Improving the Efficiency and Scalability of Multi-Drone Coverage Systems

A Decentralized Approach

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Multi-Drone Coverage Systems

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Limited Resources

- Not enough drones to cover entire area
- Some areas are more important than others

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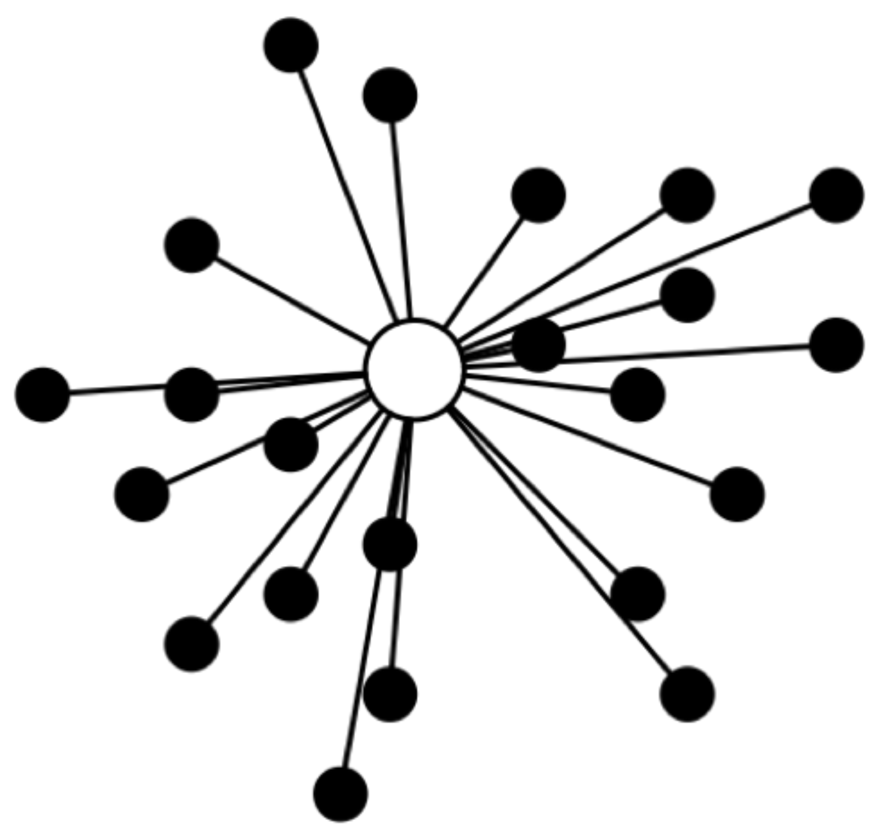
Goal: Distribute drones effectively based on the utility of each location

Centralized vs Decentralized Control

Centralized

One node decides optimal location for each drone, controls navigation

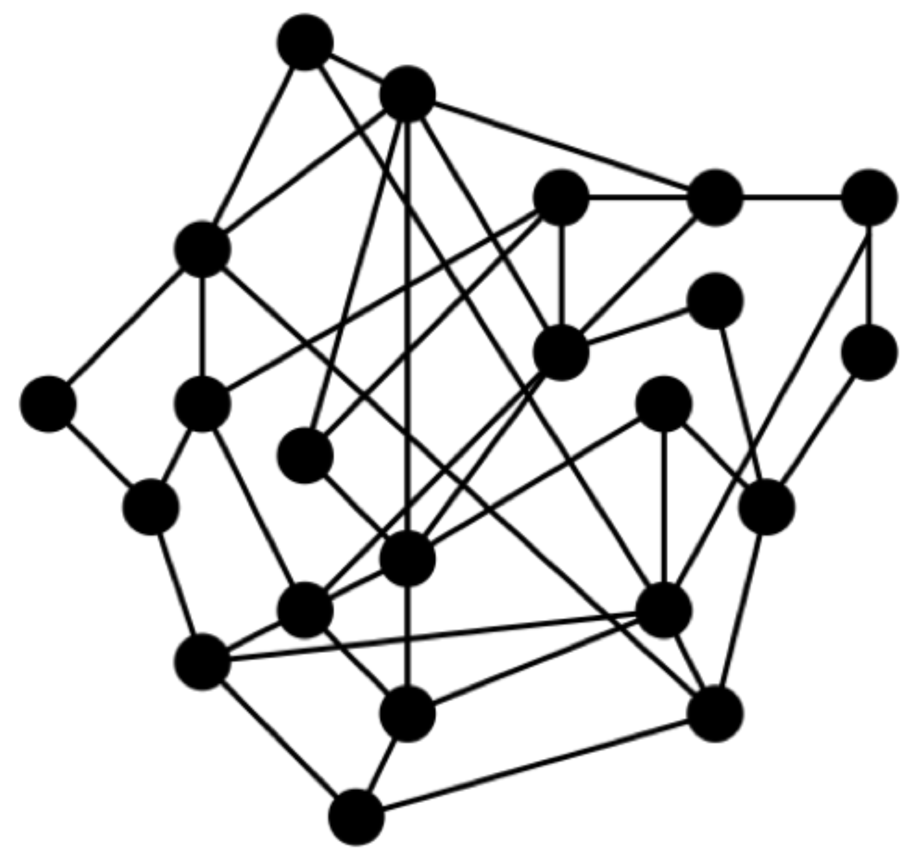
- More easily regulated
- Slower runtimes



