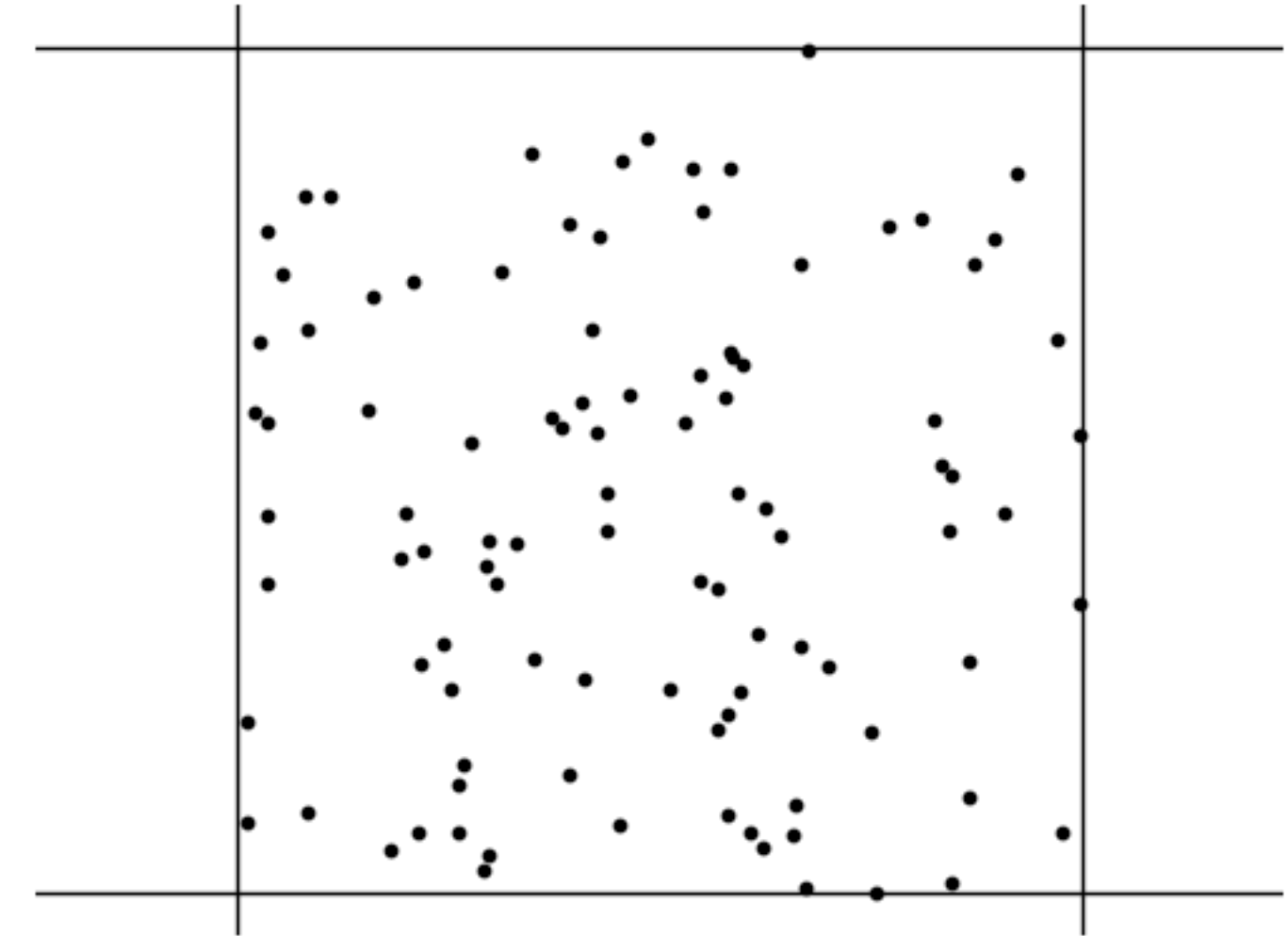


What is the evidence that my points may or may not be distributed like this?



# Validation — the null distribution

- How are proteins distributed that
  - Don't interact with each other
  - Or their surrounding
- To find out, you blindly throw darts at a board



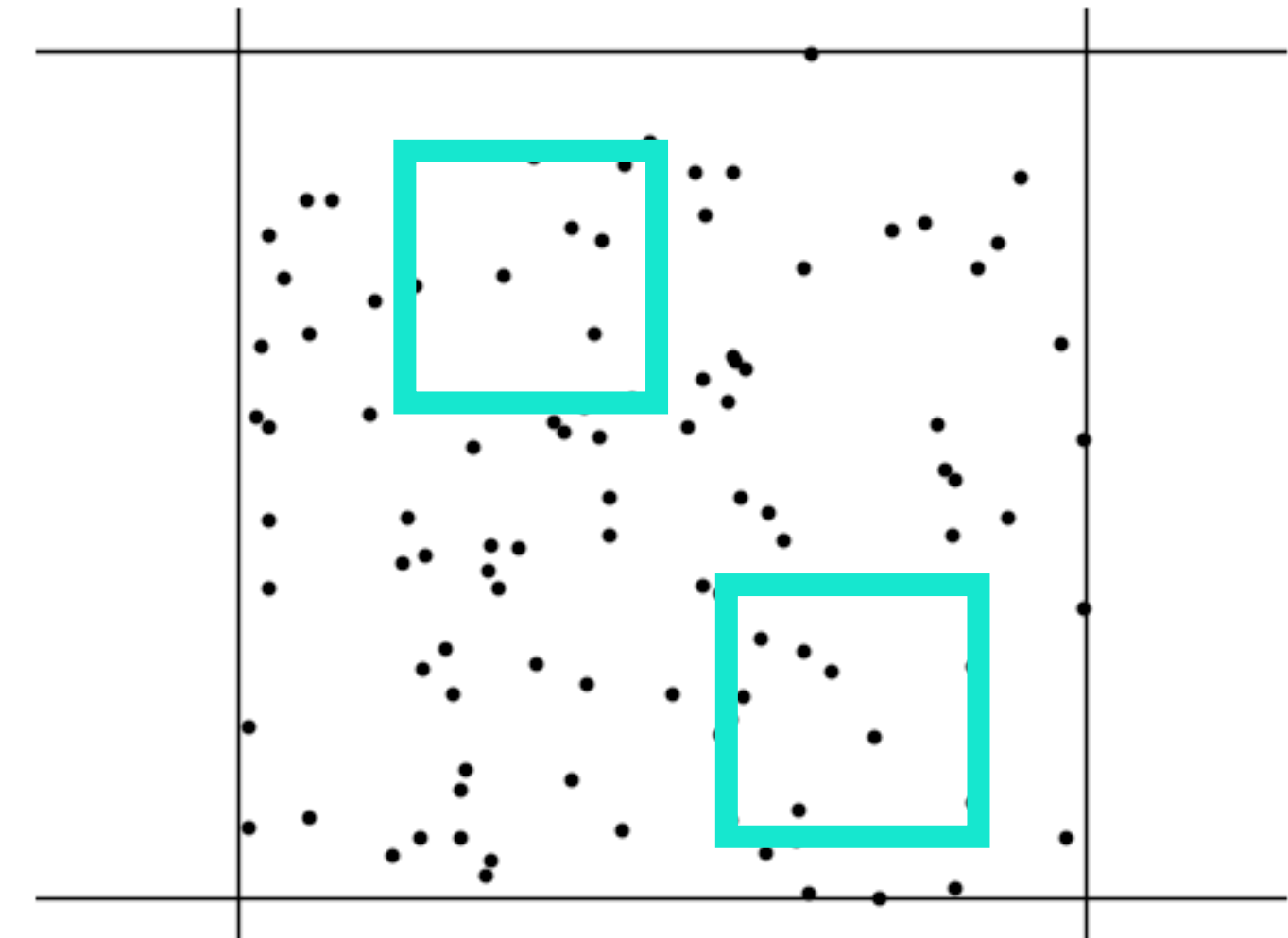
What is the evidence that my points may or may not be distributed like this?





# Validation — the null distribution

- How are proteins distributed that
  - Don't interact with each other
  - Or their surrounding
- To find out, you blindly throw darts at a board
- The chance of a dart landing is the same, no matter where on the board

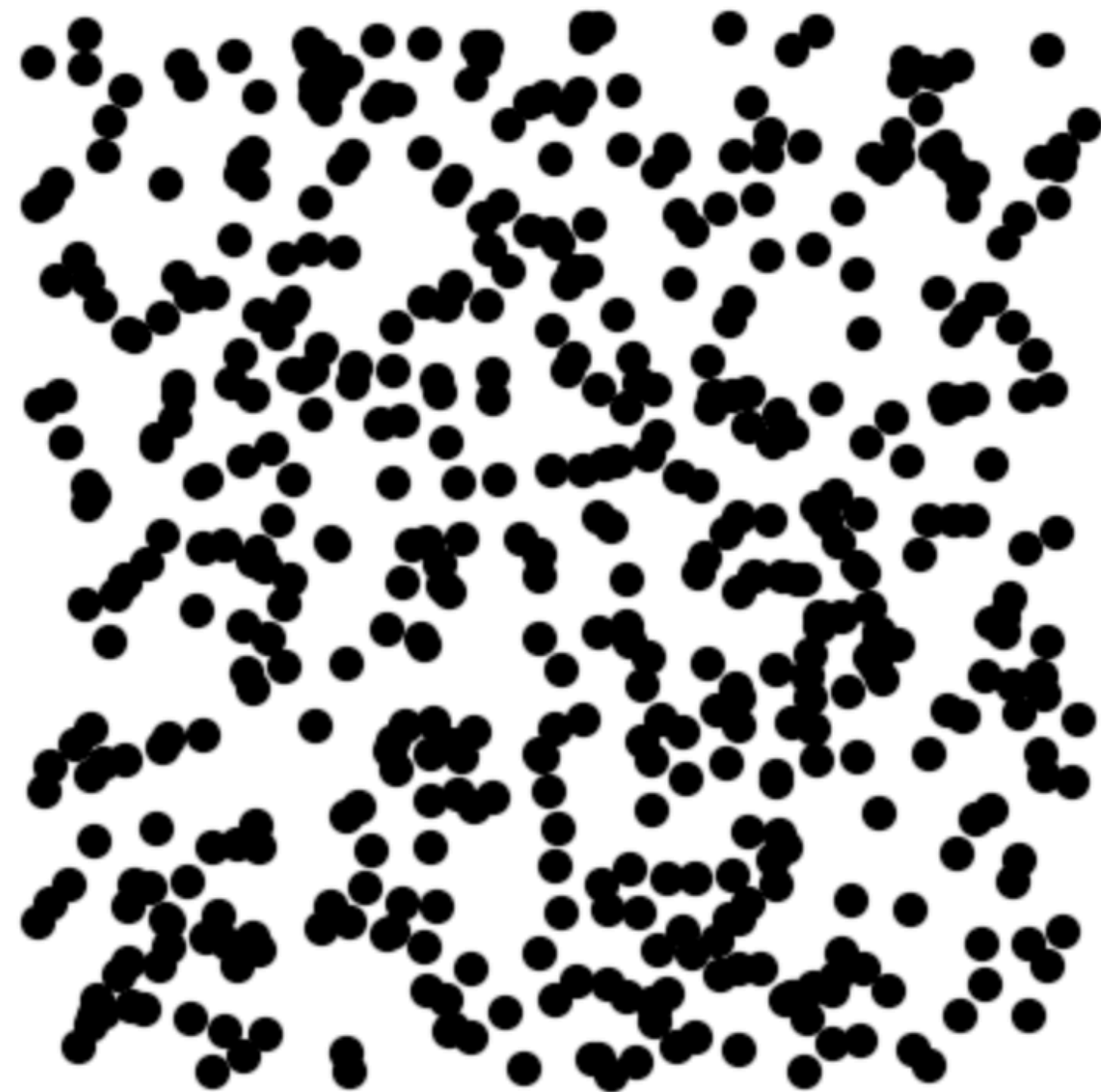


What is the evidence that my points may or may not be distributed like this?



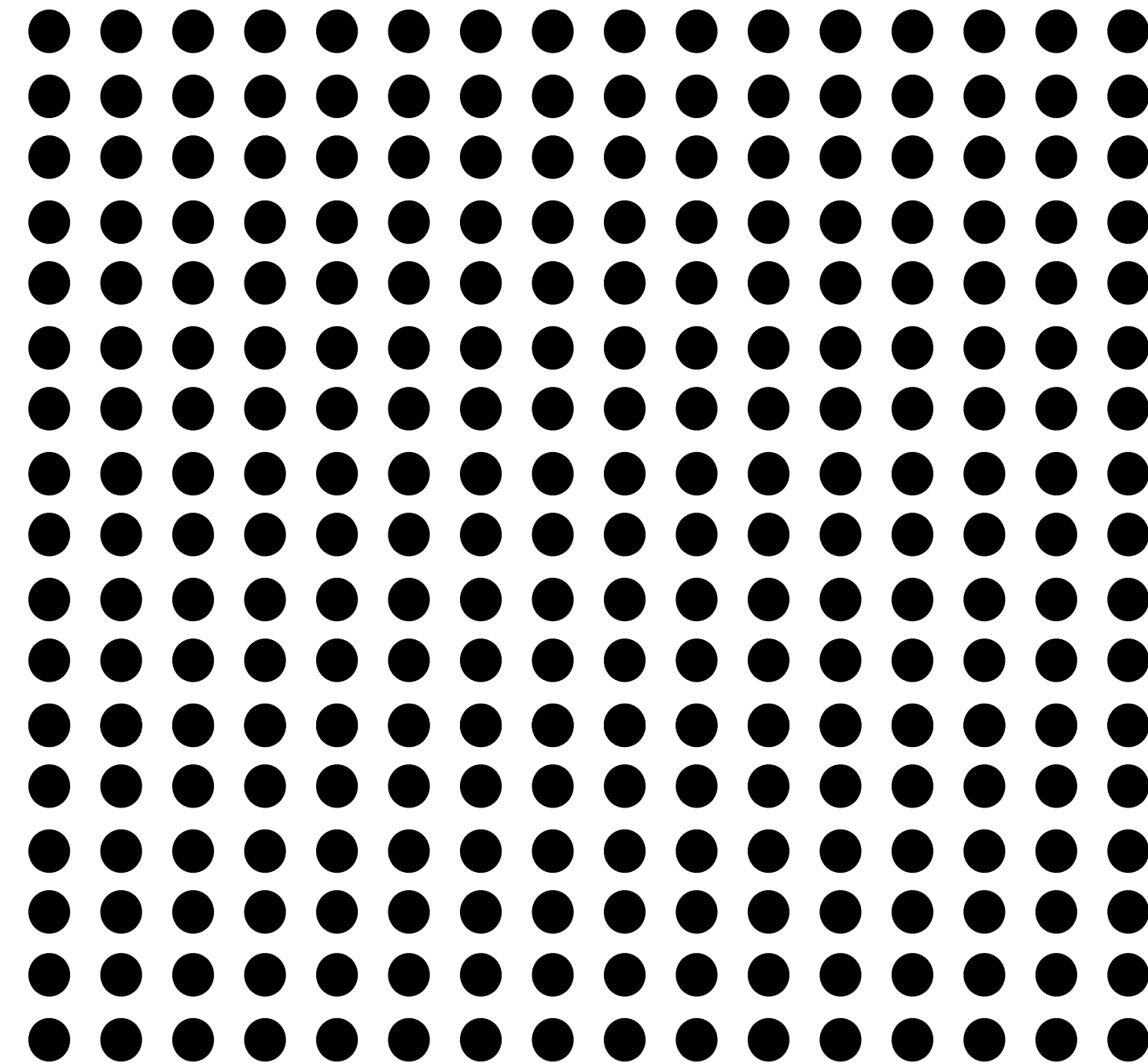
# Validation — the null distribution

“Uniformly distributed”



$\neq$

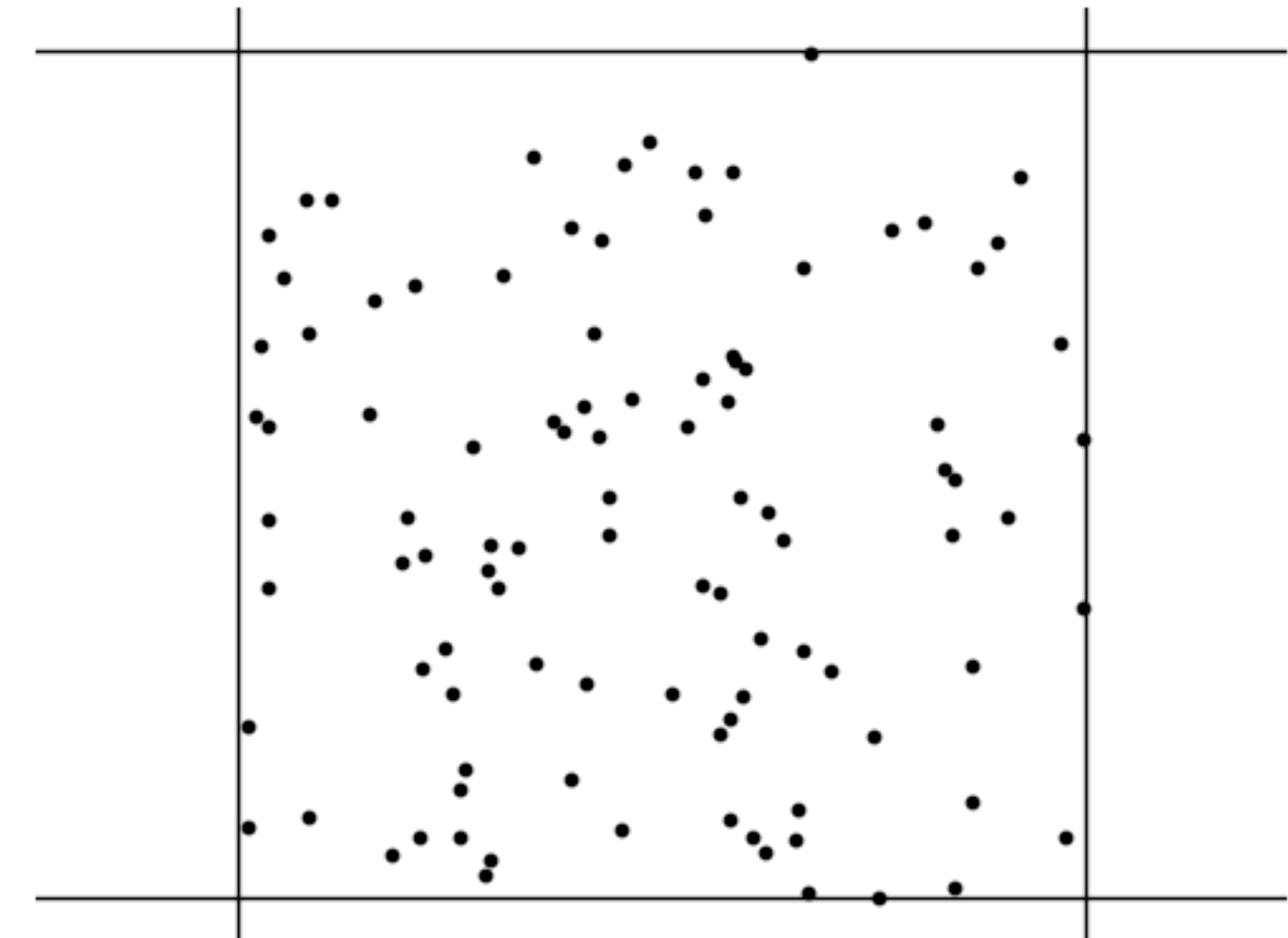
“Uniformly spaced”





# Validation — the null distribution

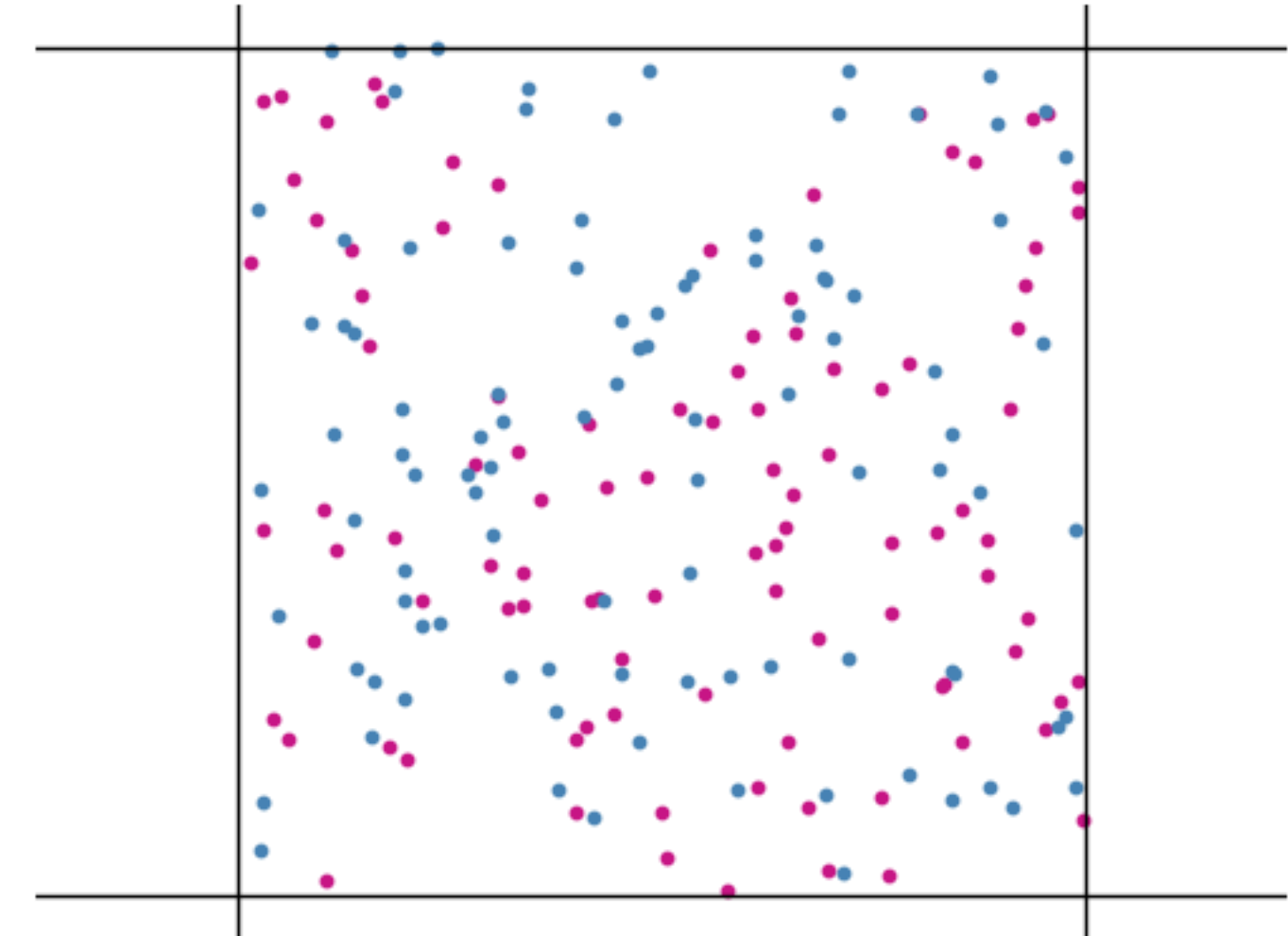
- How are proteins distributed that
  - Don't interact with each other
  - Or their surrounding
- To find out, you blindly throw darts at a board
- The chance of a dart landing is the same, no matter where on the board





