Fluctuations in the response identify soft spots in sheared jammed packings

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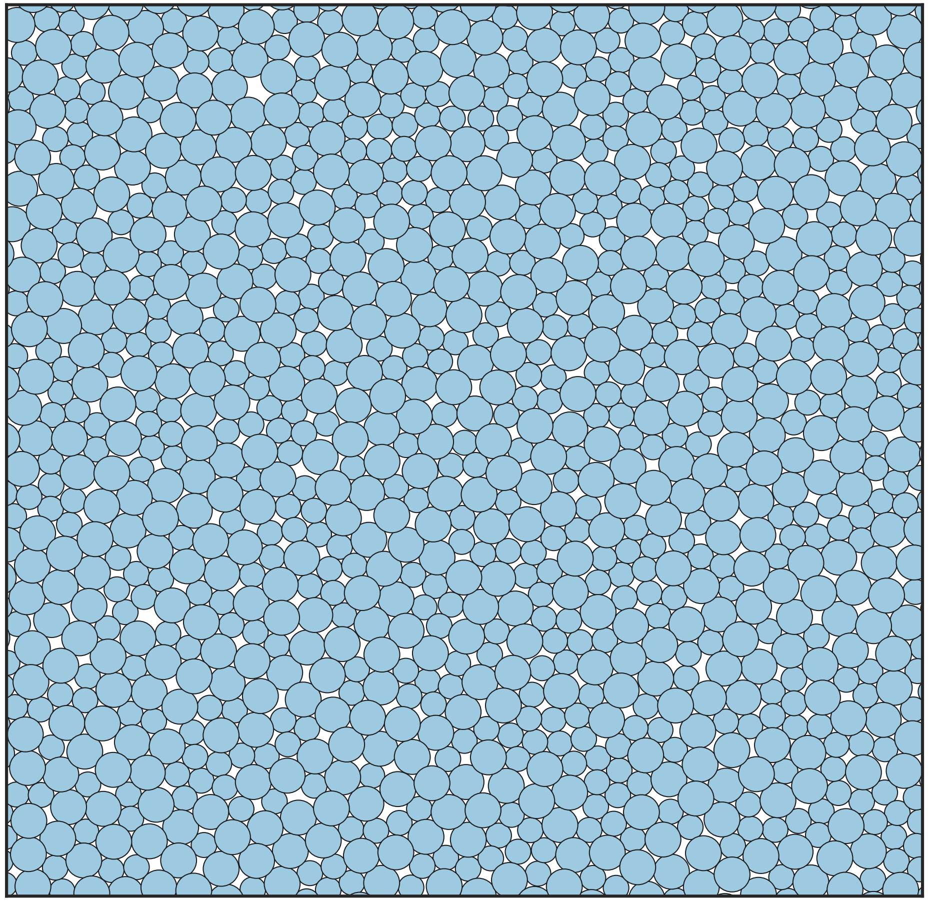
University of Pennsylvania

The problem



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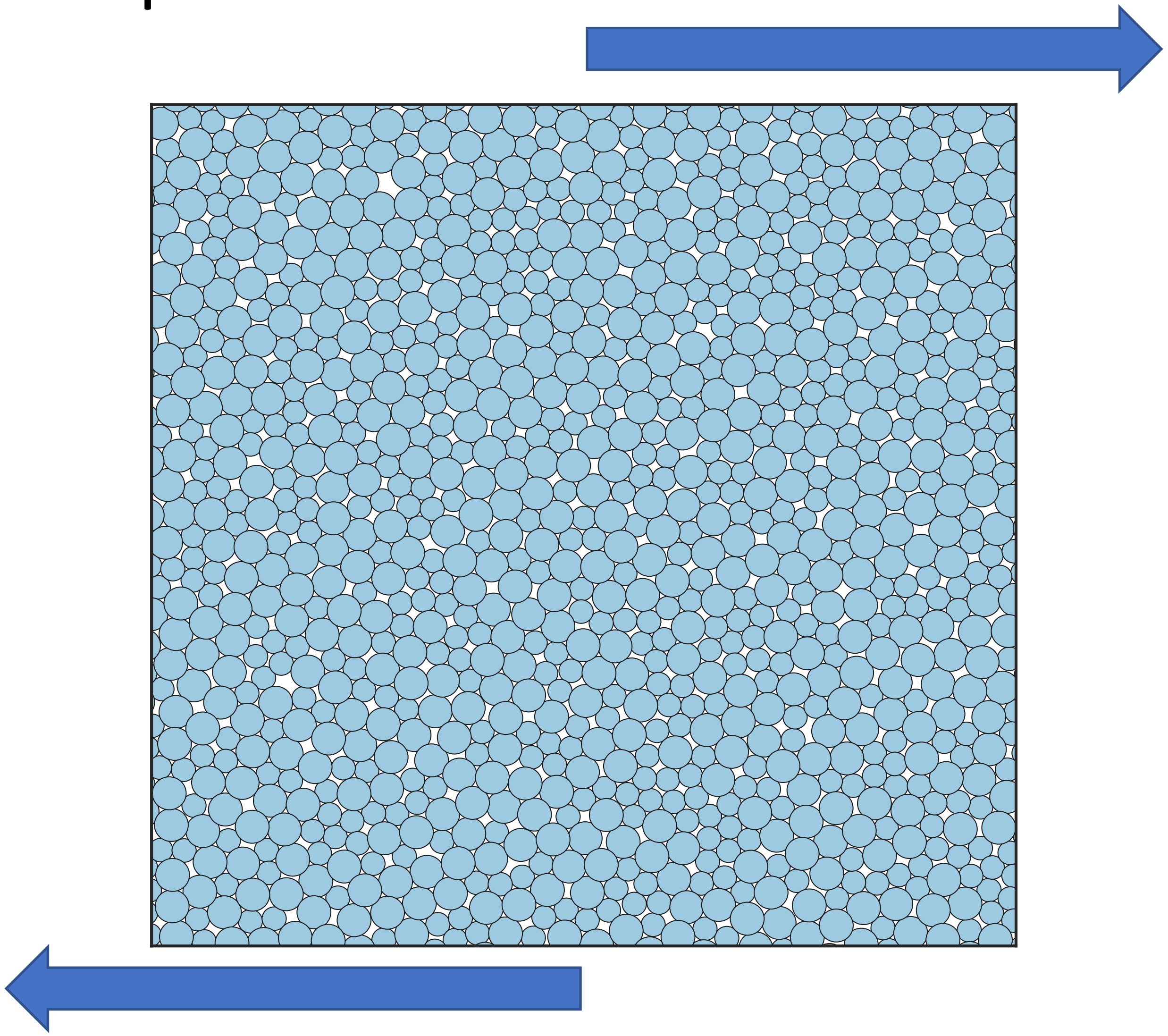

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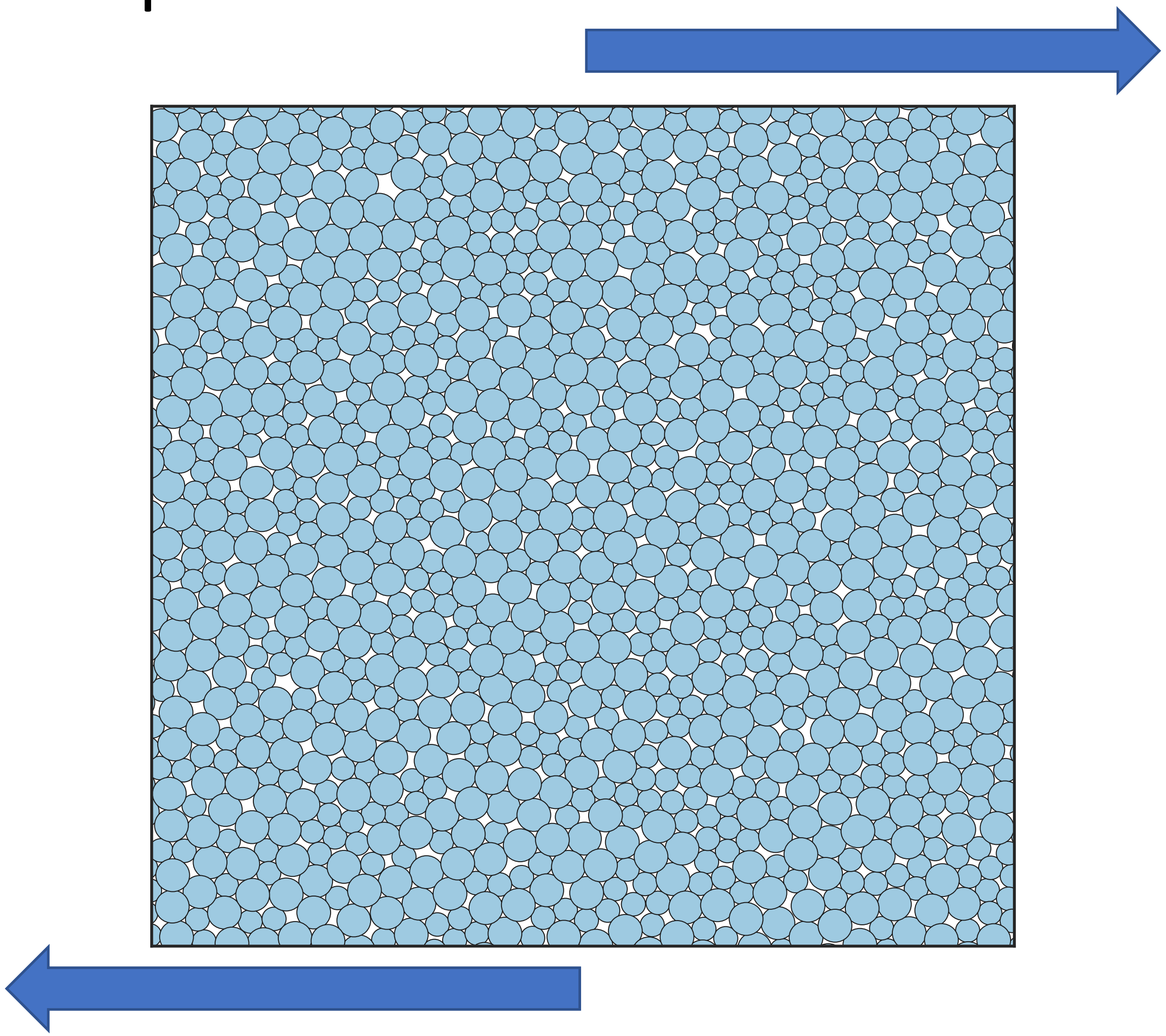
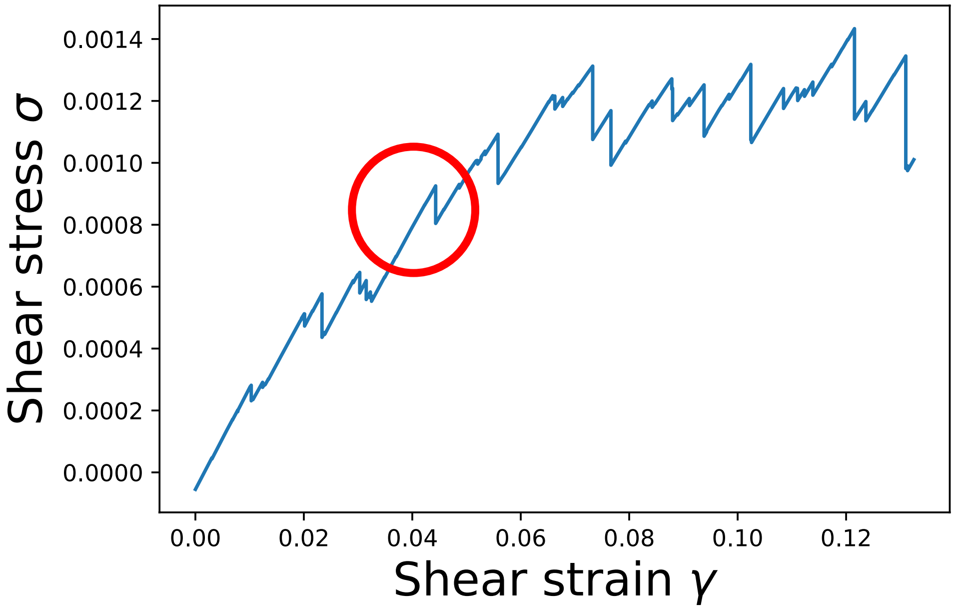
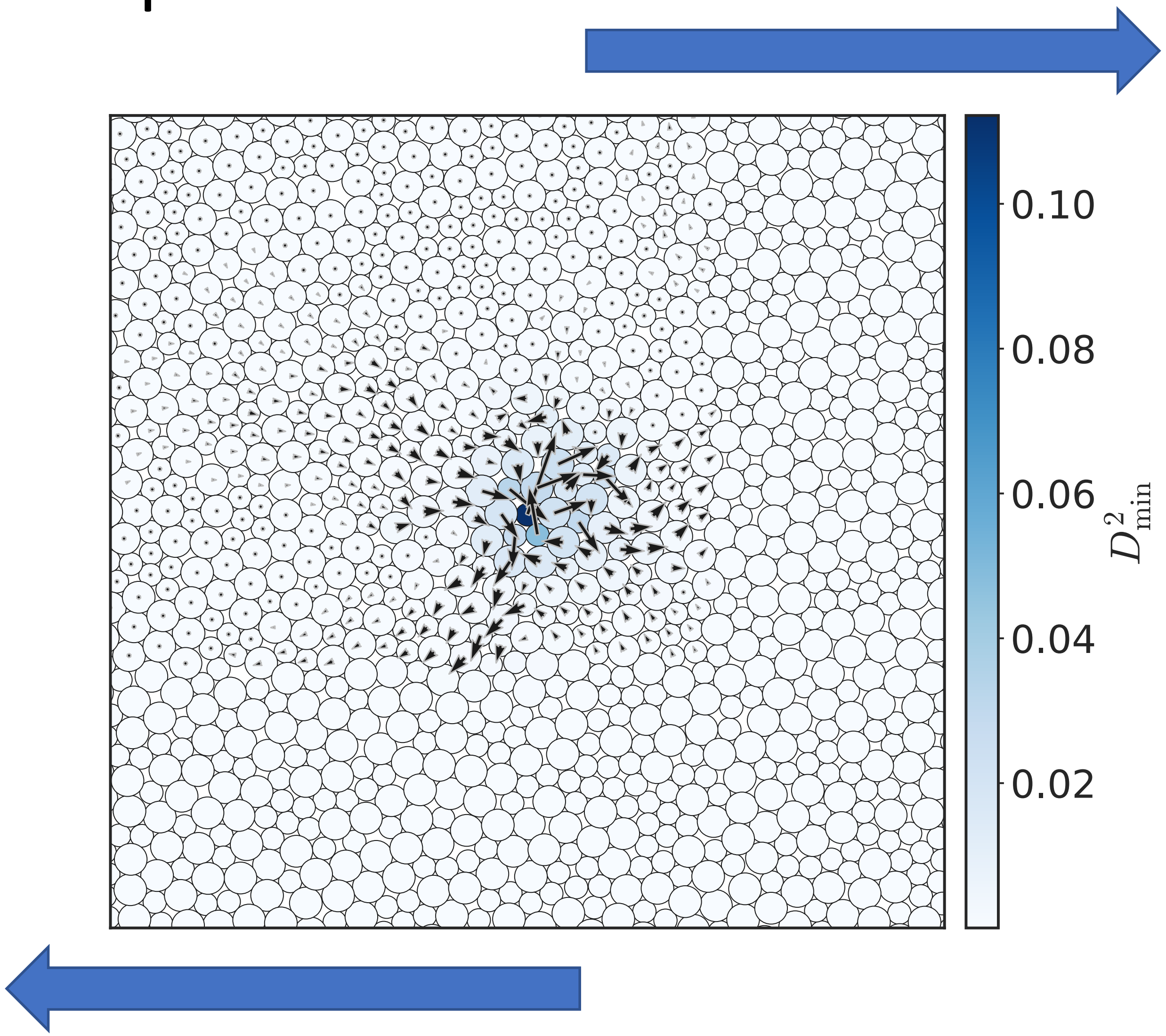
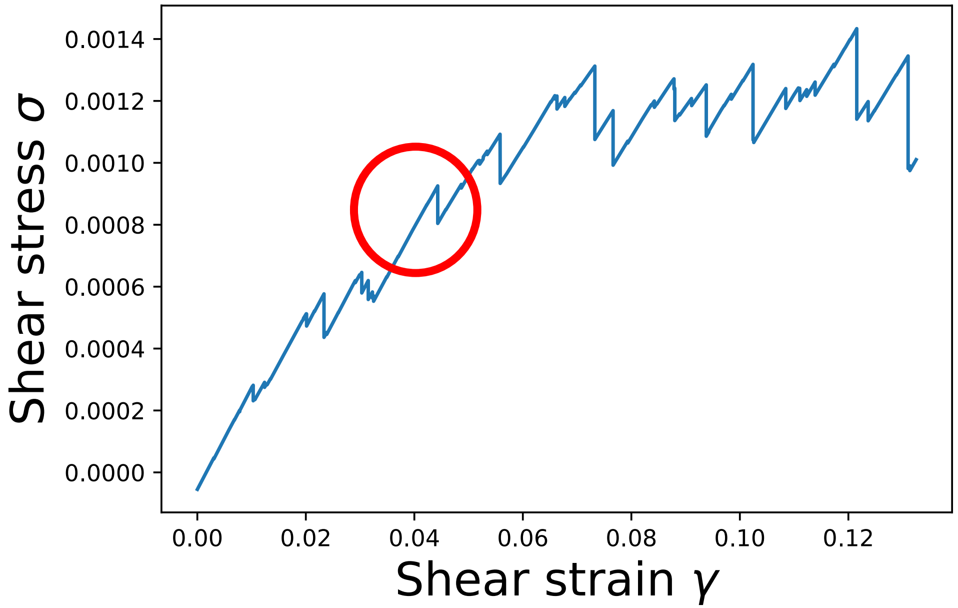