Decentralized

Each drone decides its own optimal location and navigation strategy

- More efficient and scalable
- Doesn't always find global optima



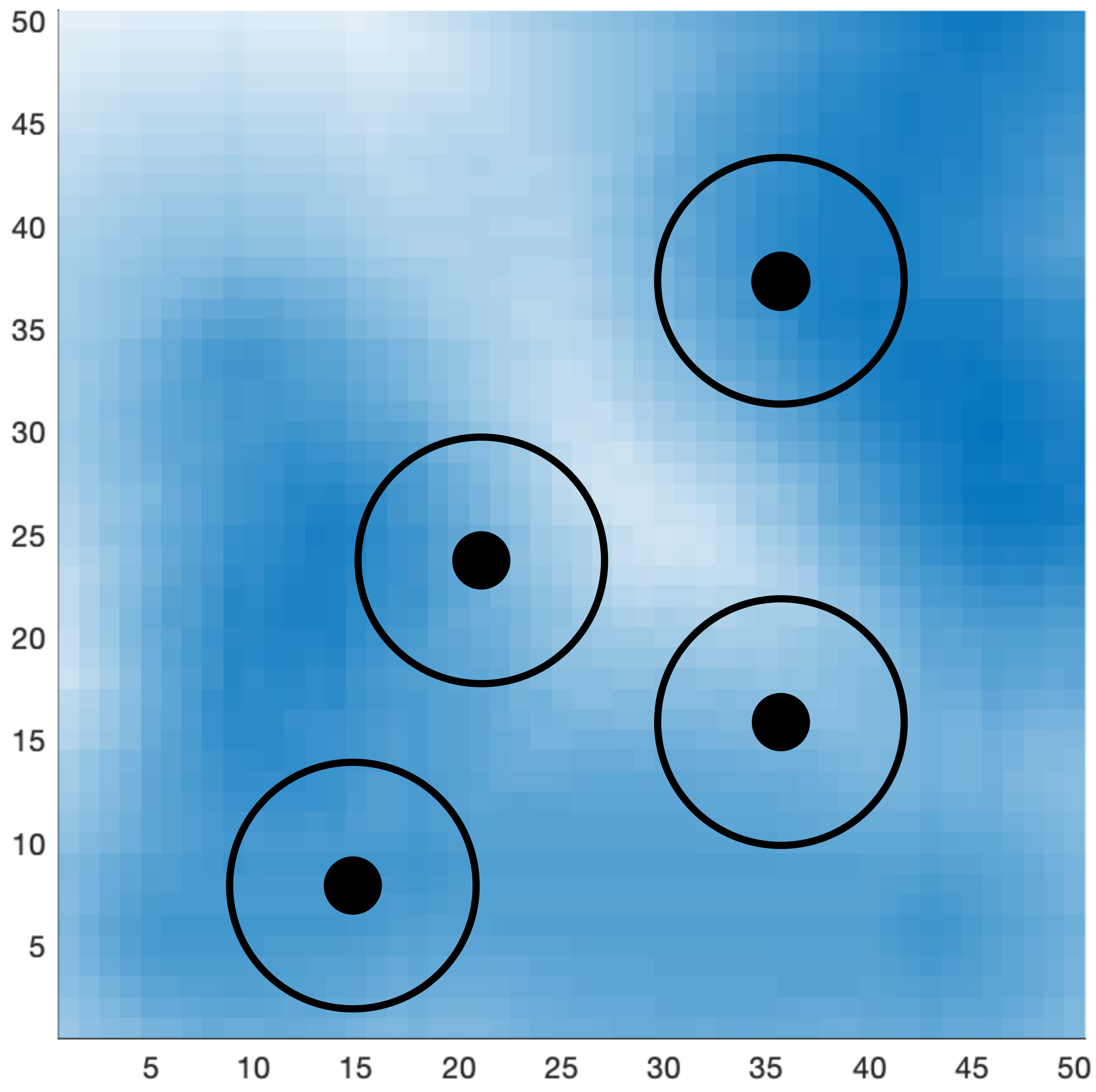
Enhancing the Decentralized Algorithm

Develop multi-drone simulation

Implement and compare algorithms

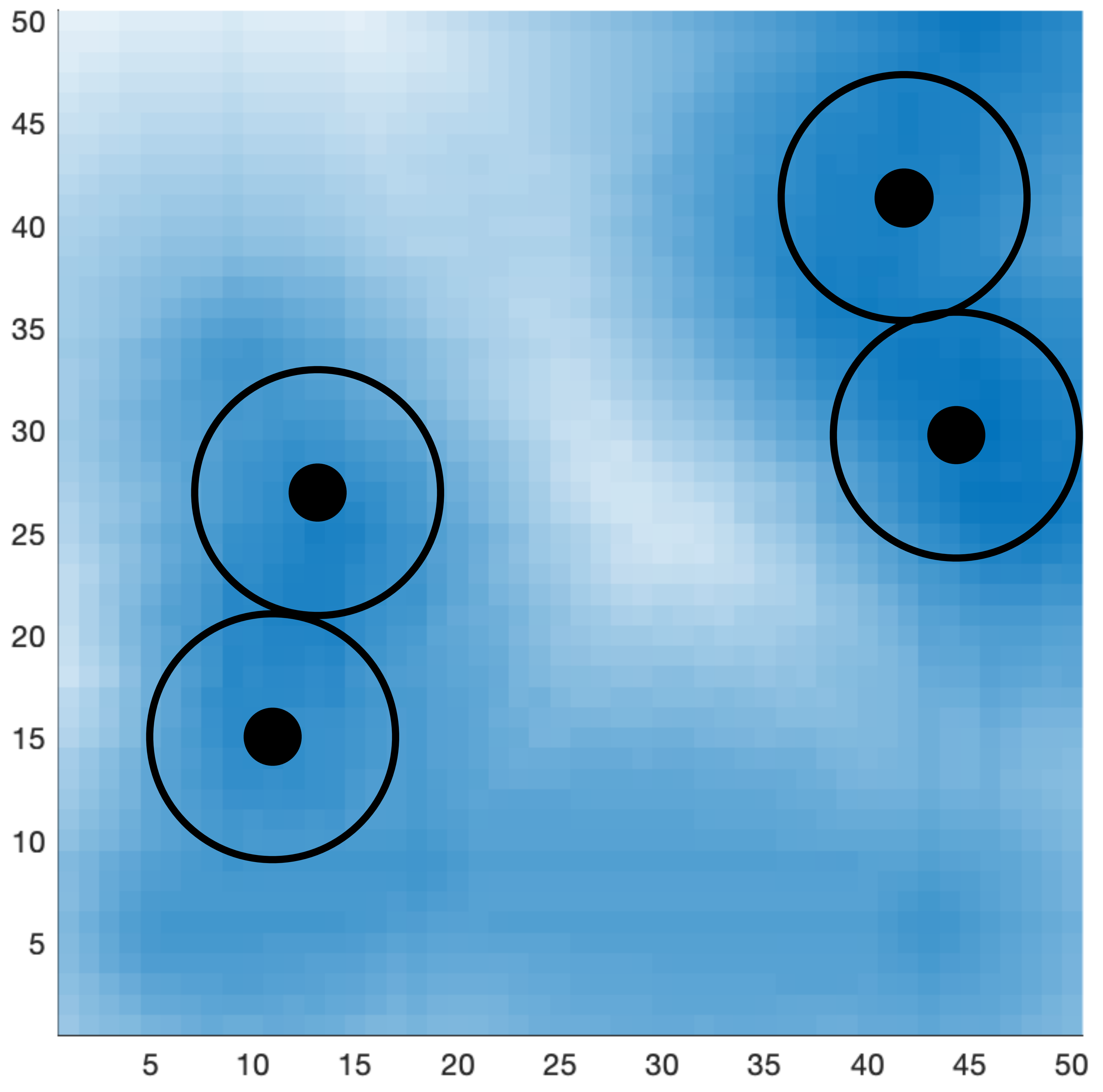
Develop and verify enhancements

Modeling the System



- Map of a region to be covered, where each cell has a utility (importance) value
- Each agent starts at either a random or pre-determined position
- The circle around each agent represents the sensing or coverage radius
- An agent is chosen at random to make a move within its movement radius
- Ultimate goal: maximize the sum of values of the covered cells

Modeling the System



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Decentralized Algorithms

Greedy Algorithm
(Baseline approach)

Drones try solely to maximize their own coverage

Log-Linear Learning (LLL)

Introduces randomness

Drones occasionally take a suboptimal decision

LLL with Automatic Tau Generation

Eliminates need for manual tuning of constants

Decentralized Algorithms

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Drones try solely to maximize their own coverage

- Agents' only goal is to maximize their utility
- Moves are only made if the new location has a higher utility value:

$$a_i(t+1) = \arg \max_{a_i \in A_i(t)} U_i(a_i, a_{-i})$$

- Can get stuck at local optima

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- Actions chosen based on a probability distribution based on utilities of each action:

$$p_i^{a_i}(t) = \frac{e^{\frac{1}{\tau}U_i(a_i, a_{-i}(t-1))}}{\sum_{\bar{a}_i \in A_i} e^{\frac{1}{\tau}U_i(\bar{a}_i, a_{-i}(t-1))}}$$

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- Value τ acts as a randomness or "exploration" constant
    - As $\tau \to 0$: Acts as a greedy system
    - As $\tau \to \infty$: Actions chosen uniformly at random
- At each time-step, τ decays by 0.997

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- In LLL, starting τ selected manually – can be automated
- Correlates with average map value, agent radius, starting configuration
- For random starting position: $\tau = \frac{1}{2}\pi R^2 \cdot \overline{M}$
- For starting in one corner: $\tau = \pi R^2 \cdot \overline{M}$

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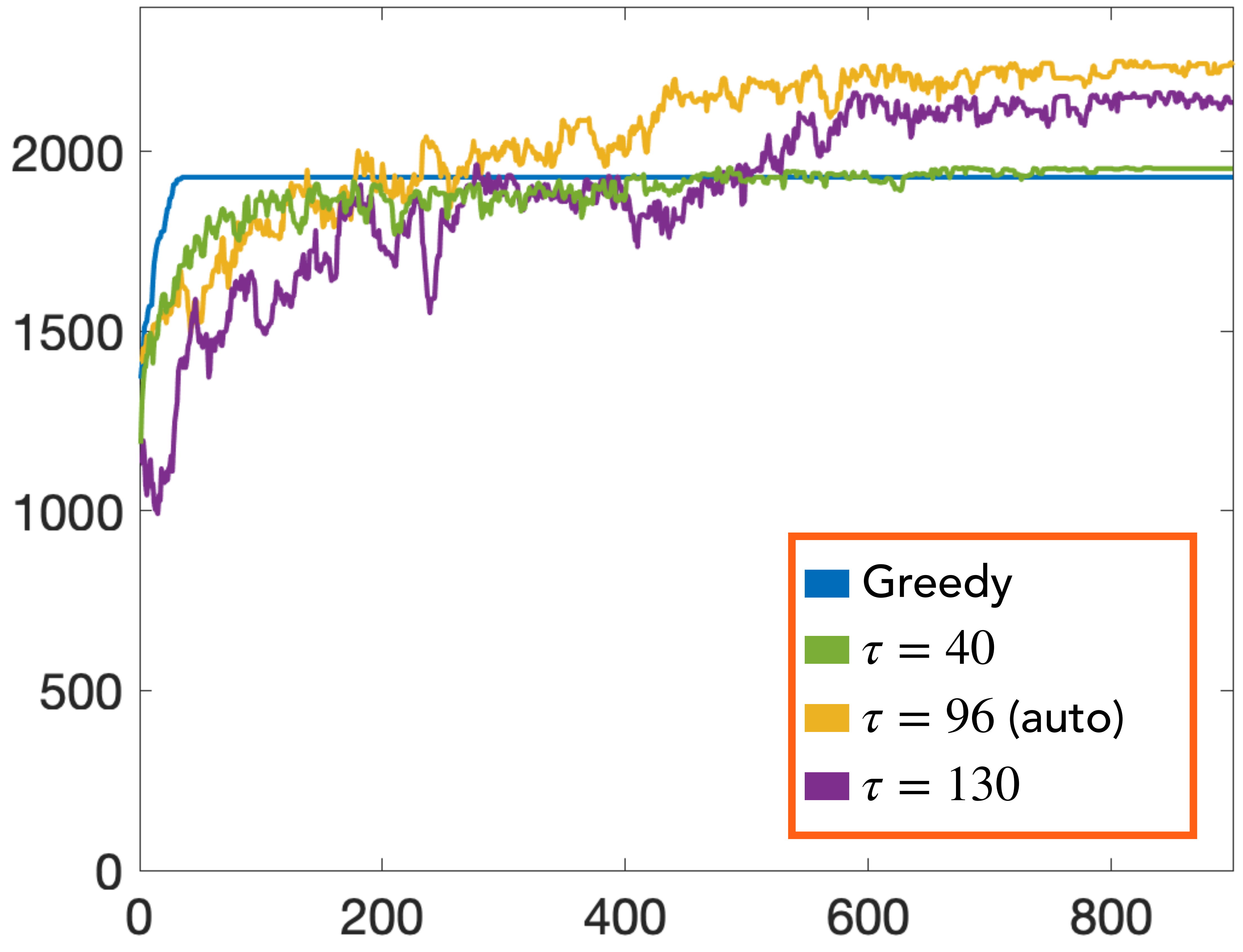
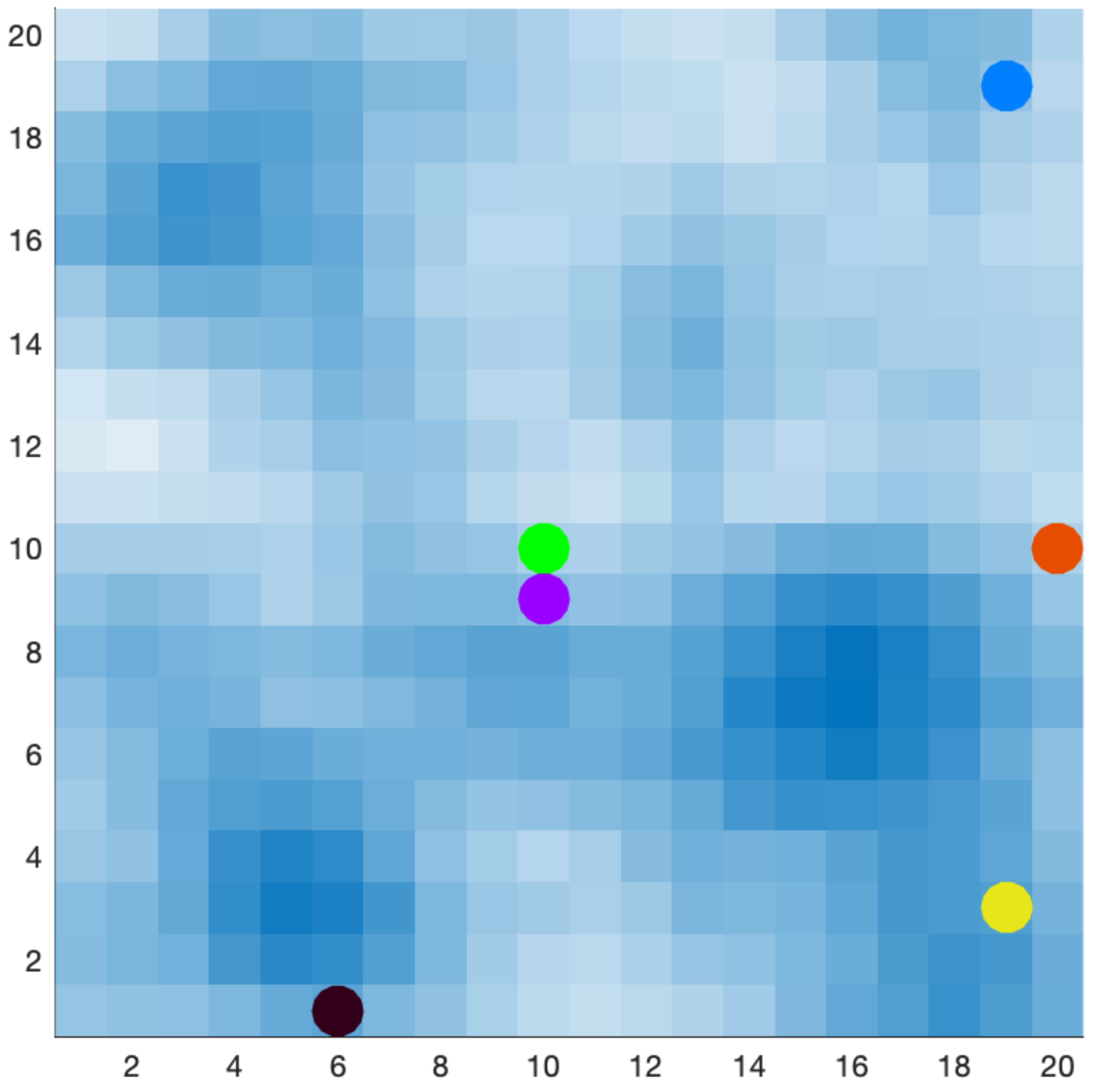
Algorithm Comparison