# Validation — the null distribution

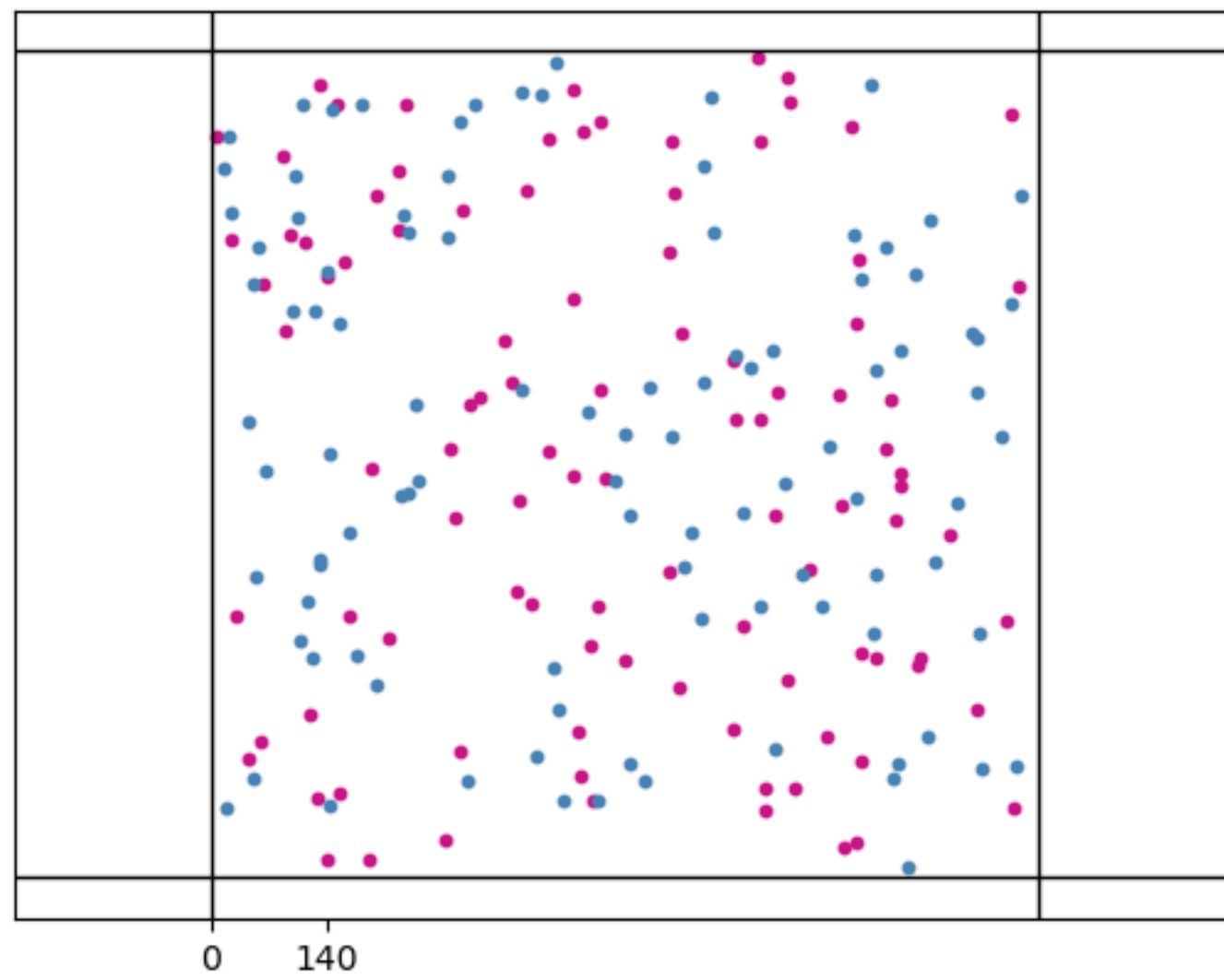
- How are proteins distributed that
  - Don't interact with each other
  - Or their surrounding
- To find out, you blindly throw darts at a board
- The chance of a dart landing is the same, no matter where on the board
- The darts can have multiple colors



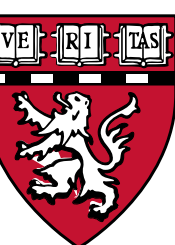
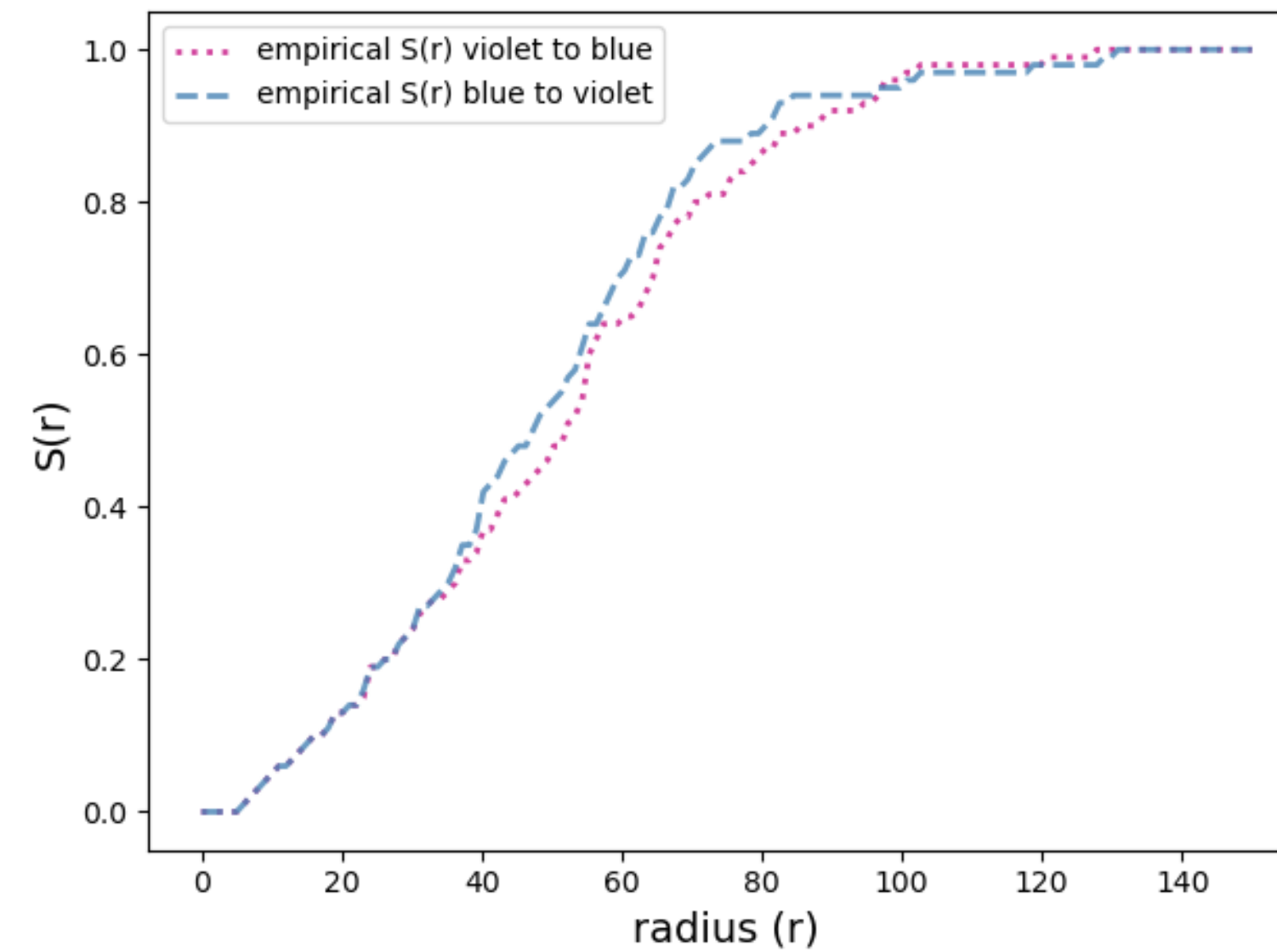




# Validation – the null distribution

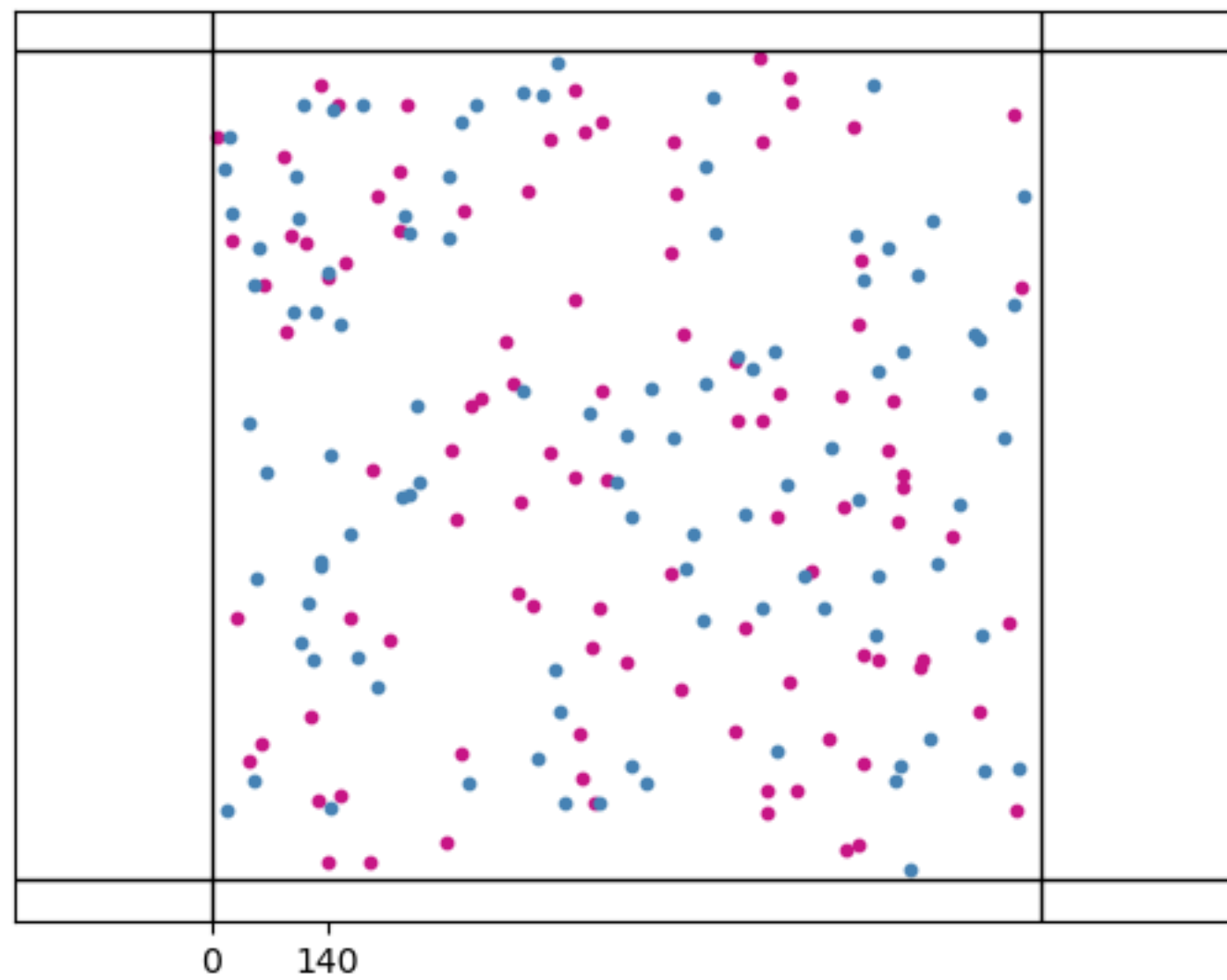


## Empirical null distributions

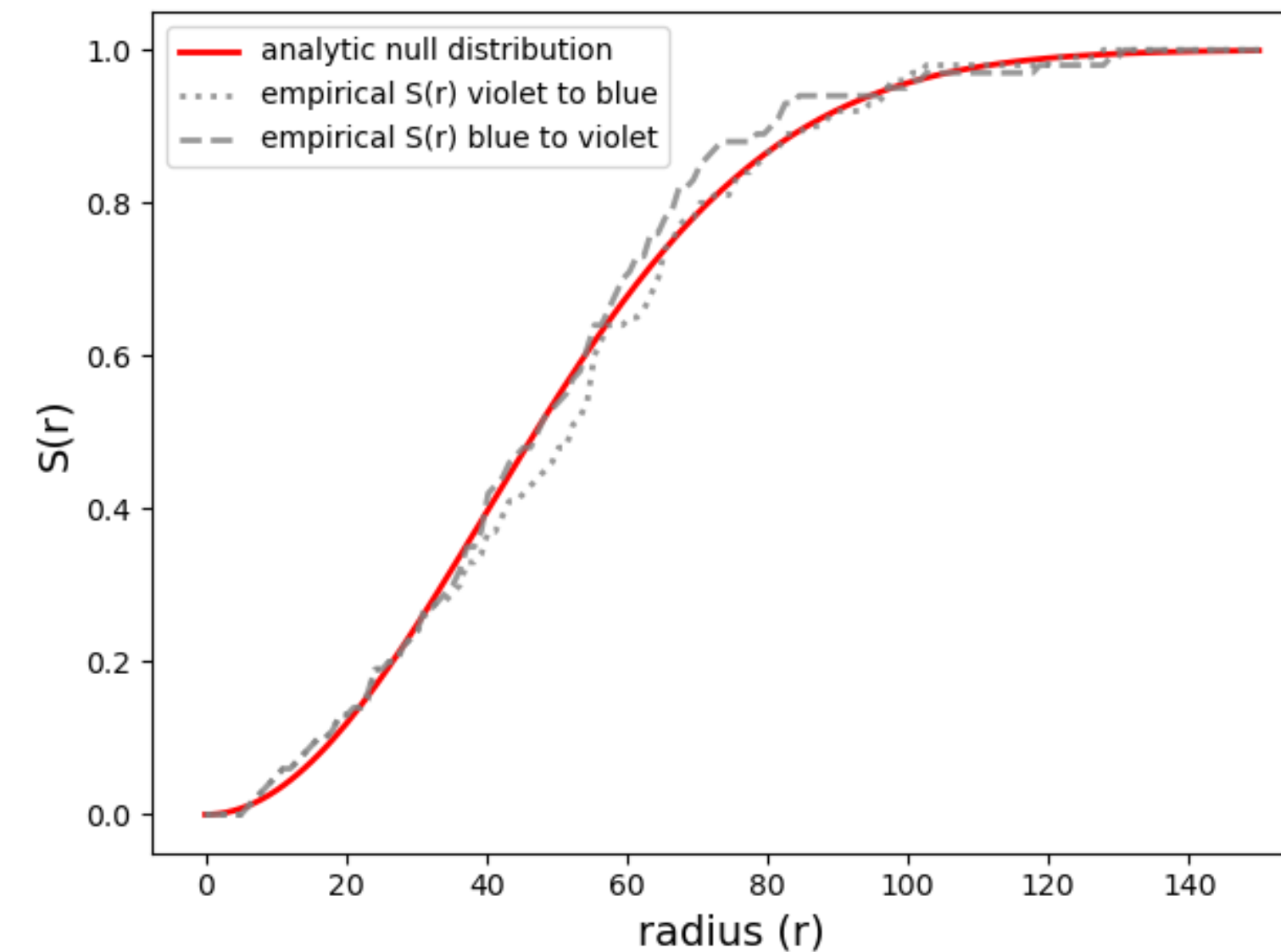




# Validation — the null distribution



## Analytic null distribution



$$S(r) = 1 - e^{-\frac{n_2}{|\Omega|}\pi r^2}$$

Density of points  $n_2$

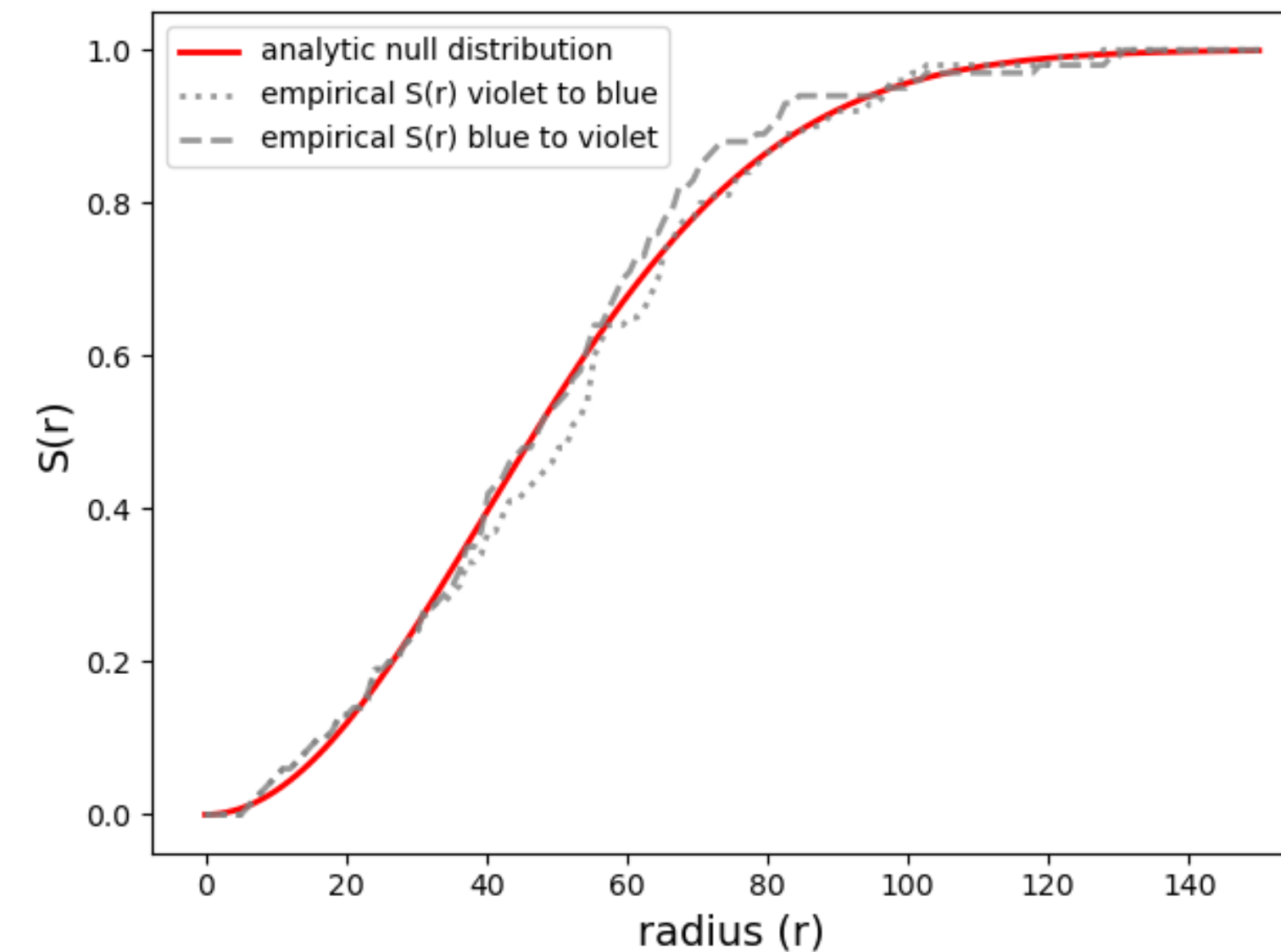
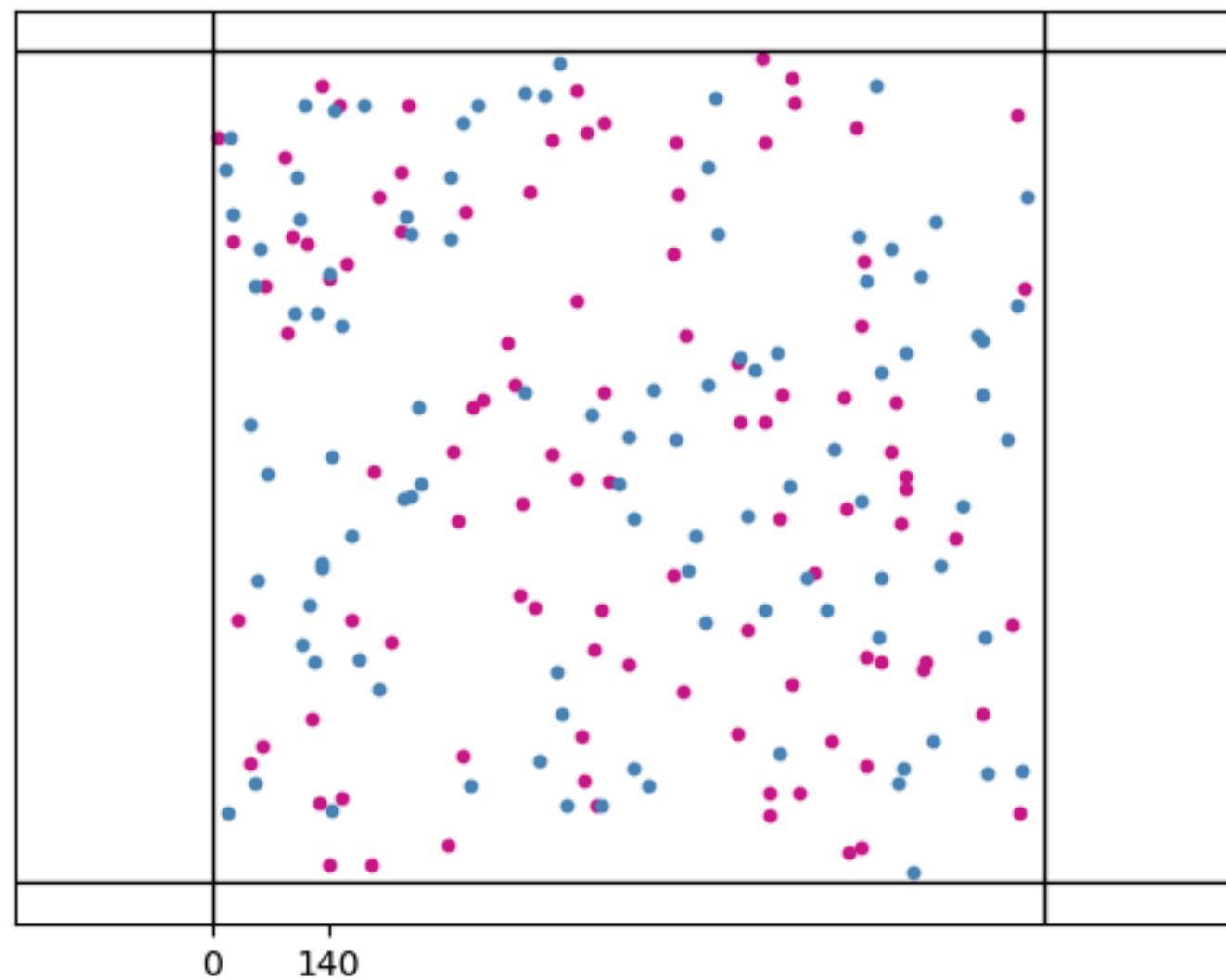
You don't need any data to compute the analytic null distribution





