

HIGH PERFORMANT SMART COMPUTATIONS FOR GRAPH ANALYSIS

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AGENDA

- Community Detection
- Communities with Deep Q-learning
- ForceAtlas
- Barnes-Hut Tree with RNN

COMMUNITY DETECTION

COMMUNITY DETECTION

- Used to reveal groups in real world data
- Louvain method
- Parallel heuristics

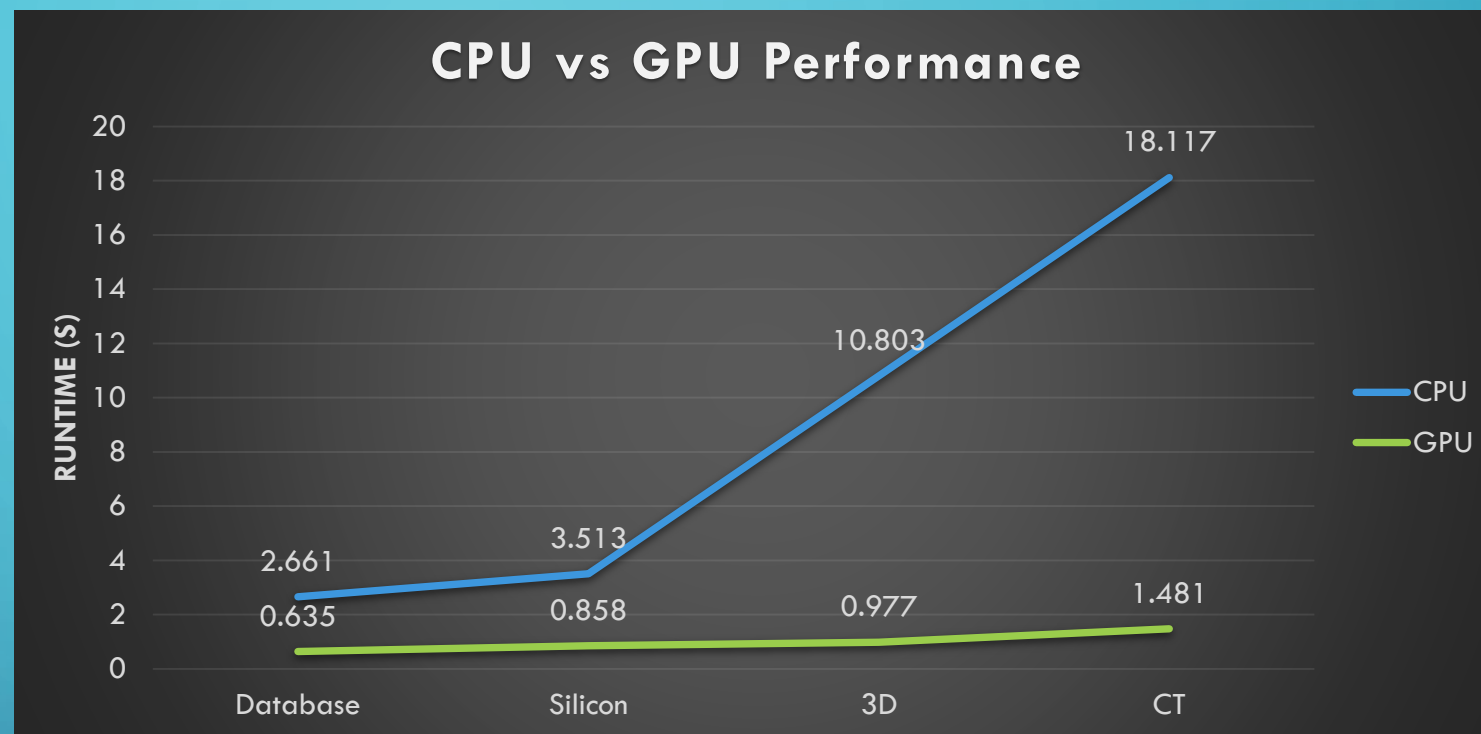
LOUVAIN METHOD

- Multi-phase, iterative, greedy algorithm
- Monotonically increasing modularity
- Inherently sequential

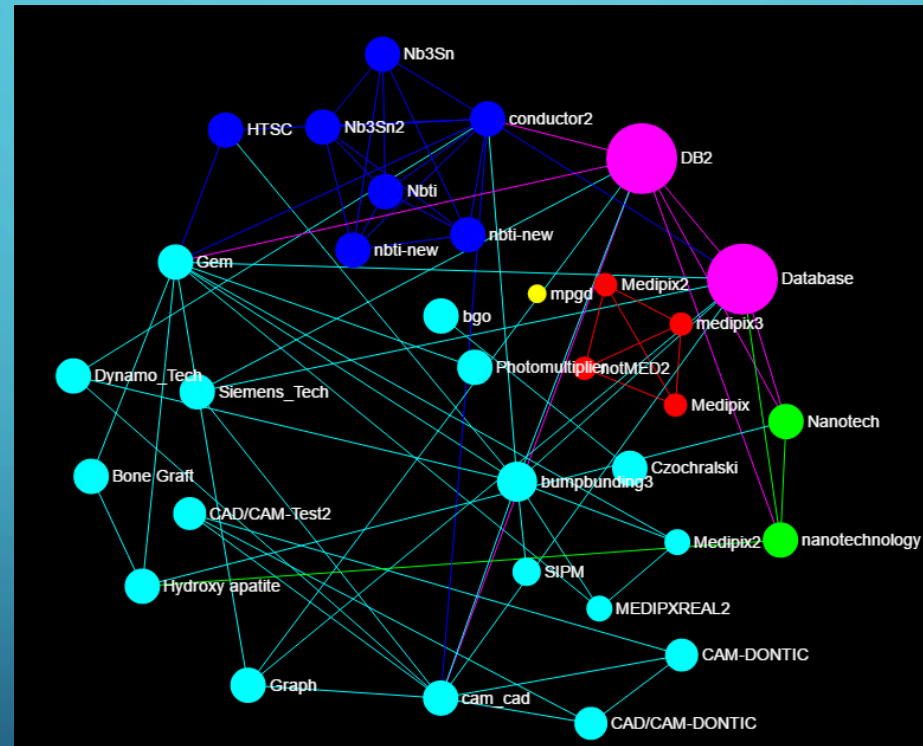
RESULTS

(COMMUNITY DETECTION)

- Database: 4x
- Silicon: 4x
- 3D: 11x
- CT: 12x



	Database	Silicon	3D	CT
Nodes	17832	24923	35763	53039
Edges	113622	185594	192336	325490



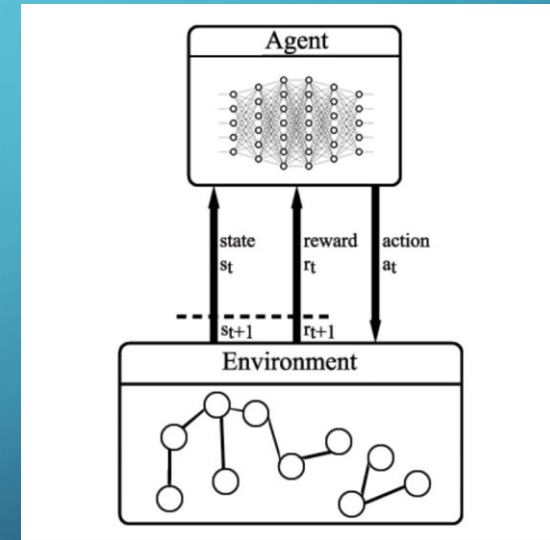
The background is a blue gradient with decorative white circuit-like lines in the corners. The title is centered in white text.

