QUAD-TREE GENERATION WITH RNN FOR EFFICIENT GRAPH VISUALIZATION

RICHARD FORSTER

AGENDA

- Graph generation
- Community Detection
- ForceAtlas
- Barnes-Hut Tree with RNN
- Future work

GRAPH GENERATION

GRAPH GENERATION

- This is a process required for every single graph by any user
- First, database returned data needs to be transformed
- Have to generate:
  - Collaborations
  - Nodes
  - Edges

GRAPH GENERATION

	Silicon	Database	3D	CT
Collaborations	33,45	13,85	18,64	12,65
Nodes	0,69	0,65	2,48	0,38
Edges	1,48	1,87	0,71	0,69

Computation time for specific parts of the graph generation in seconds

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

COMMUNITY DETECTION

COMMUNITY DETECTION

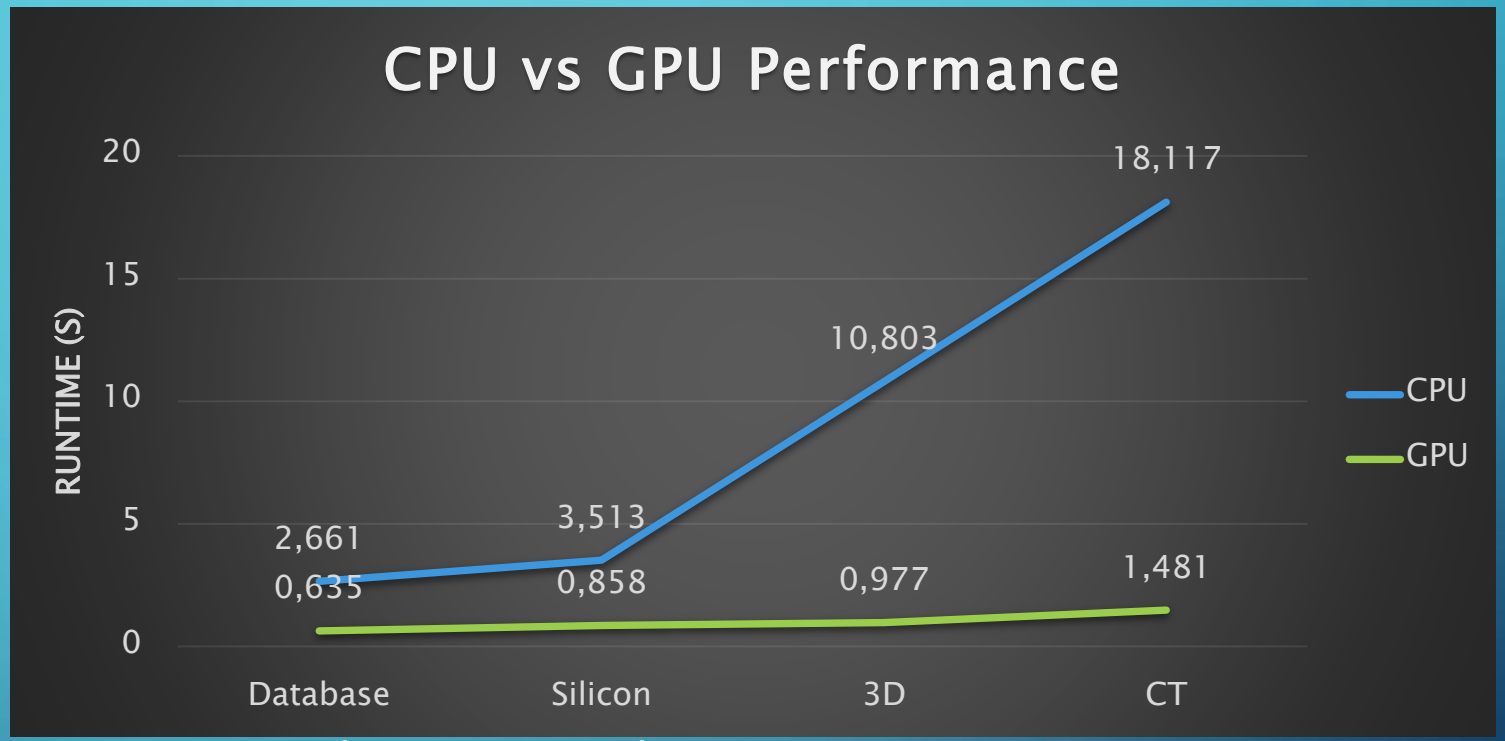
- Used to reveal groups in real world data
- Louvain method
- Parallel heuristics