Random Starting Configuration



Initial State



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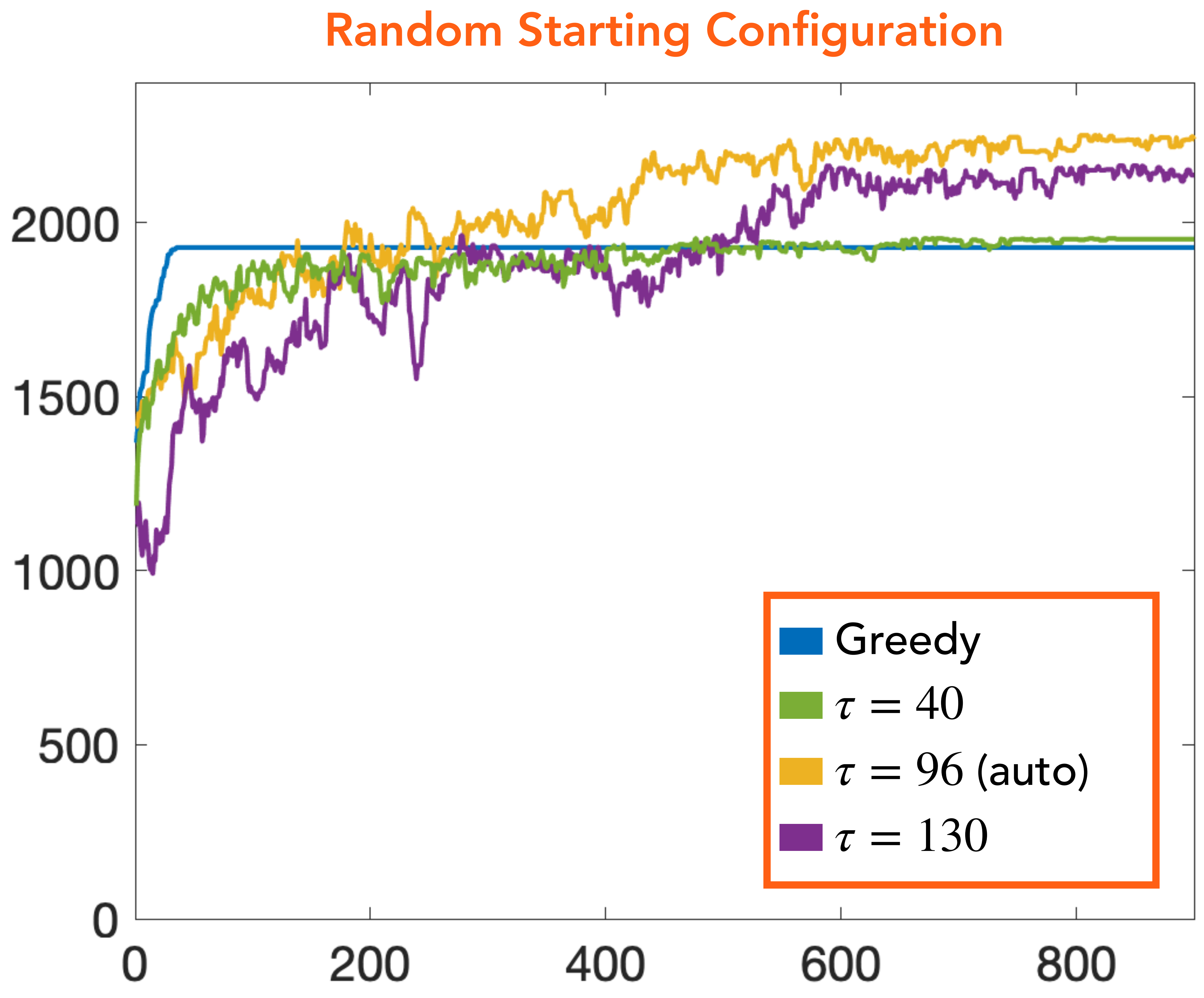

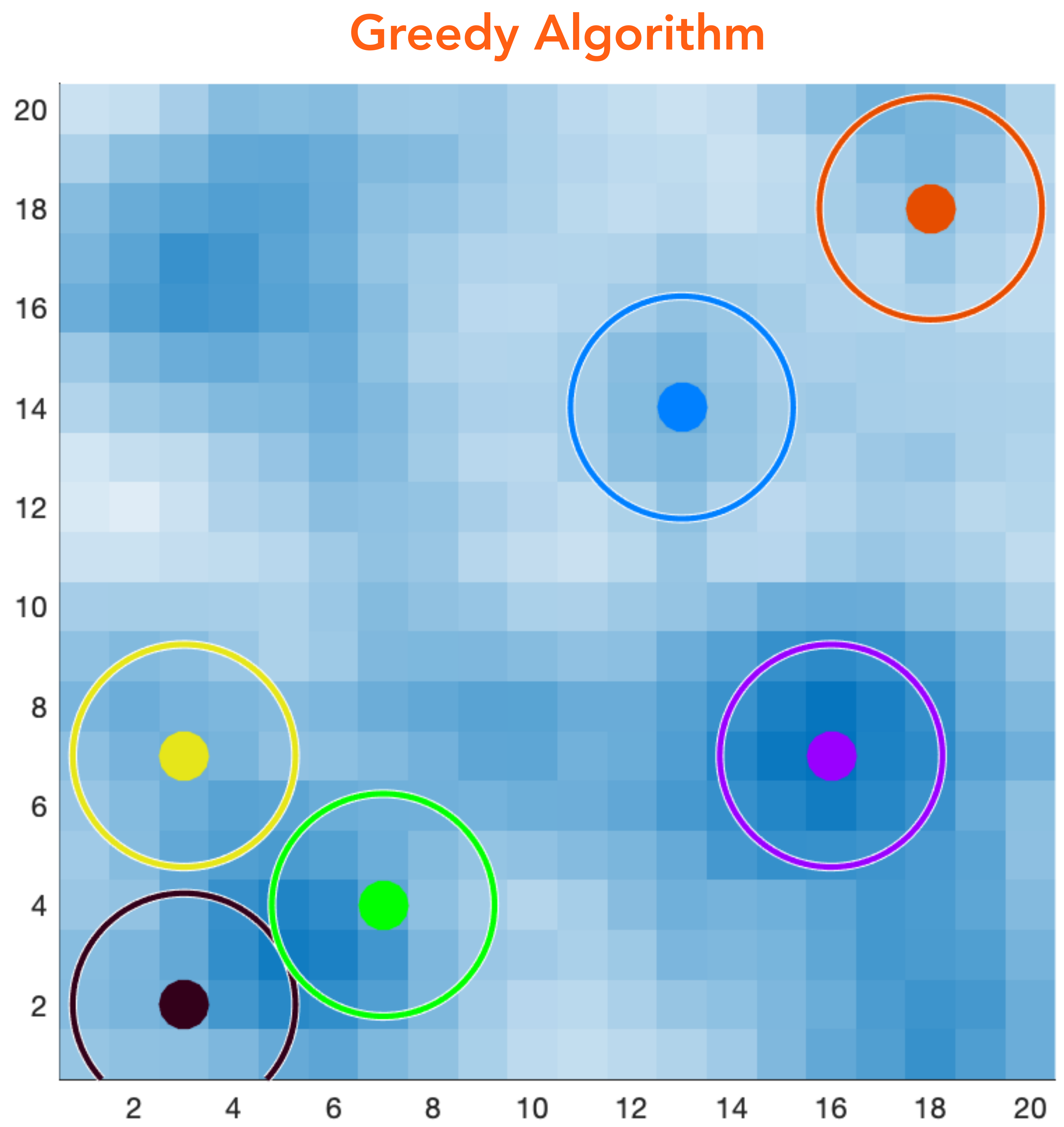

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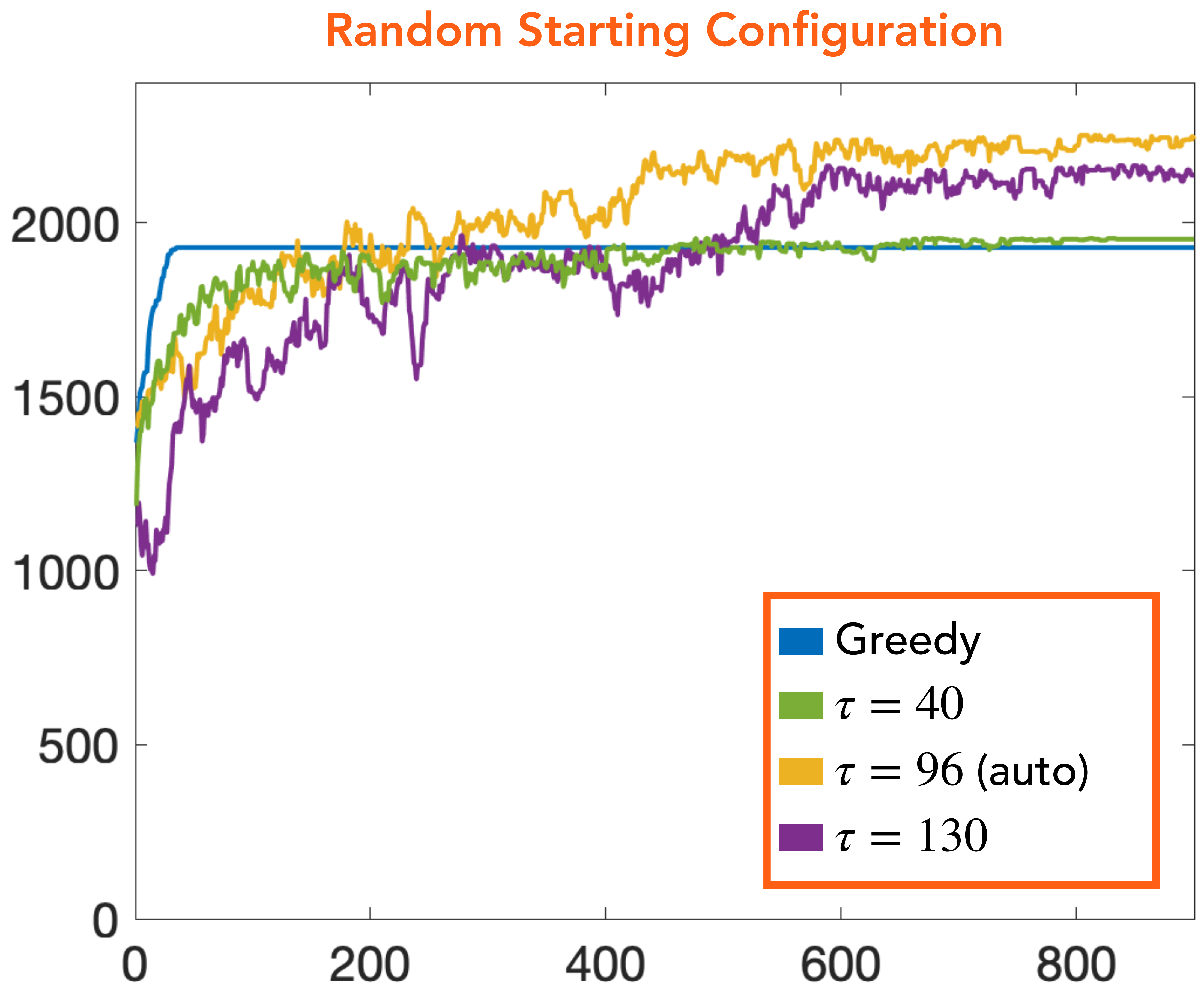