COMMUNITIES WITH DEEP Q-LEARNING

COMMUNITIES WITH DEEP Q-LEARNING

Reinforcement learning problem:

- Interactions between the environment and agent
 - Action-reward
- Goal is to maximize the reward, find appropriate π policy
- Finite action space in every timestep



COMMUNITIES WITH DEEP Q-LEARNING

Extensions for deep Q-learning:

1. Calculate Q for all possible actions in state s_t ,
2. Make prediction for Q in s_{t+1} , get action $a_{t+1} = \max_a a \in A(s_{t+1})$,
3. $Q[a] = r + \gamma Q(s_{t+1}, a_{t+1})$,
4. Update the network

Current limitations:

- Maximum 4 neighbors are explored

Processing:

- Training data contains graphs with various size and structure.
- The environment computes the real Louvain modularity to get the next community. Reward for correct prediction 10000, for wrong -1000
- The agent makes a prediction for every node

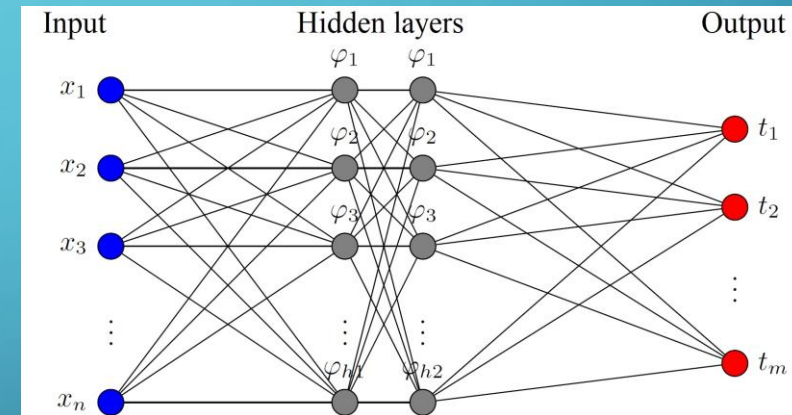
COMMUNITIES WITH DEEP Q-LEARNING

The agent:

- n : input size
- $h1$: size of hidden layer 1
- $h2$: size of hidden layer 2
- m : size of the action space
- Input size is $\text{state_size} * \text{action_size}$
- $h1 = h2 = 128$
- $m = 4$

To prevent overfitting:

- 50% dropout on both hidden layers
- Multiple independent representation



83% precision with early model after 70 epochs

The background is a blue gradient with decorative white circuit-like lines in the corners. These lines consist of straight segments and small circles, resembling a stylized electronic circuit or data paths.

FORCEATLAS

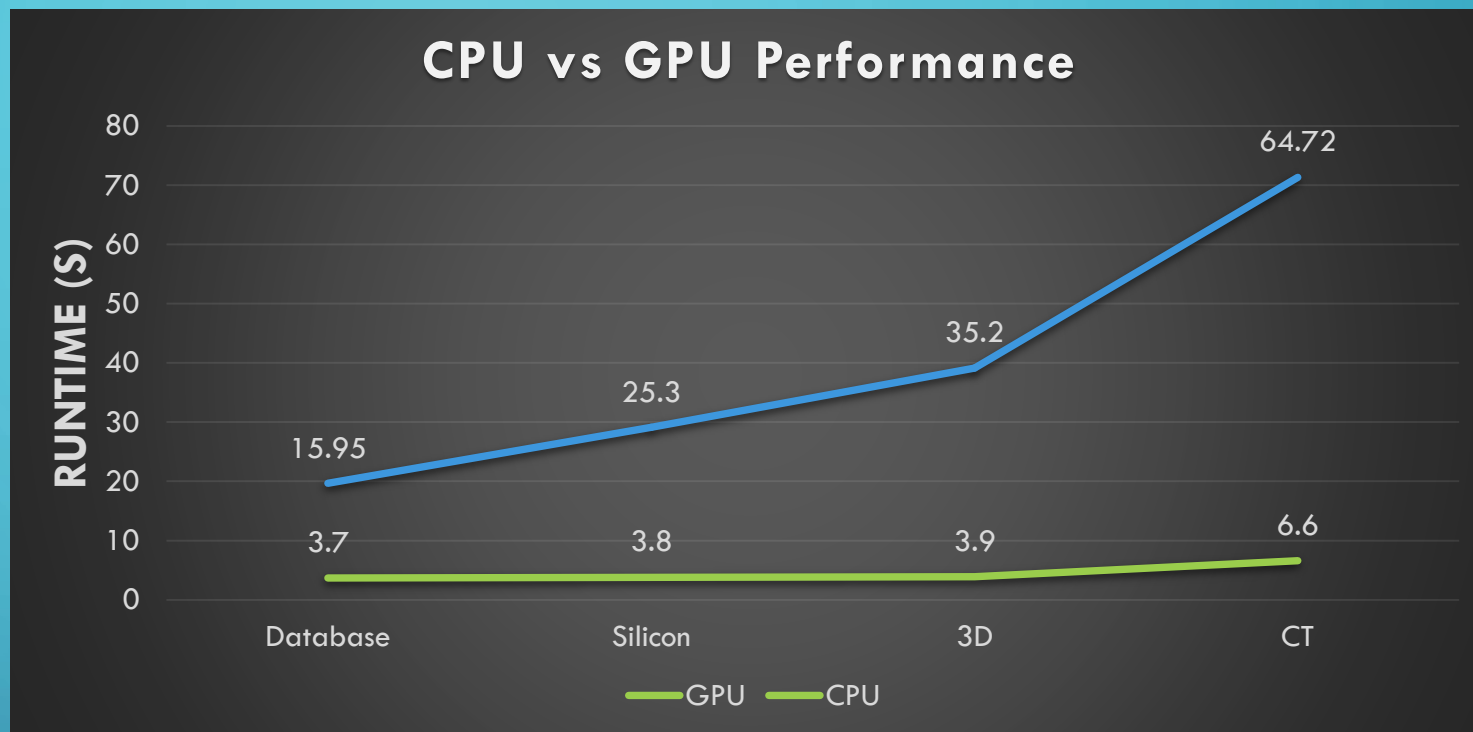
FORCEATLAS

- Force-directed layout based on n-body simulation
- Repulsion-attraction
- Makes visual interpretation easier
- Result depends on starting state