# Validation — the null distribution

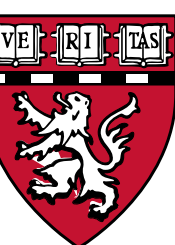
## Analytic null distribution



$$S(r) = 1 - e^{-\frac{n_2}{|\Omega|} \pi r^2}$$

Area of a circle with radius  $r$

You don't need any data to compute the analytic null distribution

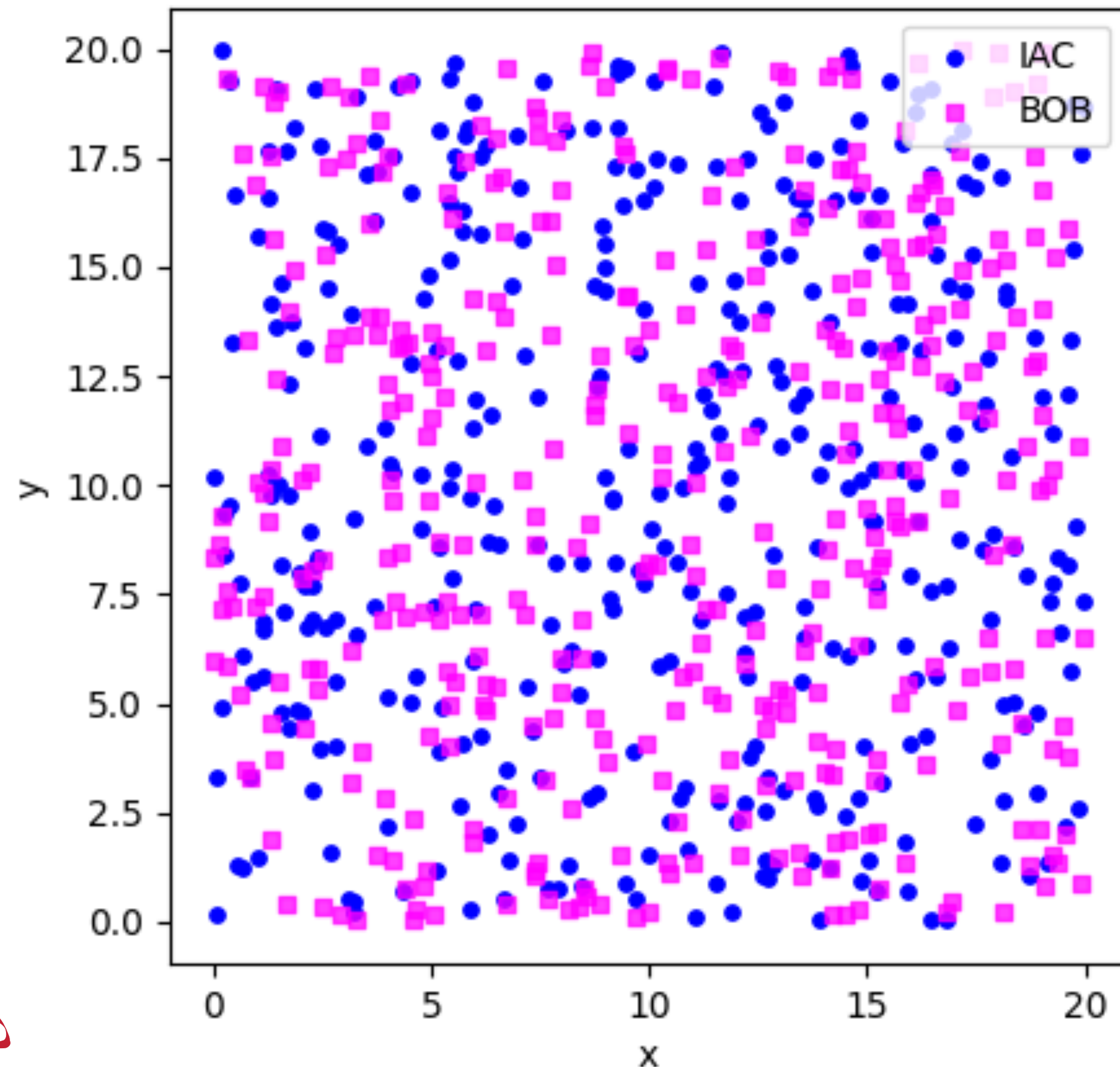




# Validation — the null distribution

BOB = 400

IAC = 400



$$S(r) = 1 - e^{-\frac{n_2}{|\Omega|}\pi r^2}$$

Exercise: Find good values for  $n_2$  and  $|\Omega|$

```
n = 1345345 # number of points in the dataset
area = 4056780 # area of the FOV

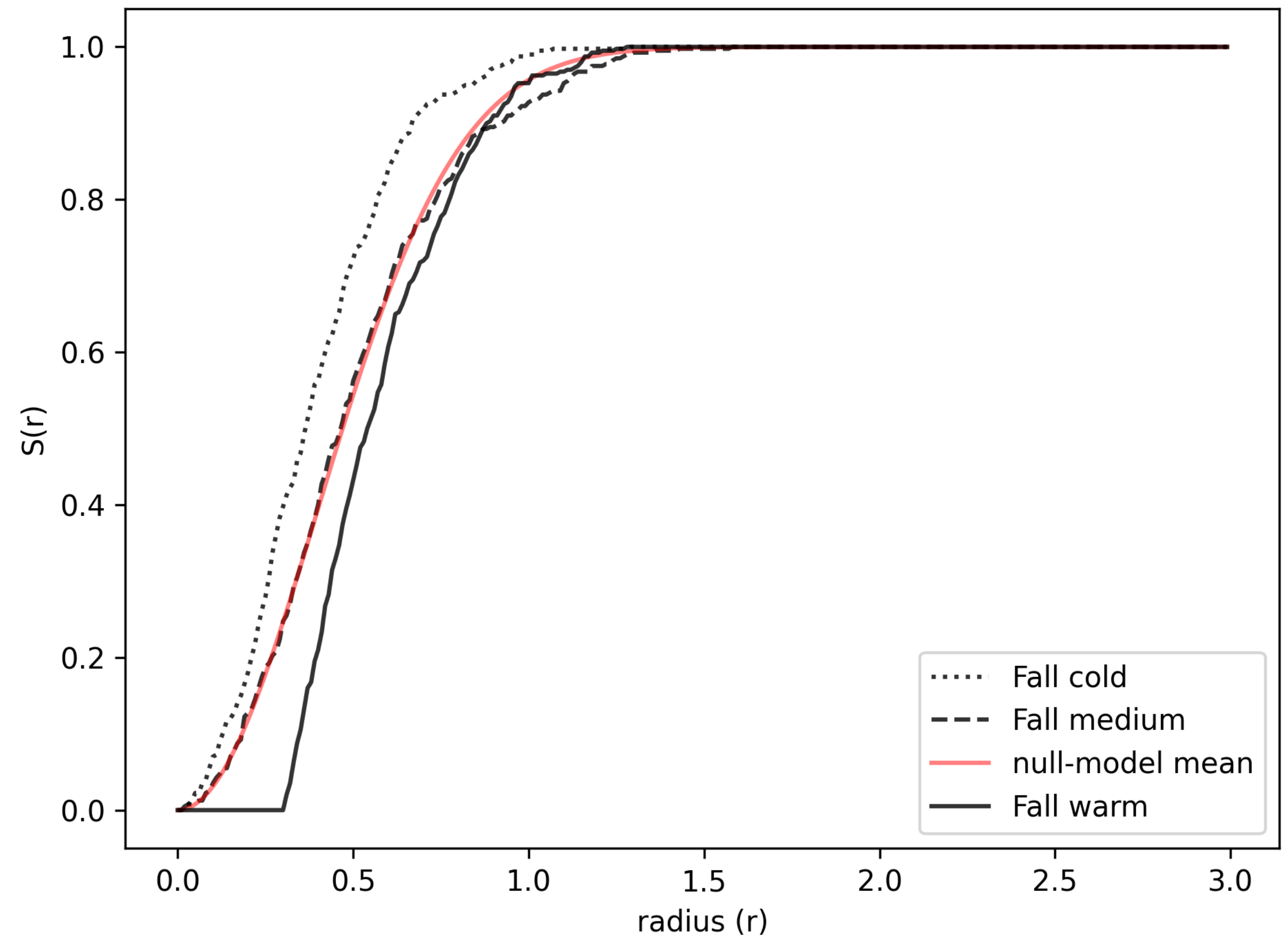
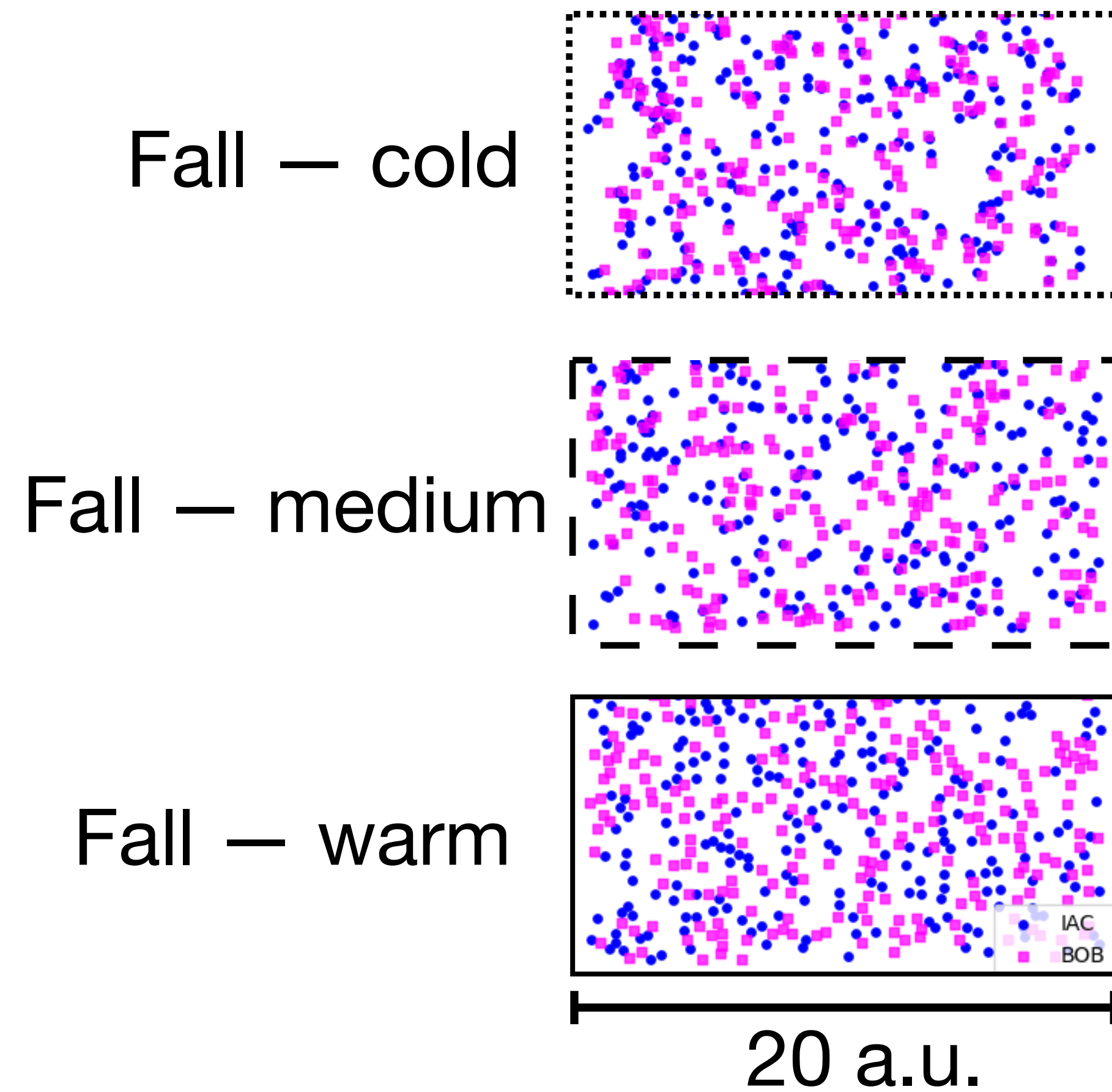
nulldist = getnulldist(
    n=n, area=area, radii=radii
) # These are not good values for n and area. Change them!
```





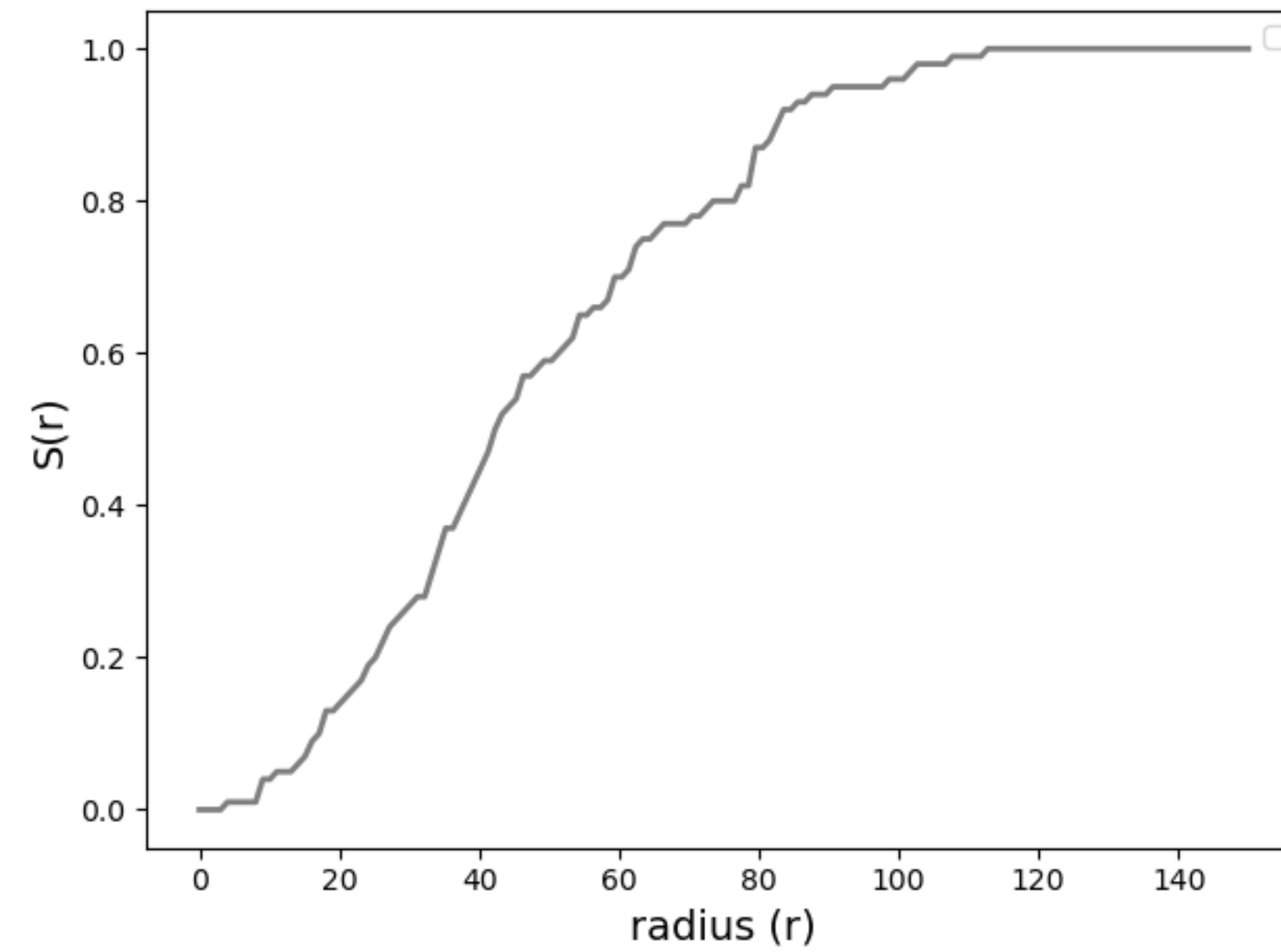
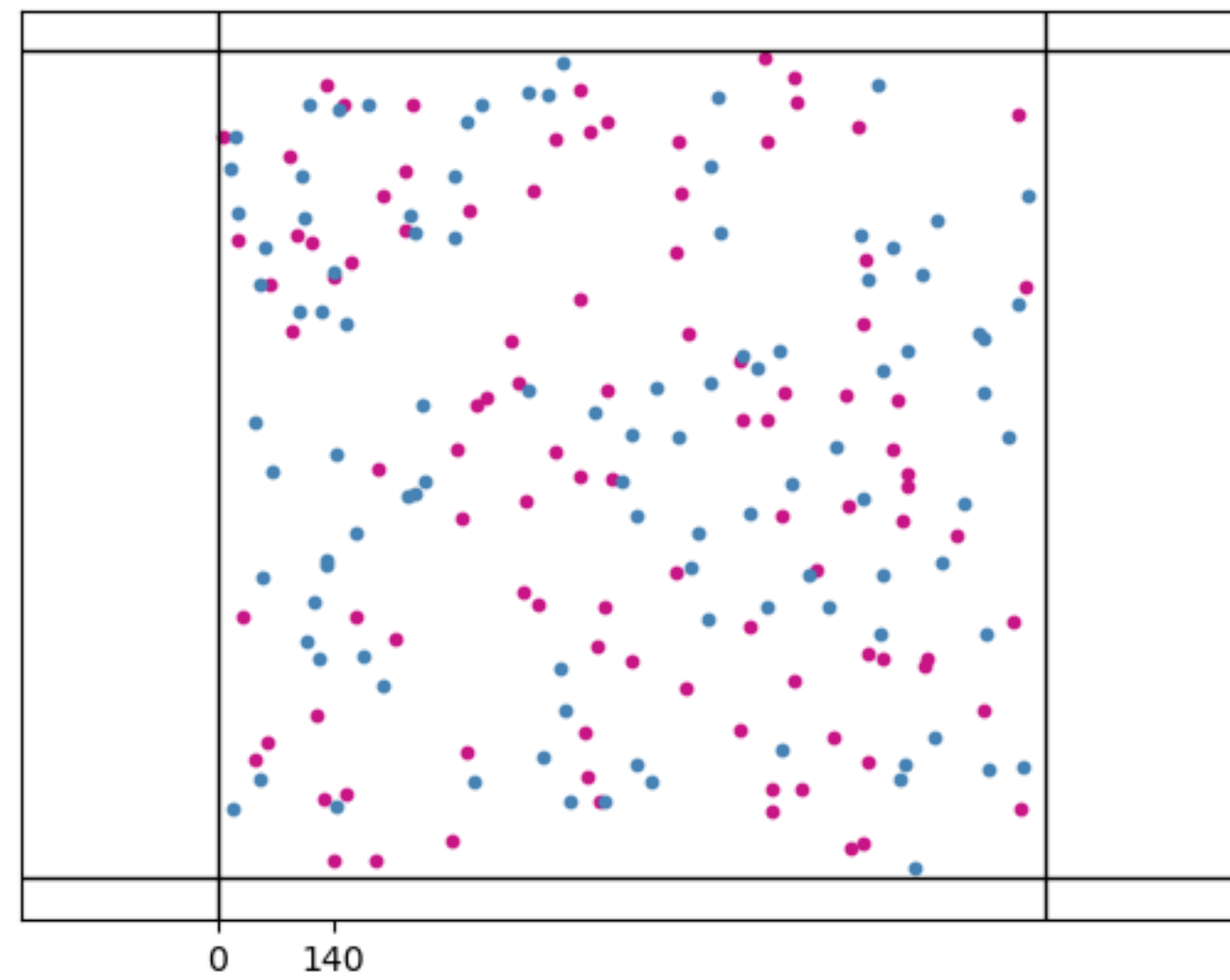