0.0014
0.0012
0.0010
0.0008
0.0006
0.0004
0.0002
0.0000
Shear stress σ
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Shear strain γ

The problem


0.10
0.08
0.06
0.04
0.02
D^2_{min}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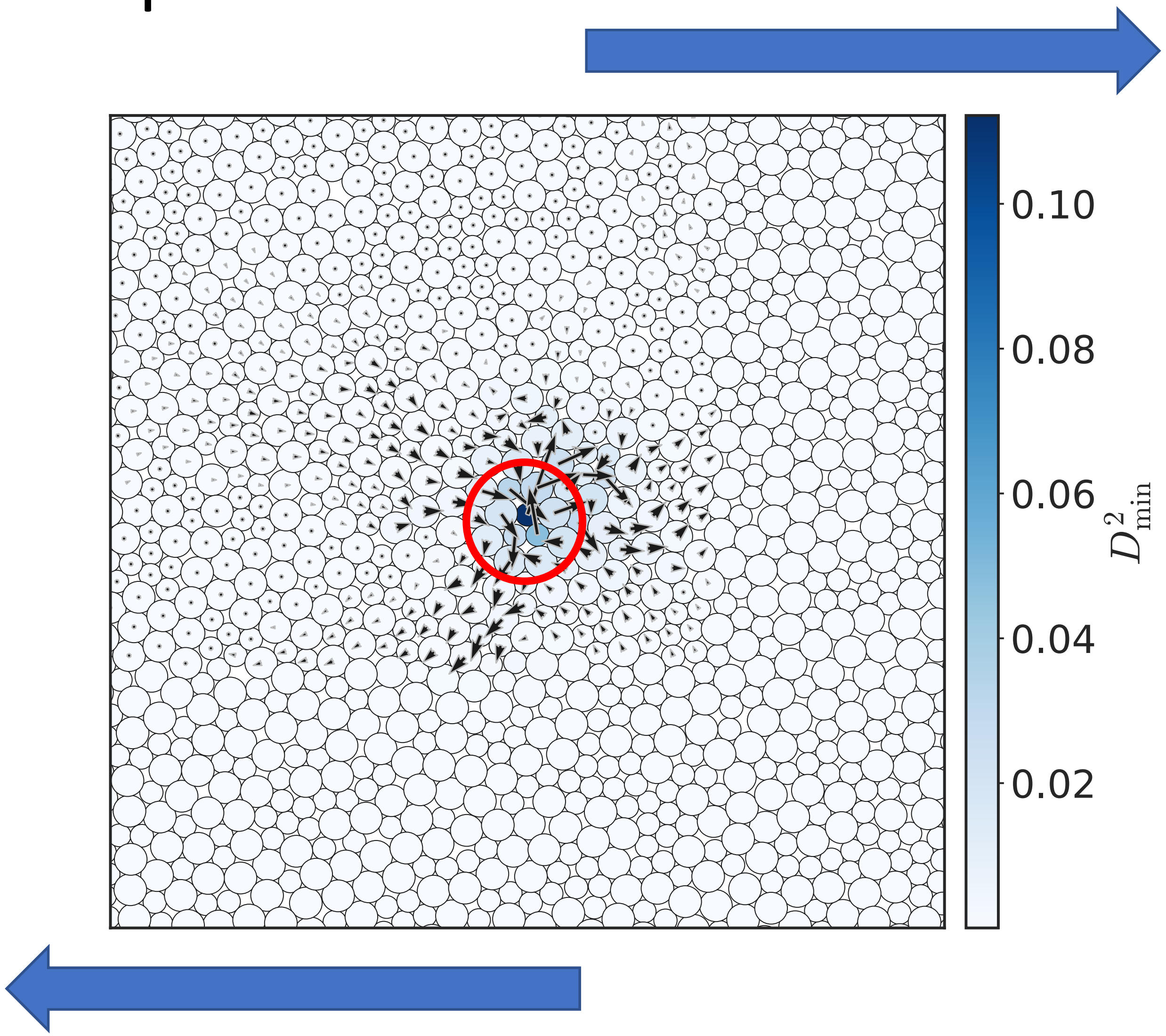
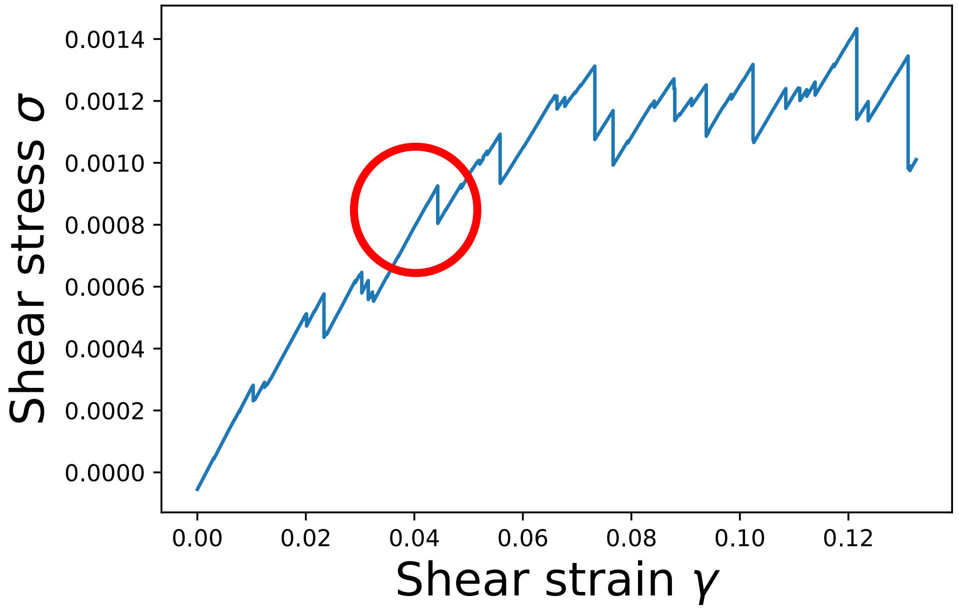
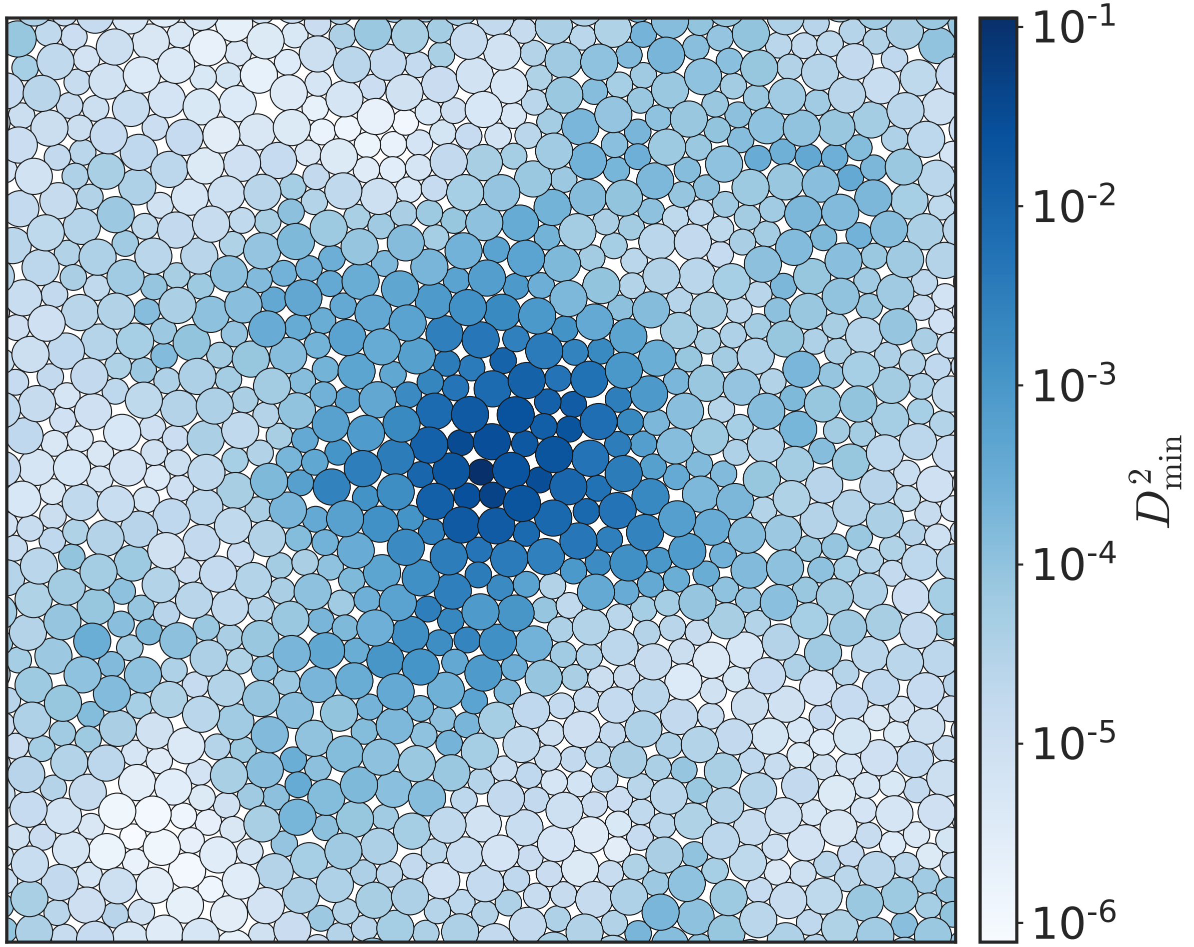


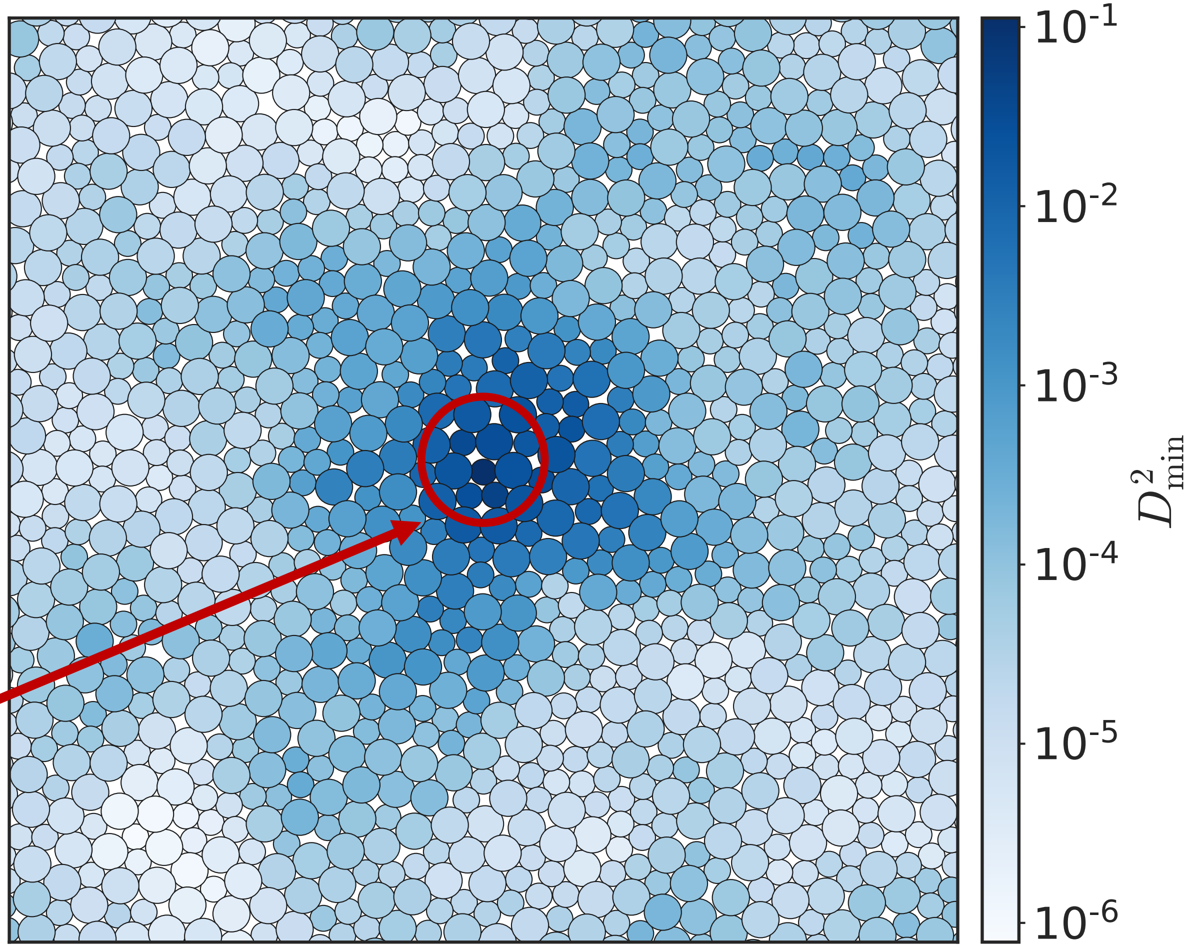


What structural features make a particle likely to rearrange?