RESULTS

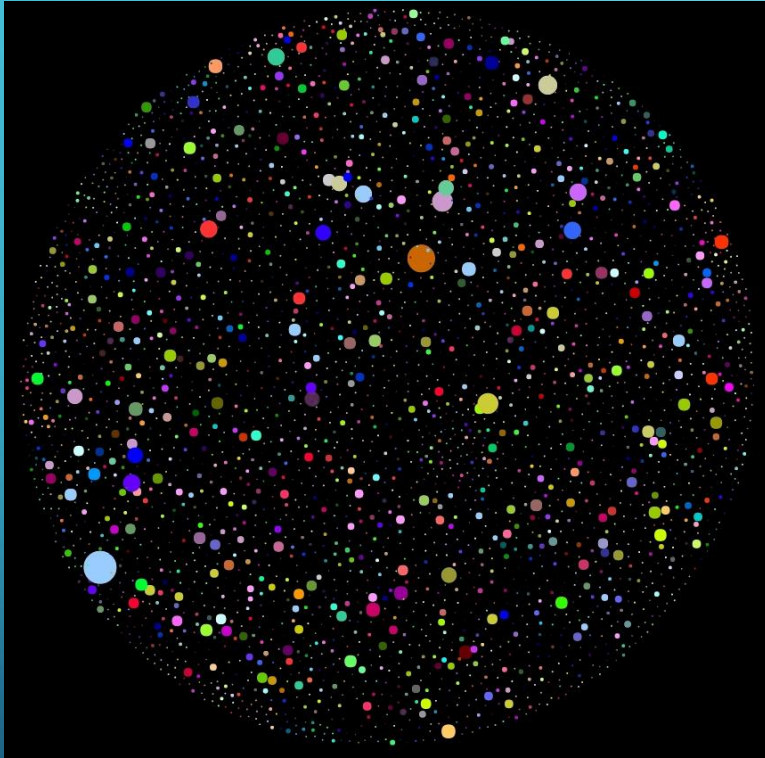
(FORCEATLAS)