# Results — the null distribution





# Monte-Carlo-based significance testing

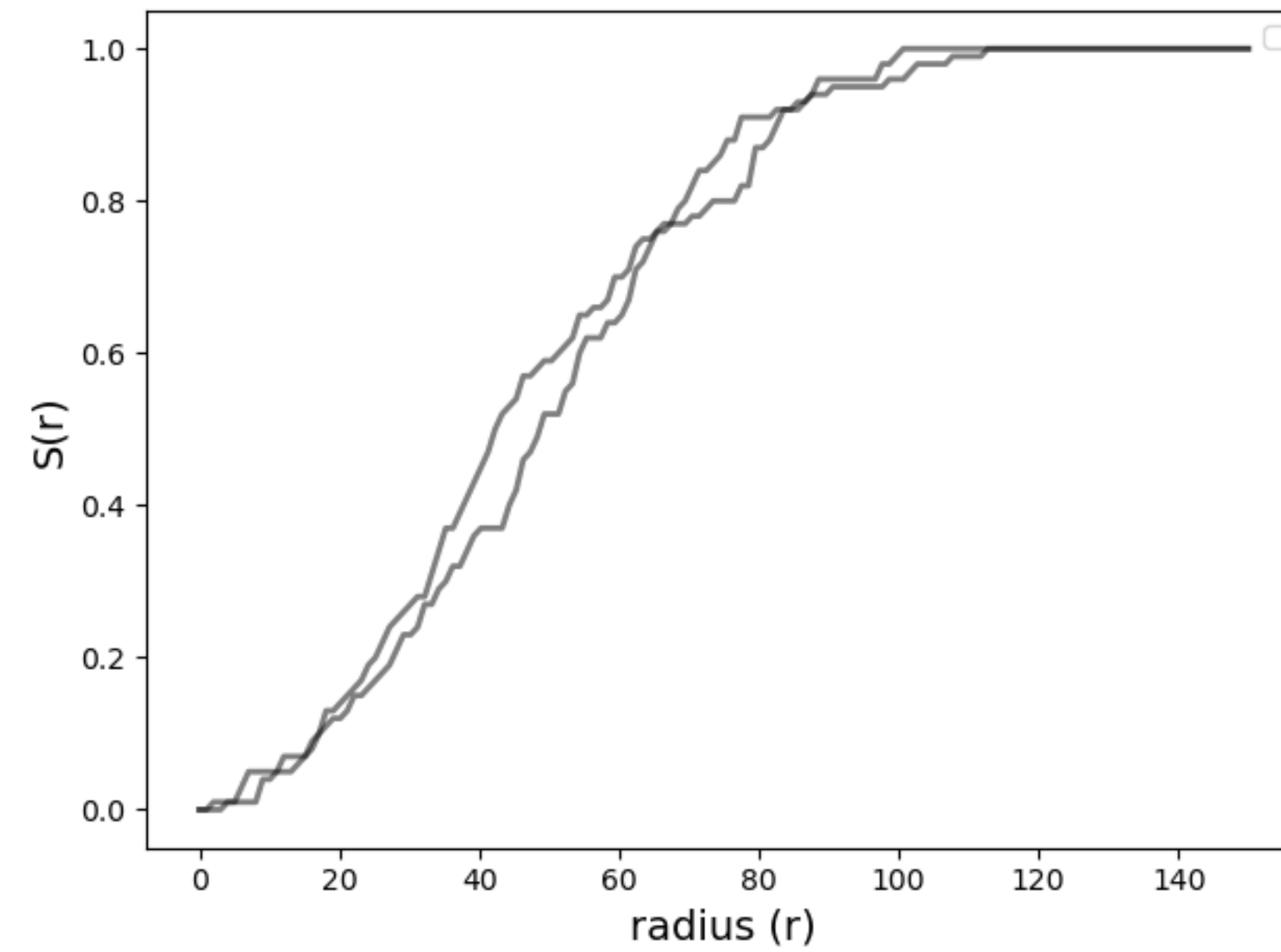
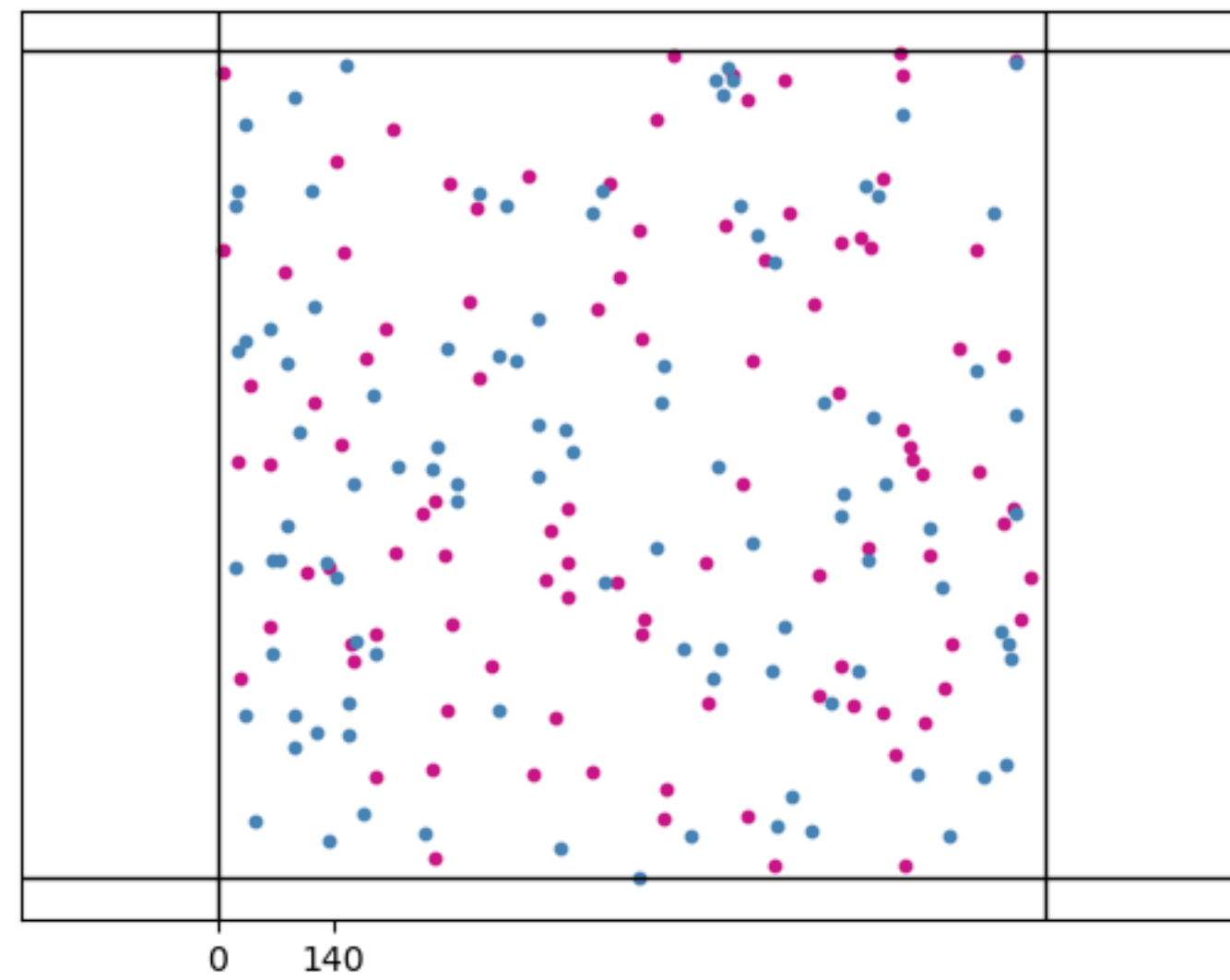


1





# Monte-Carlo-based significance testing

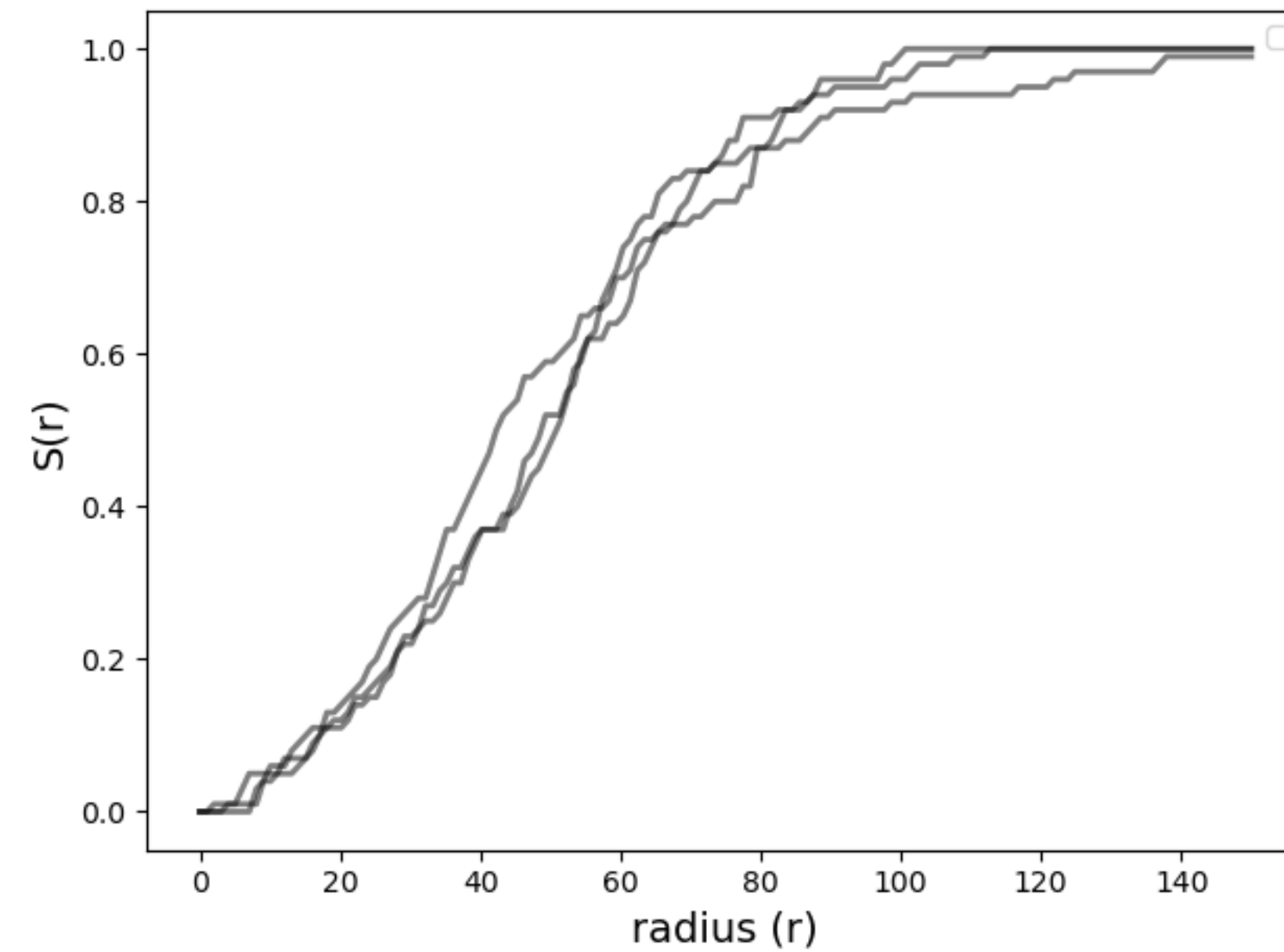
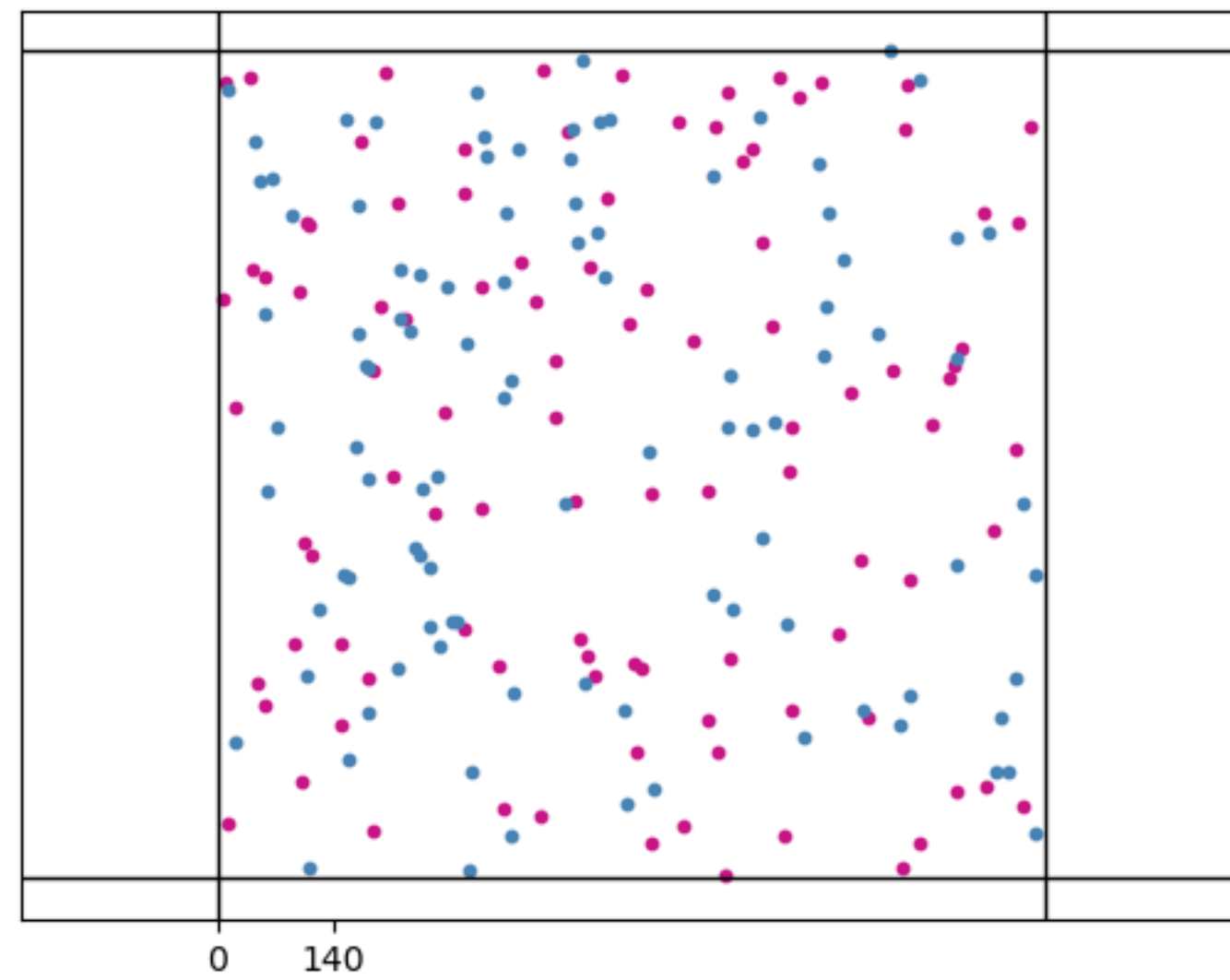


2





# Monte-Carlo-based significance testing



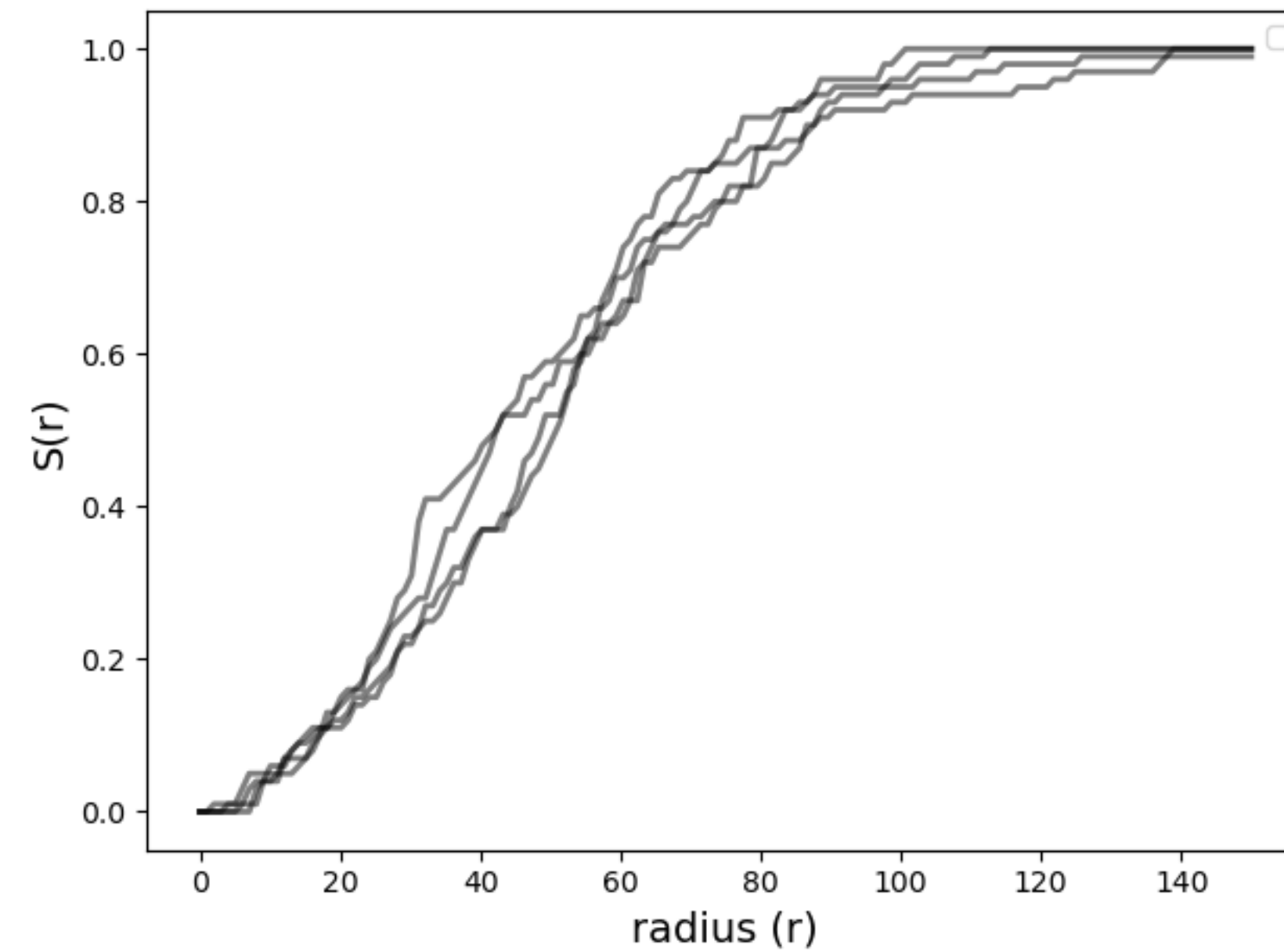
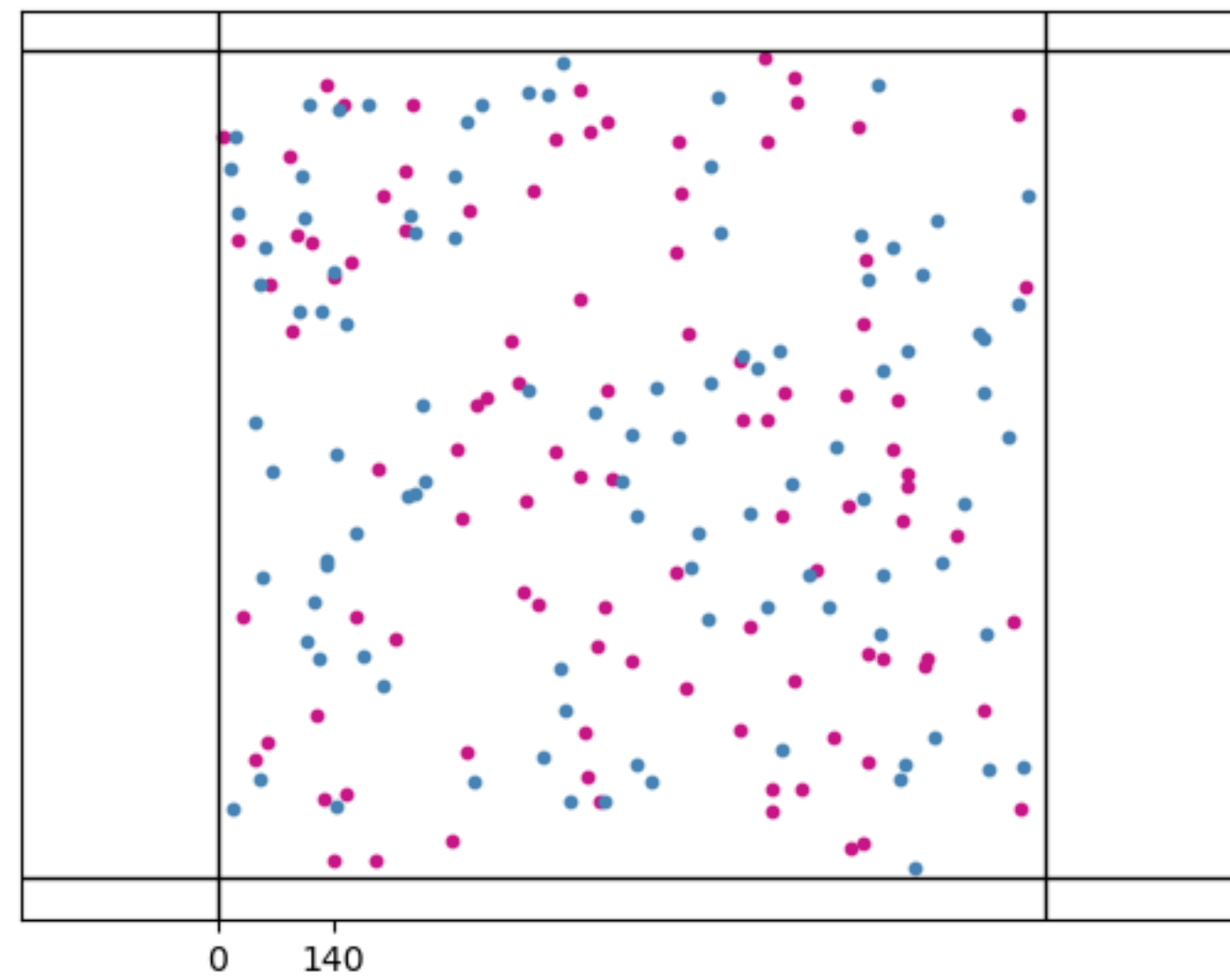
3