A closer look at the displacement field

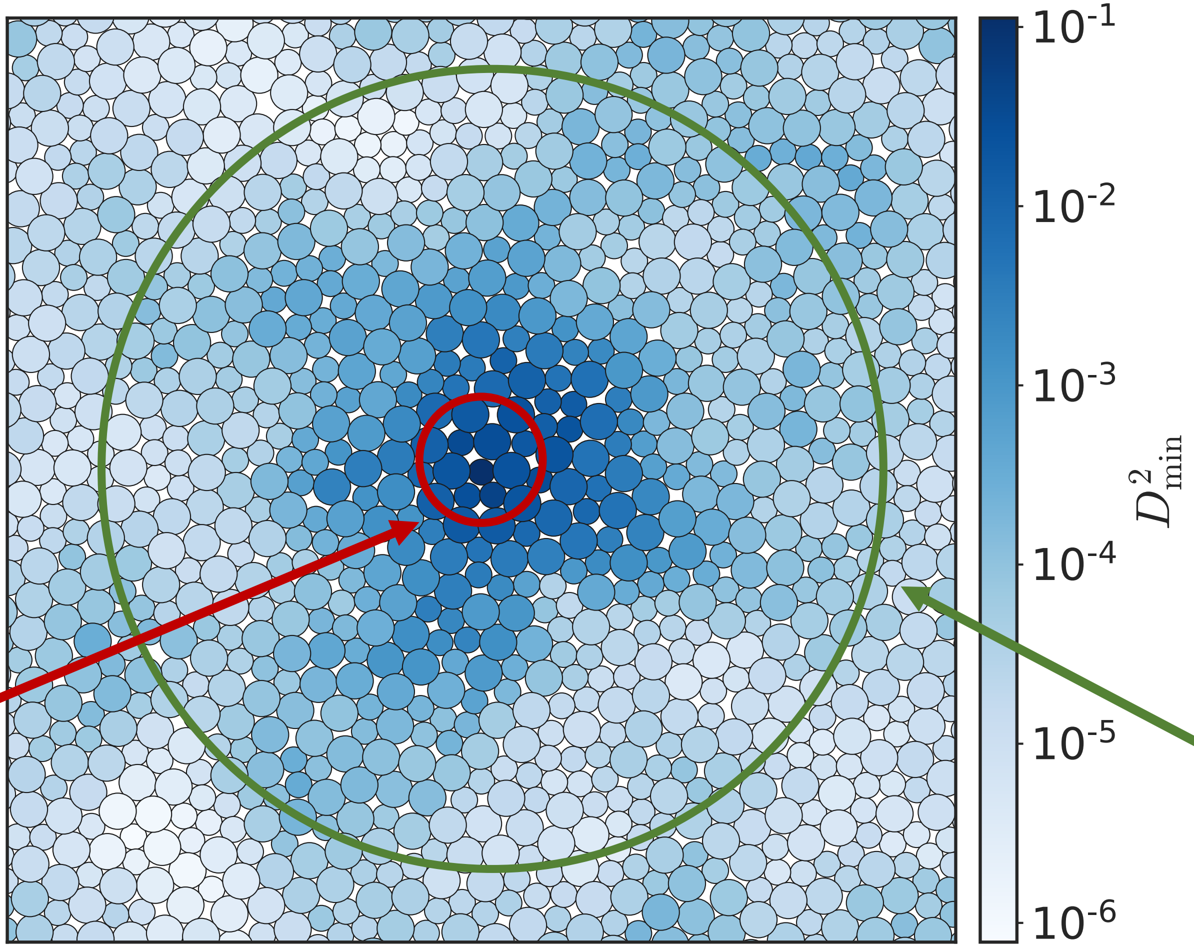


A closer look at the displacement field



Localized
plastic event

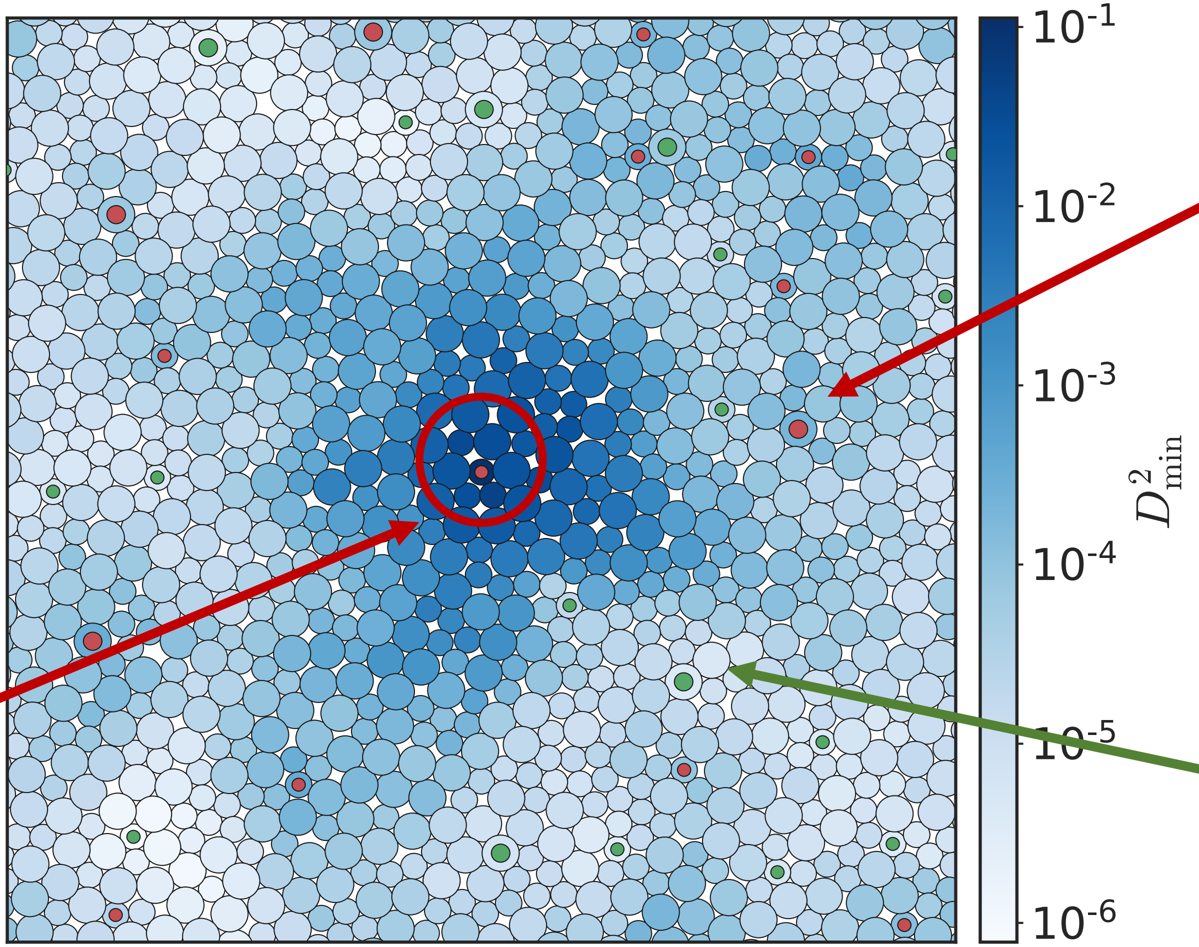
A closer look at the displacement field



Localized plastic event

$1/r^{\alpha}$ elastic response

A closer look at the displacement field

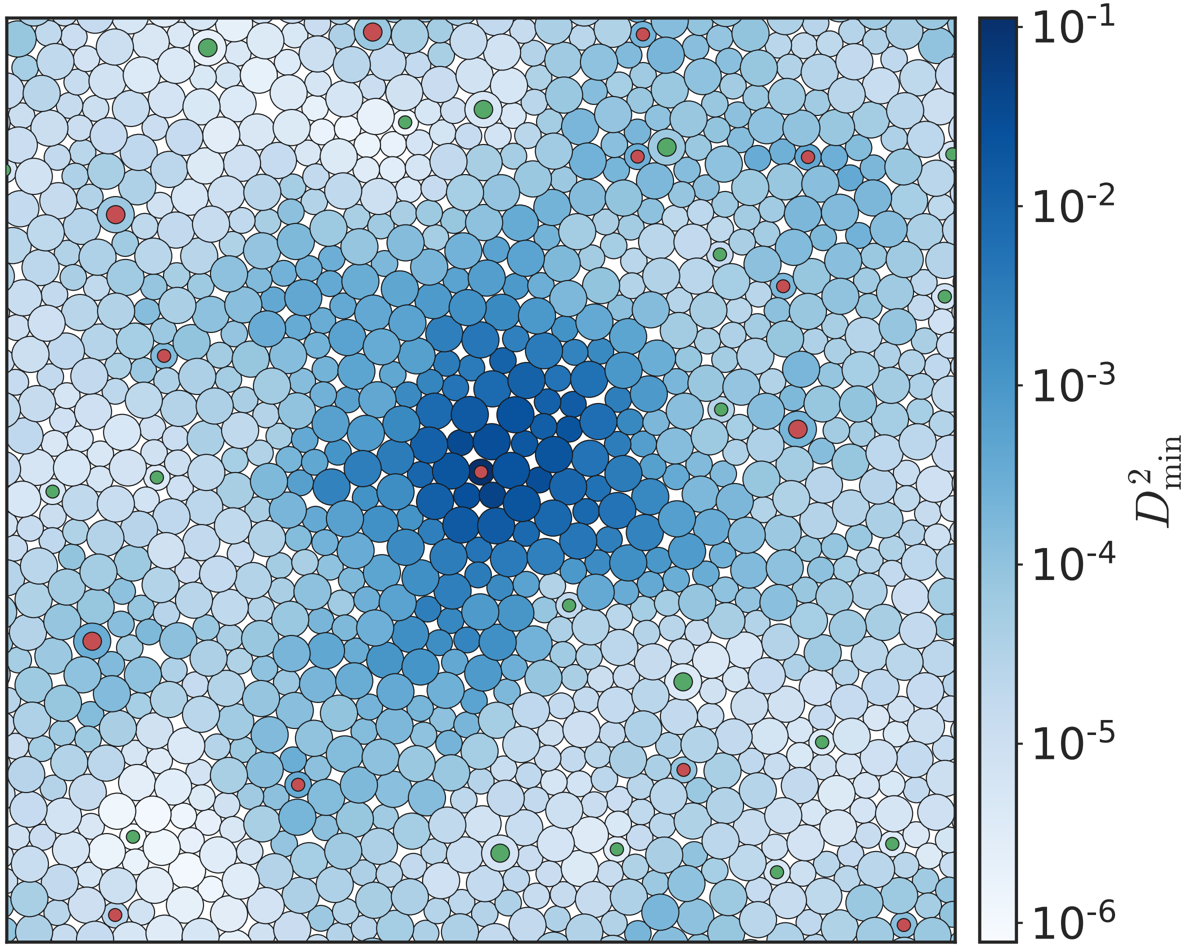


Local maxima of response

Localized plastic event

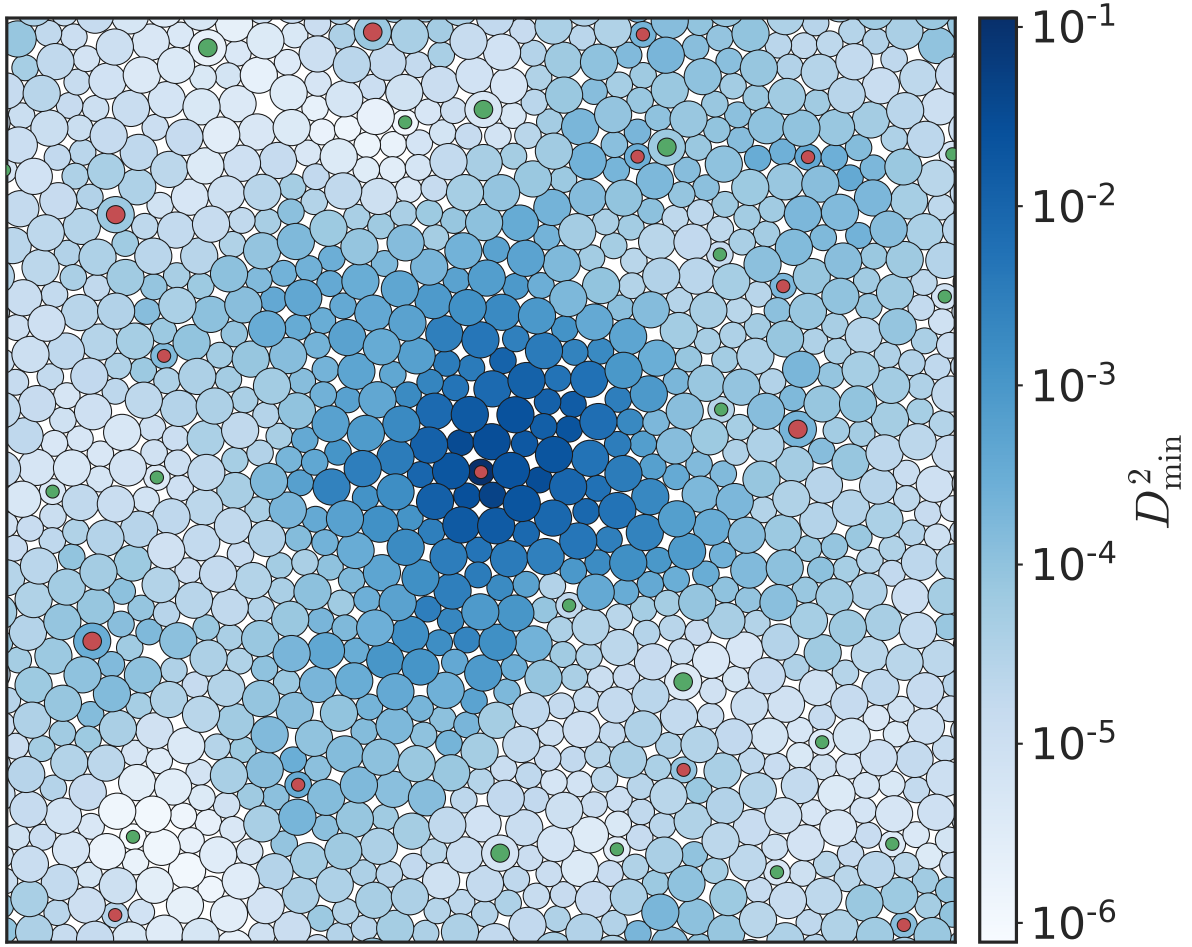
Local minima of response

A closer look at the displacement field



- Local extrema are extensive (a few percent of particles)
- **Hypothesis:** Local maxima are “soft spots” whose structure predisposes them to move