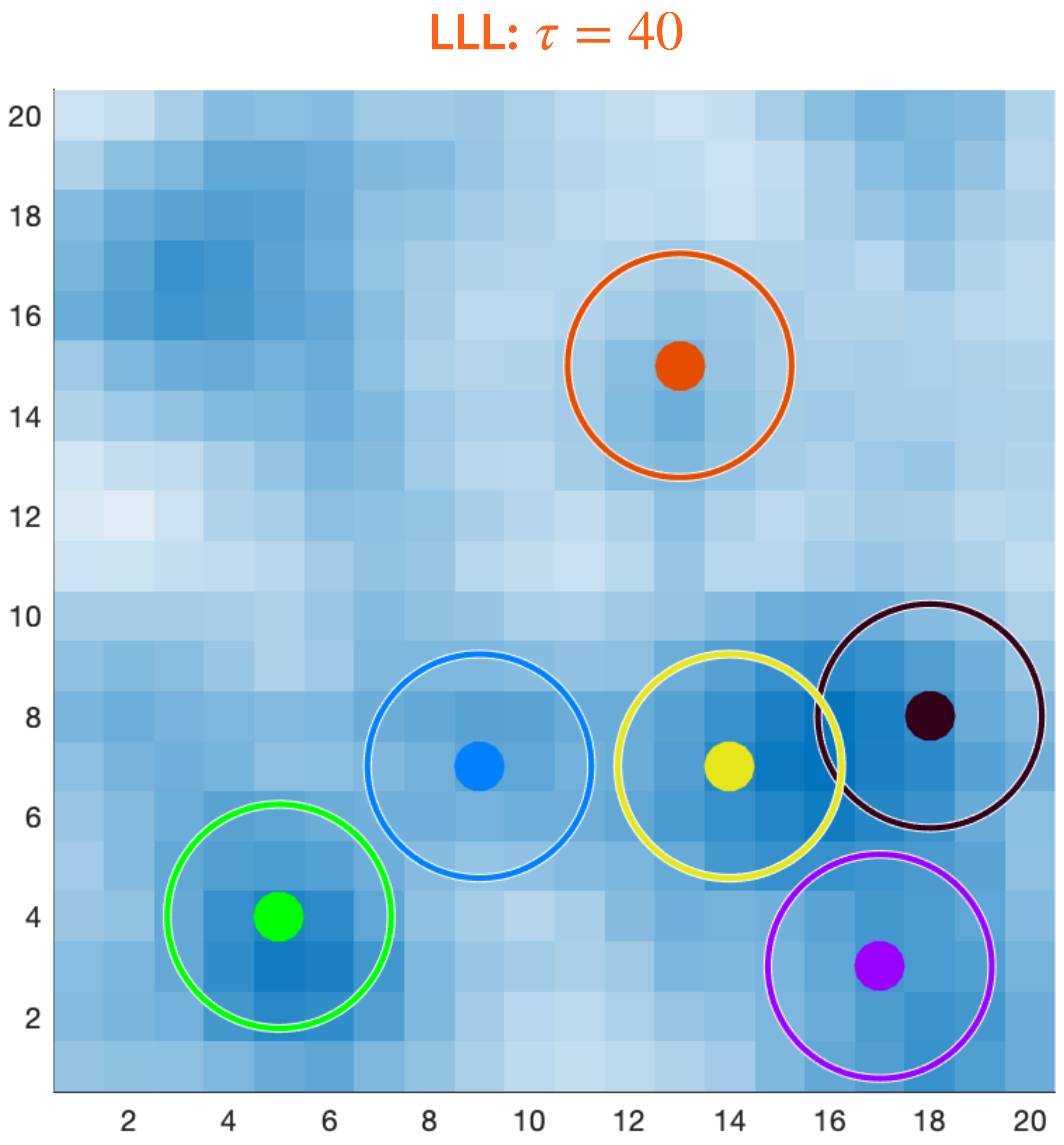

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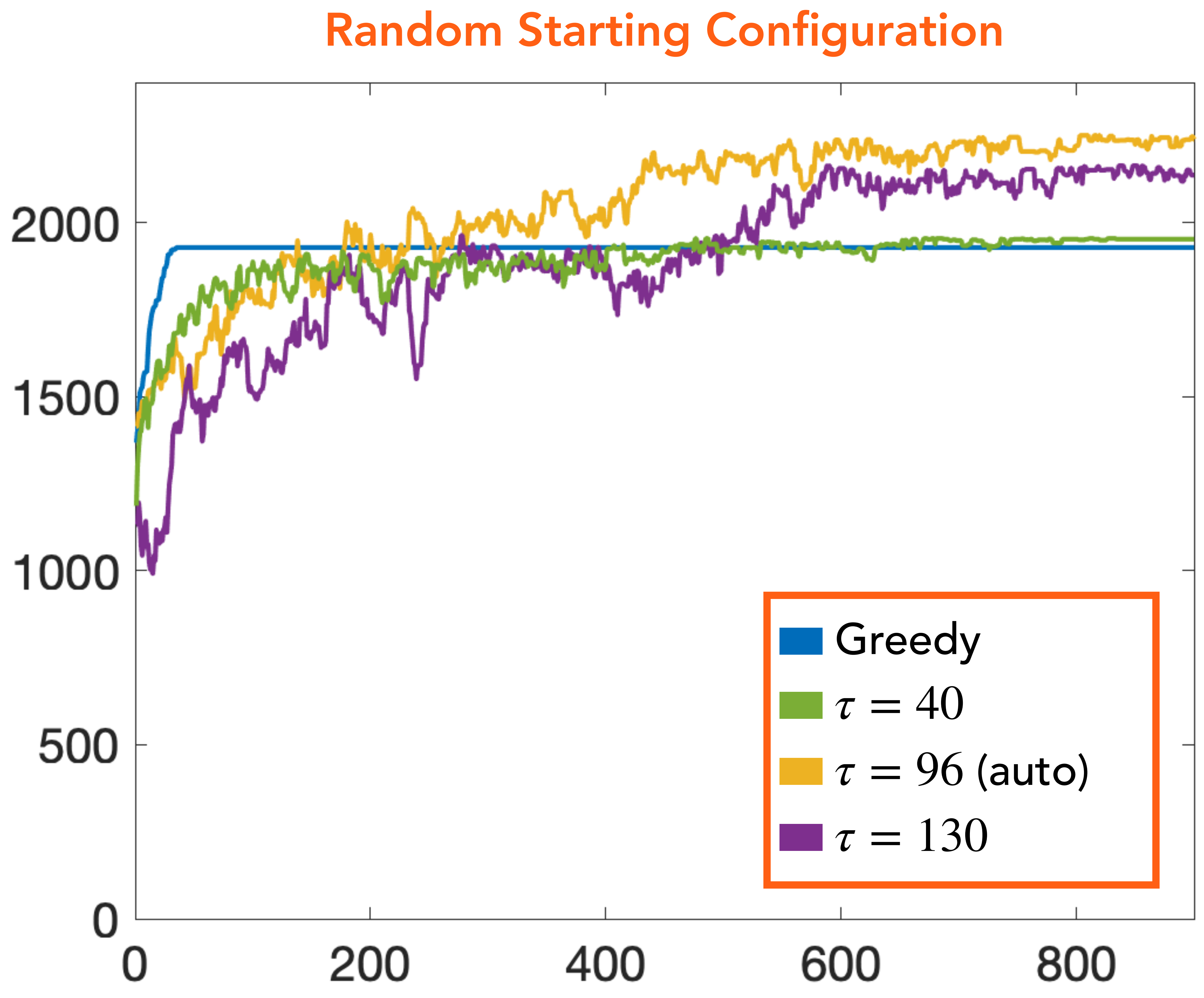