# Monte-Carlo-based significance testing

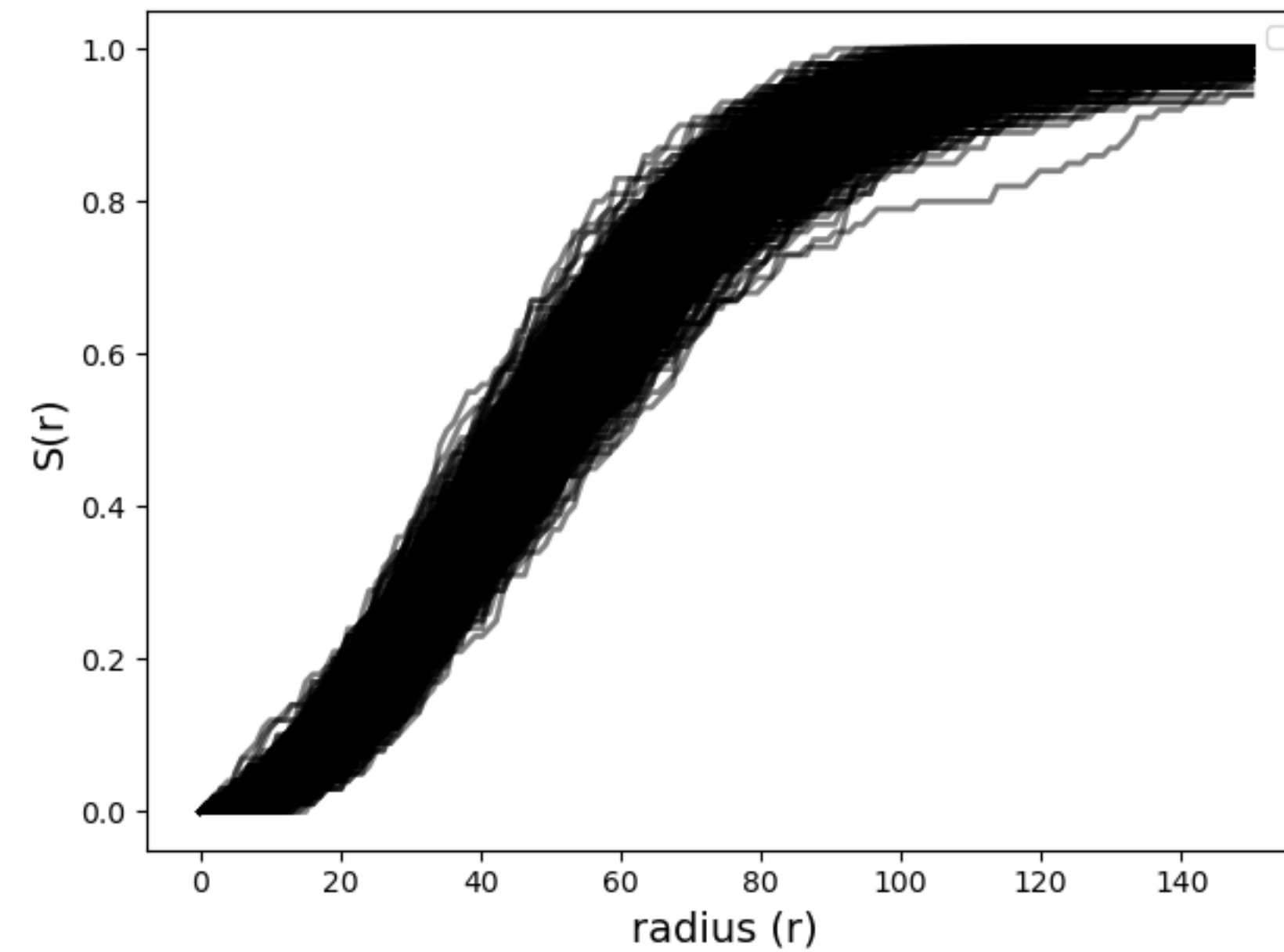
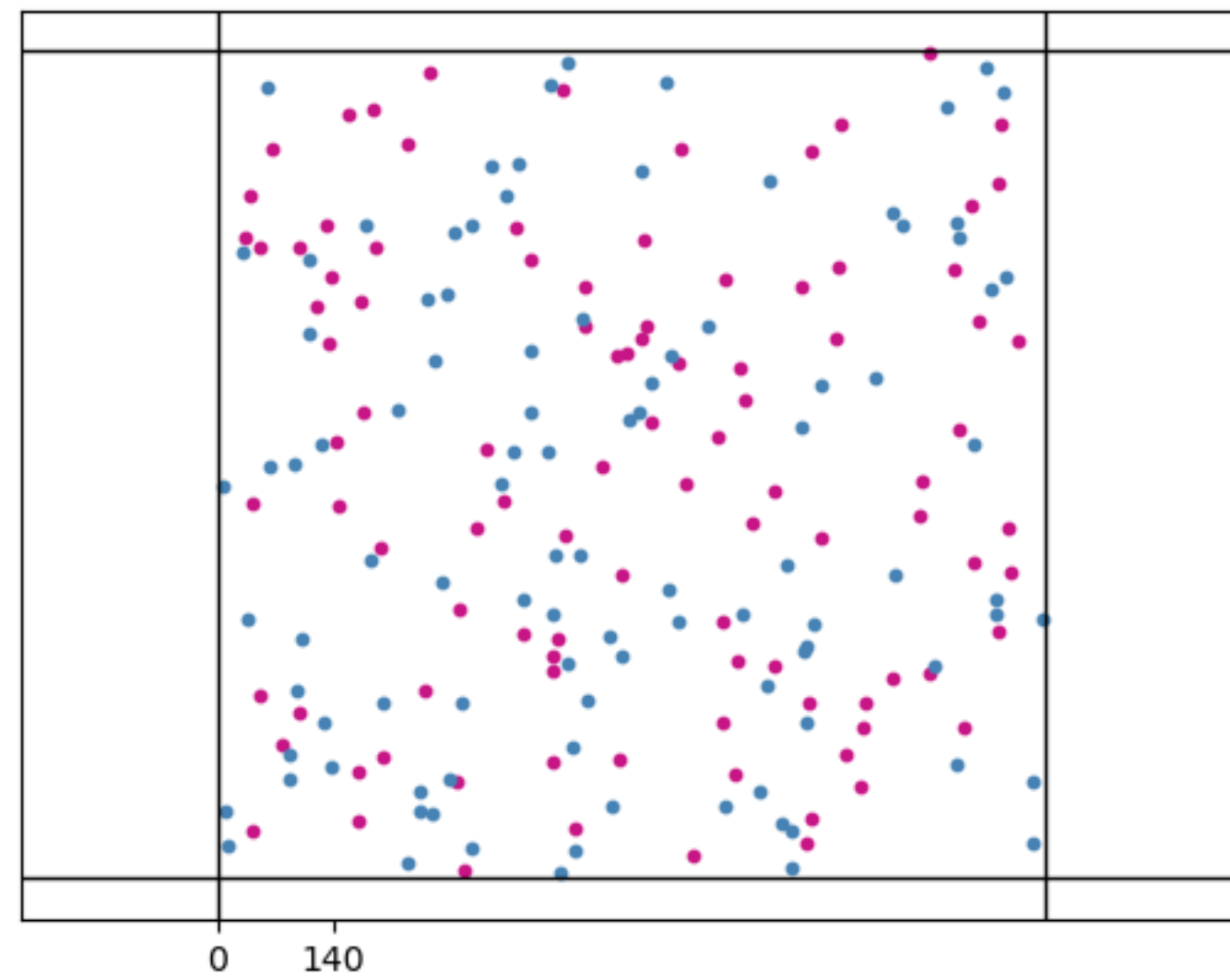


4





# Monte-Carlo-based significance testing

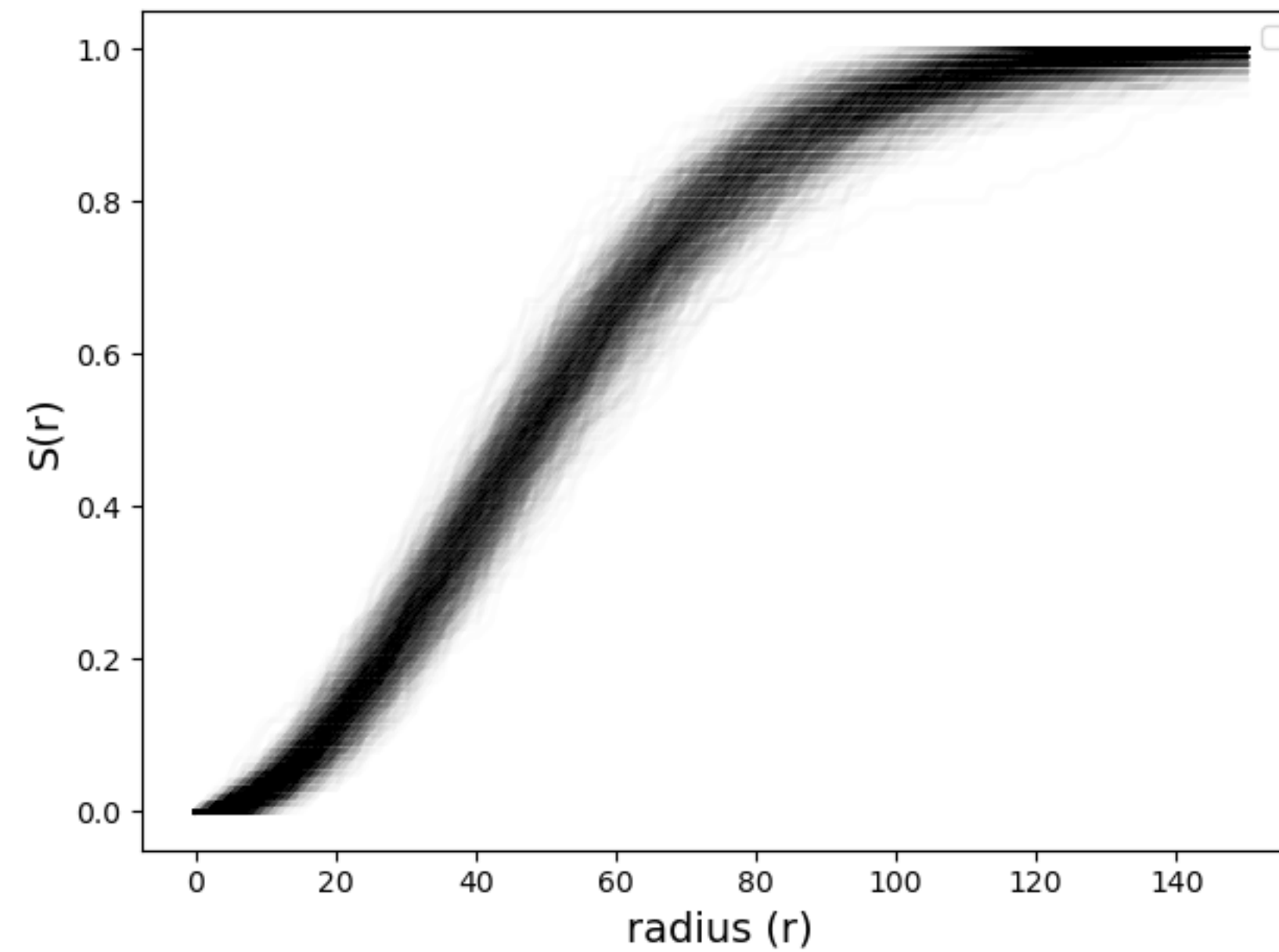
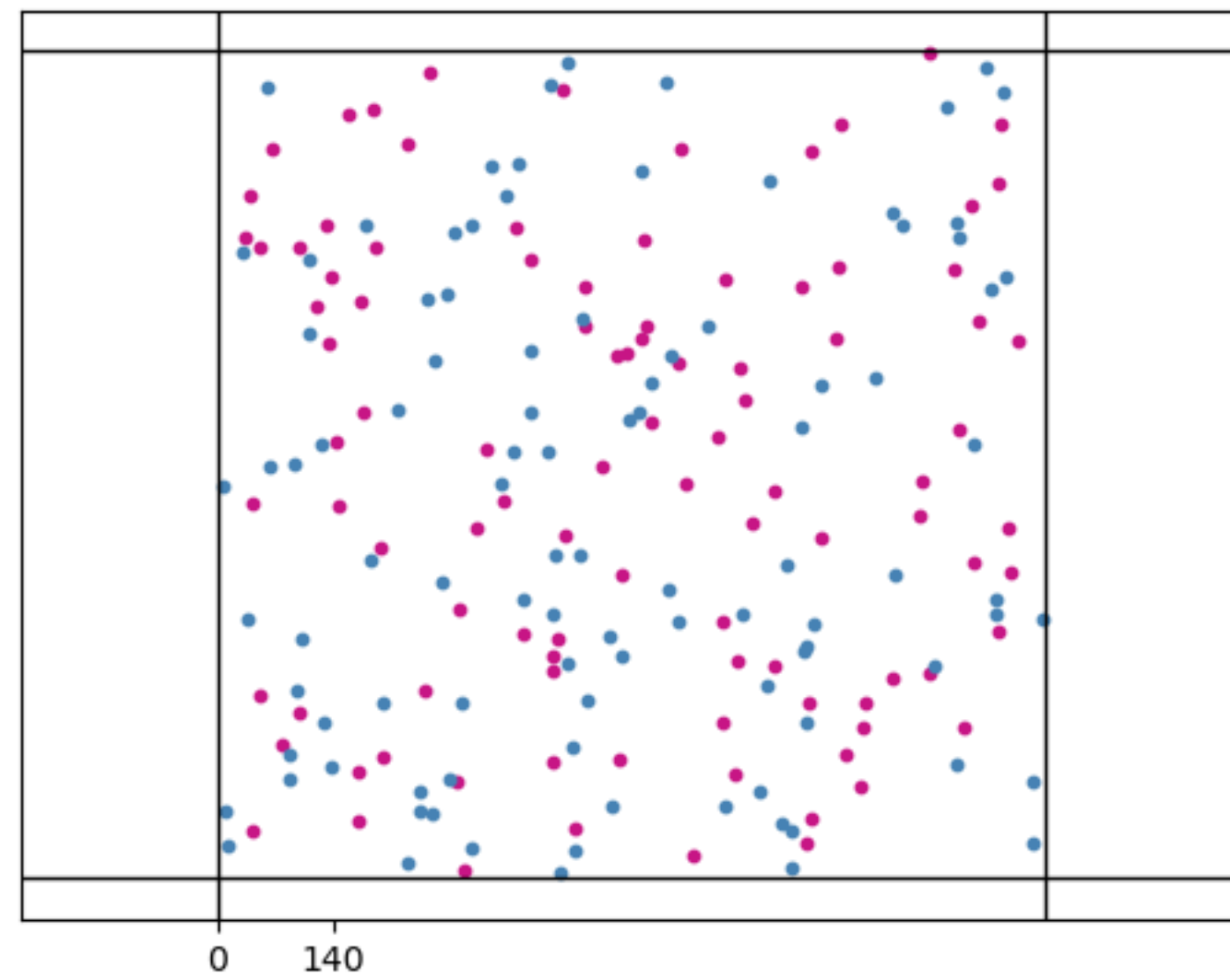


1000

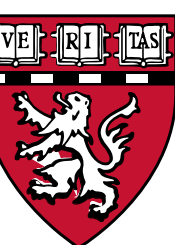




# Monte-Carlo-based significance testing

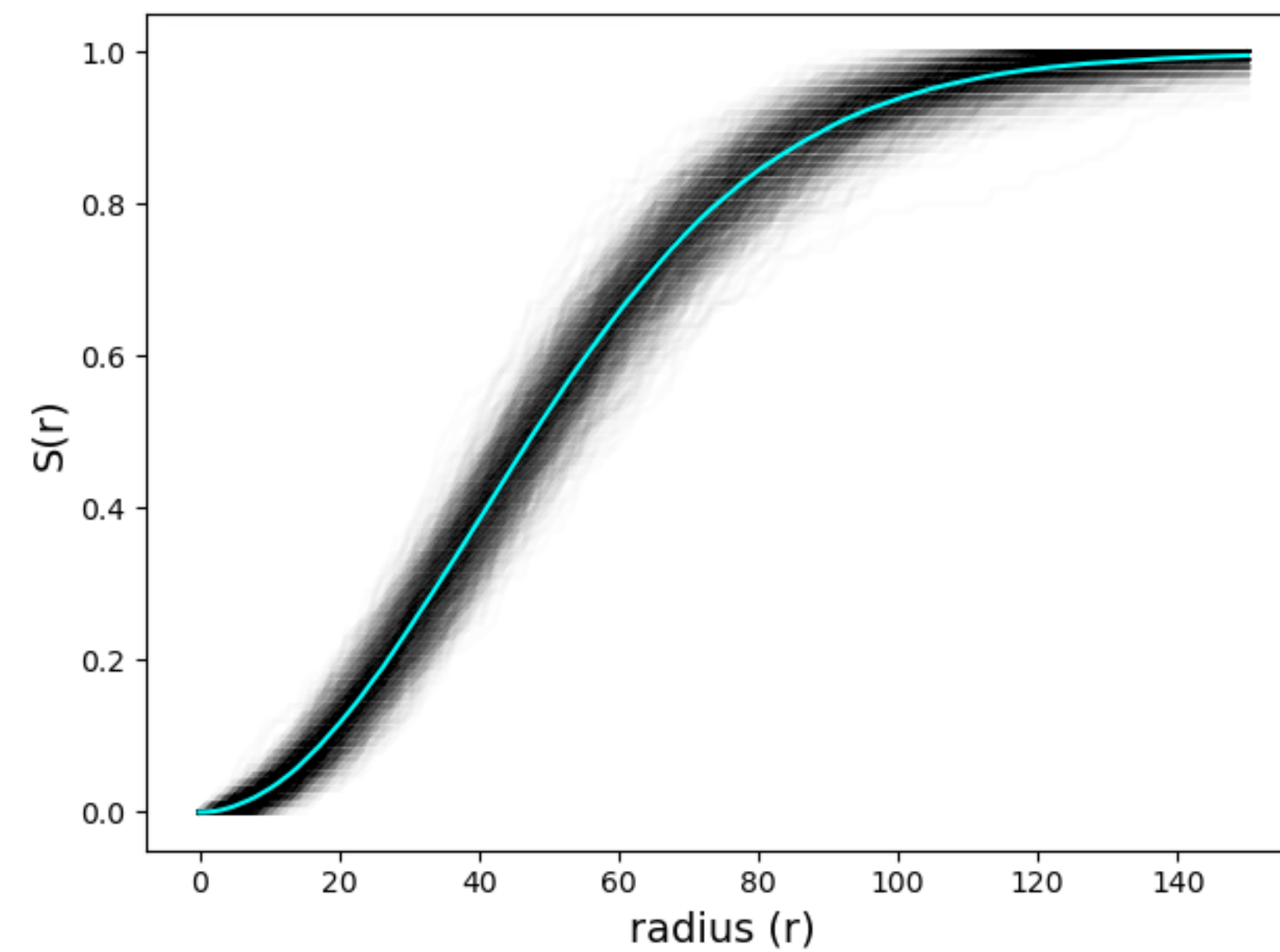
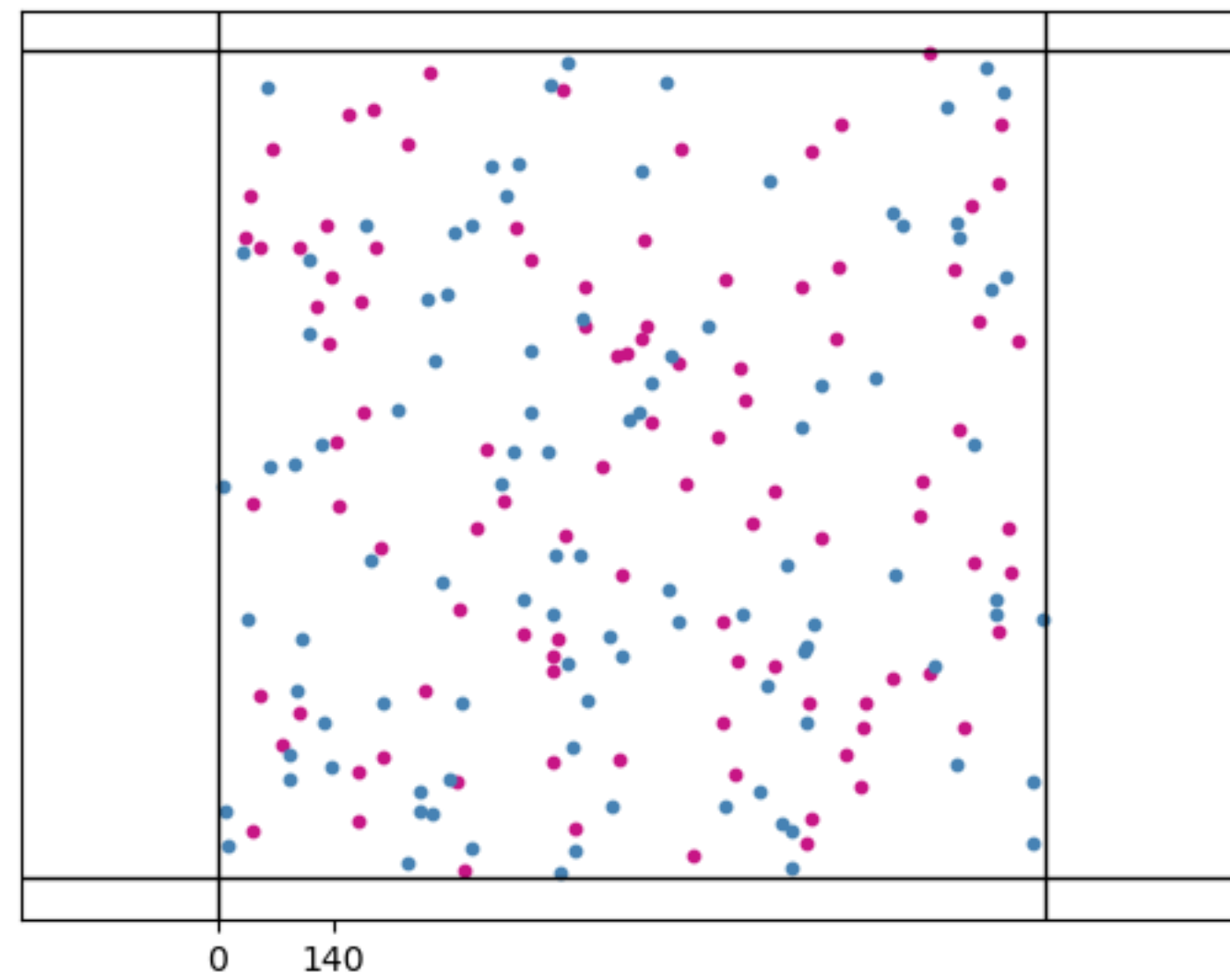


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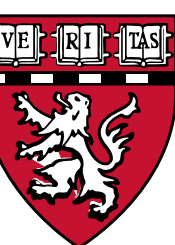