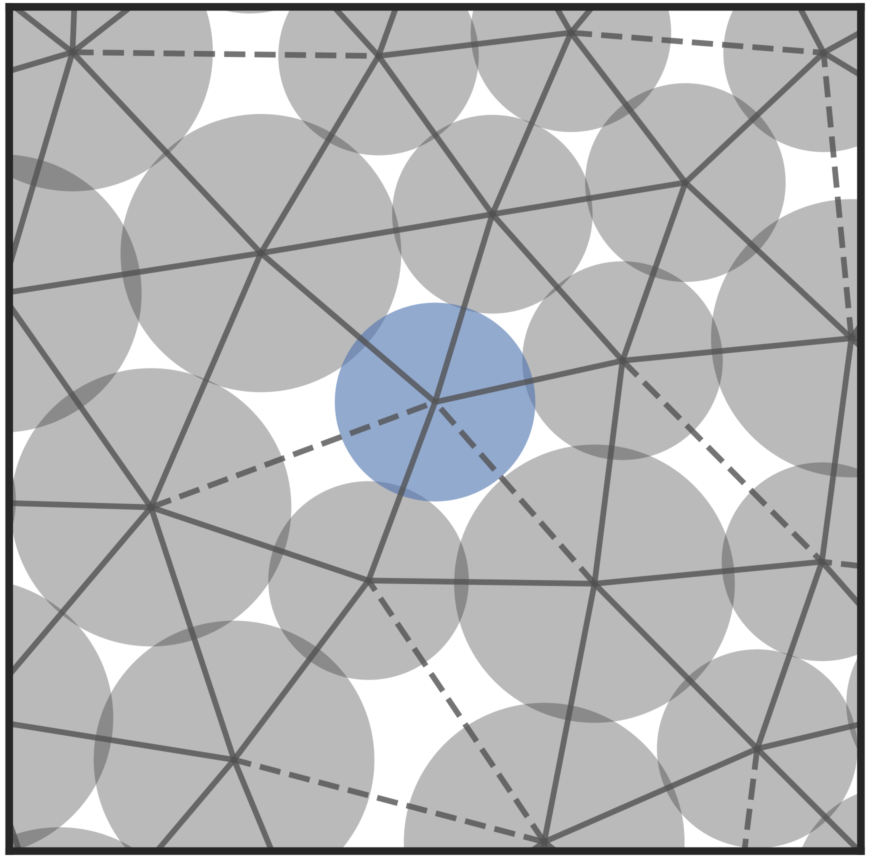
Our plan of attack



- Use "machine learning" to see if local structural features can distinguish local maxima from local minima
- Test if the structural features we identify are also predictive of where subsequent plastic events will occur

Characterizing local structure

- Use triangulation of packing:



Characterizing local structure

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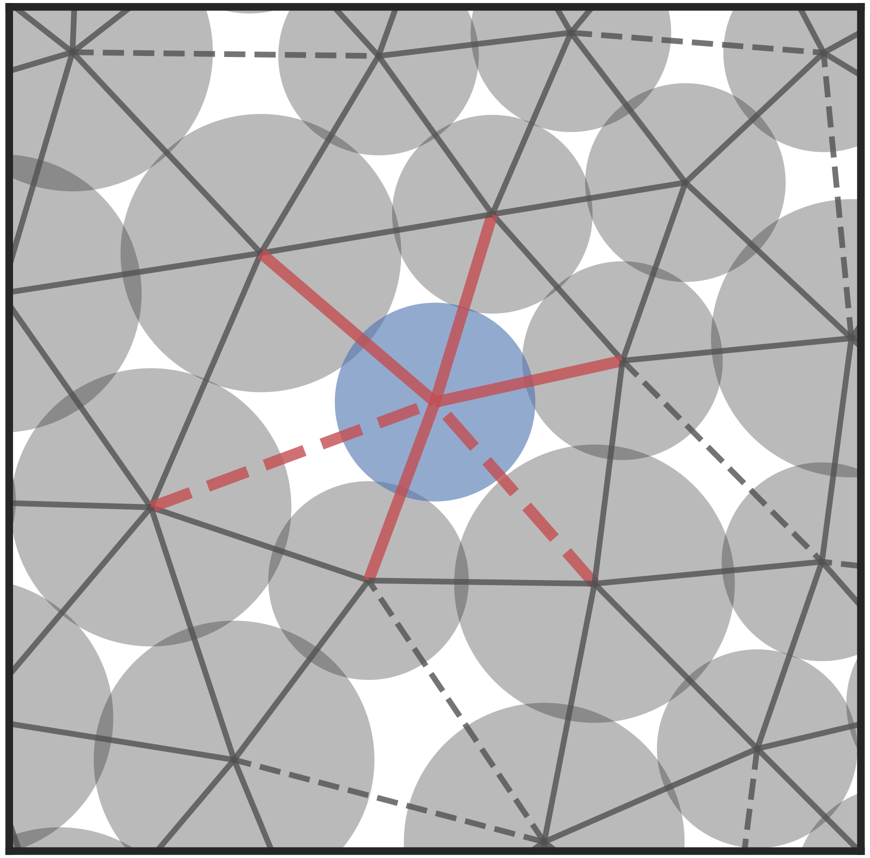
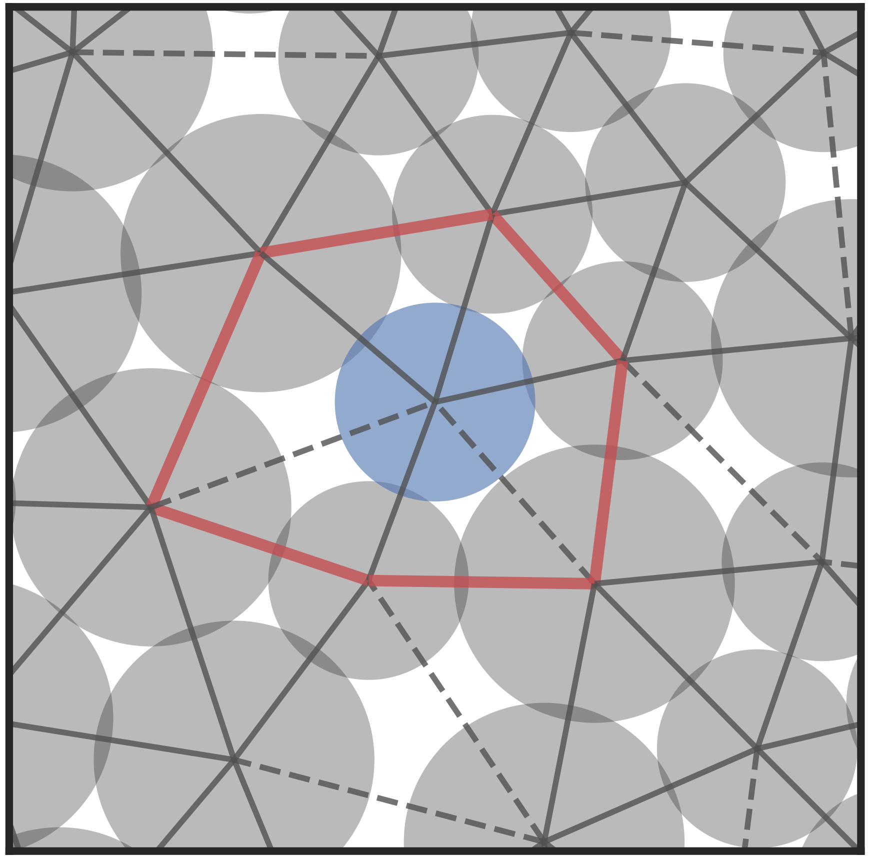


4 contacts at distance 1

2 gaps at distance 1

Characterizing local structure

- Use triangulation of packing:



4 contacts at distance 1

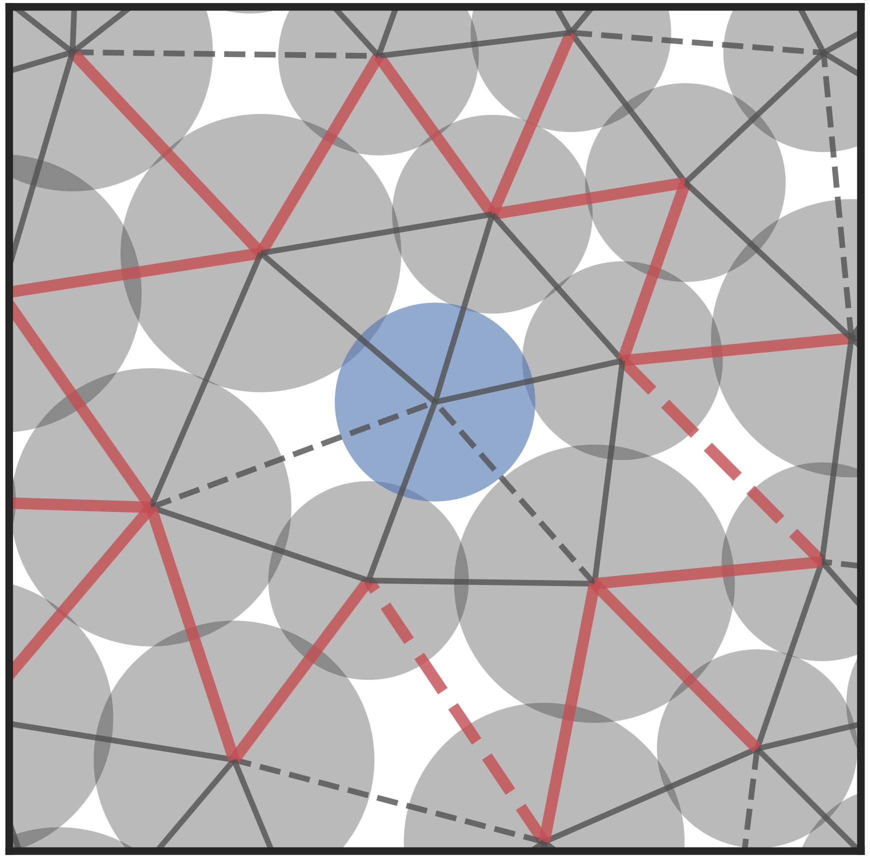
2 gaps at distance 1

6 contacts at distance 2

0 gaps at distance 2

Characterizing local structure

- Use triangulation of packing:



4 contacts at distance 1
2 gaps at distance 1
6 contacts at distance 2
0 gaps at distance 2
16 contacts at distance 3
2 gaps at distance 3

Characterizing local structure

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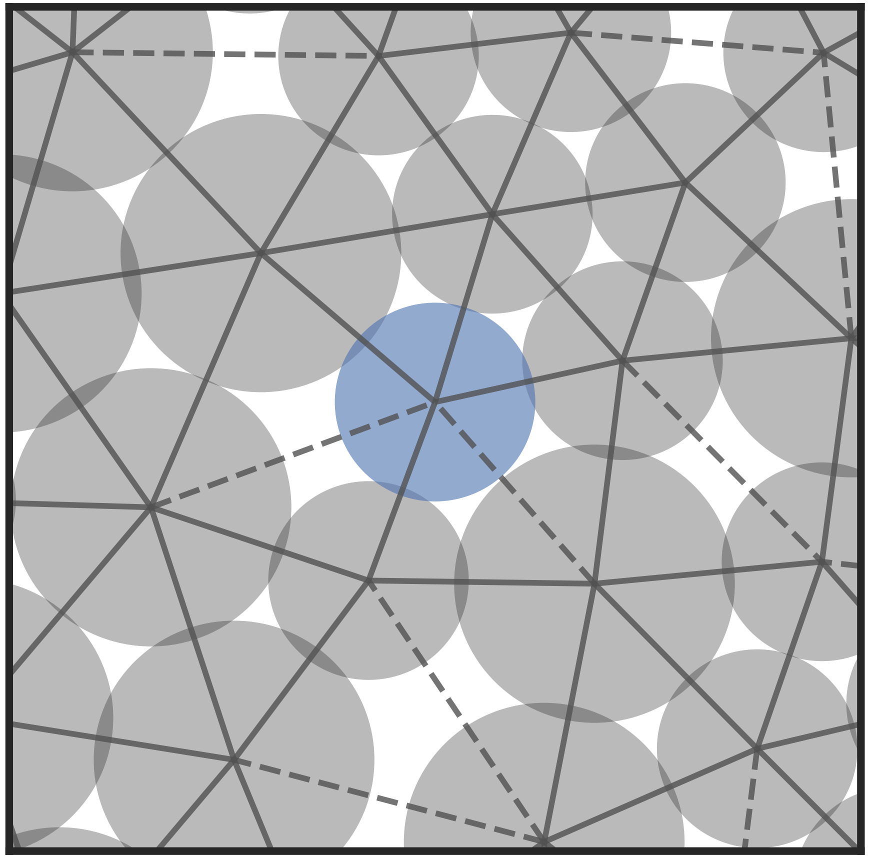
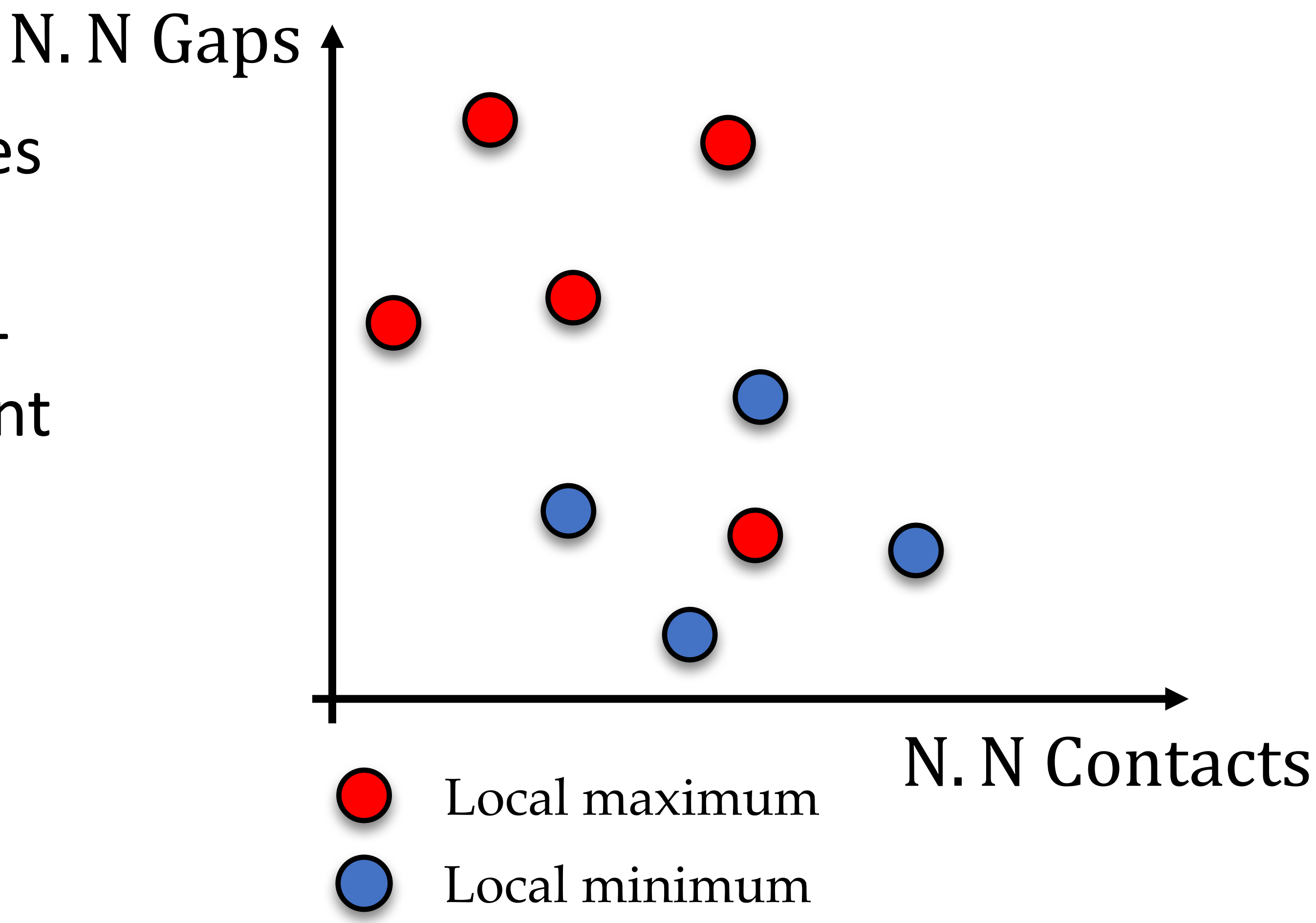