LOUVAIN METHOD

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

RESULTS
(COMMUNITY DETECTION)

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



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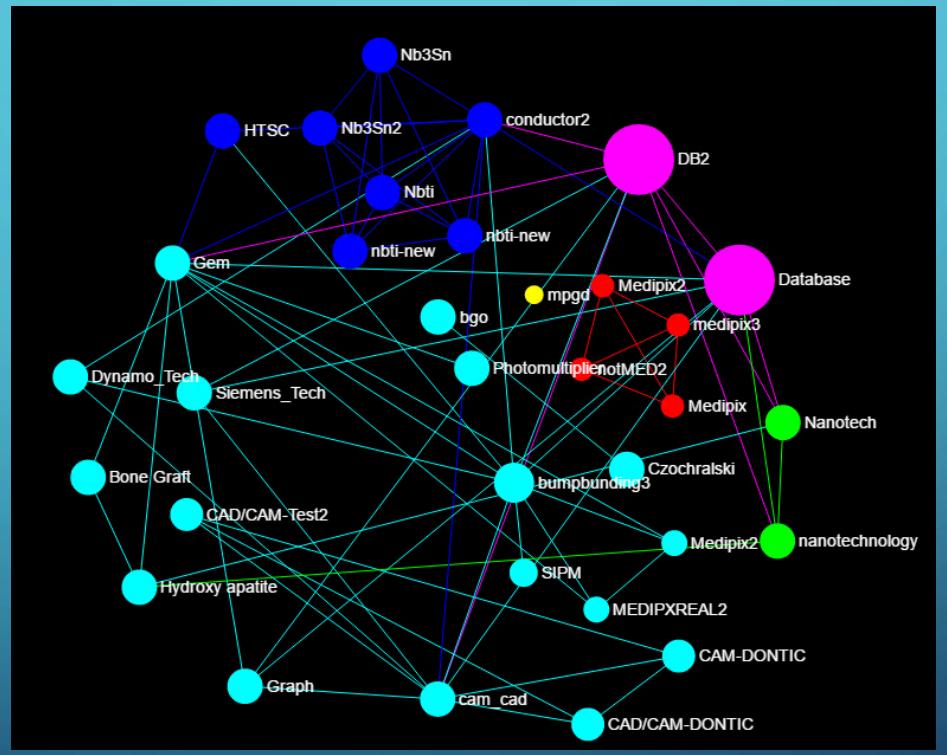

Nb3Sn
HTSC
Nb3Sn2
conductor2
DB2
Nbti
nbti-new
nbti-new
Gem
Database
mpgd
Medipix2
bgo
medipix3
Photomultiplier
notMED2
Dynamo_Tech
Siemens_Tech
Medipix
Nanotech
Bone Graft
Czochralski
bumpbunding3
CAD/CAM-Test2
Medipix2
nanotechnology
SIPM
Hydroxy apatite
MEDIPXREAL2
CAM-DONTIC
Graph
cam_cad
CAD/CAM-DONTIC