- Database: 4,31x
- Silicon: 6,65x
- 3D: 9x
- CT: 9,8x

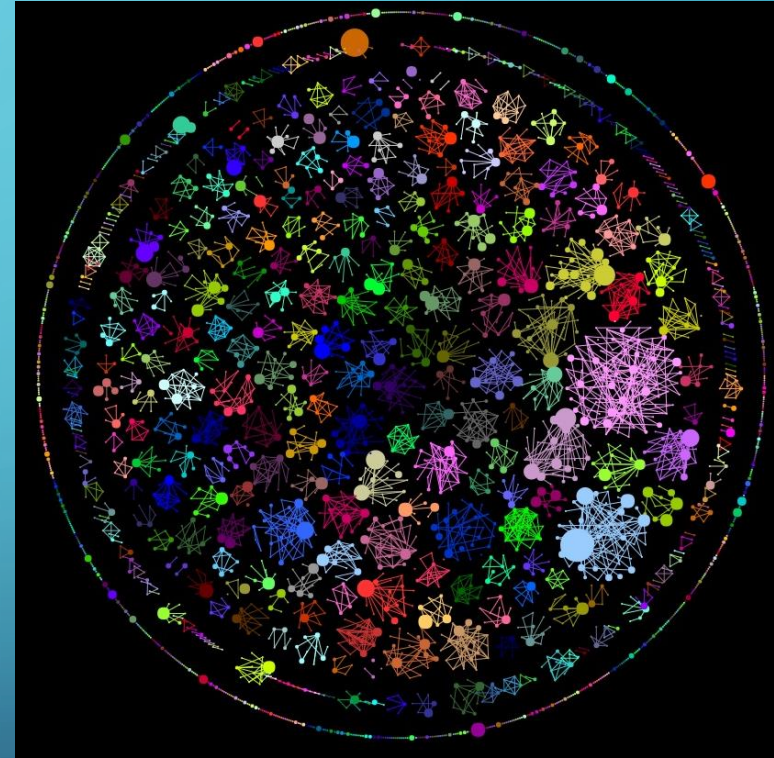


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FORCEATLAS LAYOUT TYPES



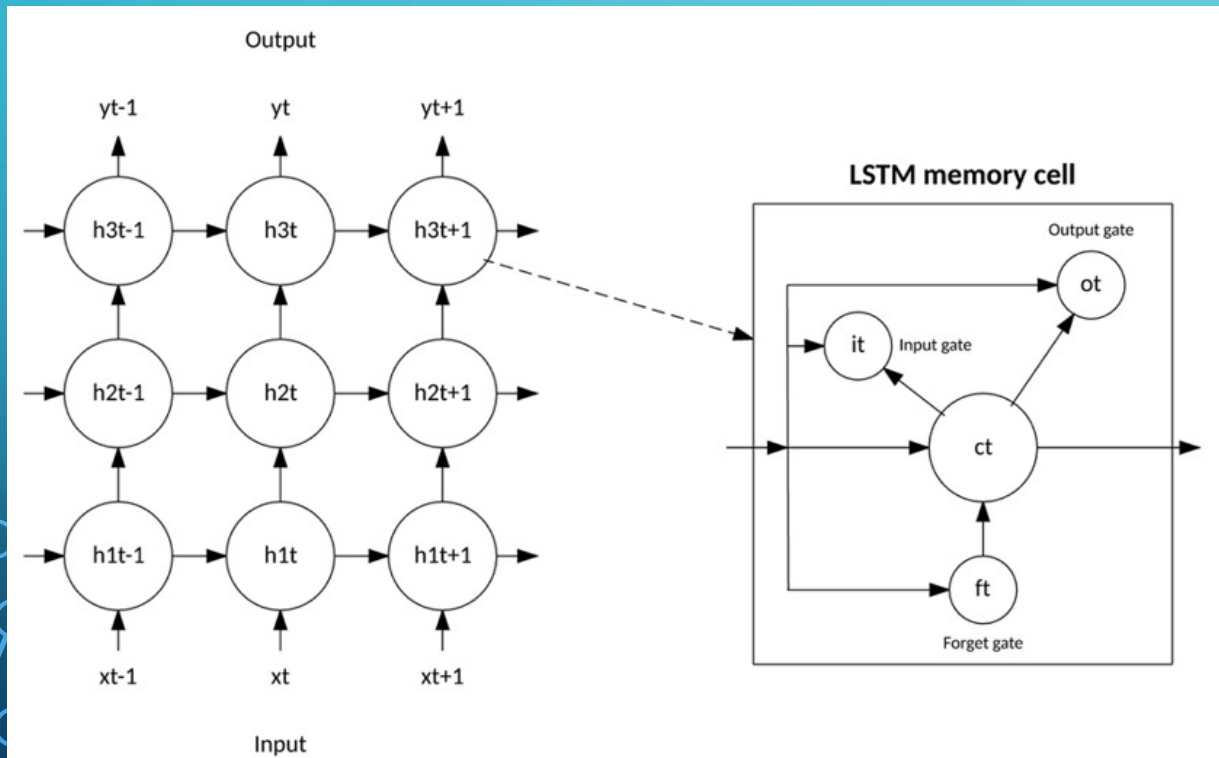
Original layout



Community based layout

BARNES-HUT TREE WITH RNN

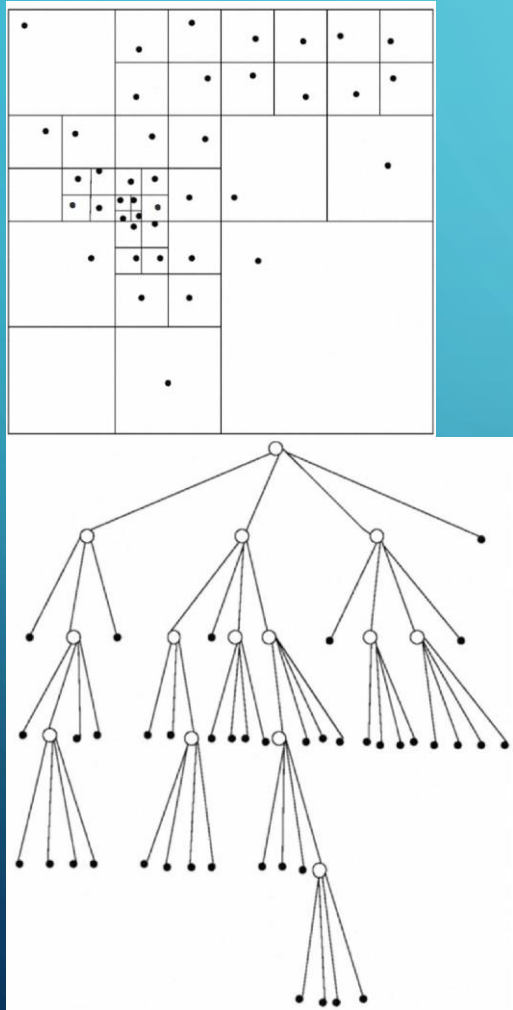
BARNES-HUT TREE WITH RNN



$$h_t = \phi(Wx_t + Uh_{t-1})$$

- h_t : hidden state in timestep t
- x_t : input in timestep t
- h_{t-1} : hidden state in timestep $t-1$
- U : transformation matrix
- Φ : activation function(logistic sigmoid, tanh)

BARNES-HUT TREE WITH RNN



- Generation provides a quadratic tree
- Plane is halved until only 1 node remains in a region.
- For RNN system is provided as a time series

BARNES-HUT TREE WITH RNN

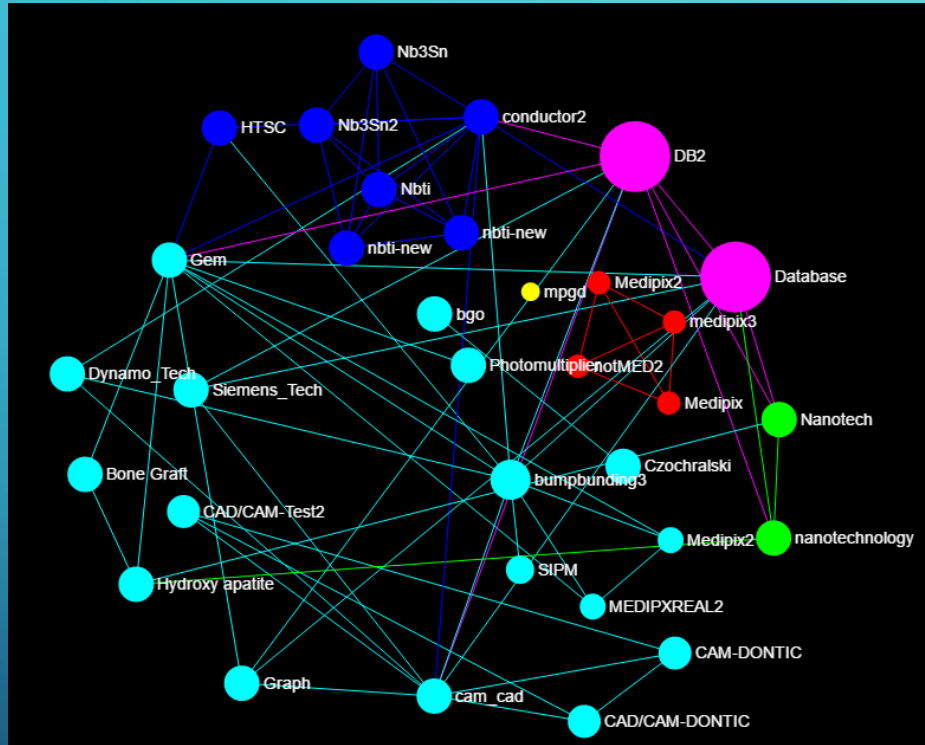
$t, x, y, \text{old_n_1}, \text{old_n_2}, \text{old_n_3}, \dots, \text{old_n_N}, \text{new_n_1}, \text{new_n_2}, \dots, \text{new_n_N}$

- t : timestep
- x, y : coordinates of node in timestep t
- old_n_N : state generated in timestep $t-1$ (initially -1)
- new_n_N : state generated in timestep t (no -1 at the end)
- N : number of nodes
- Model trained for graphs with 1000 nodes: 94% accuracy.