4 contacts at distance 1
2 gaps at distance 1
6 contacts at distance 2
0 gaps at distance 2
16 contacts at distance 3
2 gaps at distance 3

Continuing out to distance 8, local environment is described by 16 numbers

“Machine learning”

- Define many structural variables
- Put our local maxima and local minima (“training examples”) – taken from many rearrangement events - in a space of these variables



“Machine learning”

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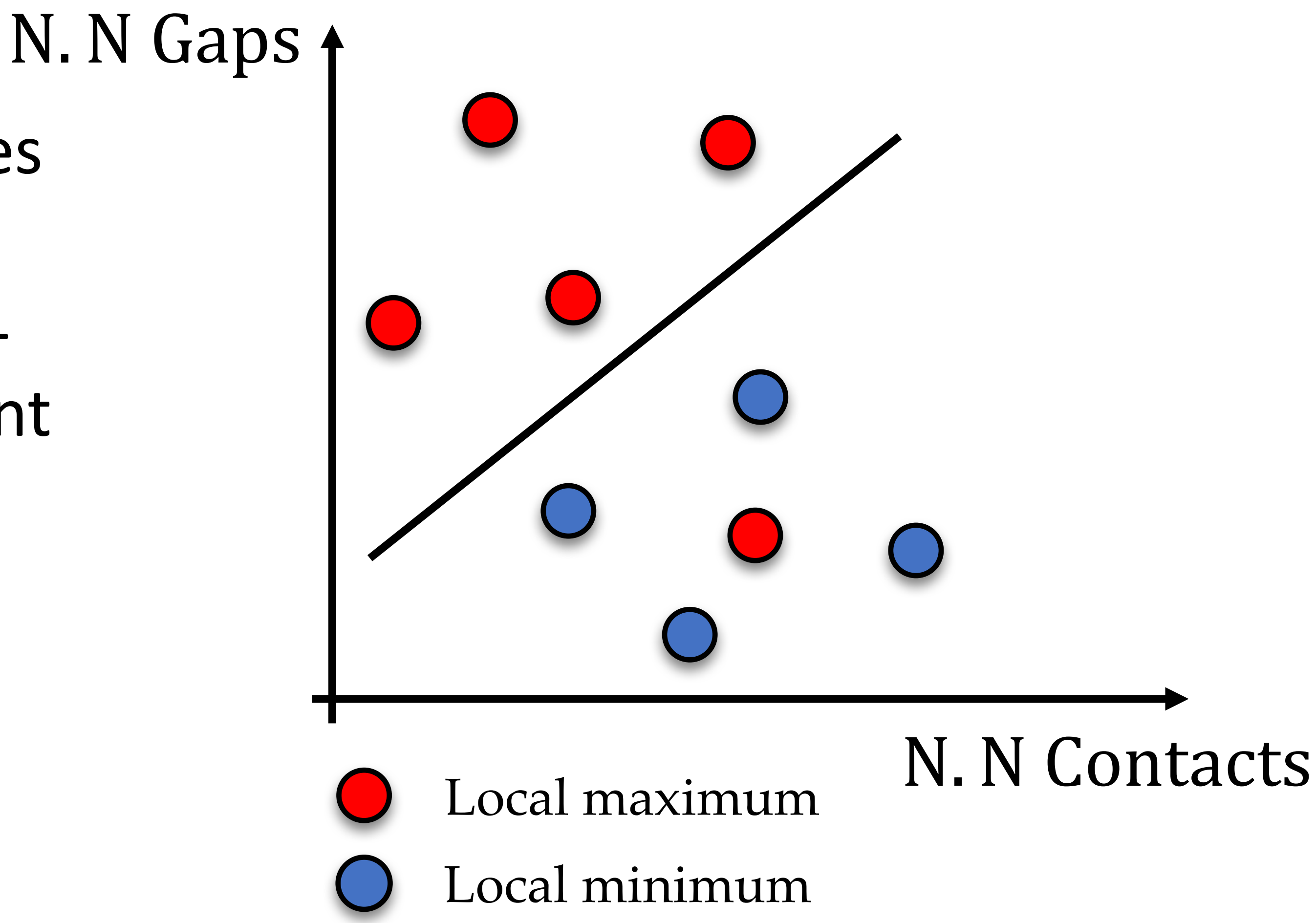
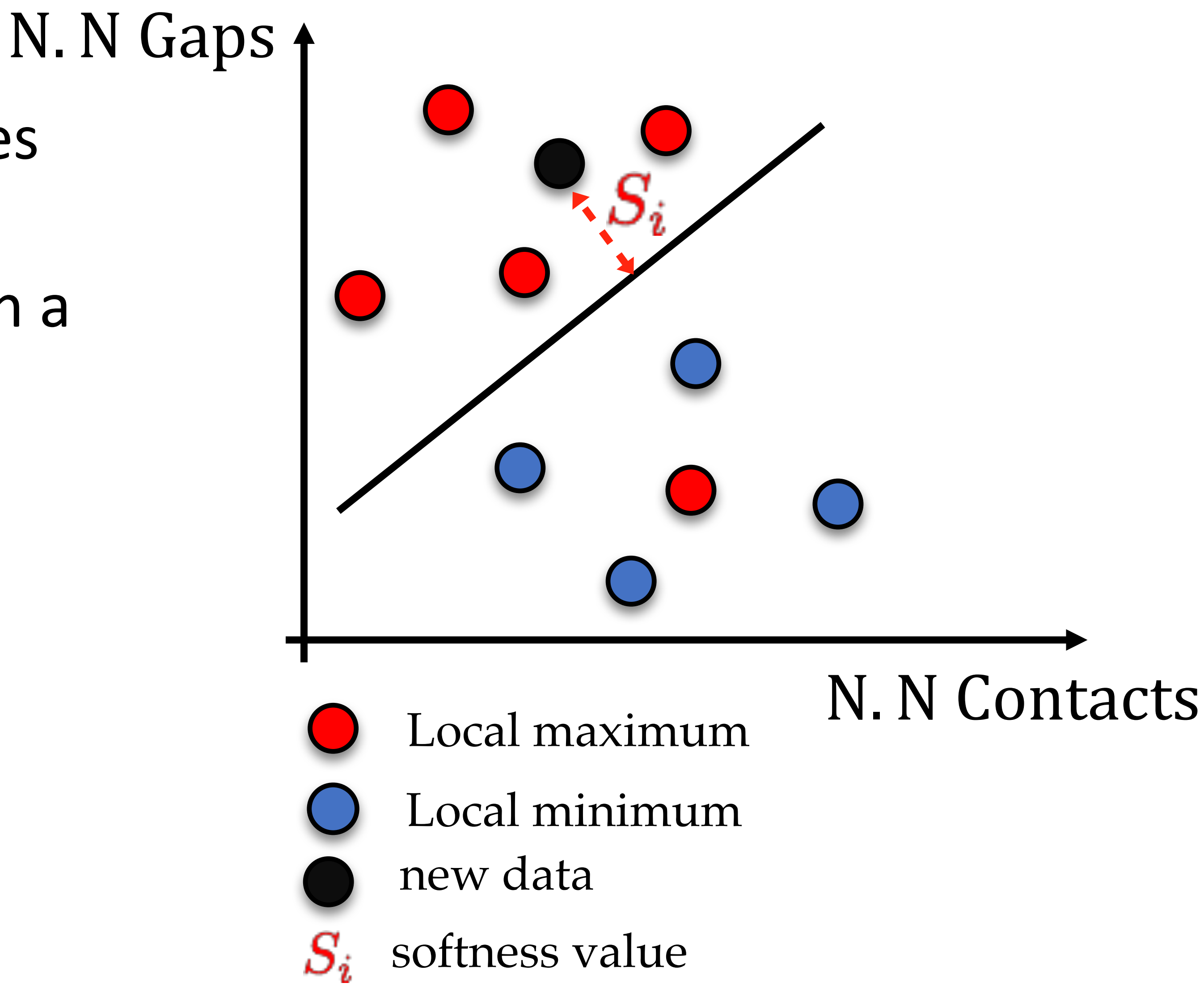
- Construct hyperplane best separating training examples



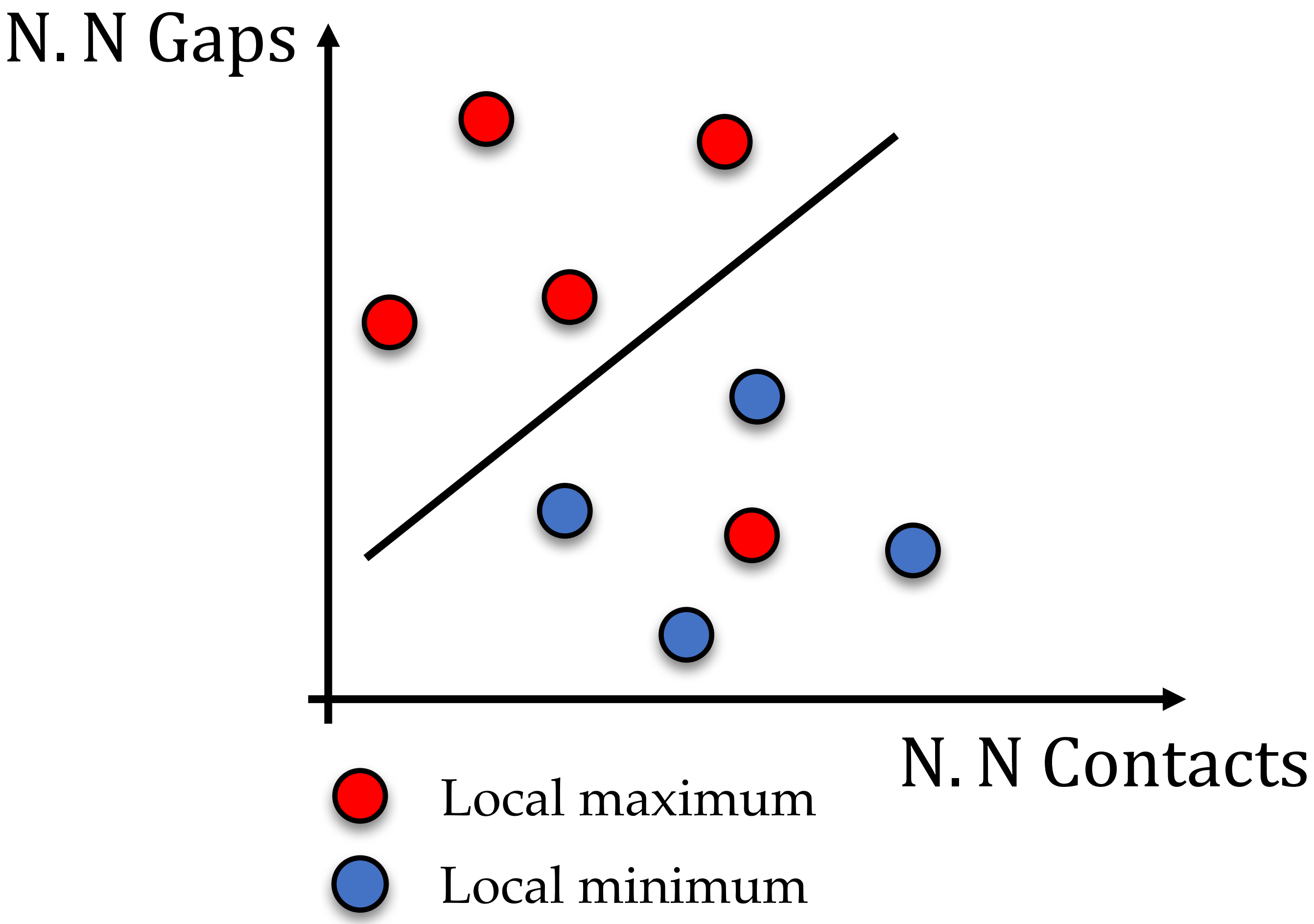
“Machine learning”

- Define many structural variables
- Put our local maxima and local minima (“training examples”) in a space of these variables
- Construct hyperplane best separating training examples
- Signed distance from plane is a scalar classifying variable, “softness”