# Monte-Carlo-based significance testing



— mean of 1000 realizations

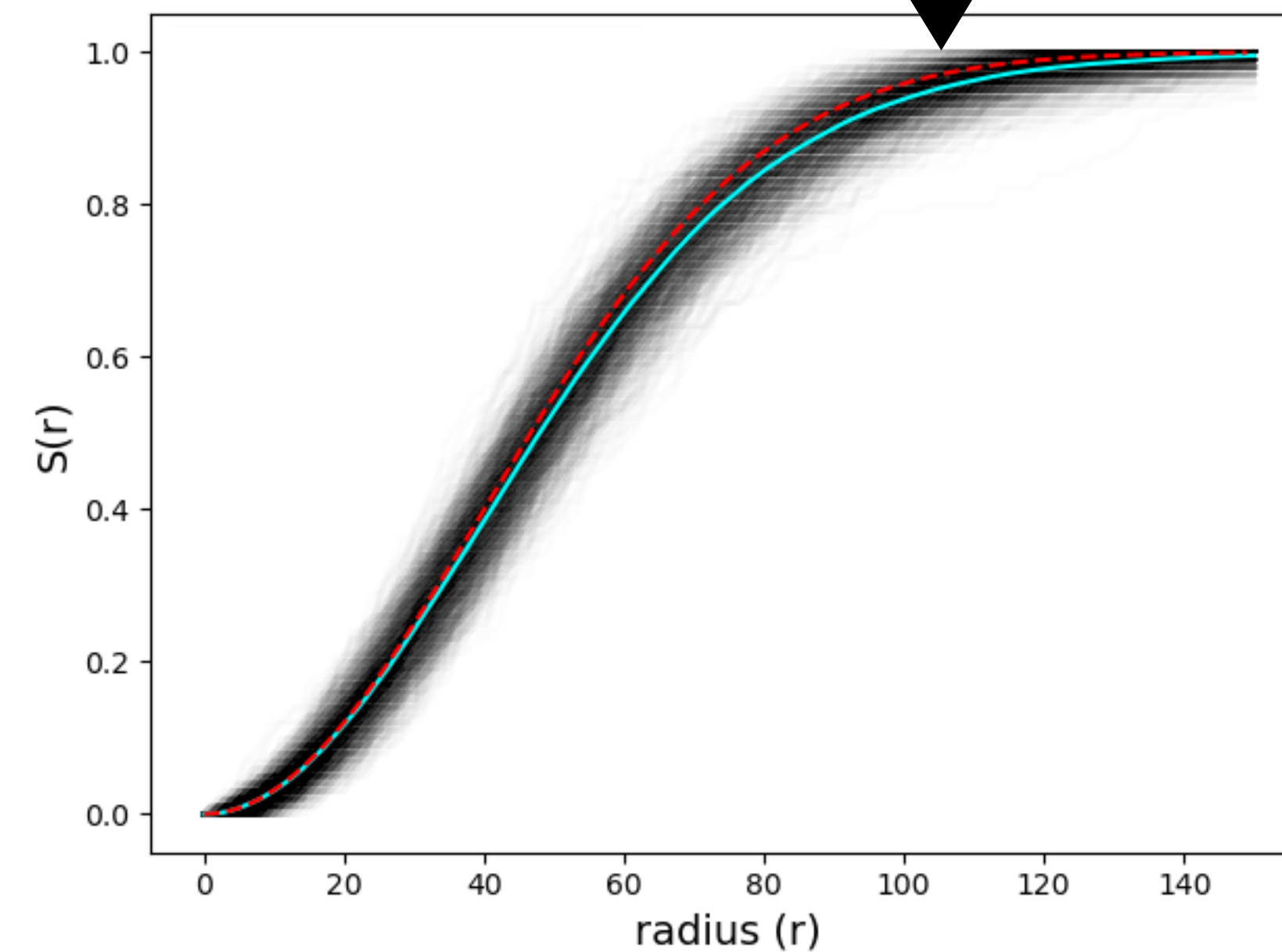
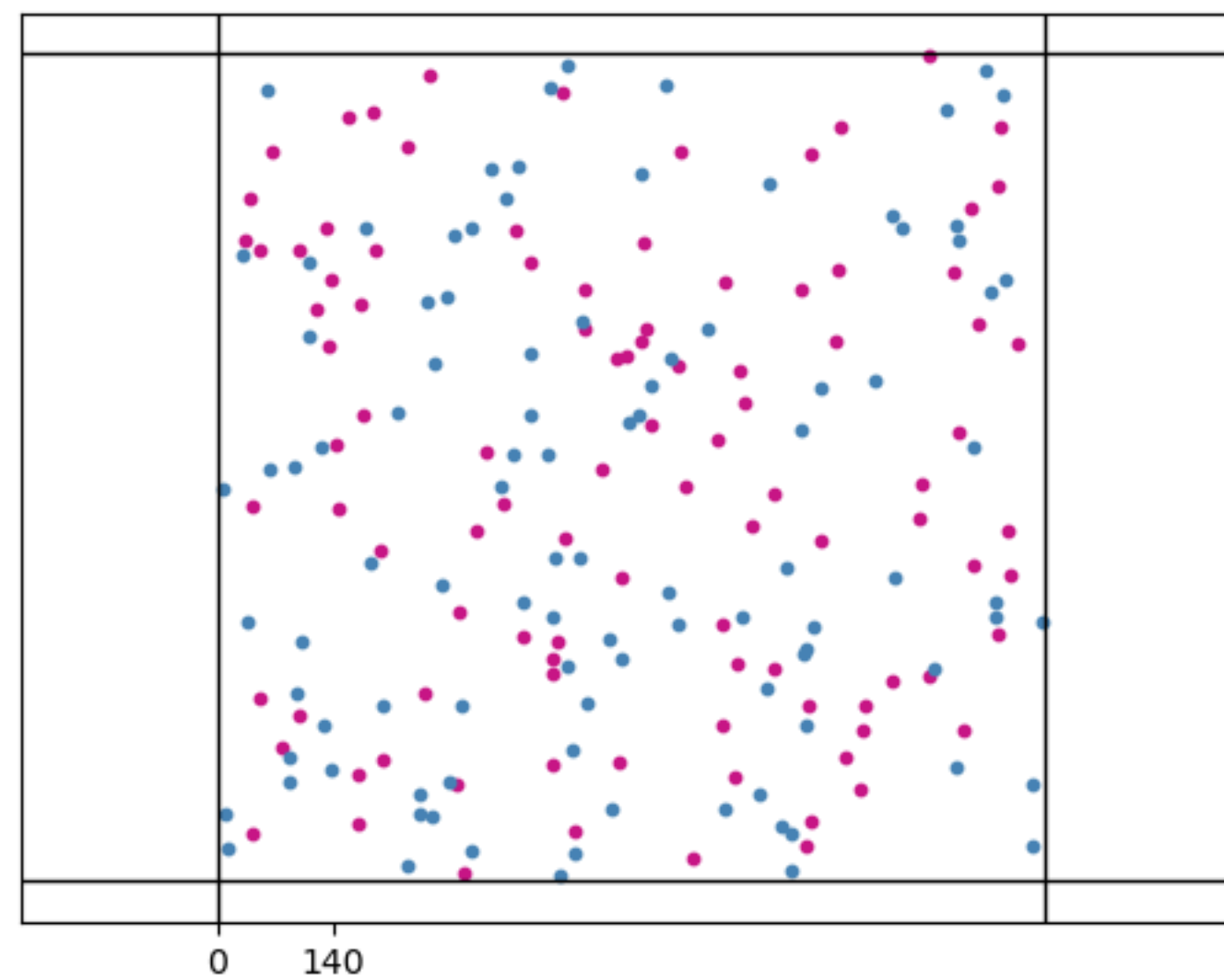
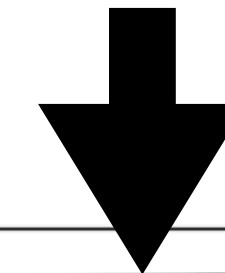




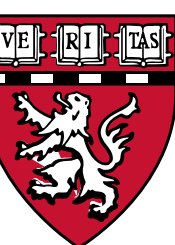


# Monte-Carlo-based significance testing

Why?



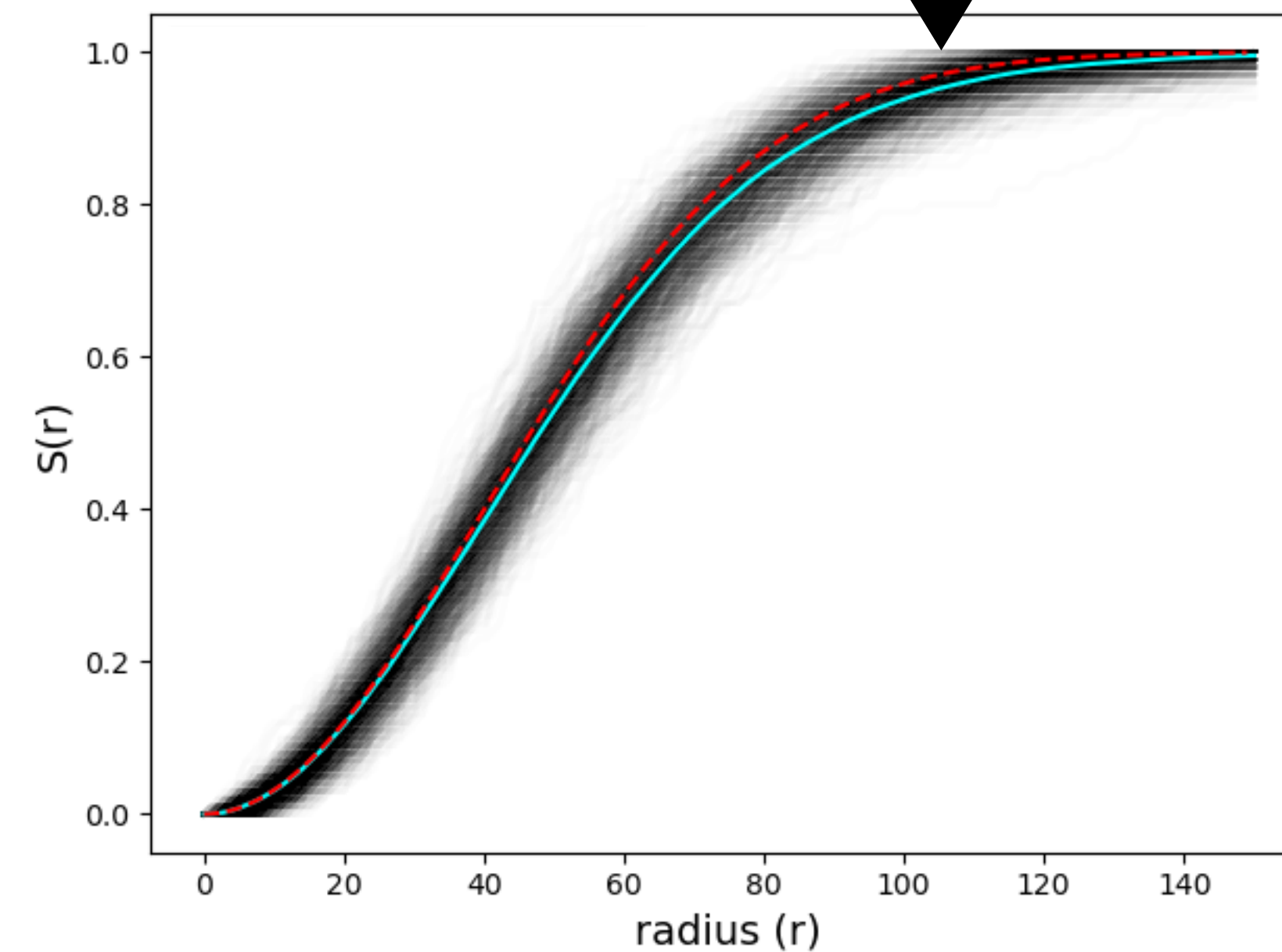
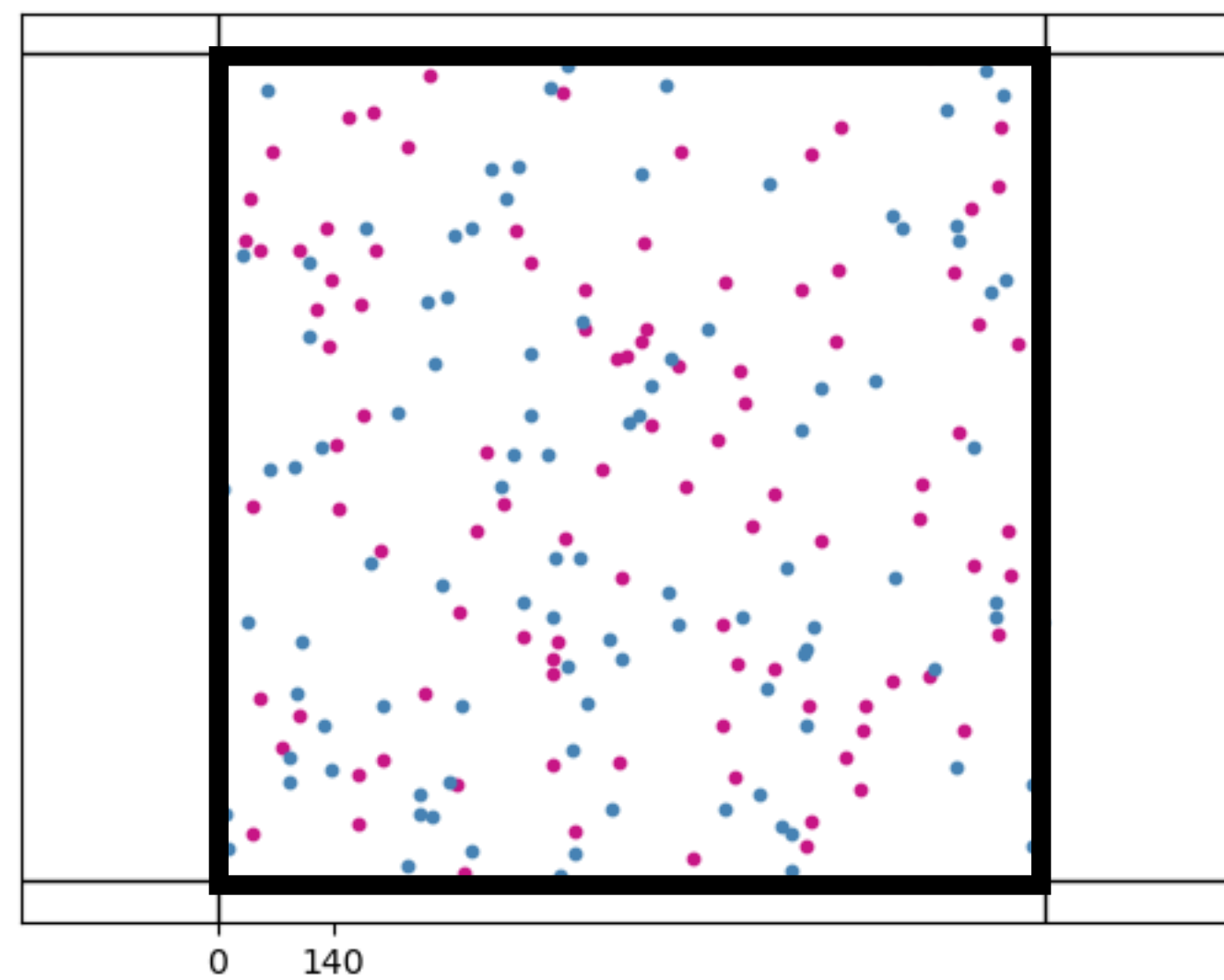
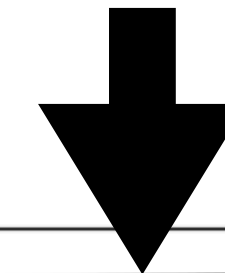
— mean of 1000 realizations  
- - - analytic null distribution



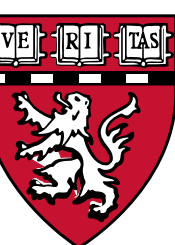


# Monte-Carlo-based significance testing

Why?

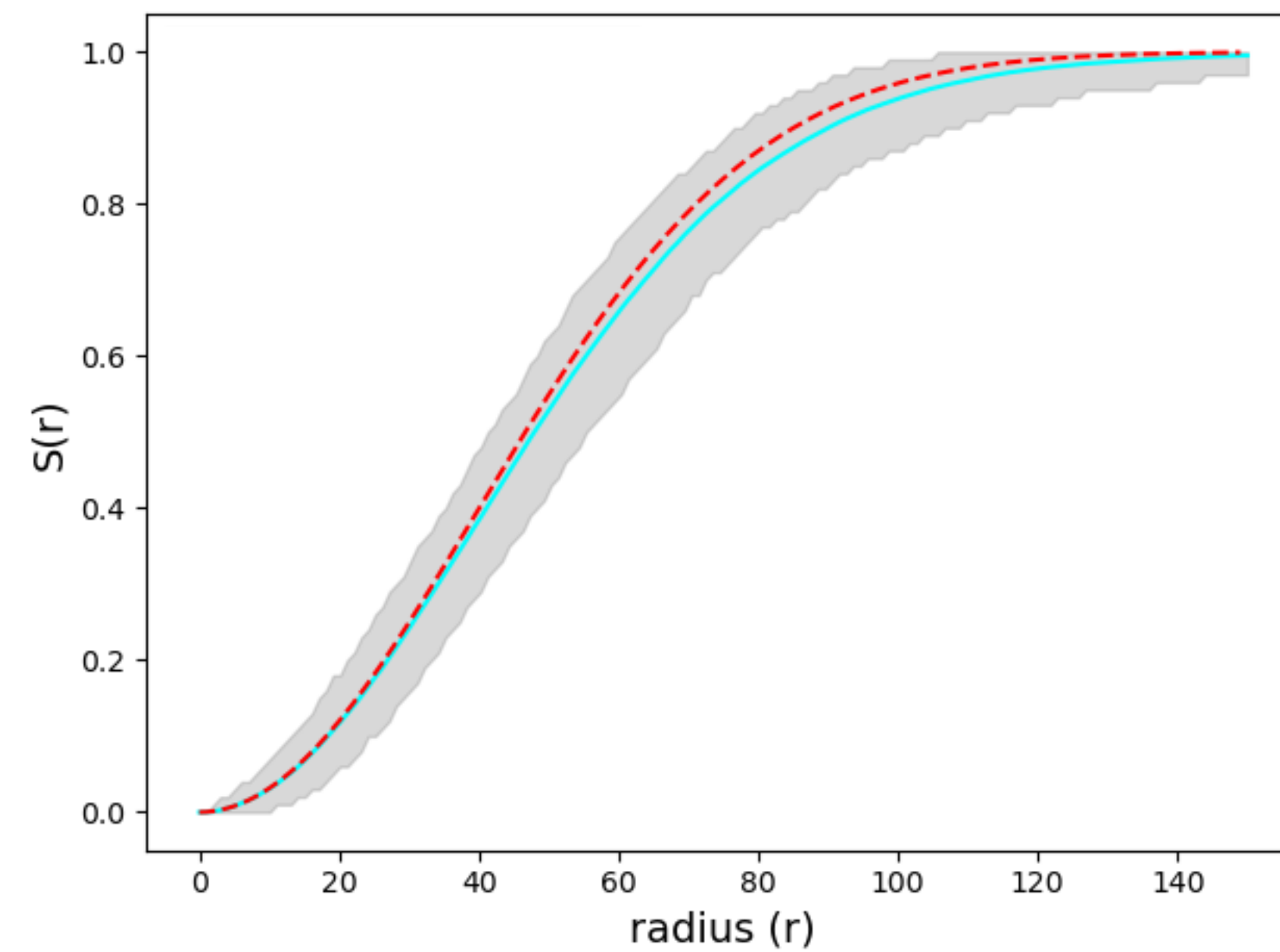
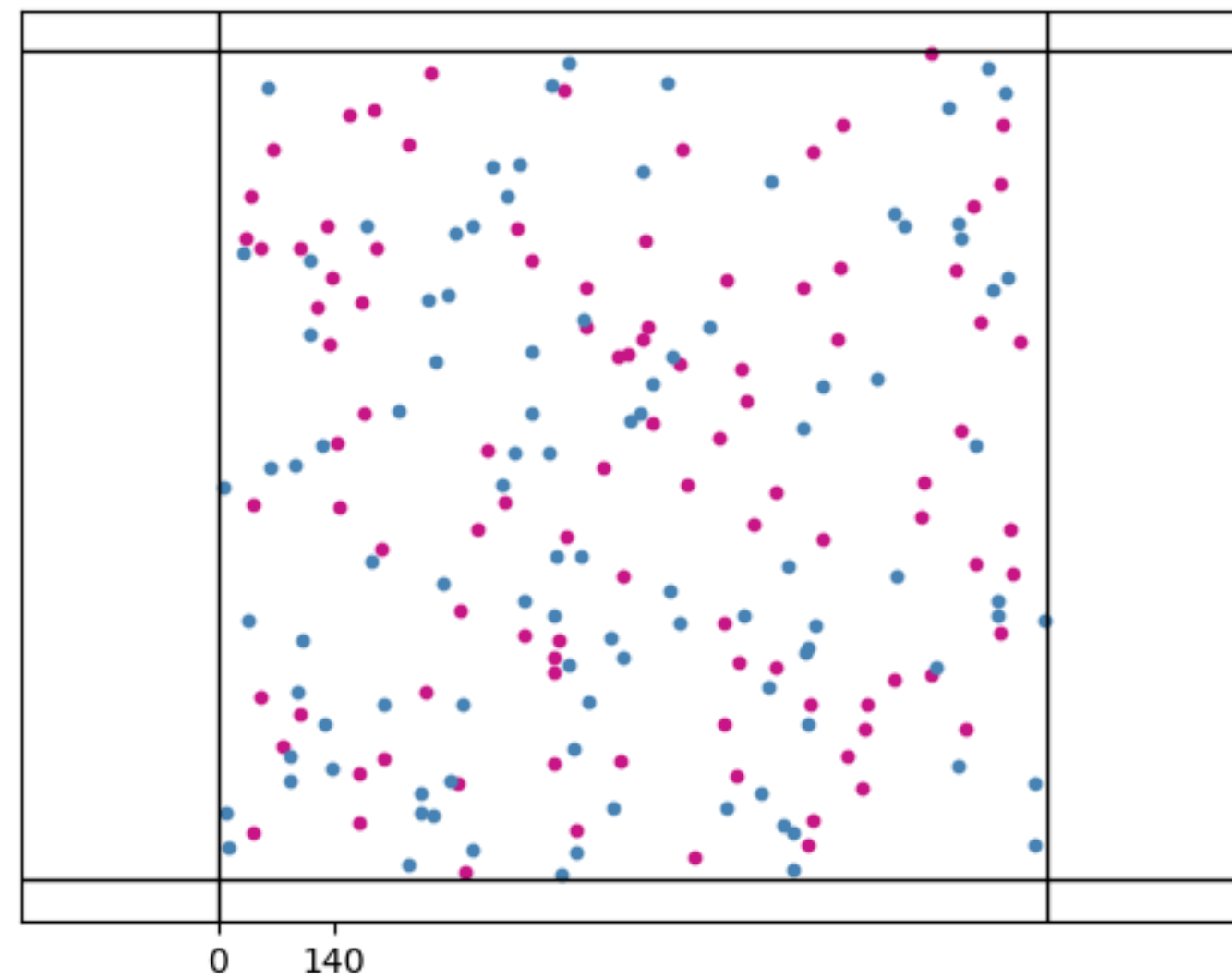


— mean of 1000 realizations  
- - - analytic null distribution

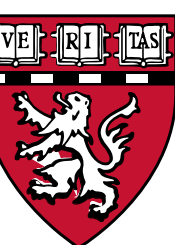




# Monte-Carlo-based significance testing

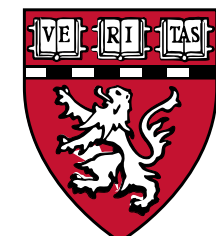


- mean of 1000 realizations
- 2.5-97.5% quantile range
- - analytic null distribution