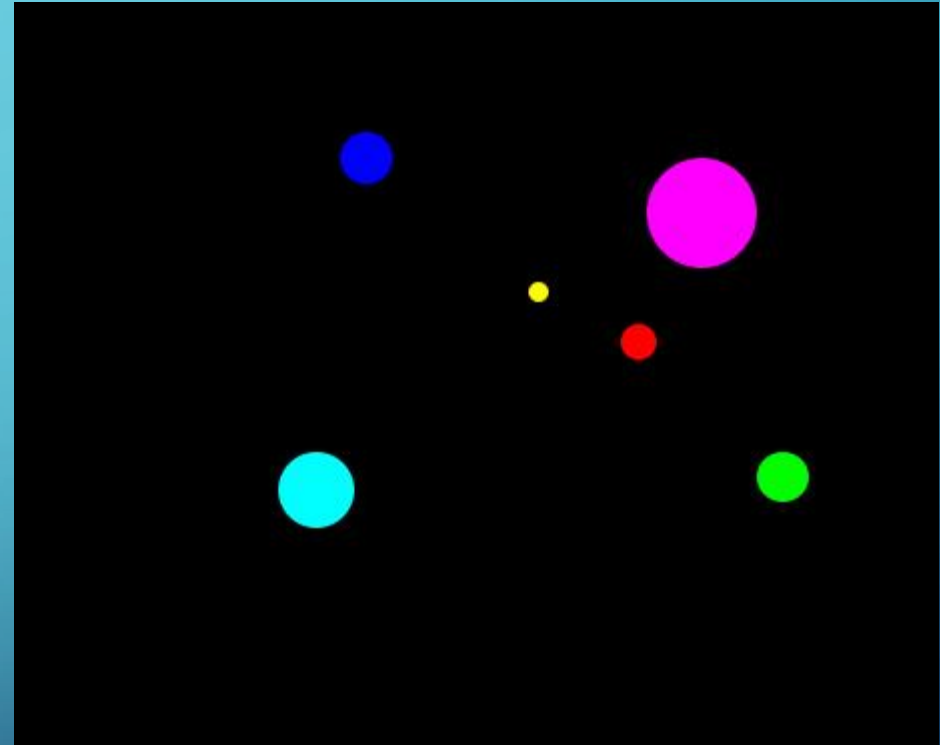
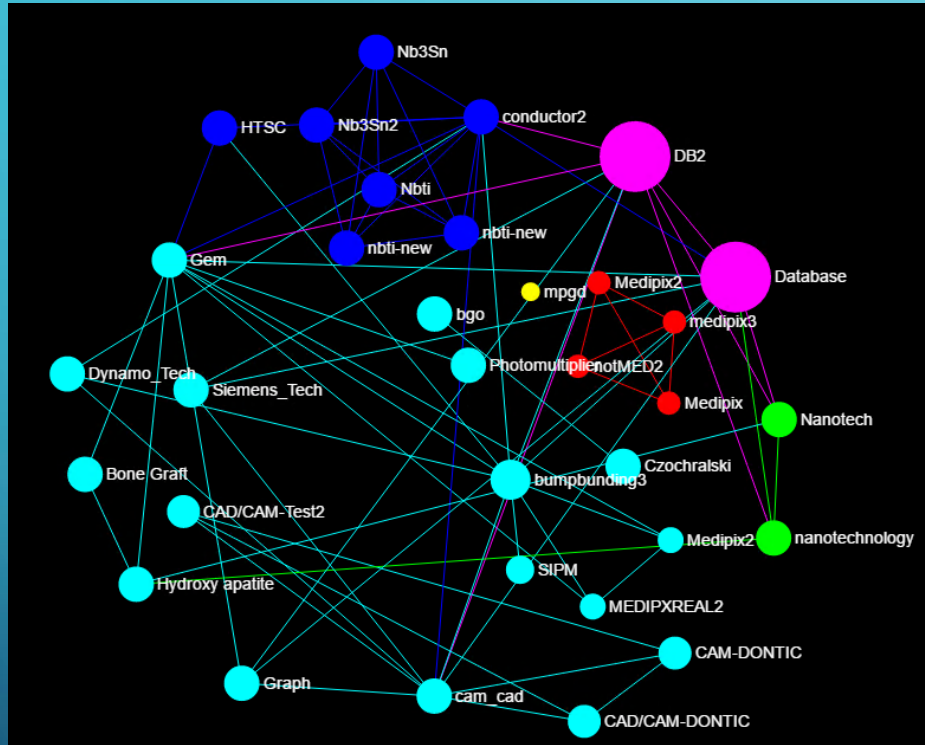
BARNES-HUT TREE WITH RNN

How to use this approach to increase the visual experience?