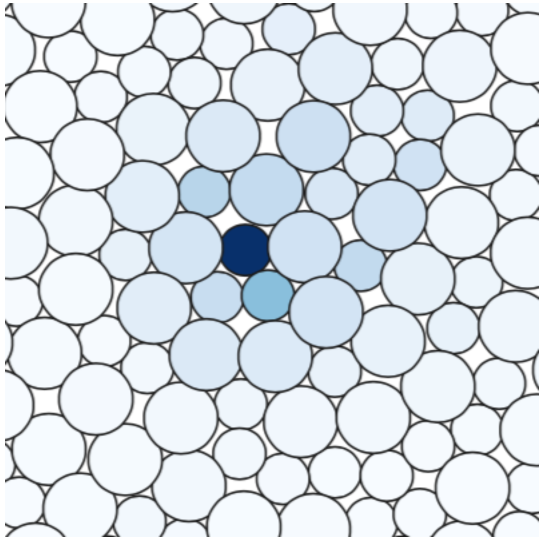
Results – training accuracy

- We can classify this local extremum training set with 90% accuracy
- **Local minima and local maxima, statistically, have different local structures**



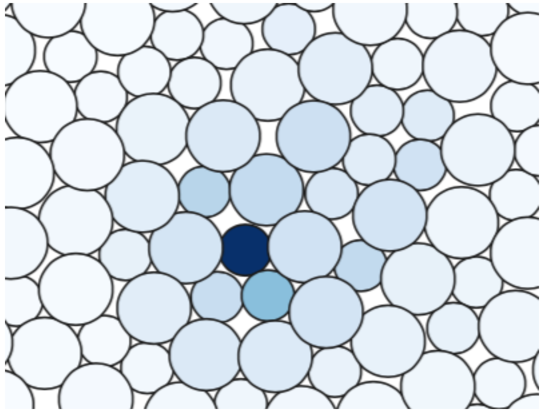
Predictiveness of rearrangement center

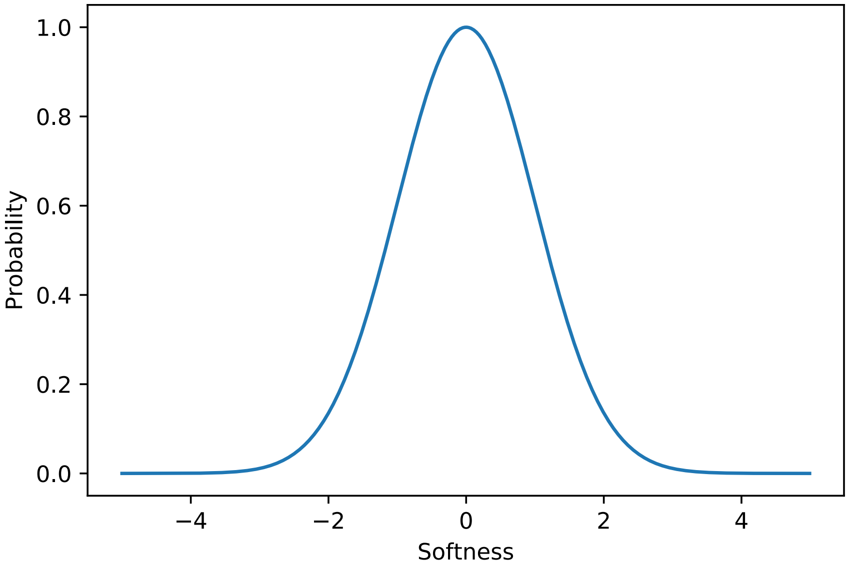
- Does this “softness” which classifies local extrema succeed at identifying likely locations for rearrangements?



Predictiveness of rearrangement center

- Does this “softness” which classifies local extrema succeed at identifying likely locations for rearrangements?
- To quantify, look at softness of global maxima

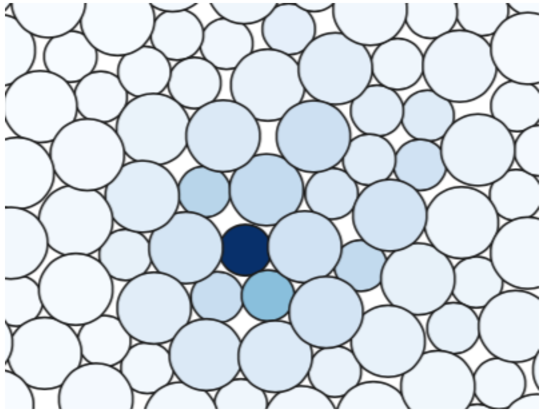


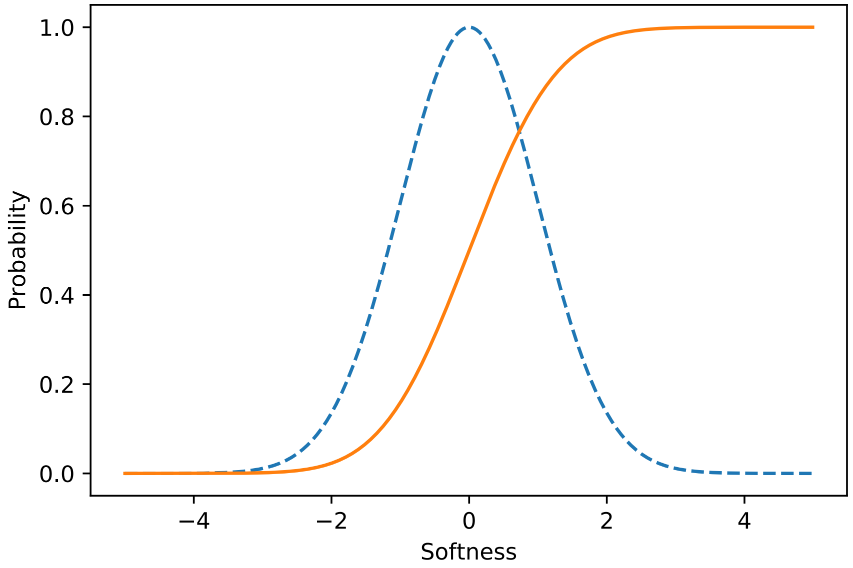


Predictiveness of rearrangement center

- Does this “softness” which classifies local extrema succeed at identifying likely locations for rearrangements?
- To quantify, look at softness of **global maxima**
- Following Patinet et al., define:

$$C = \langle \mathrm{CDF}(\mathrm{S}|\mathrm{global\ max}) \rangle$$





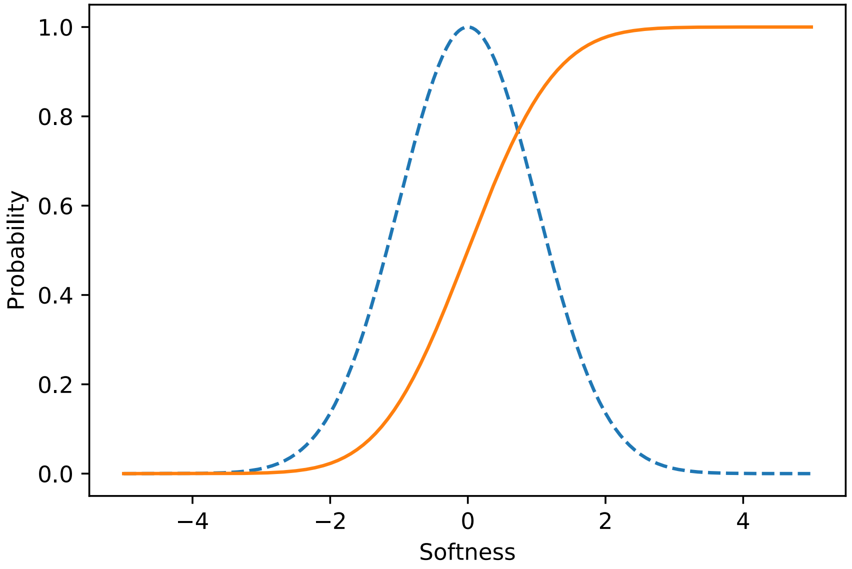
Predictiveness of rearrangement center

- Identify the "center" of the rearrangement with the **global** maximum of D2min.
- A structural variable is more "predictive" if the rearrangement center always lies in a very high percentile of its distribution
- Following Patinet et al., define:

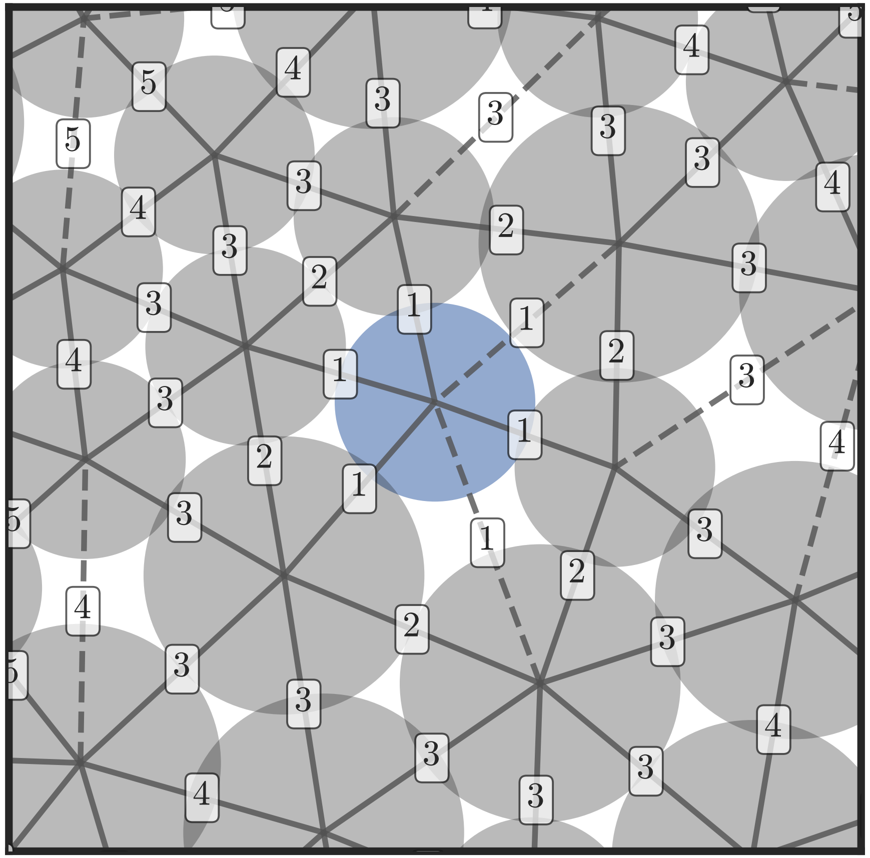
$$C = \langle \mathrm{CDF}(\mathrm{S}|\mathrm{global\ max}) \rangle$$

Training on local extrema

$$C = 0.87$$



How much information is necessary?



Include only descriptors up to distance ℓ

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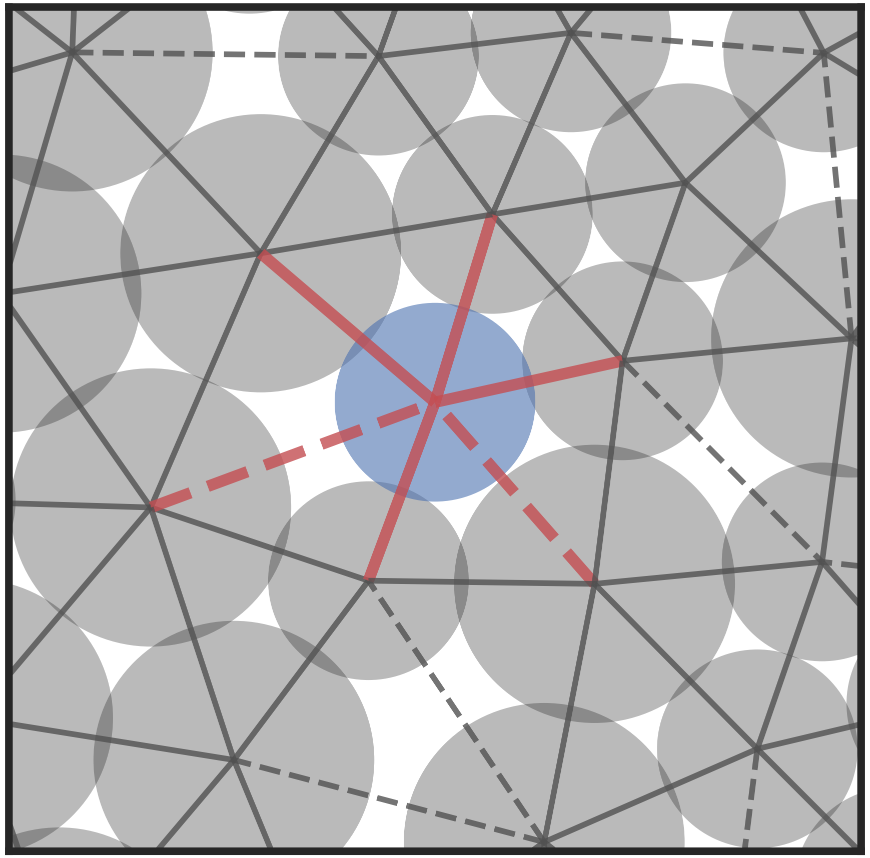