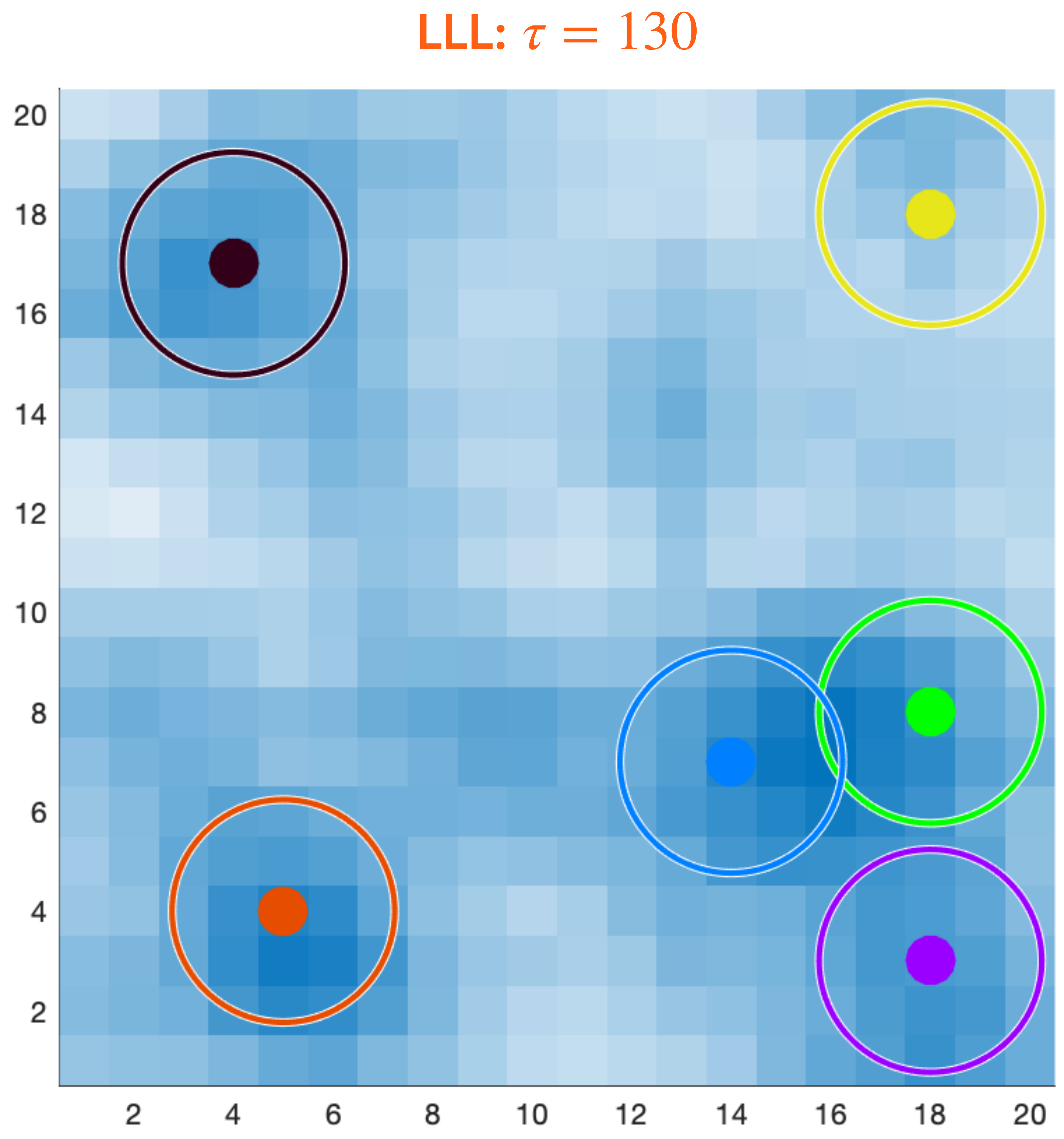

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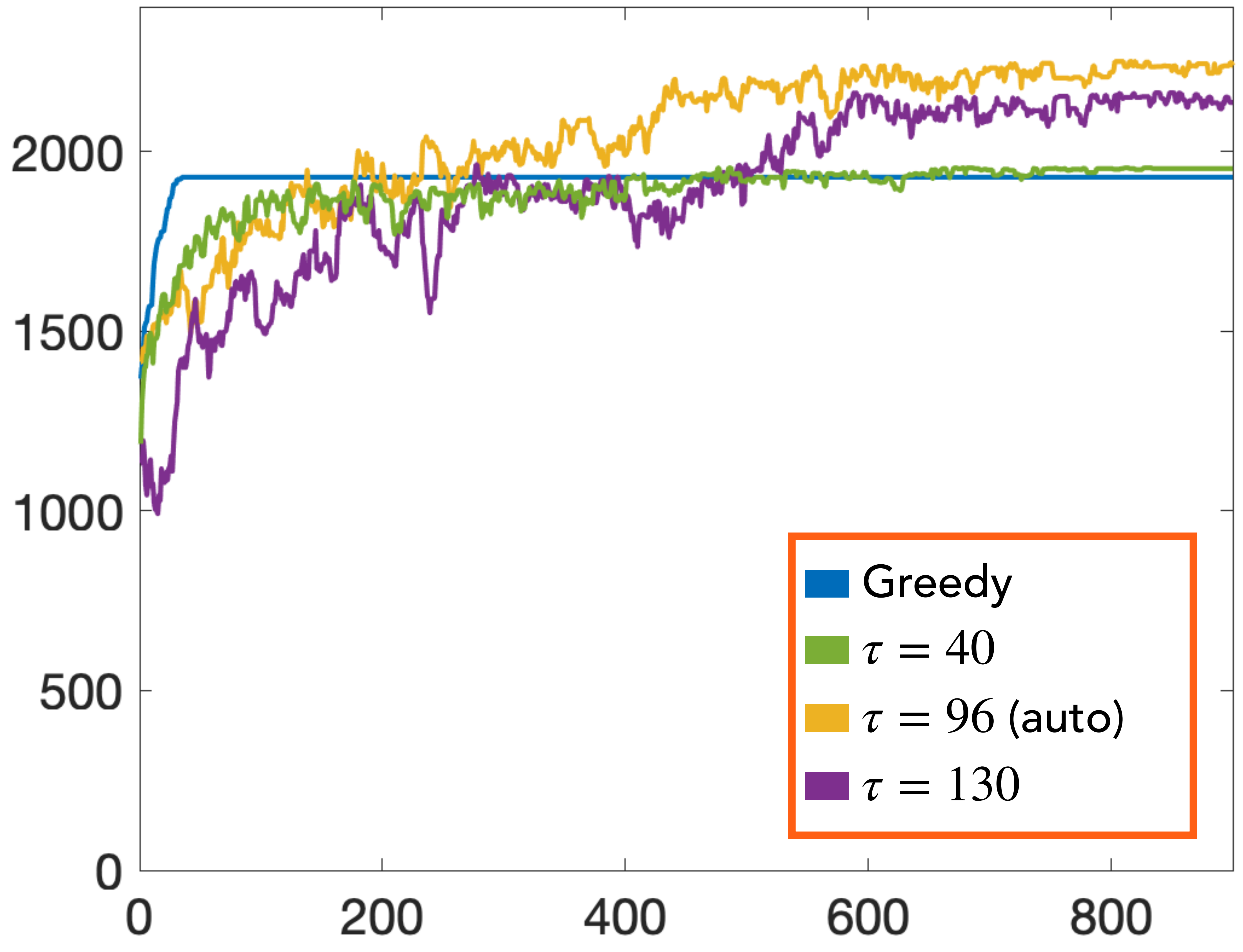
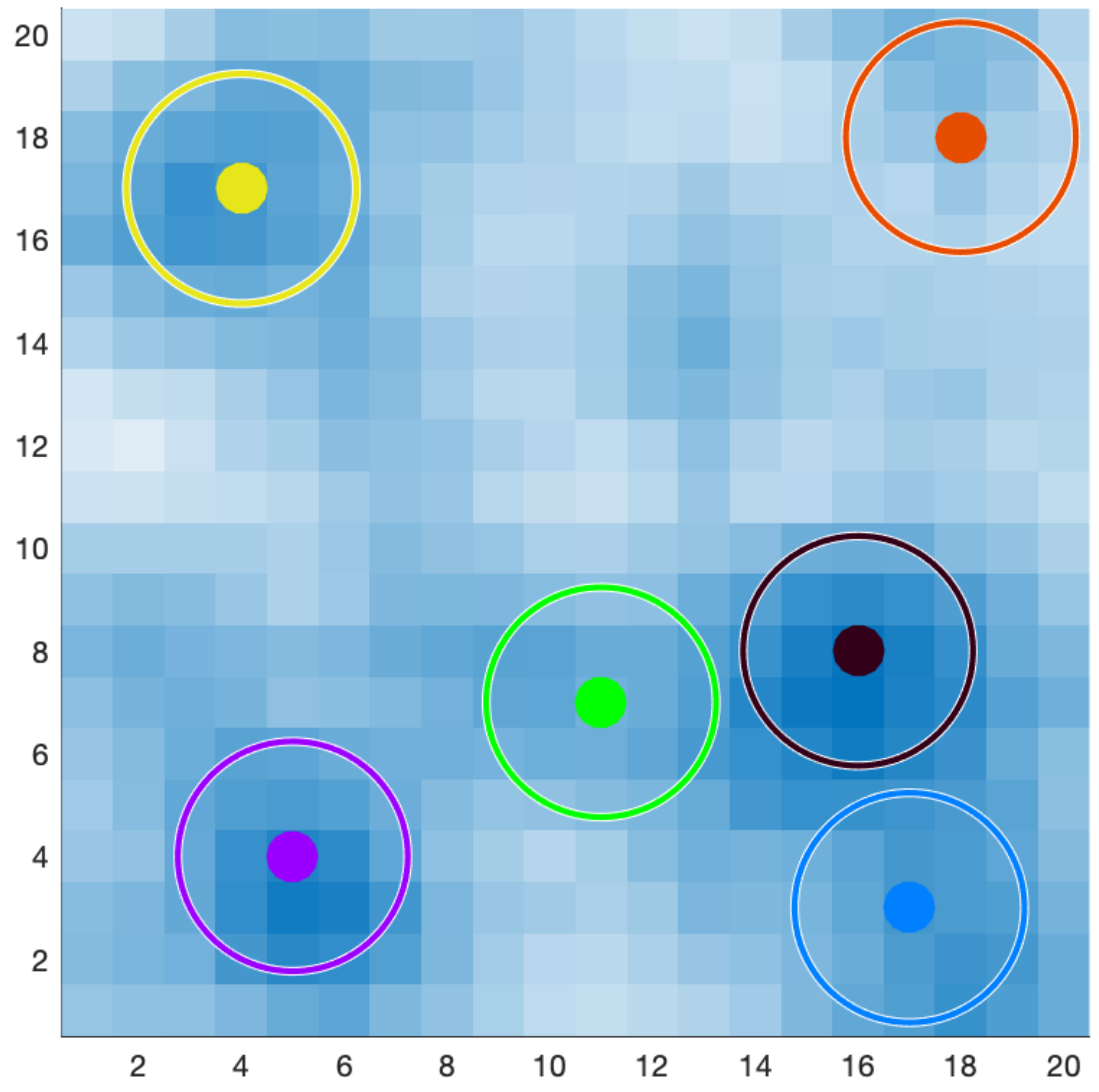
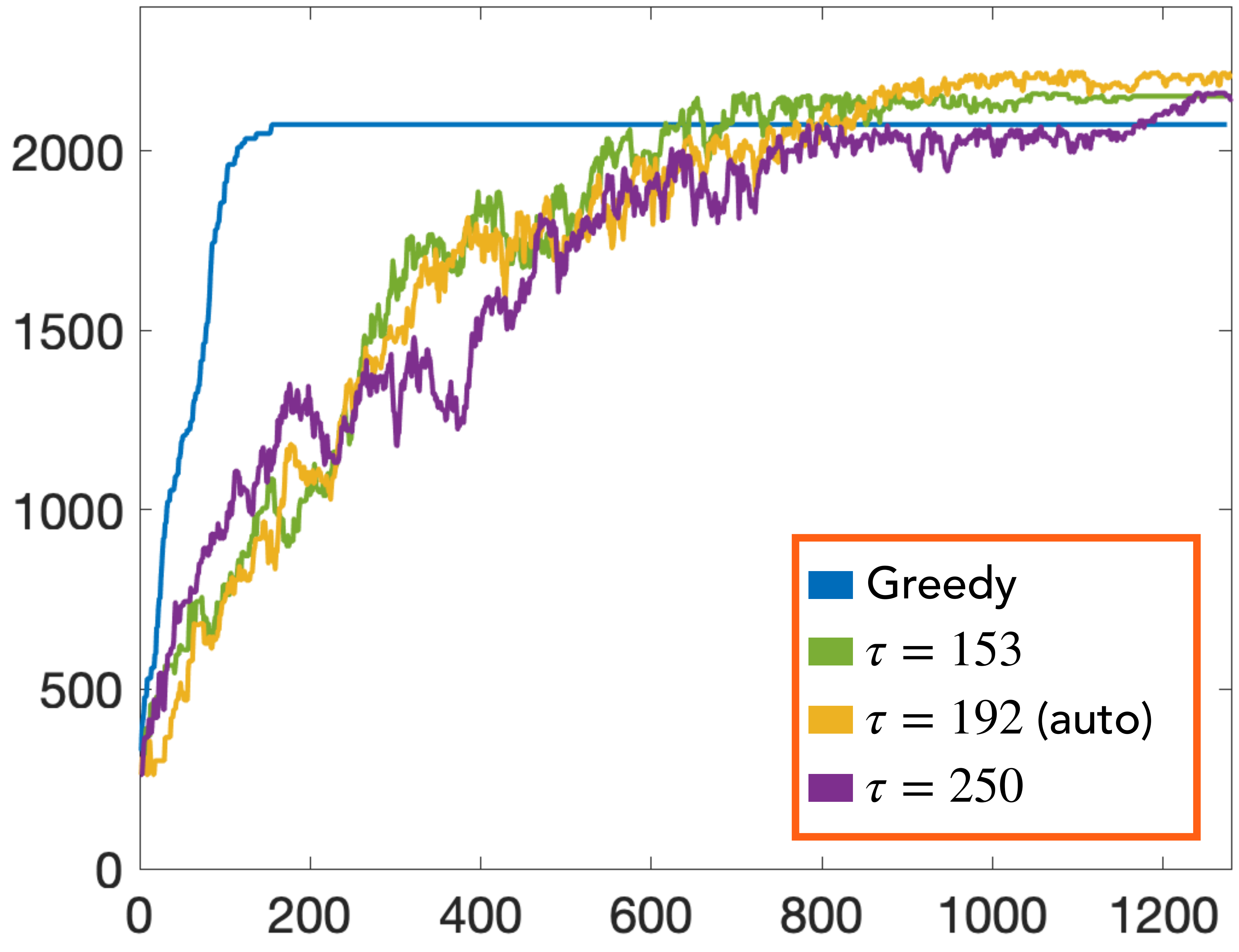


LLL: $\tau = 96$ (auto)