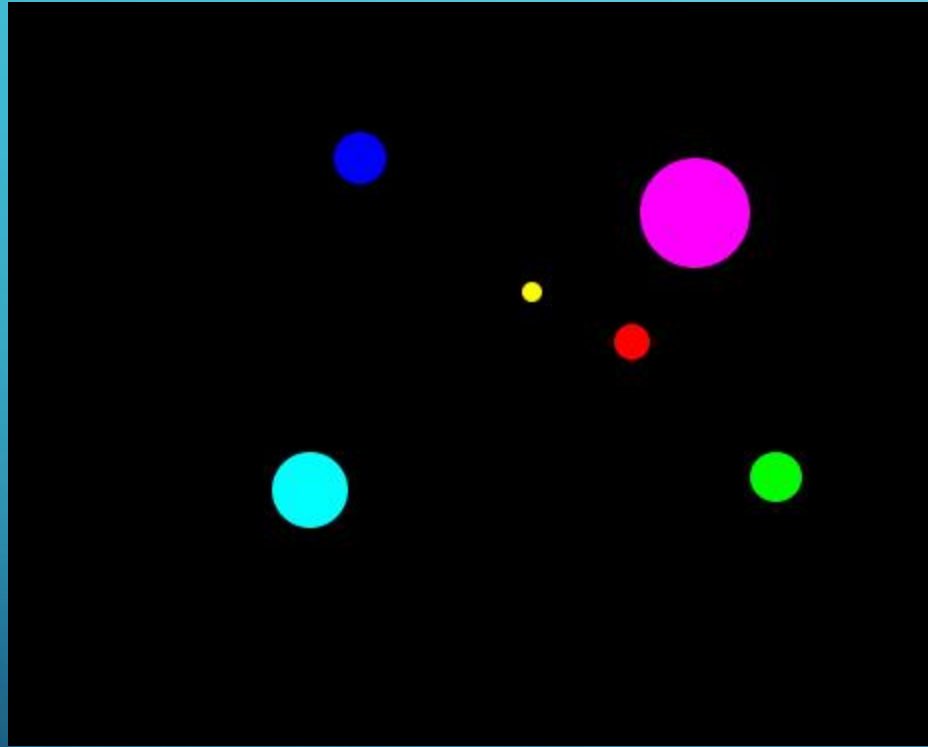
BARNES-HUT TREE WITH RNN



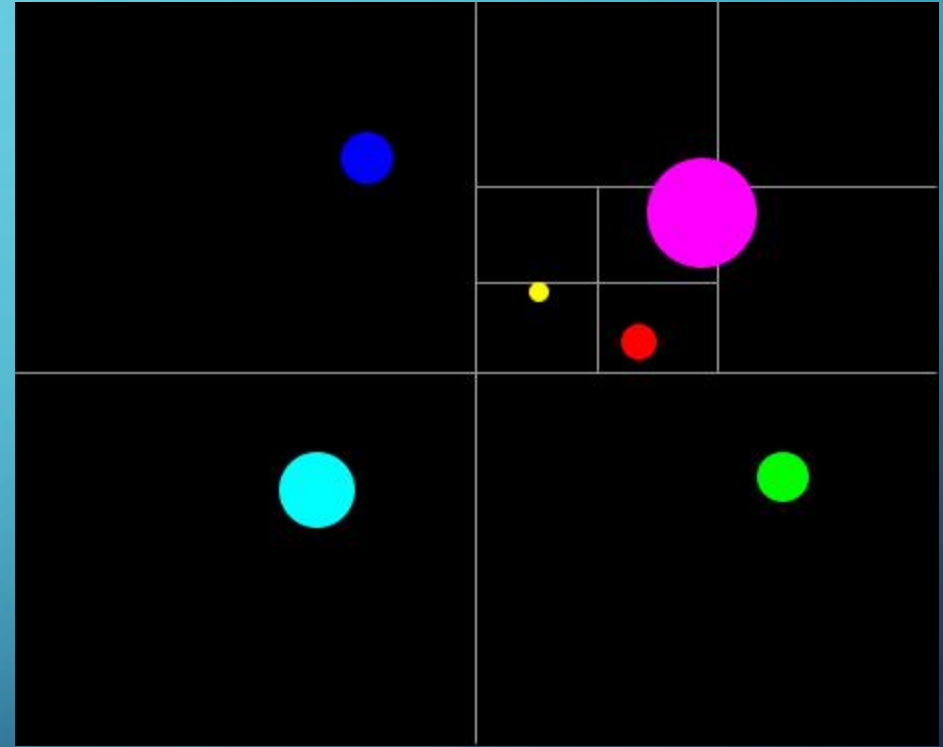
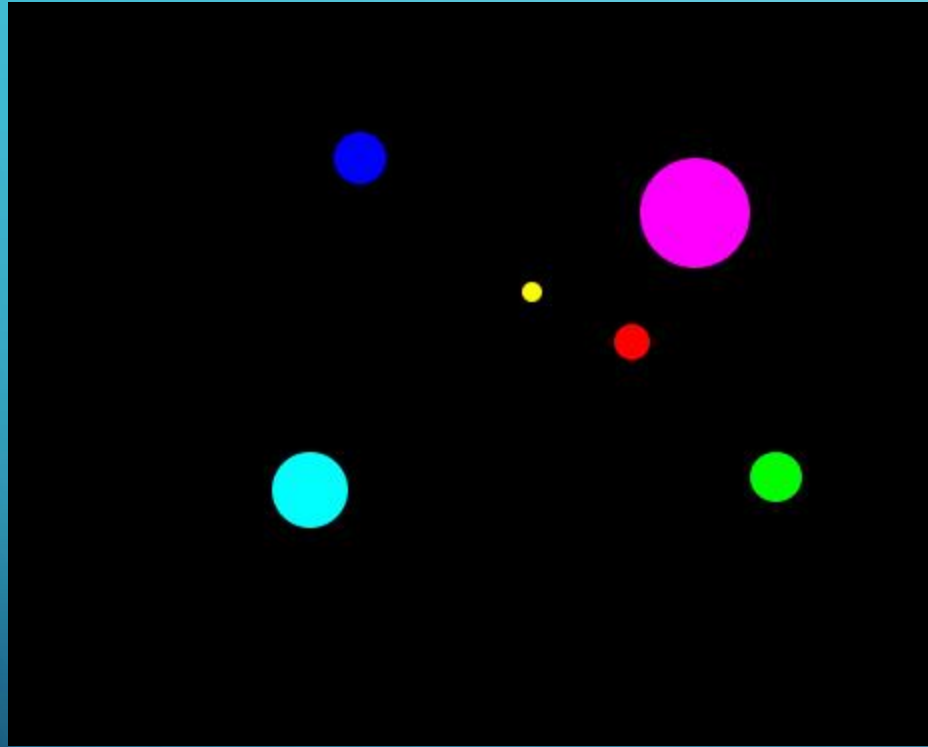
BARNES-HUT TREE WITH RNN