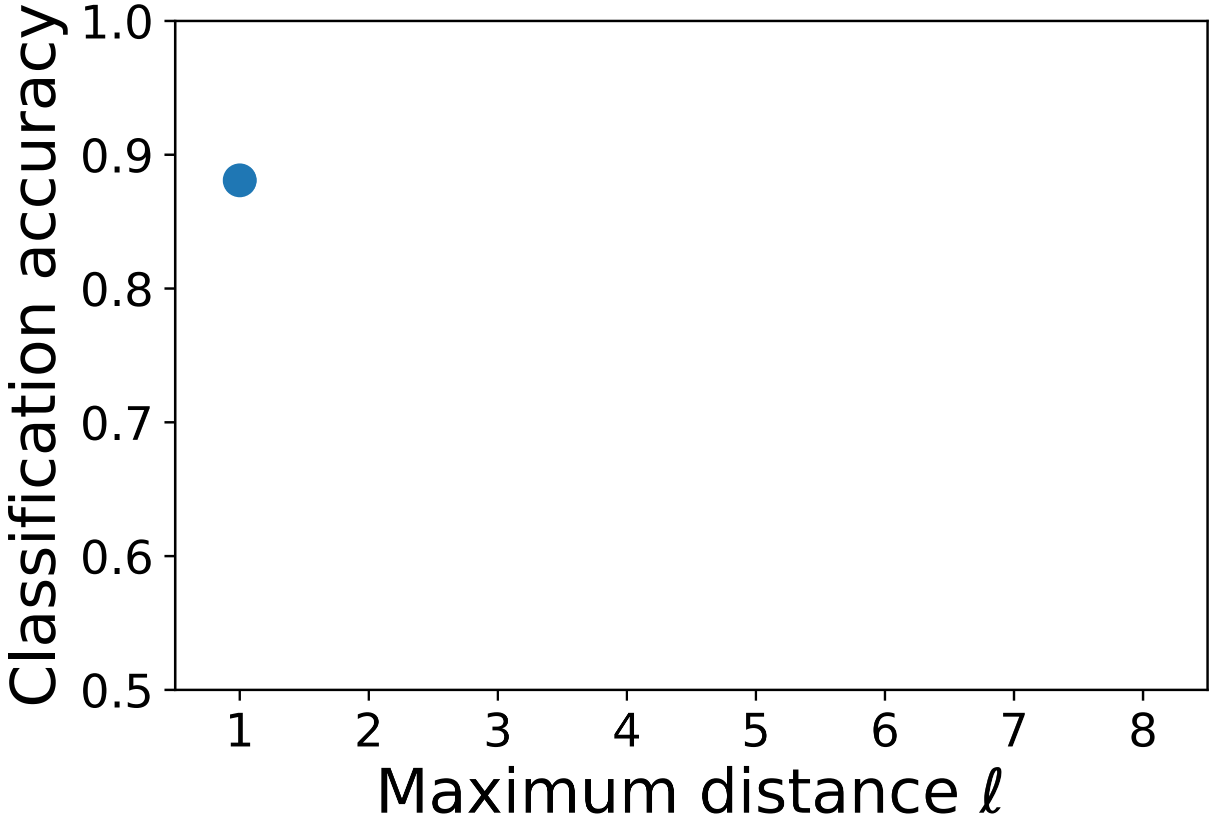

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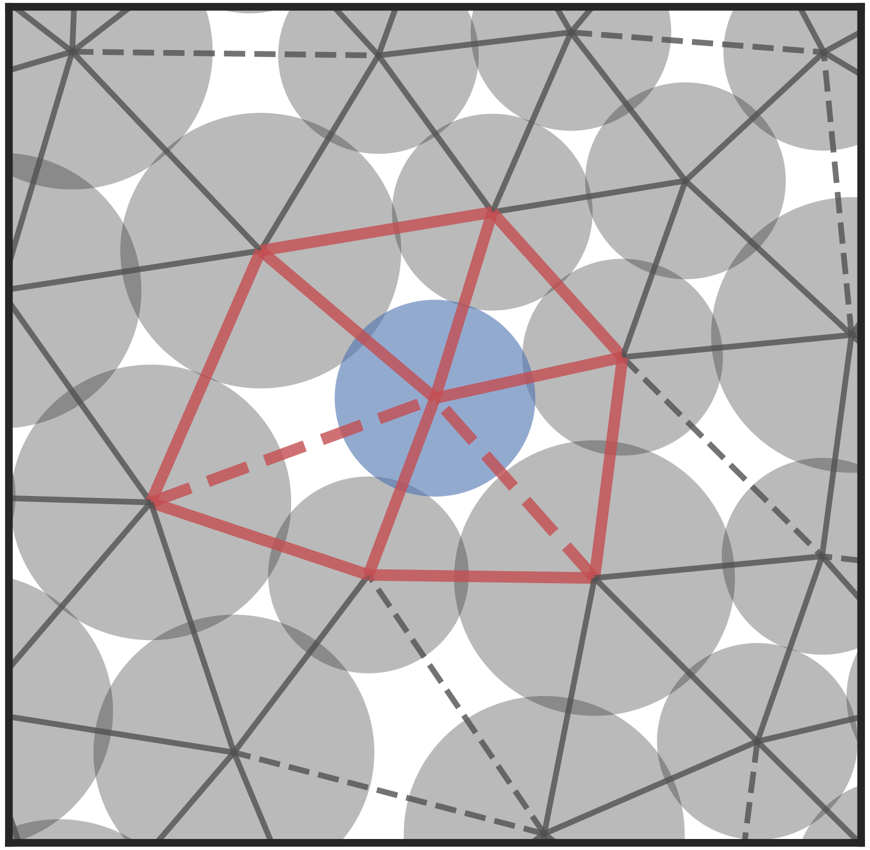

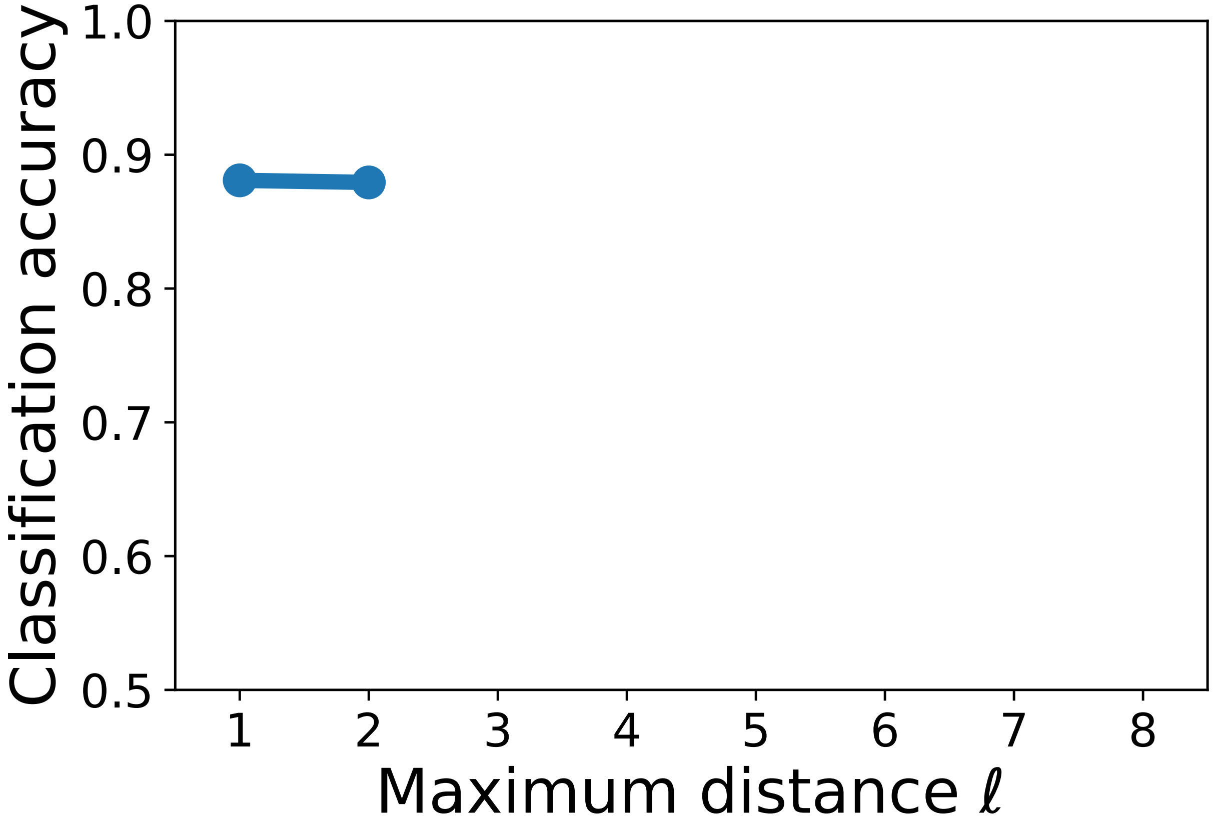

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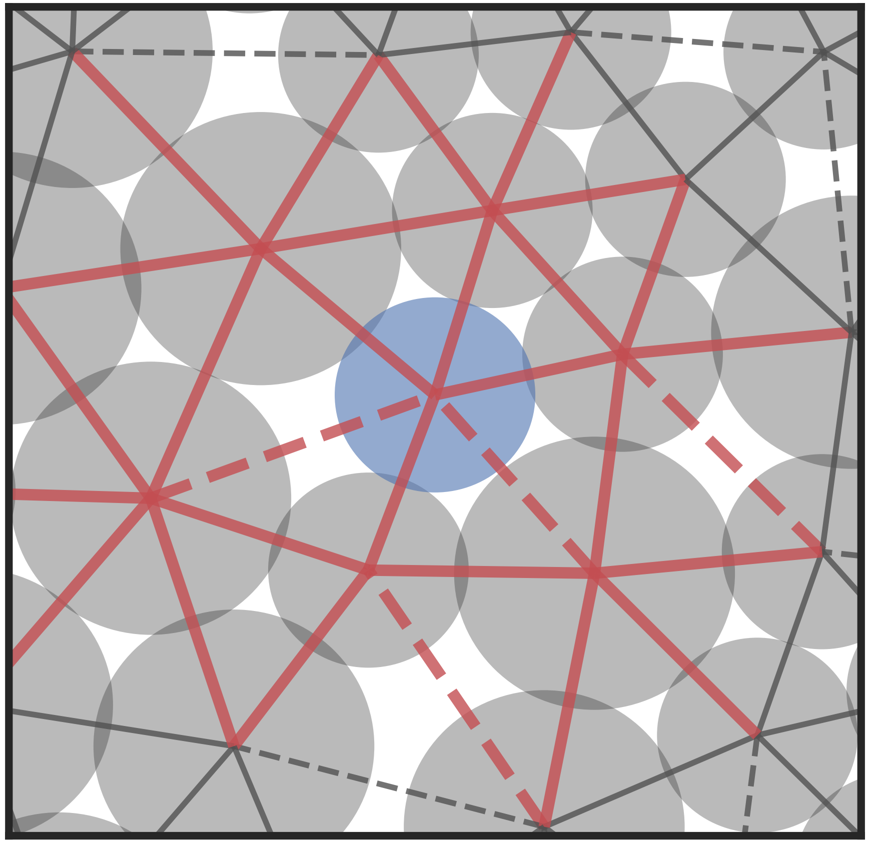

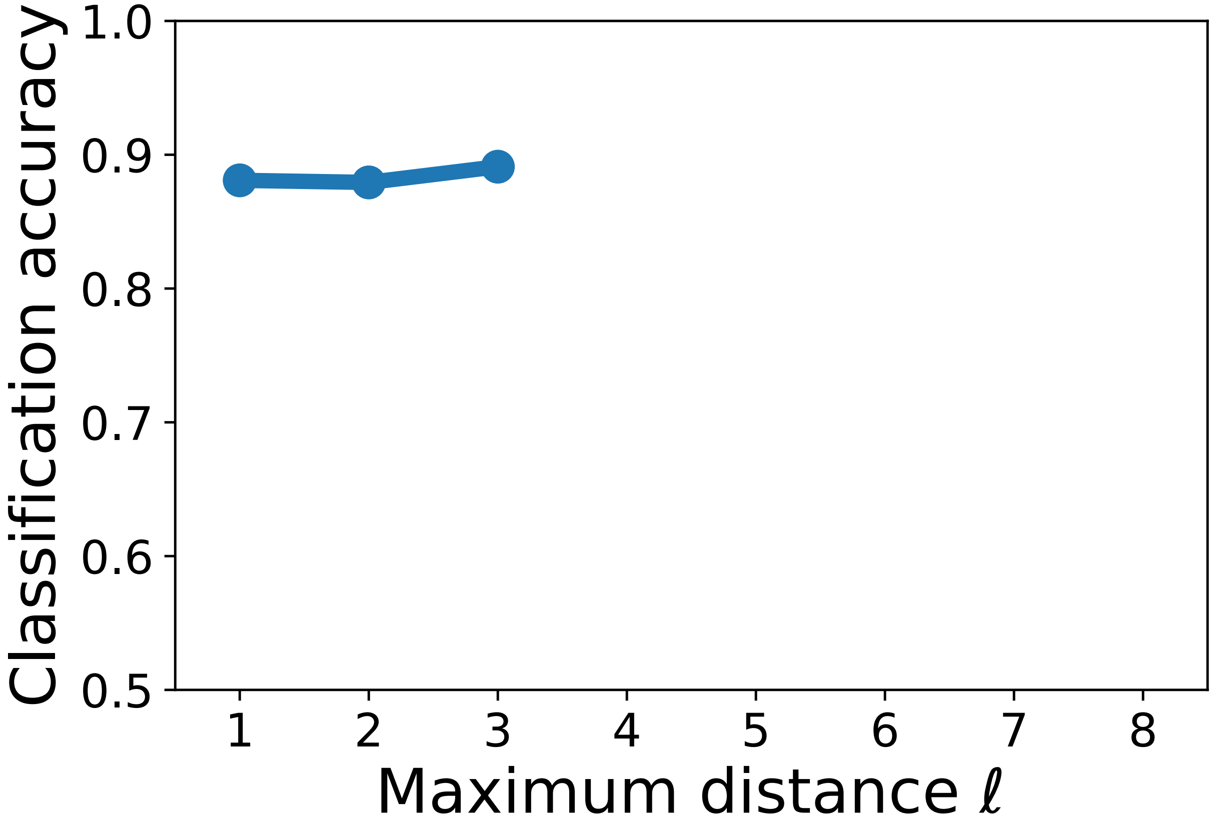

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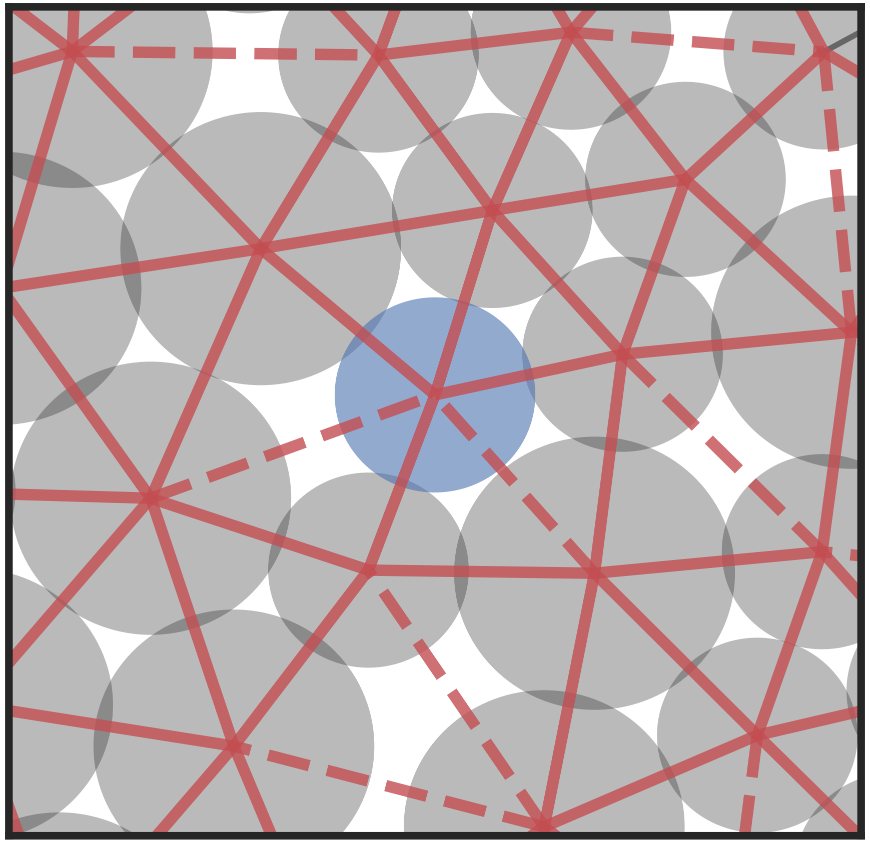