Algorithm Comparison

Corner Starting Configuration



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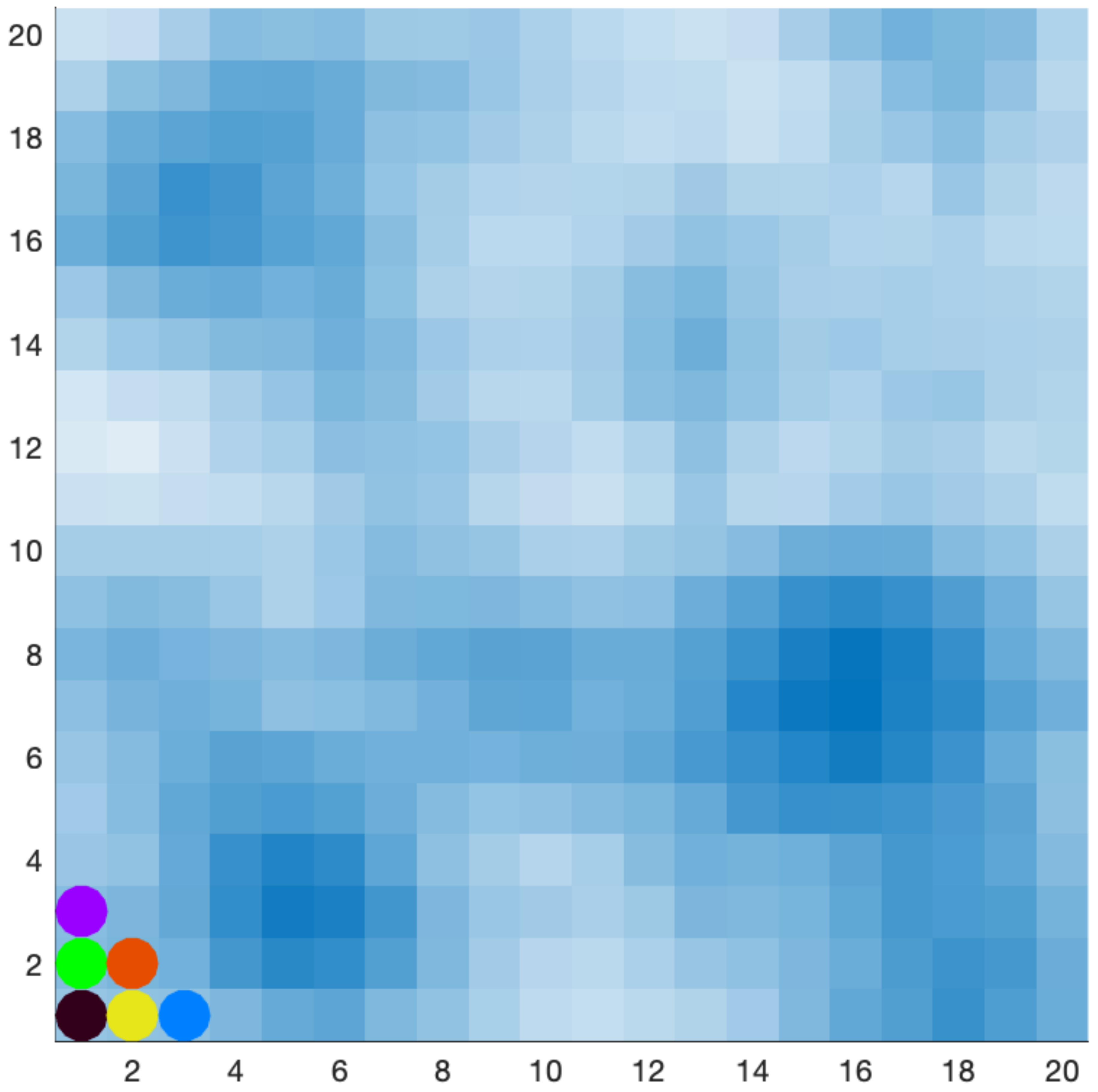

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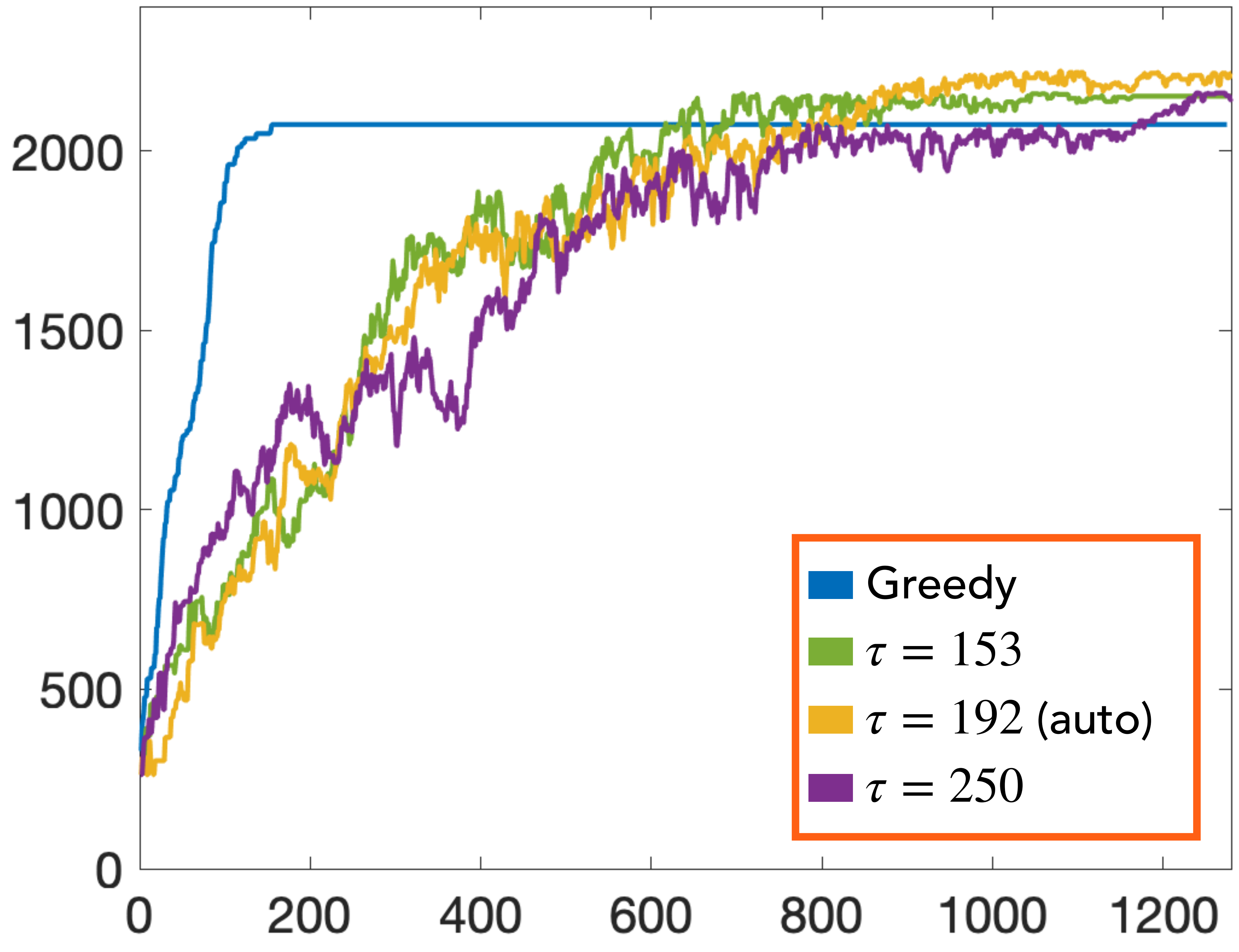
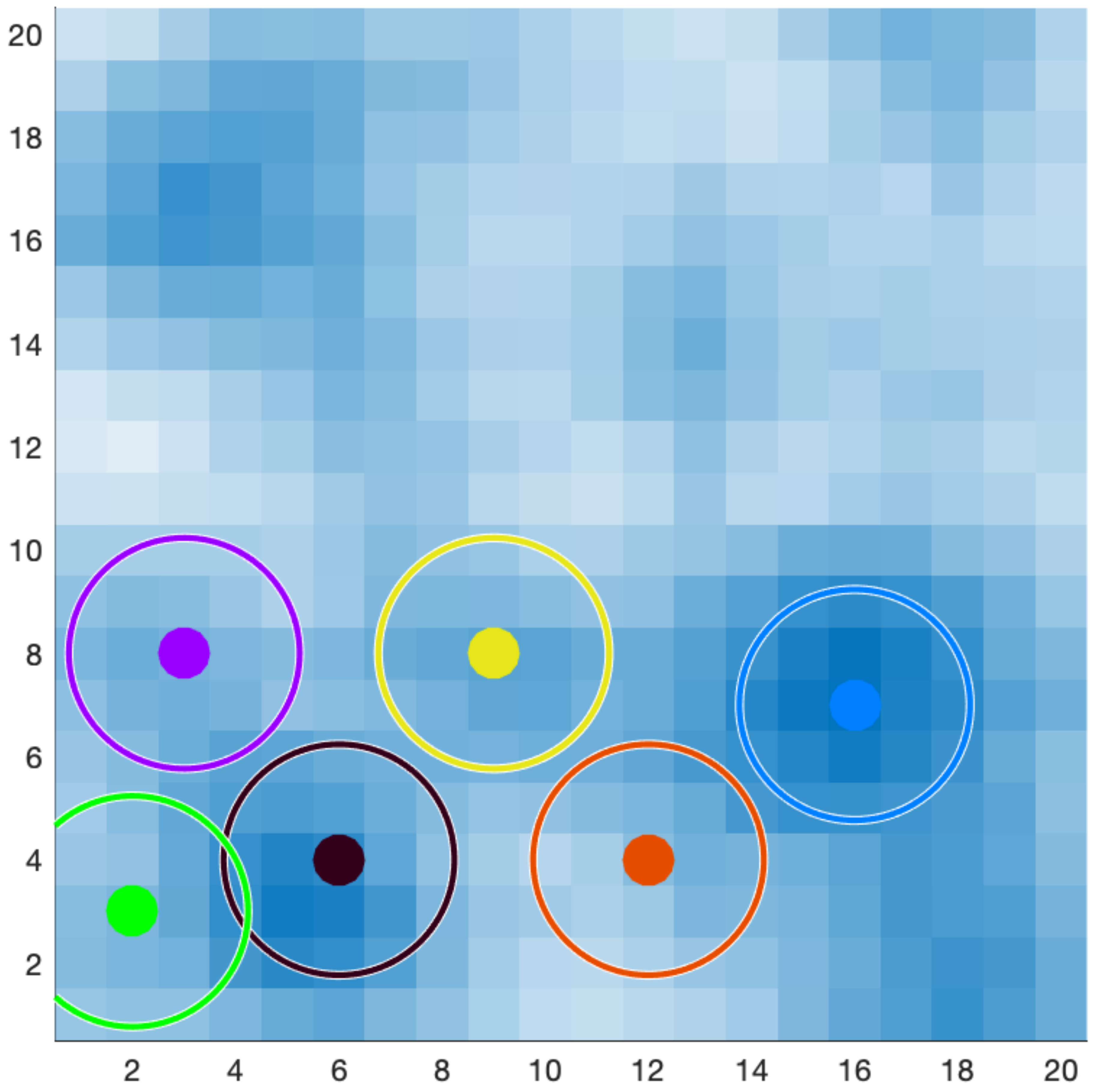