BARNES-HUT TREE WITH RNN

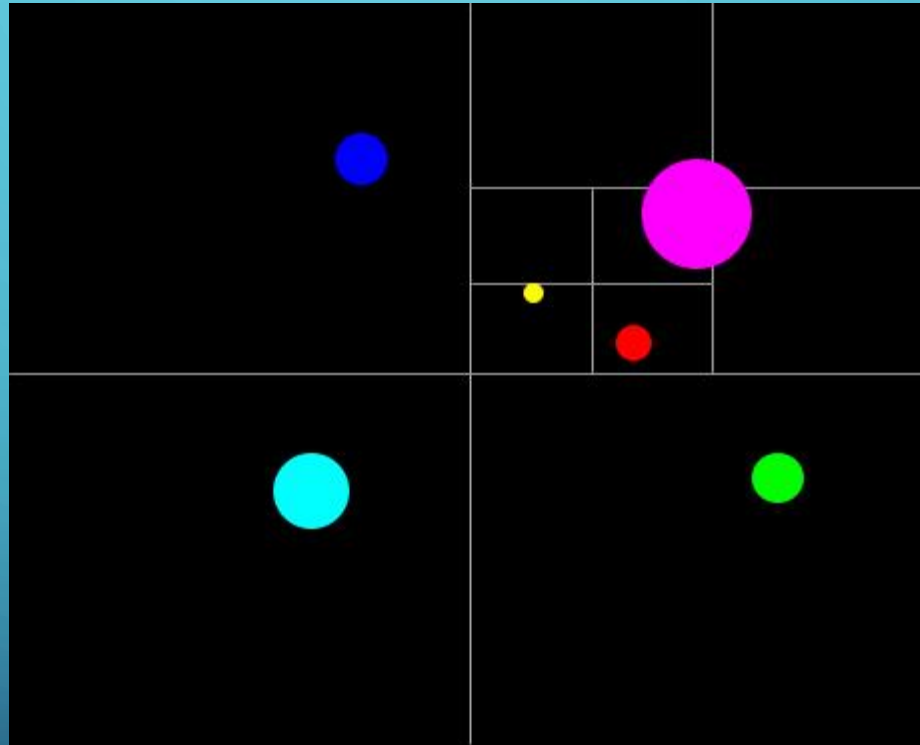


BARNES-HUT TREE WITH RNN



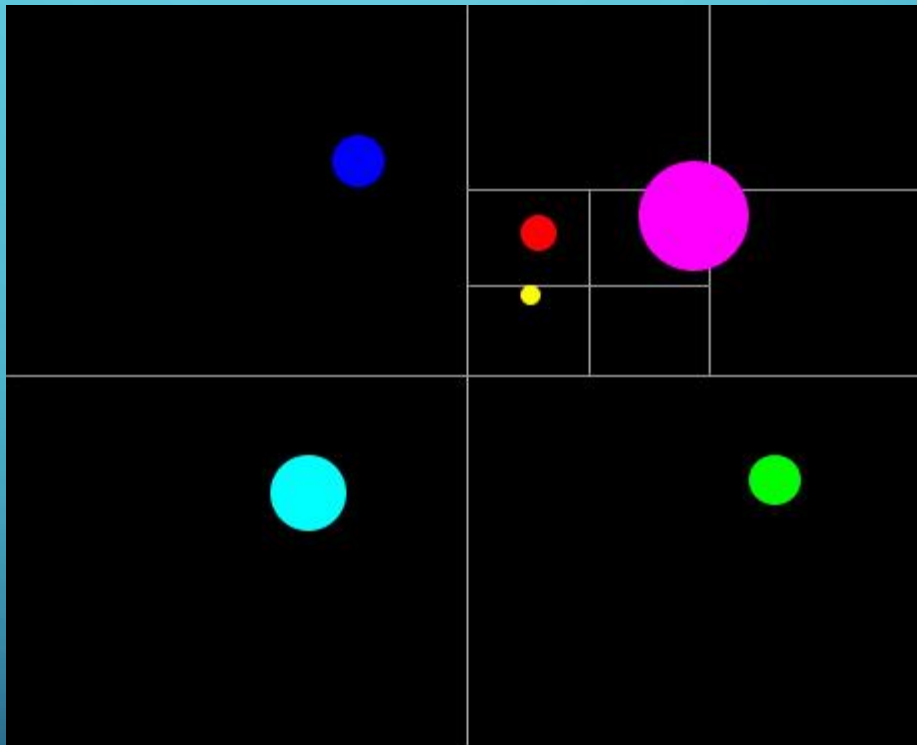
BARNES-HUT TREE WITH RNN

- We would like to analyse Medipix (red node)
- This time the top right corner is the hot zone