# Exercise: throw darts at a board

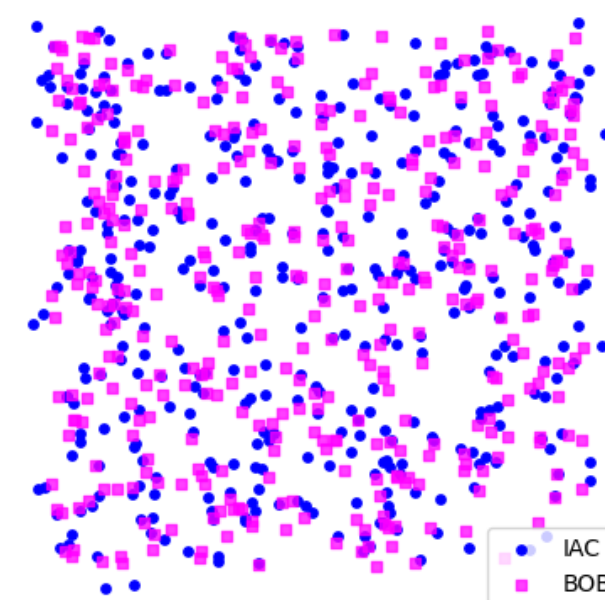




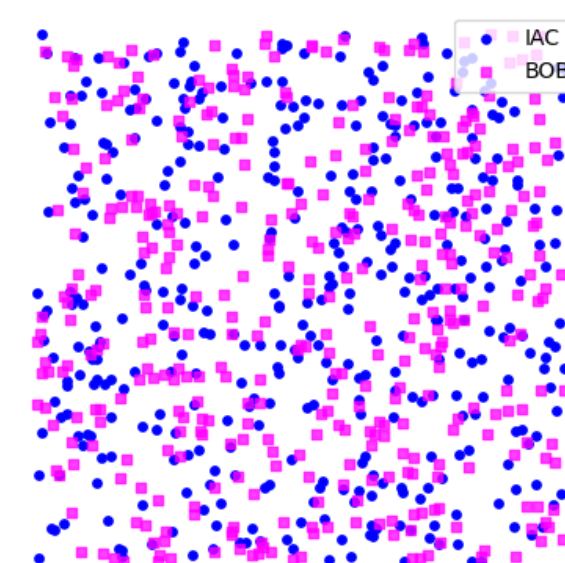


# Results: Mean distance IAC -> BOB

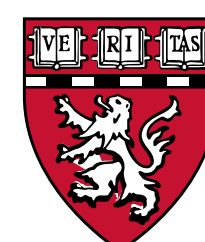
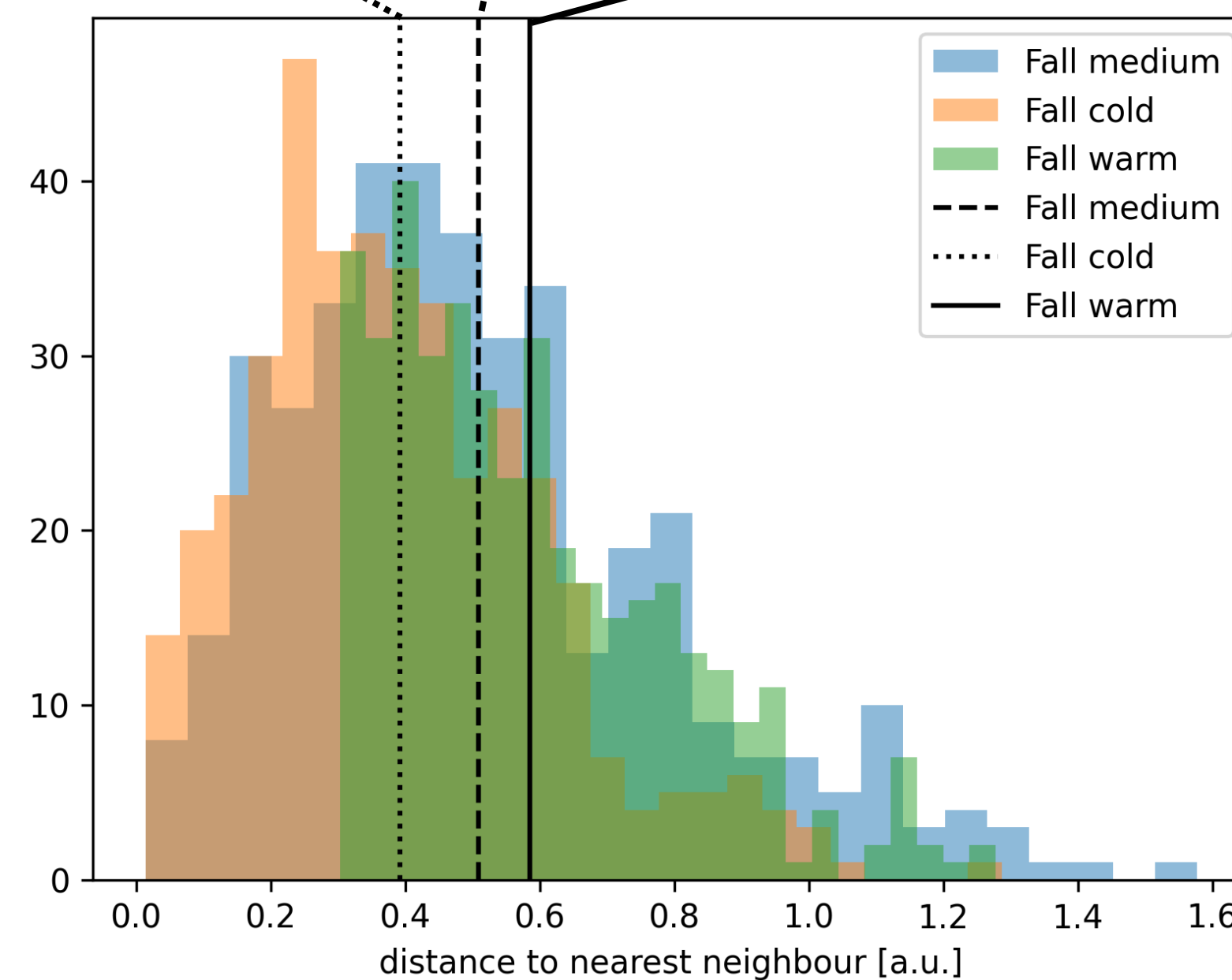
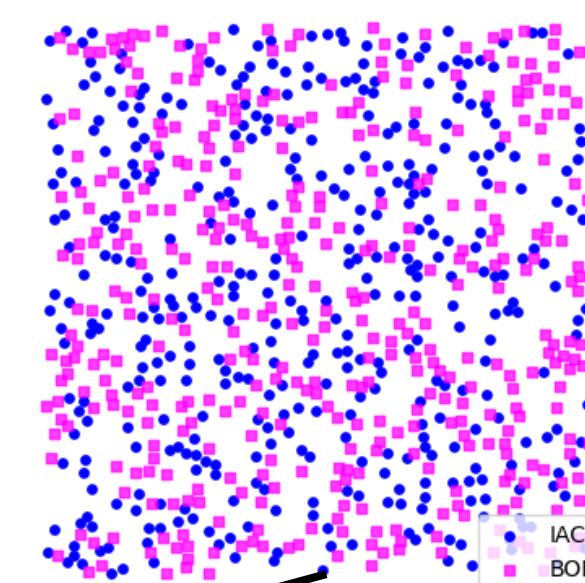
Cold



Medium



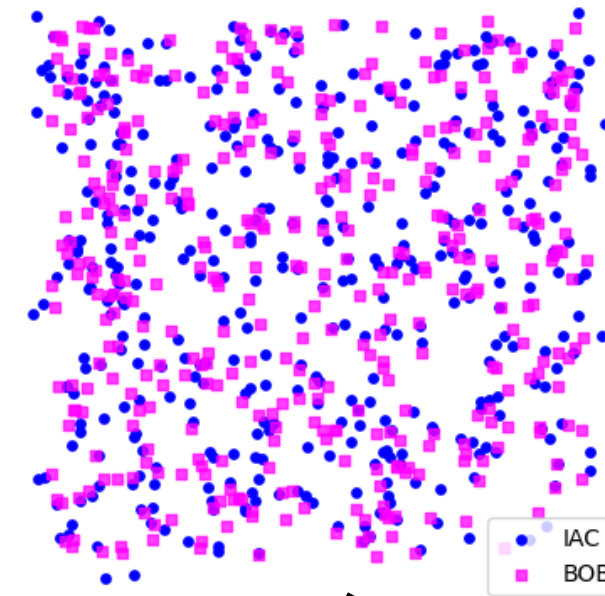
Warm



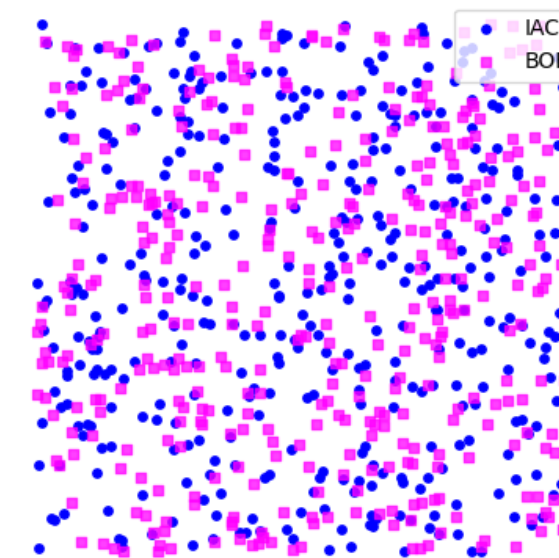


# Results: Mean distance IAC -> BOB

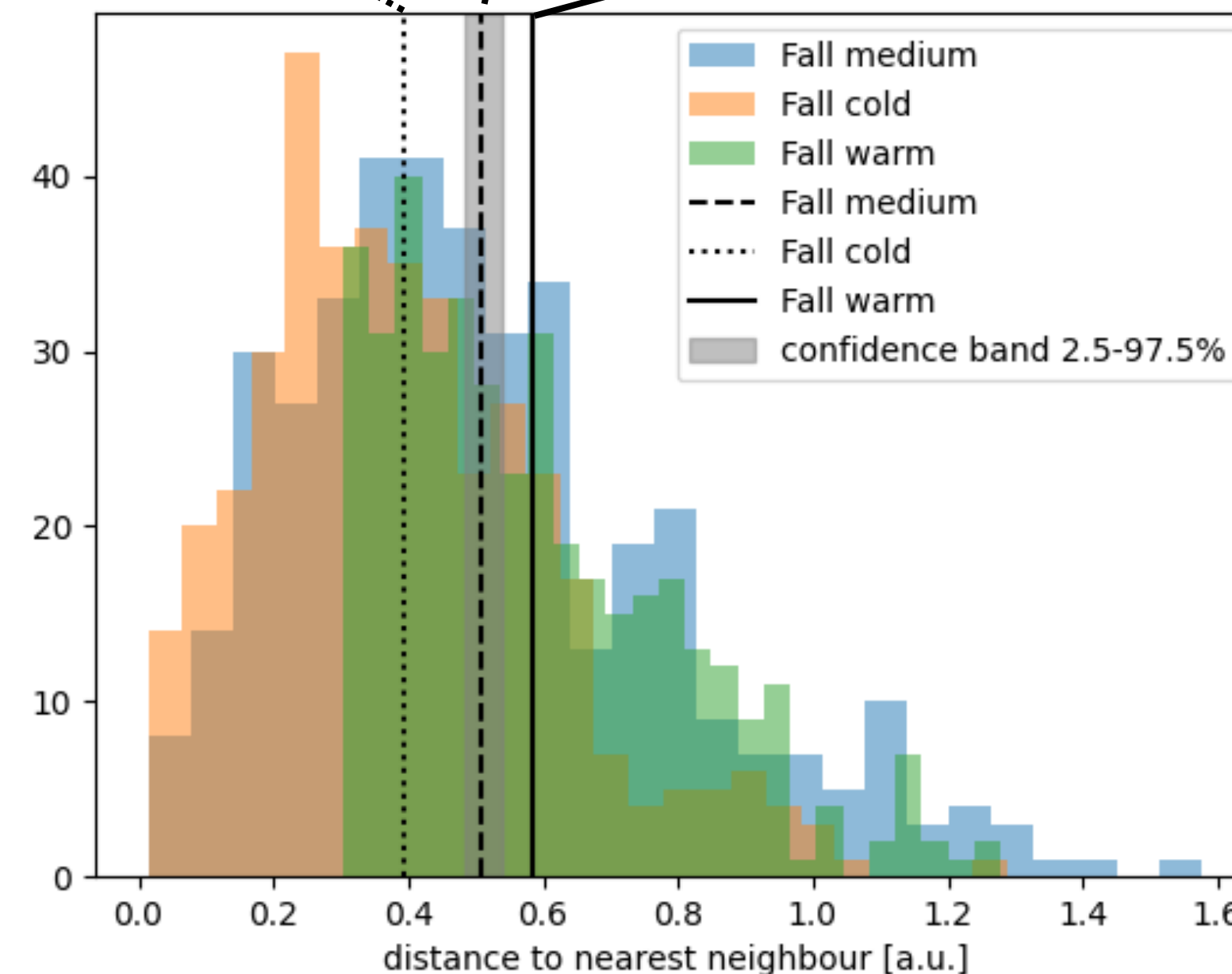
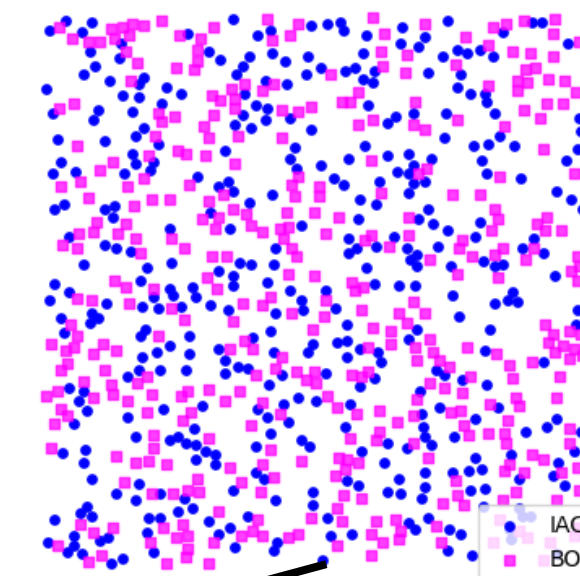
Cold



Medium



Warm

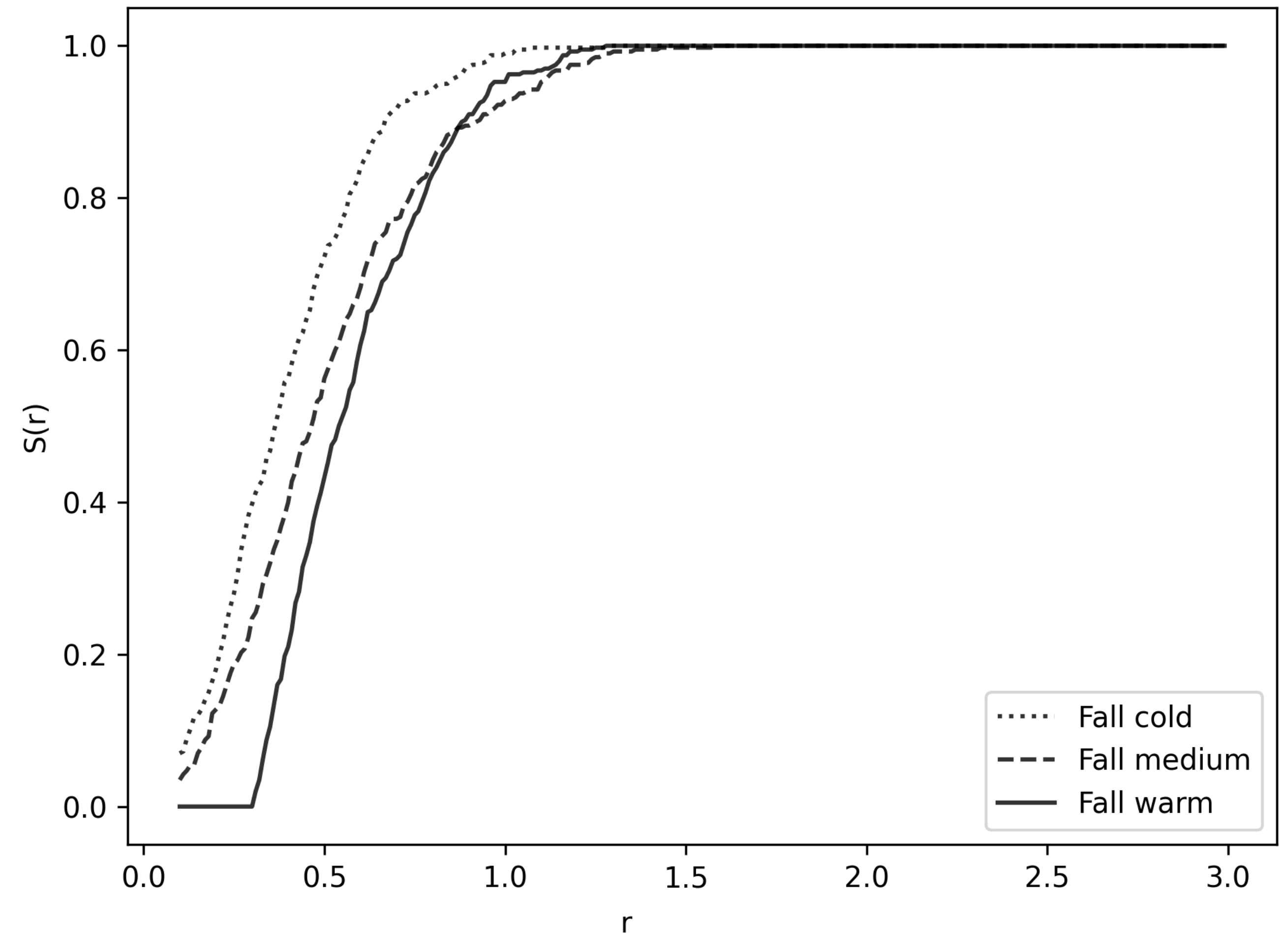
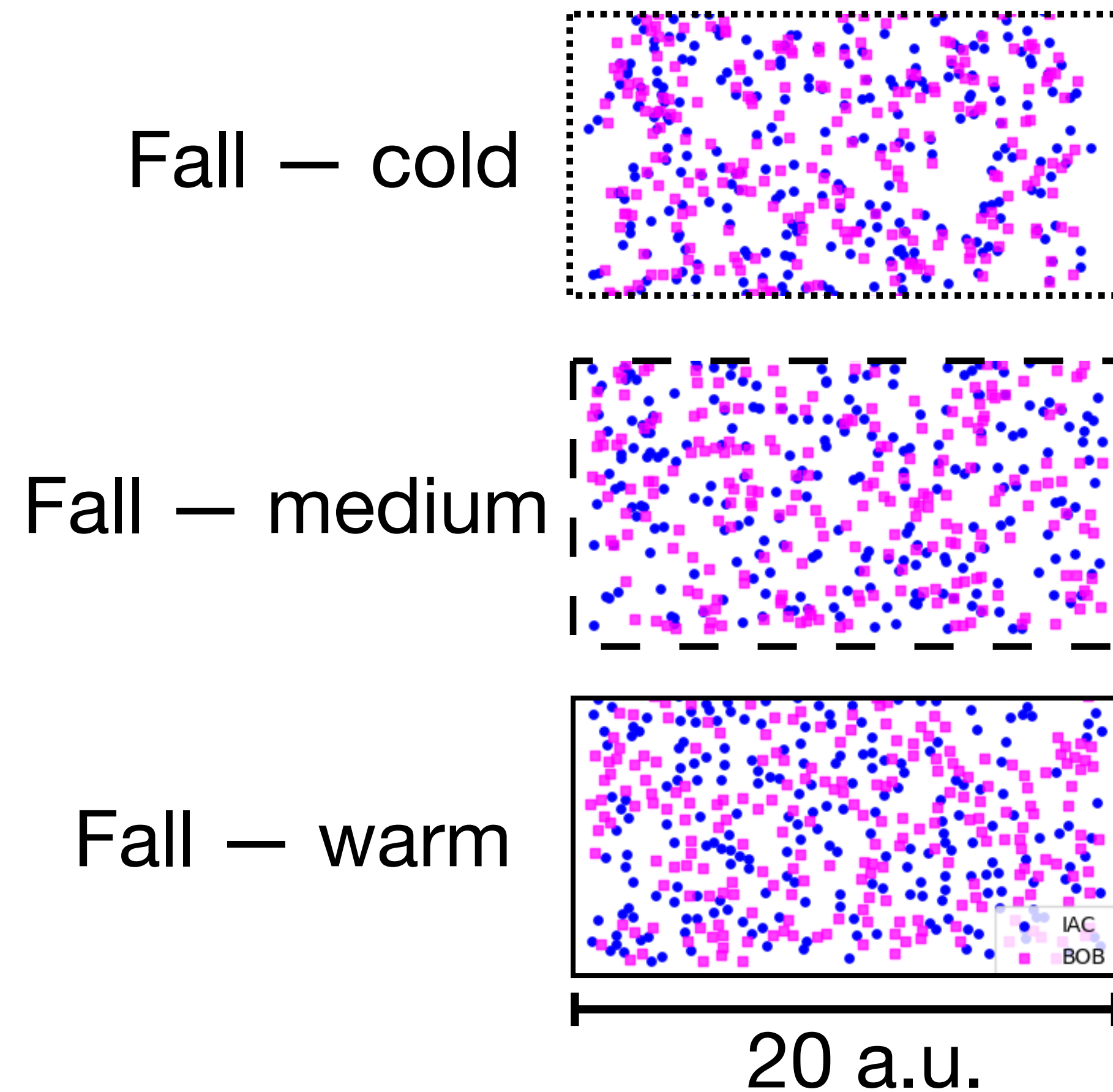


Cold IAC->BOB are closer to each other than random under the 95% significance level

Warm IAC->BOB are further apart from each other than random under the 95% significance level