Greedy Algorithm



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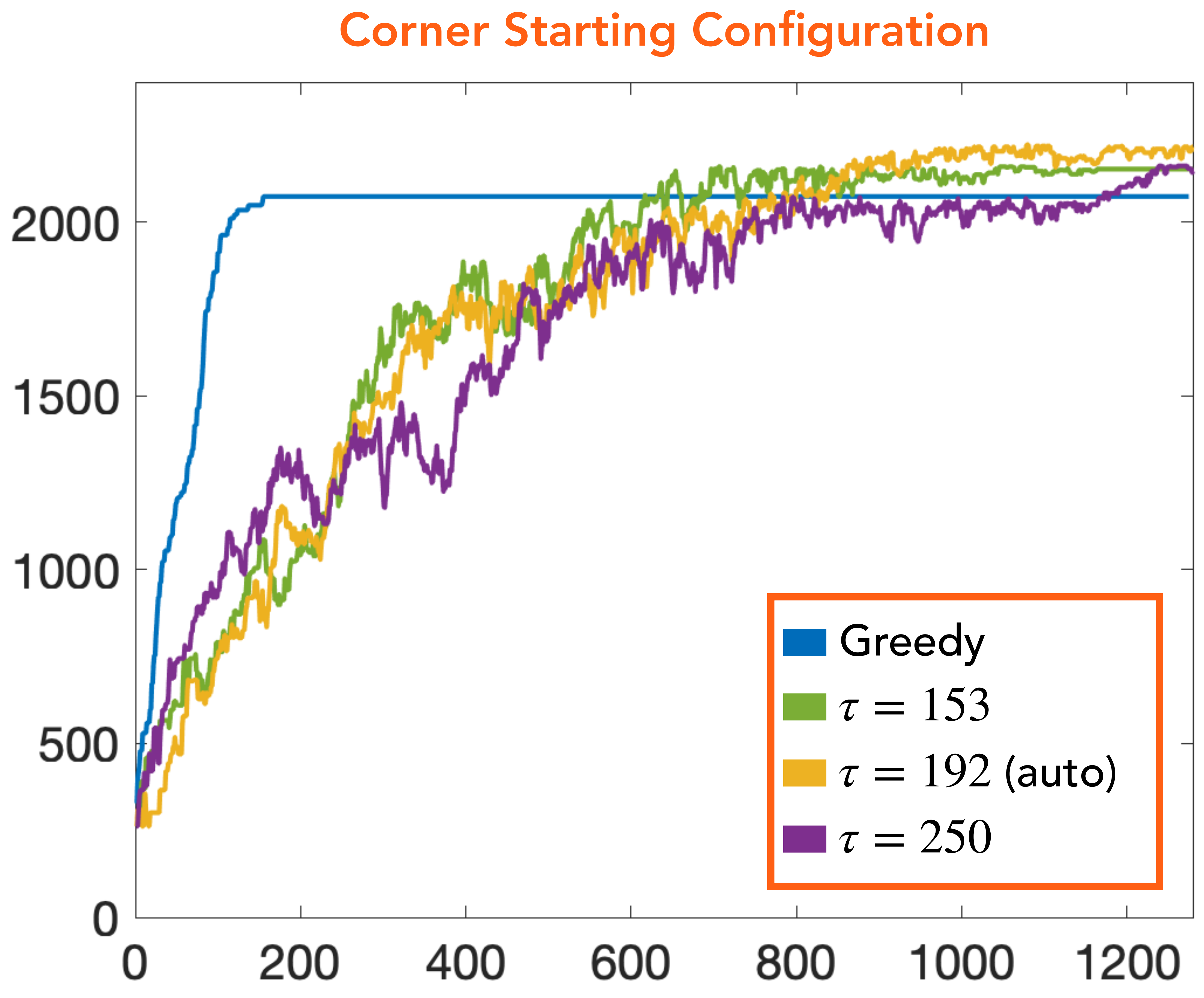

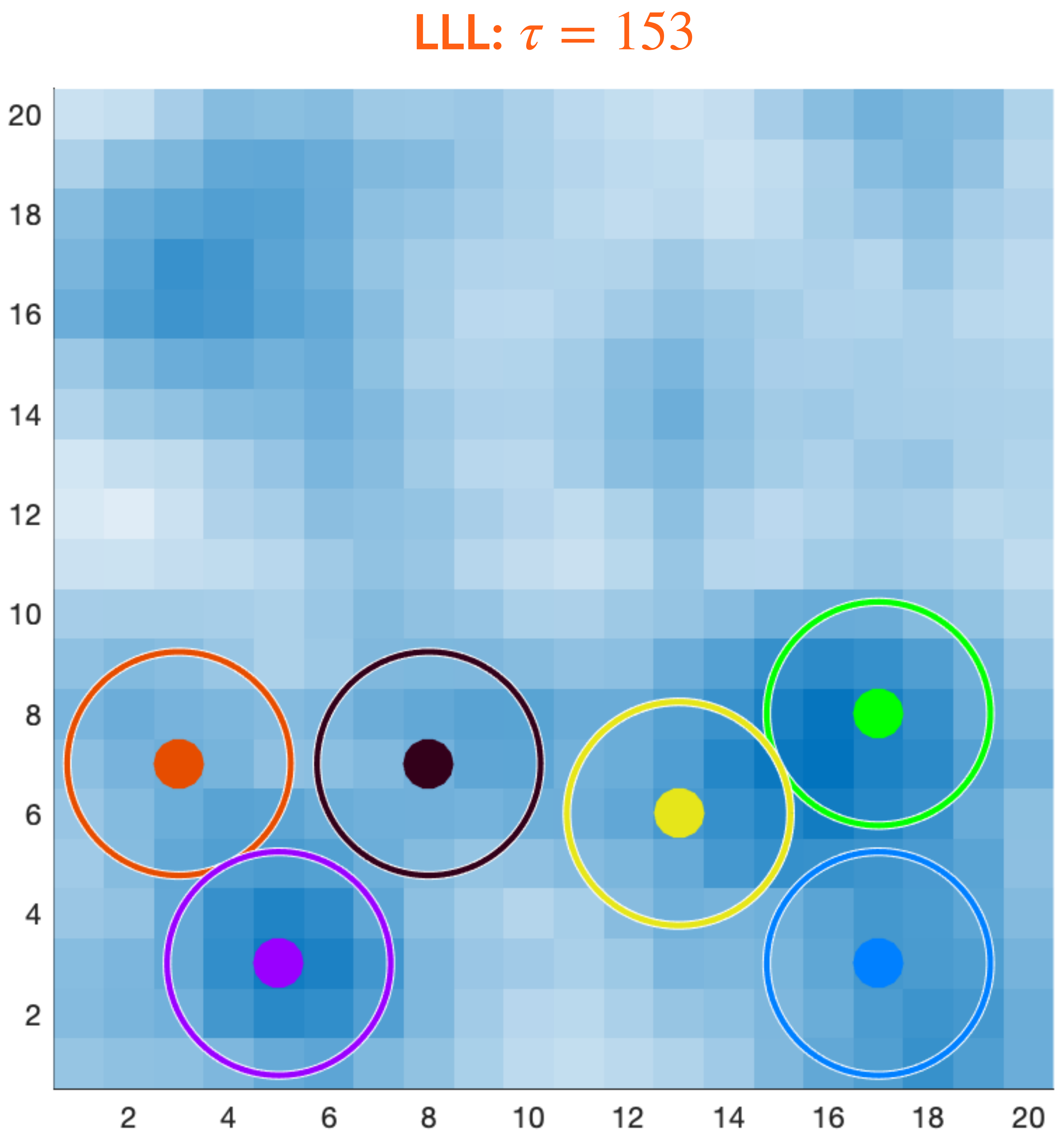

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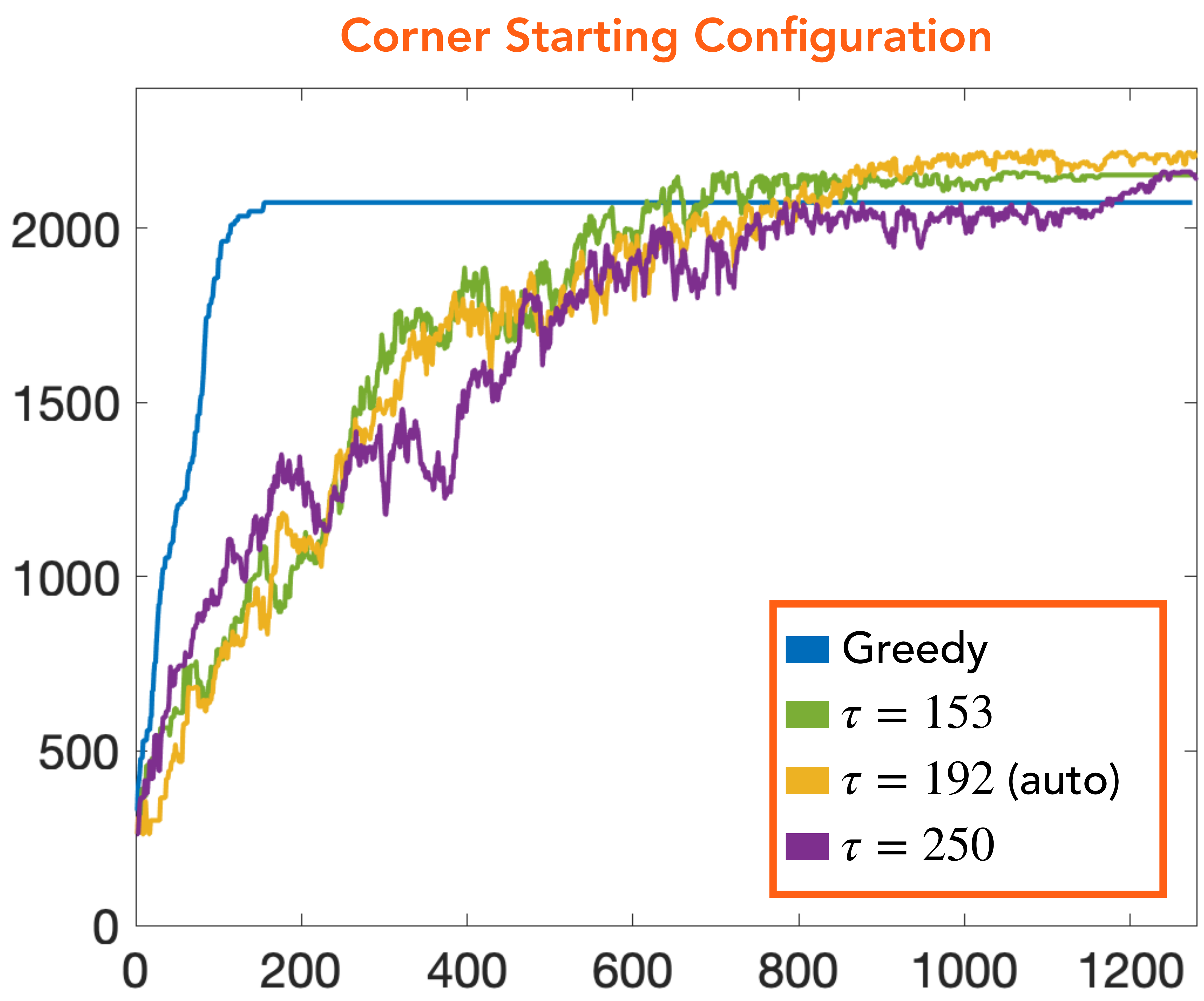