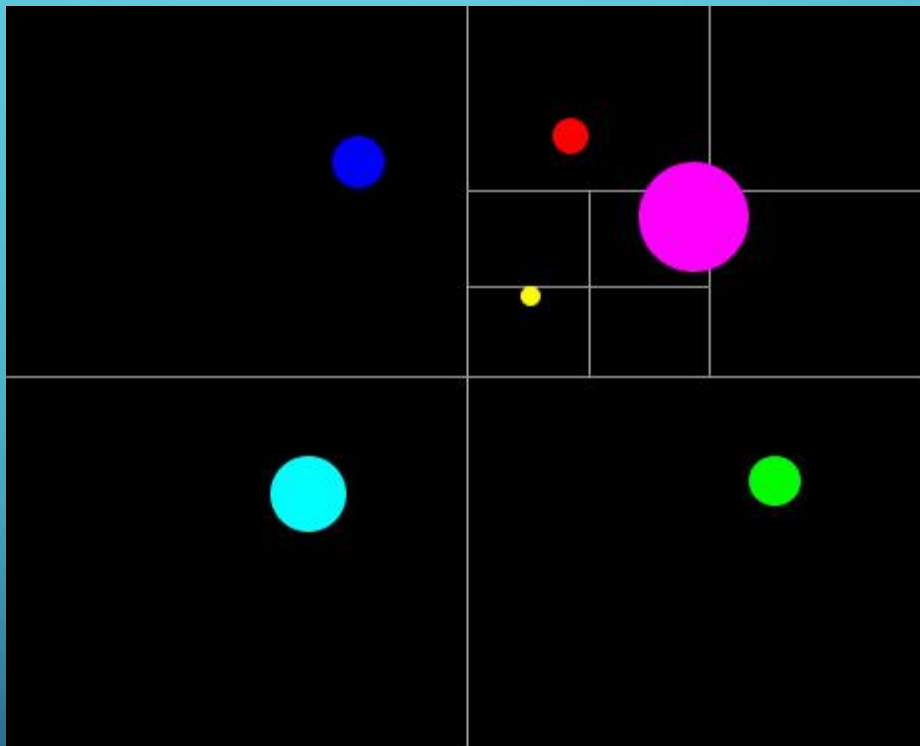
BARNES-HUT TREE WITH RNN

We move the red node,
recompute the tree and store
the state for future training



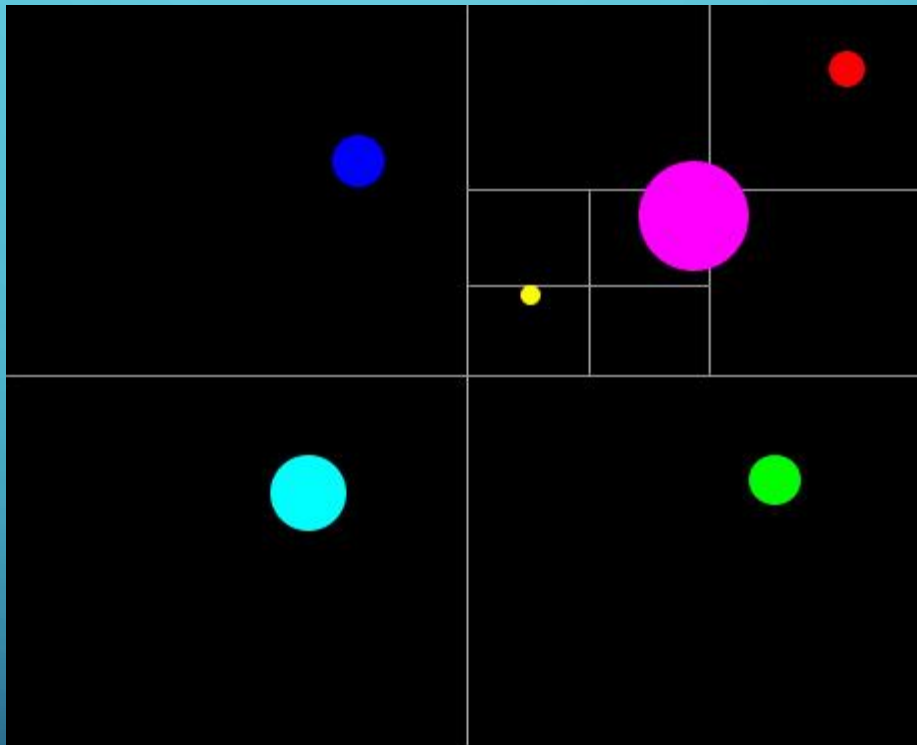
BARNES-HUT TREE WITH RNN

Red node advancing



BARNES-HUT TREE WITH RNN

Red node advancing to final position

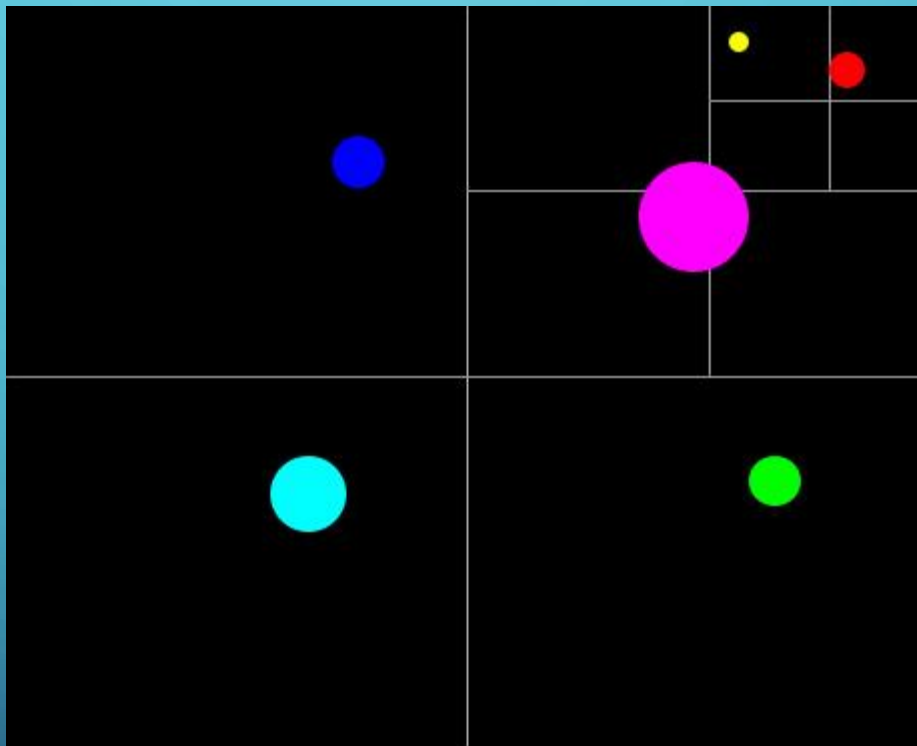


BARNES-HUT TREE WITH RNN

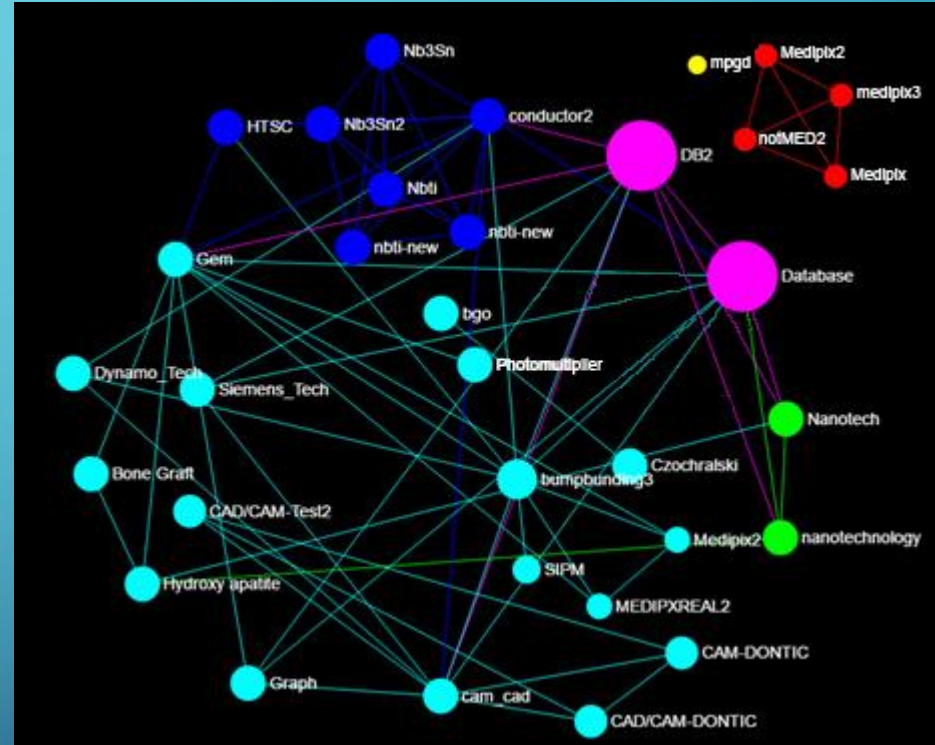
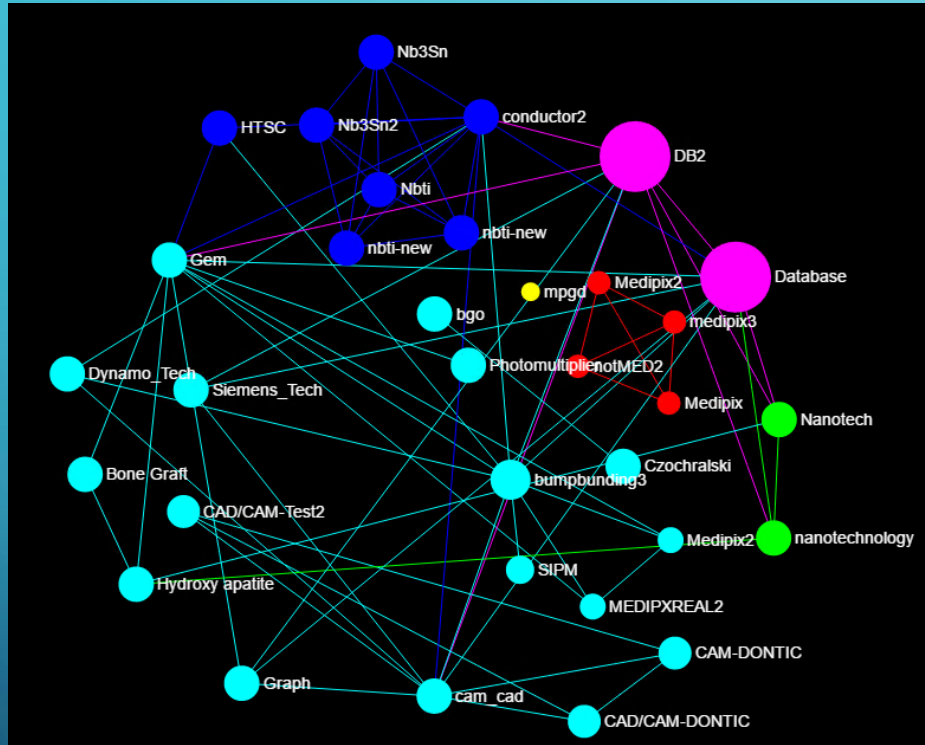
- States stored for one node (Medipix)
- Train a model for Medipix
- The model will move the node through the regions

BARNES-HUT TREE WITH RNN

Graph preprocessed based
on Medipix (red) and mpgd
(yellow)



BARNES-HUT TREE WITH RNN



A decorative graphic on the left side of the slide, consisting of a network of white lines and small circles on a blue gradient background, resembling a circuit board or a neural network.

THANK YOU