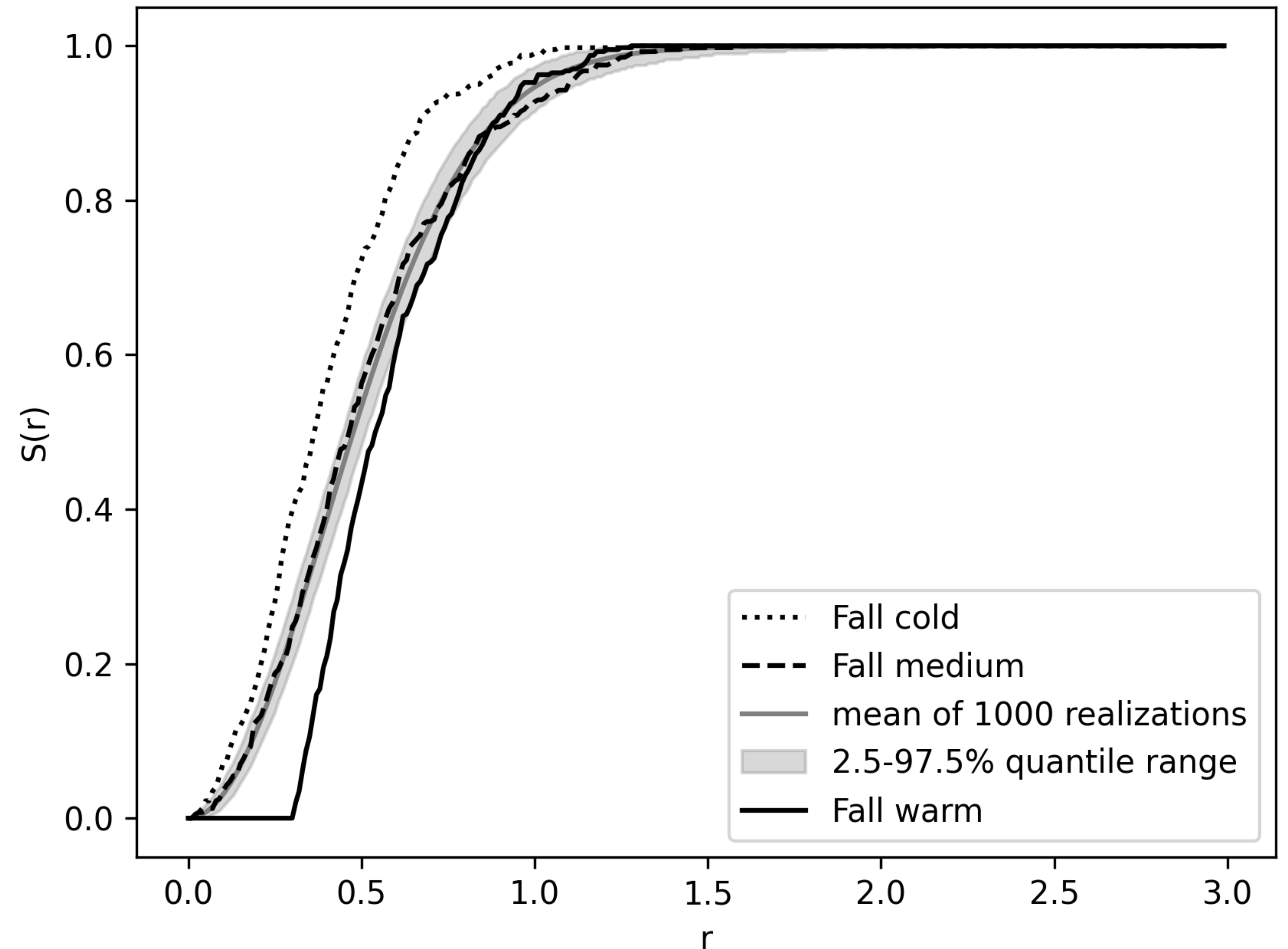
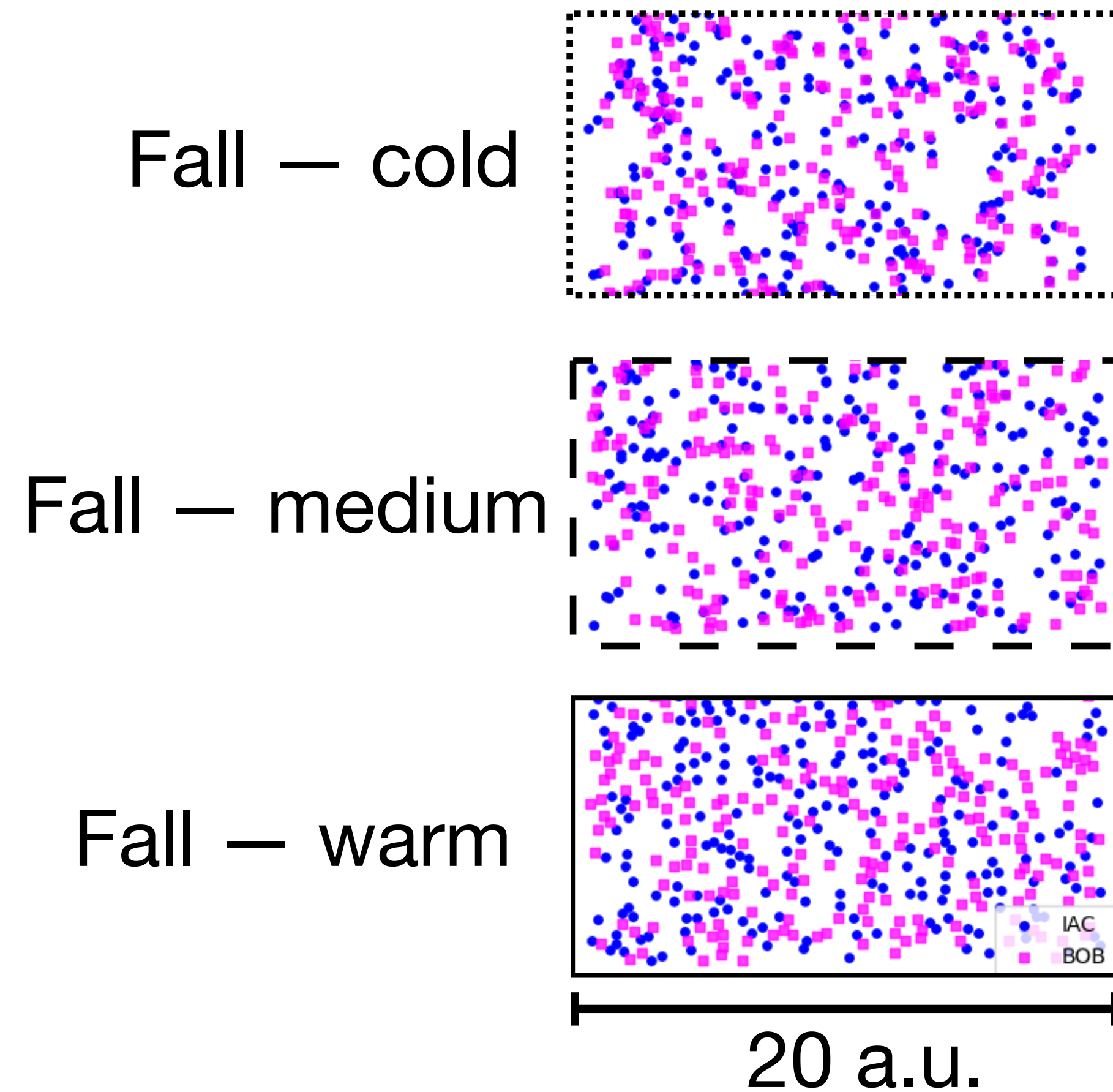
# Results: Nearest neighbor function







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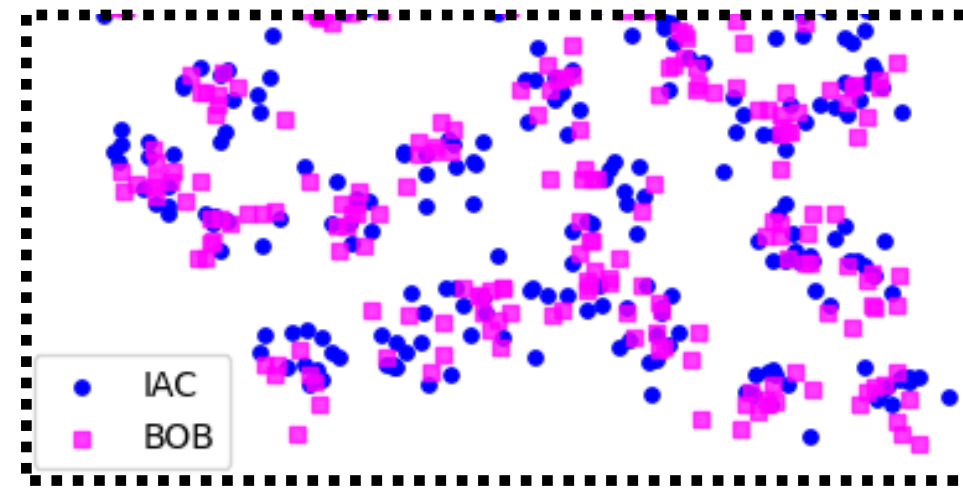




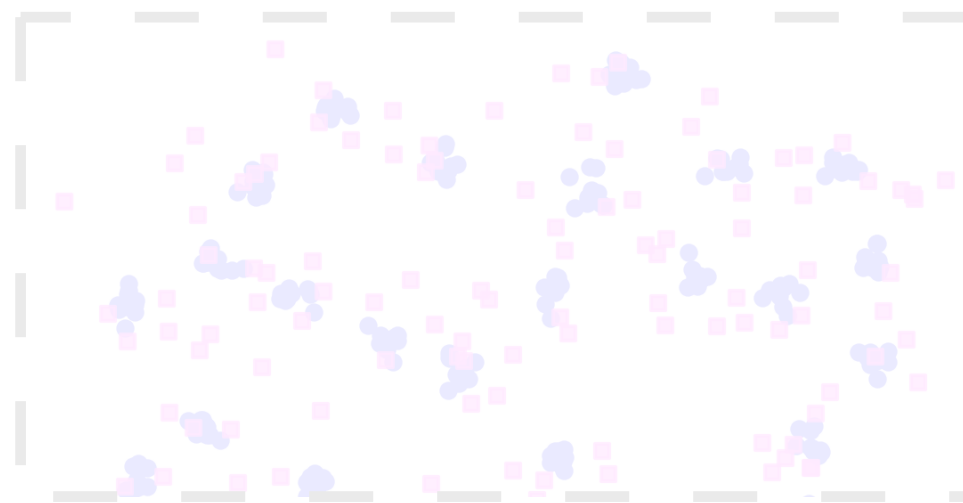


# Results: Ripley's K function

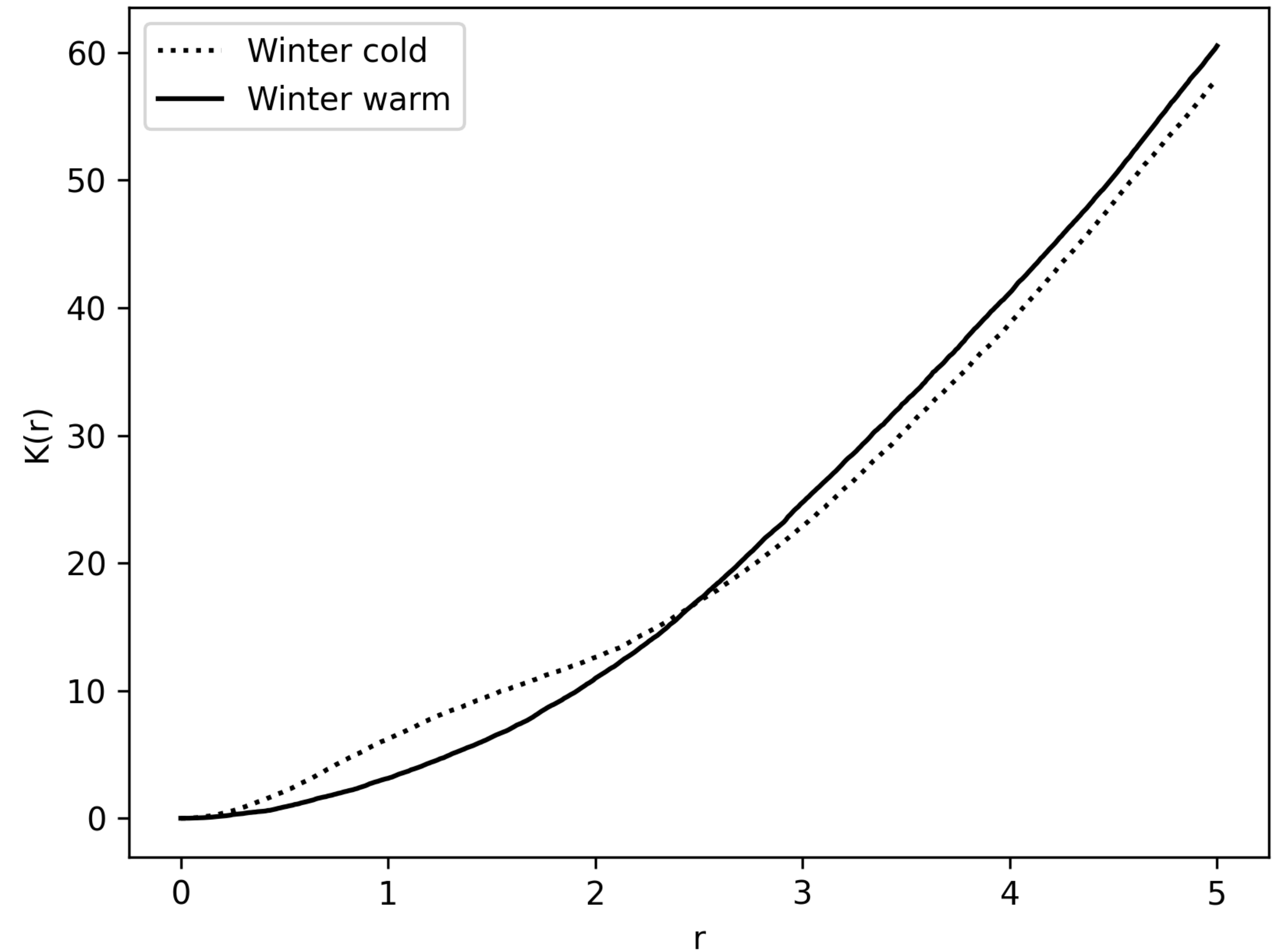
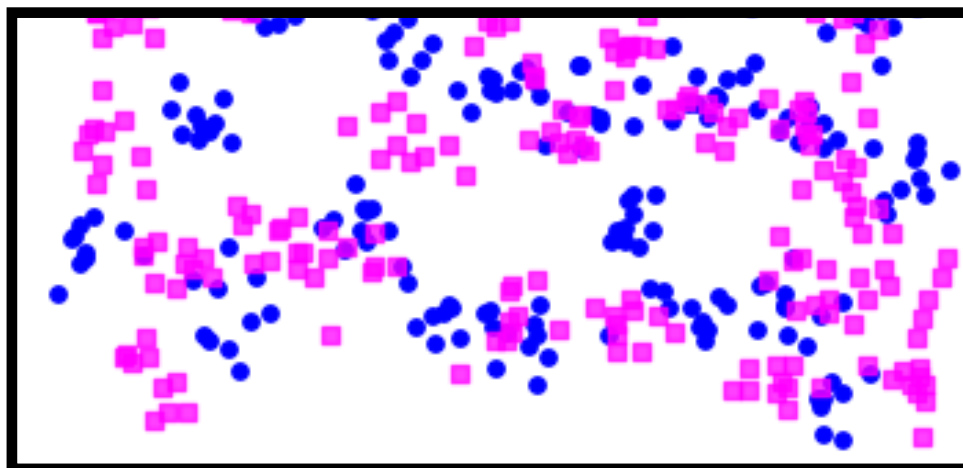
Winter — cold



Winter — medium



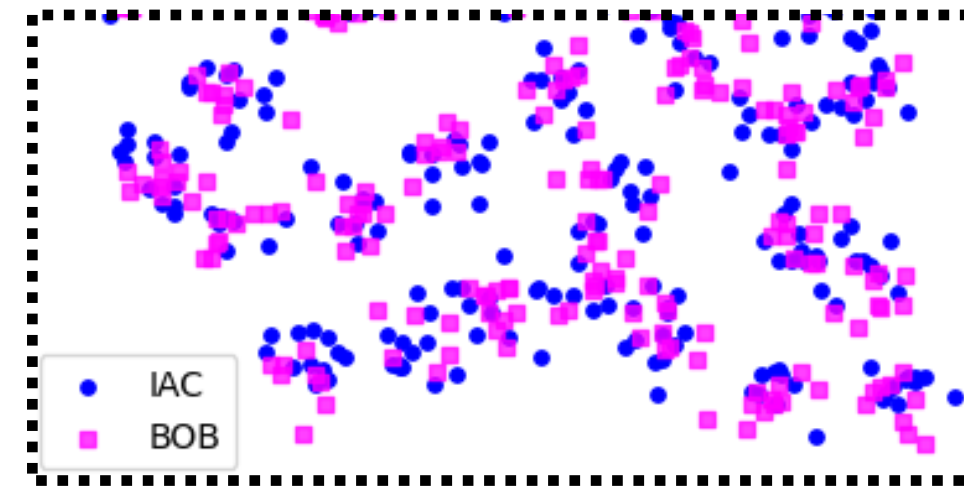
Winter — warm



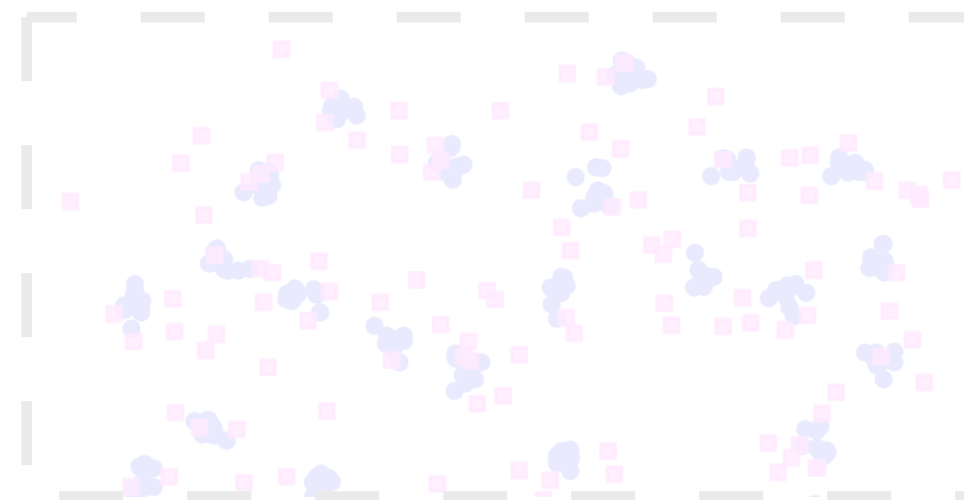


# Results: Ripley's K function

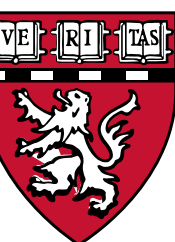
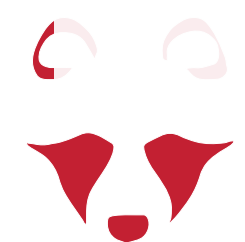
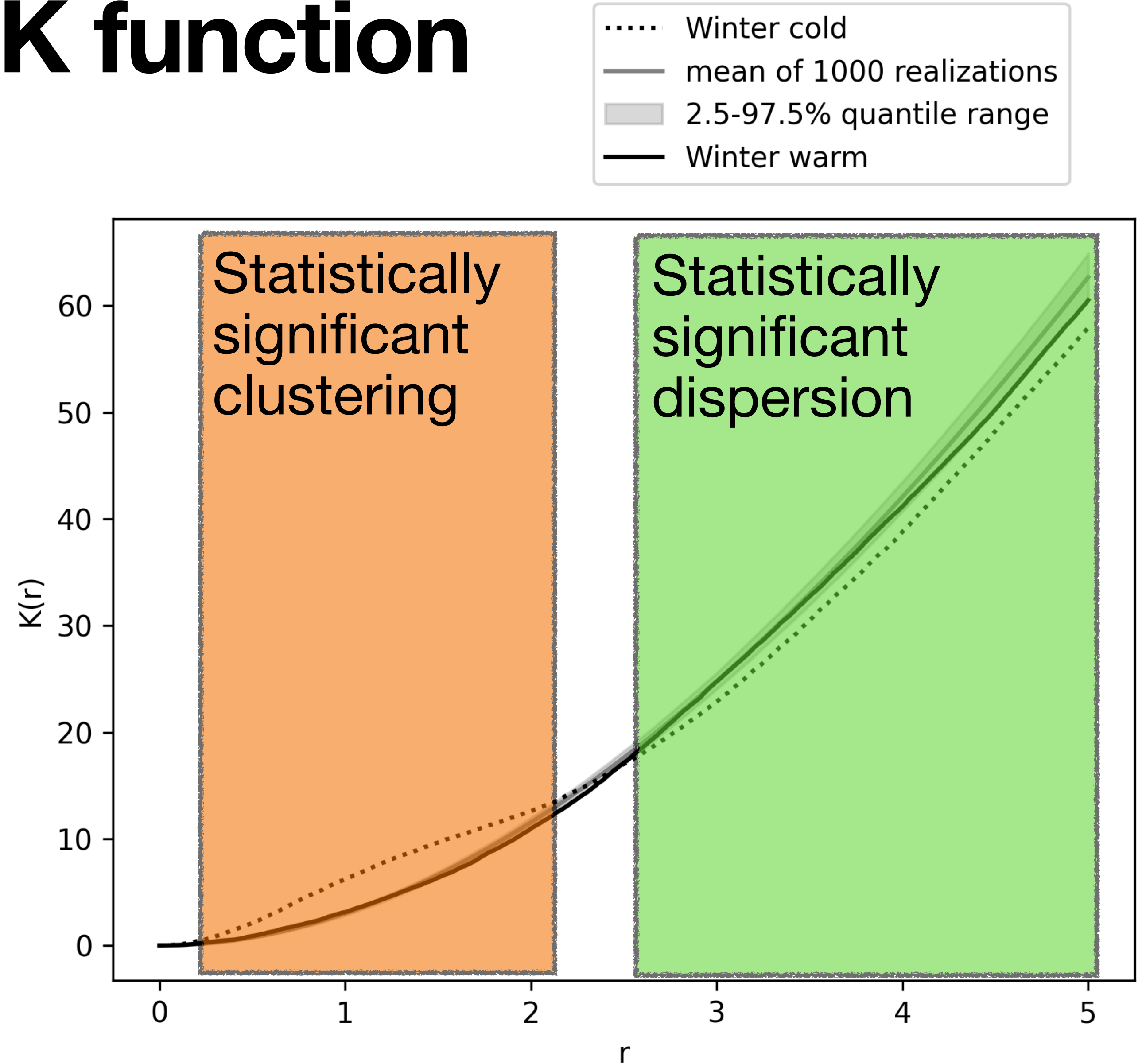
Winter — cold



Winter — medium



Winter — warm





# The bigger picture: Monte-Carlo-based significance testing

- Just because your sample isn't uniformly distributed doesn't mean it is biologically meaningful!
- It is possible to simulate hypotheses beyond uniform distributions.





# Python notes



Our implementation of Ripley's K was tested against the Locan library implementation:

[https://locan.readthedocs.io/en/latest/tutorials/notebooks/Analysis\\_Ripley.html#](https://locan.readthedocs.io/en/latest/tutorials/notebooks/Analysis_Ripley.html#)







# References

Lagache T, Sauvonnnet N, Danglot L, Olivo-Marin JC. Statistical analysis of molecule colocalization in bioimaging. *Cytometry A*. 2015 Jun;87(6):568-79. doi: 10.1002/cyto.a.22629. Epub 2015 Jan 20. PMID: 25605428.

Ripley, B. D. “The Second-Order Analysis of Stationary Point Processes.” *Journal of Applied Probability*, vol. 13, no. 2, 1976, pp. 255–66. *JSTOR*, <https://doi.org/10.2307/3212829>. Accessed 13 July 2025.