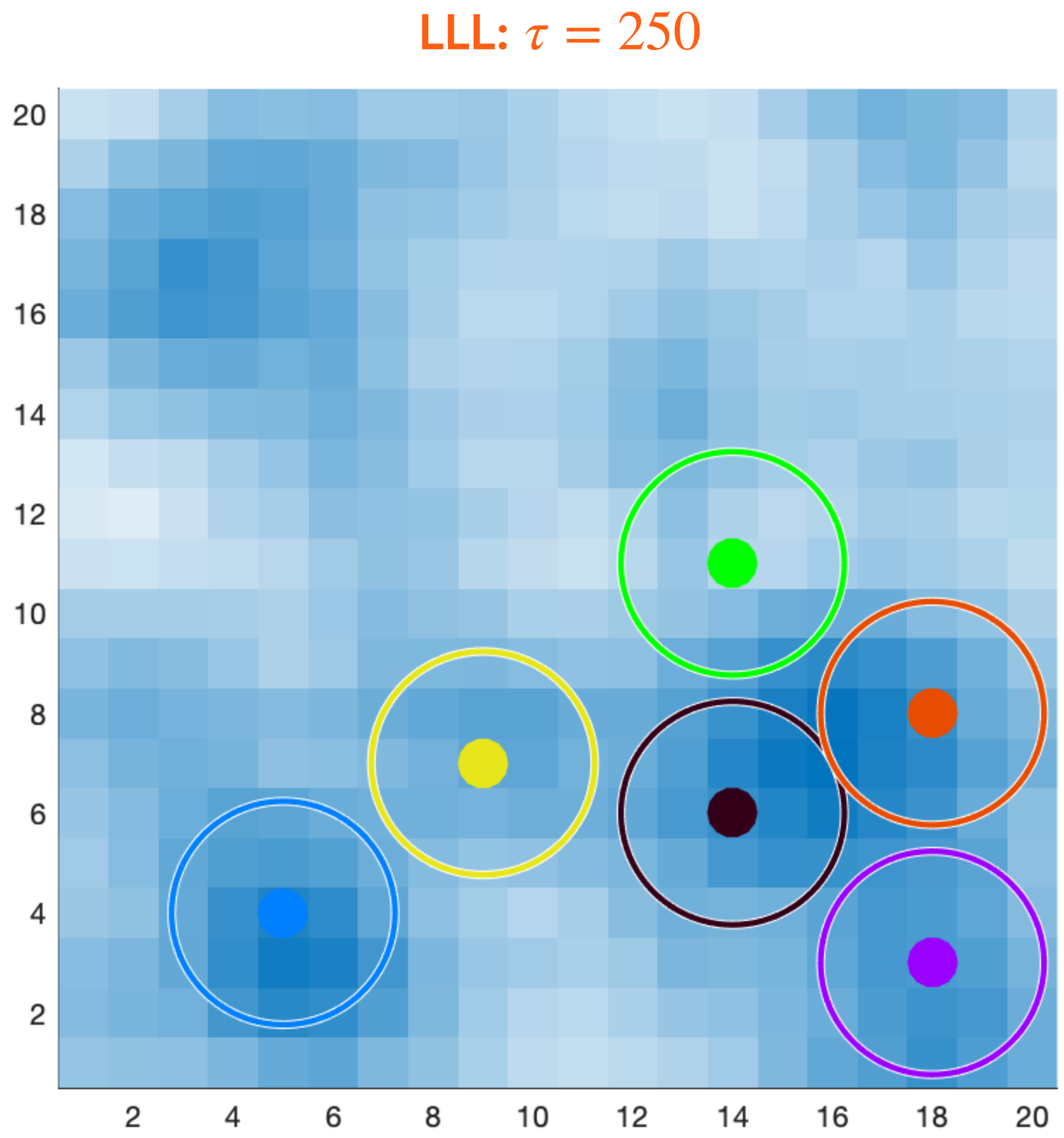

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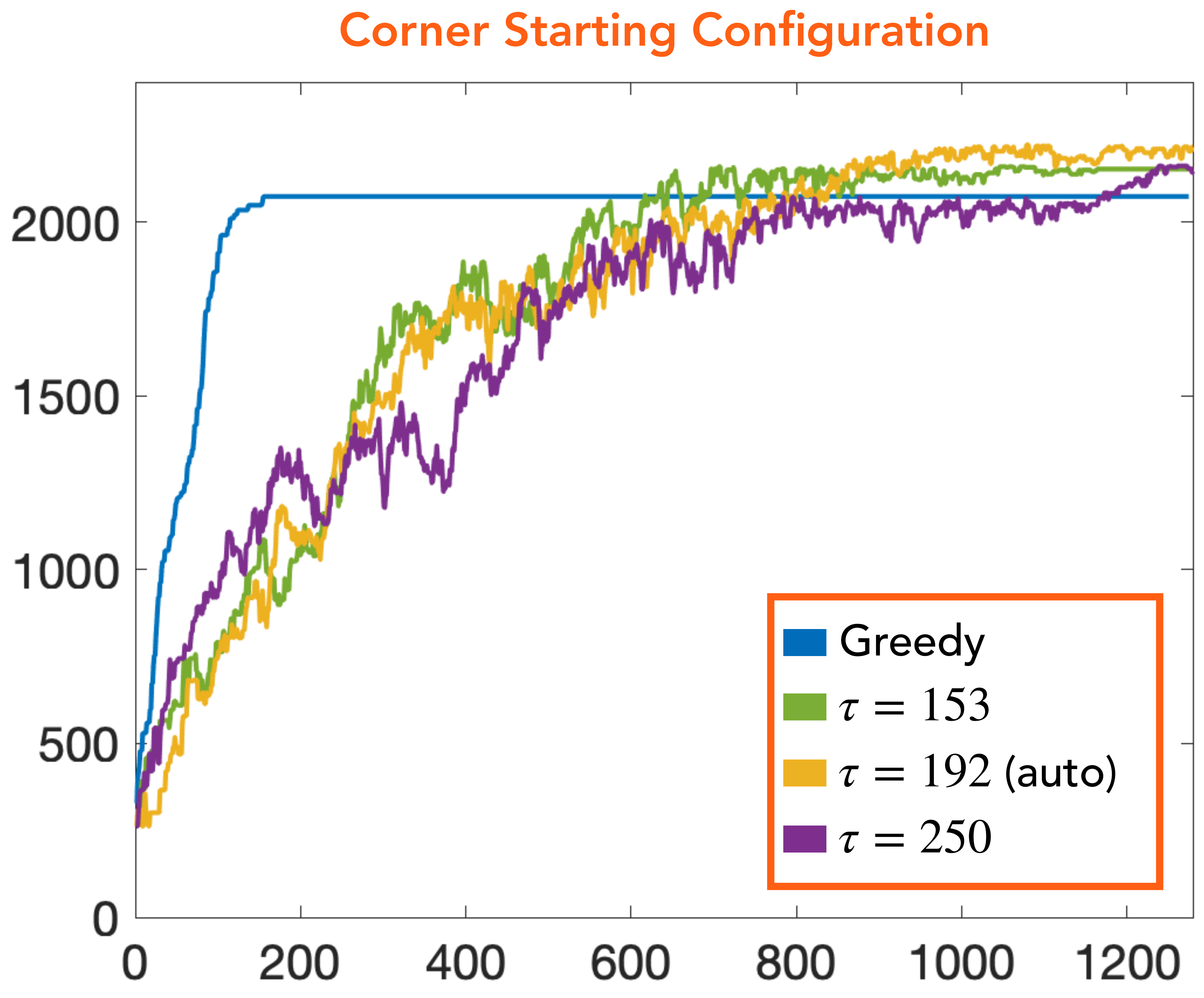

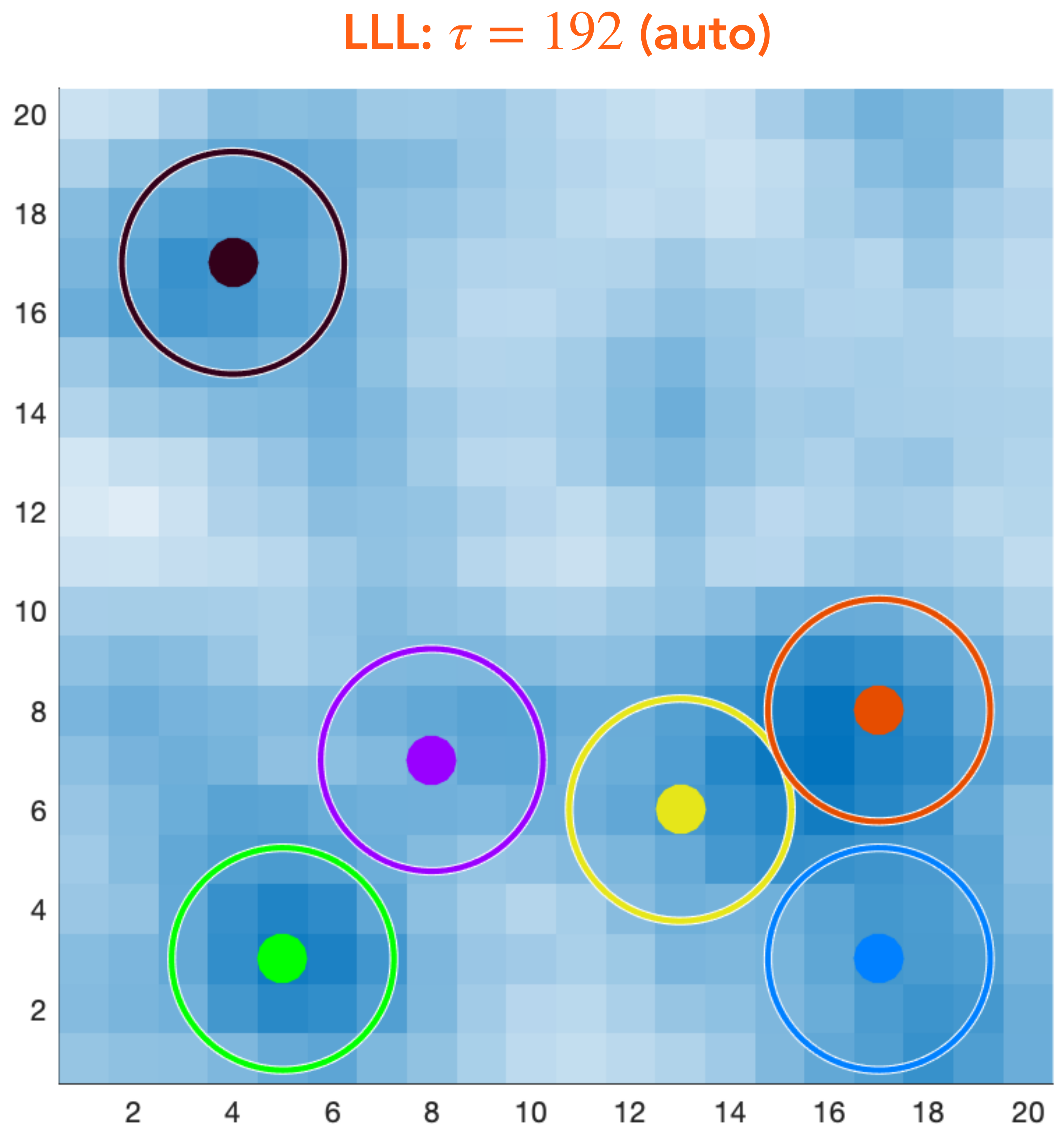

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Summary

- Simulated multi-agent coverage system
- Implemented and compared greedy, log-linear learning, and automatic τ generation algorithms
- Demonstrated that LLL with automatic τ generation has the best performance

Future Work

- Test algorithms on maps with different characteristics
- Additional starting configurations
- Analyze effect of other variables on utility
  - Sensing radius, movement radius, number of agents, distance from other agents, and adding obstacles, limited communication
  - Take into account for τ generation
- Verify algorithms on physical multi-drone systems

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