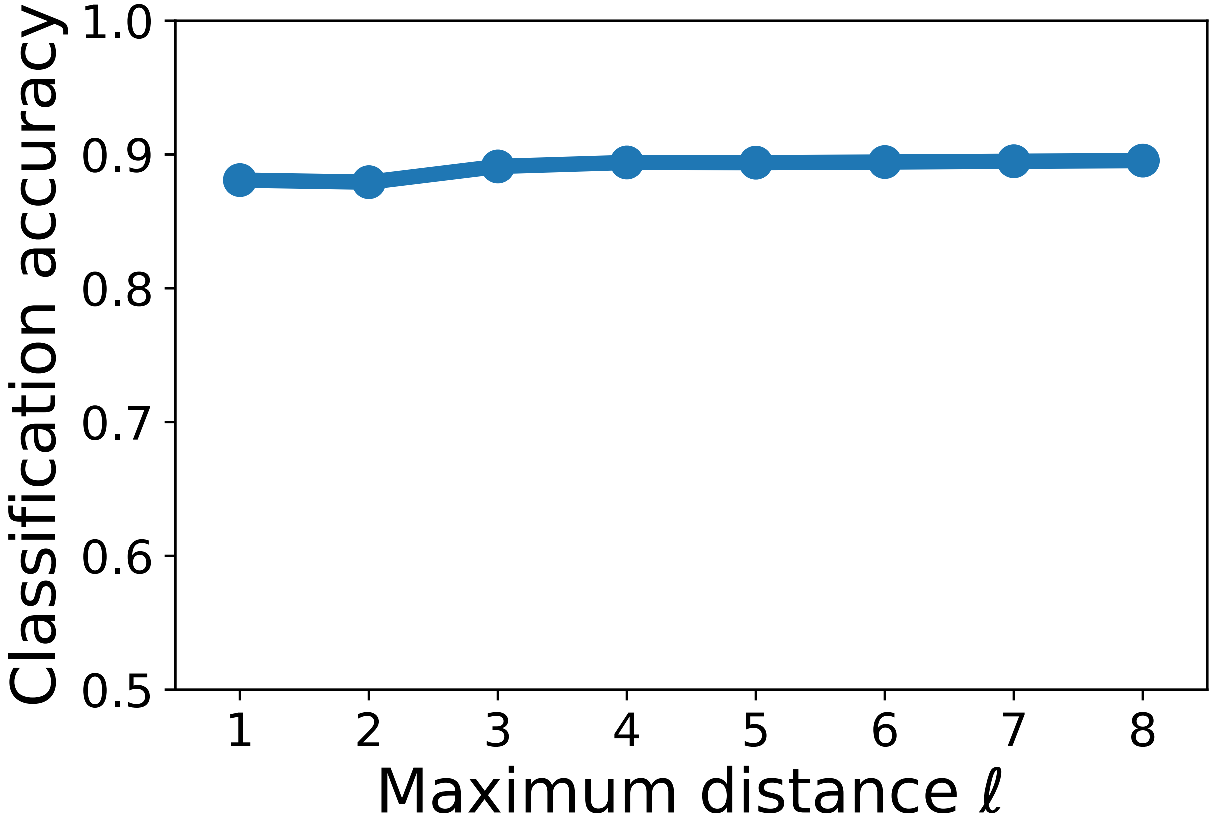

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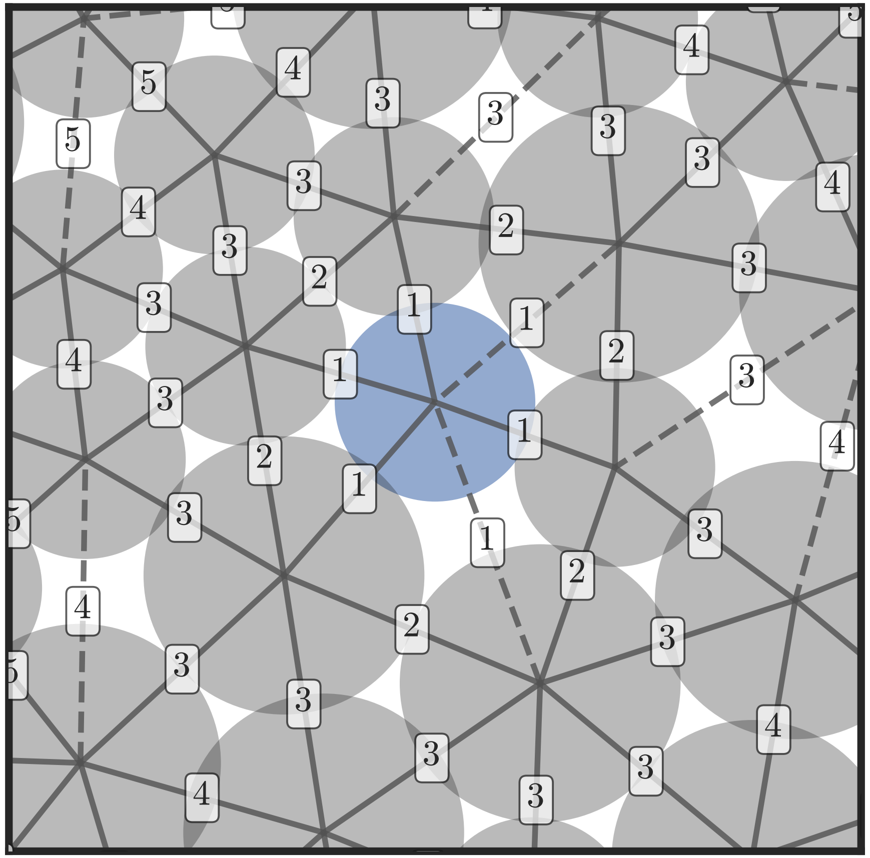

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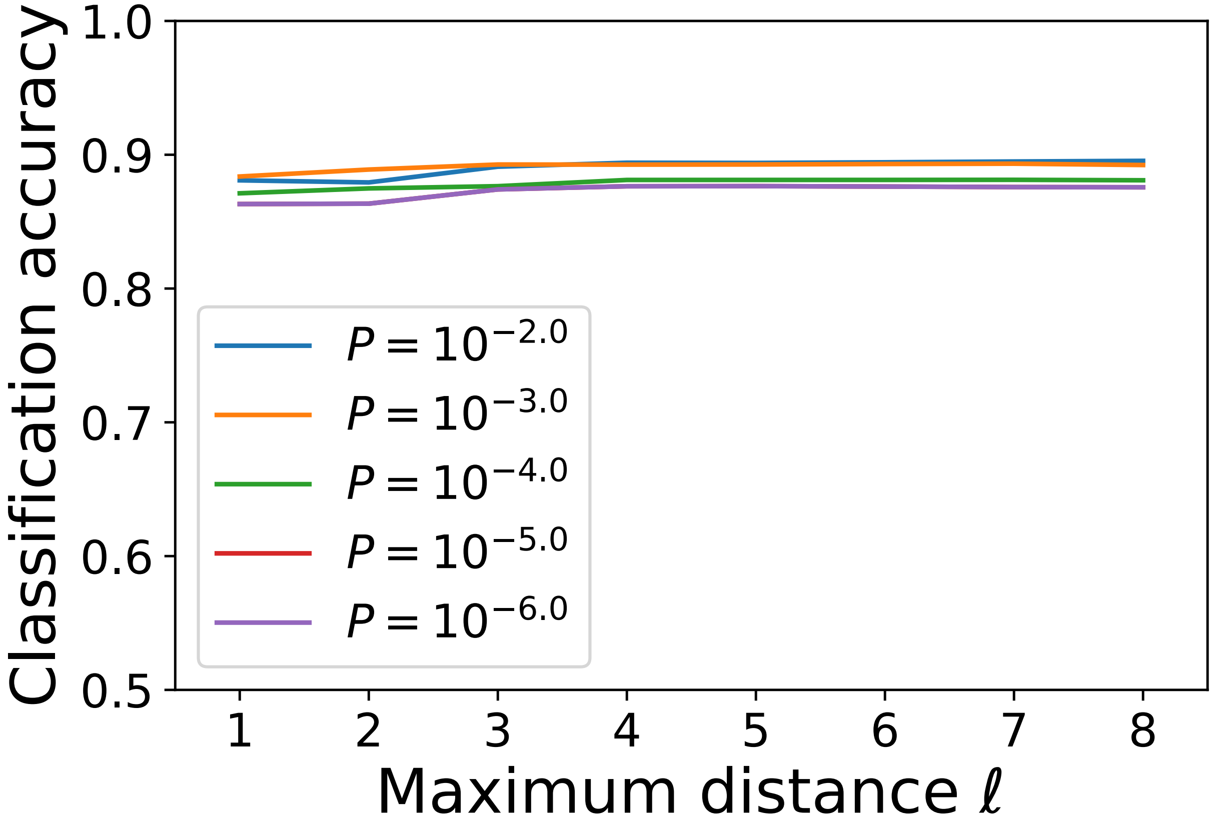
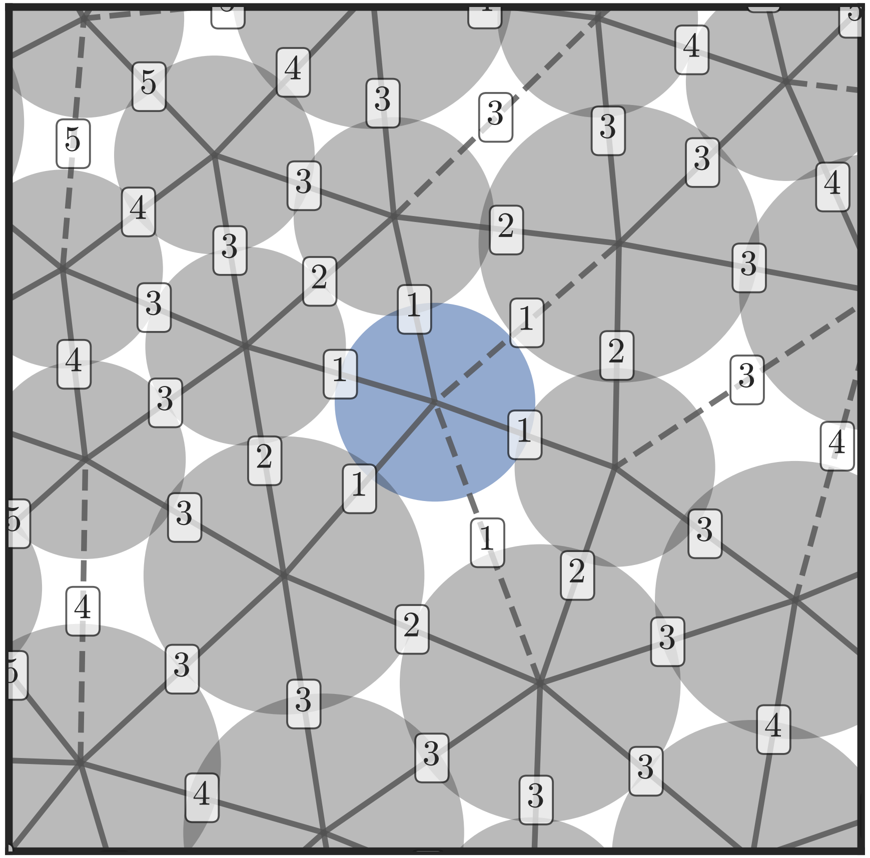


No signature of diverging lengthscale

How much information is necessary?



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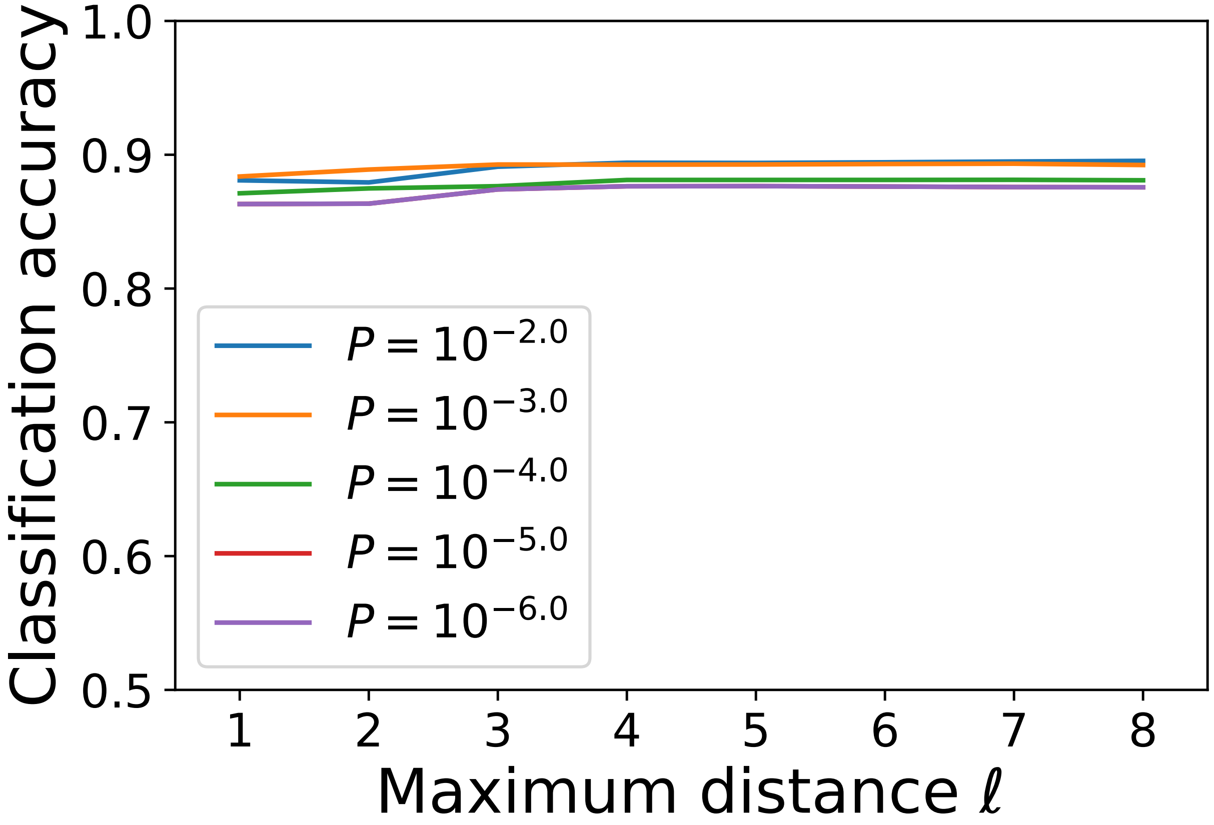

At low pressures, however, contacts aren't enough – need both contacts and gaps

Conclusions

- Local fluctuations in the initial rearrangement for a plastic event correlate very well with local structure
- The same structural features which correlate with local fluctuations are also highly predictive of where the rearrangement itself will localize

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