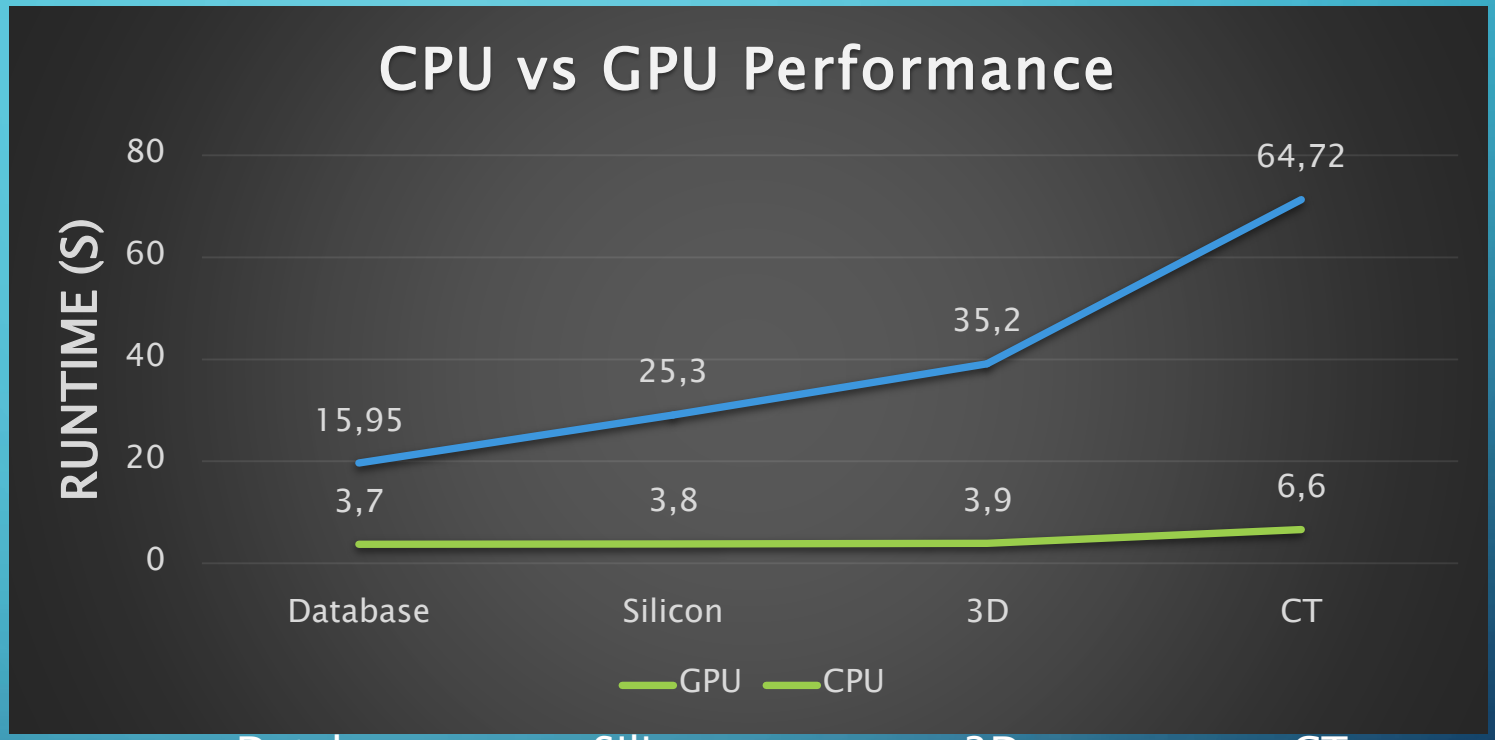
FORCEATLAS

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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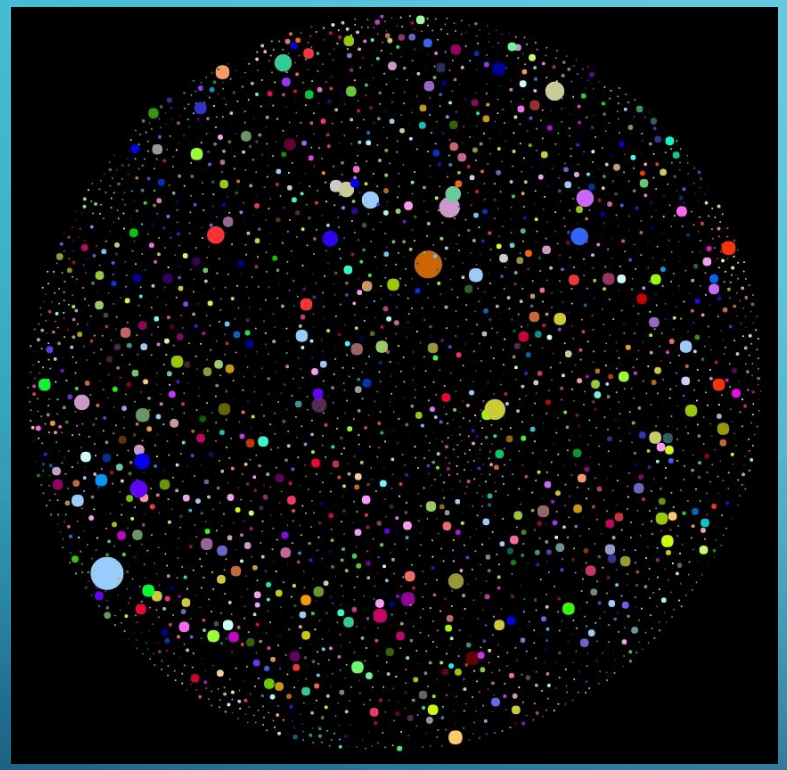
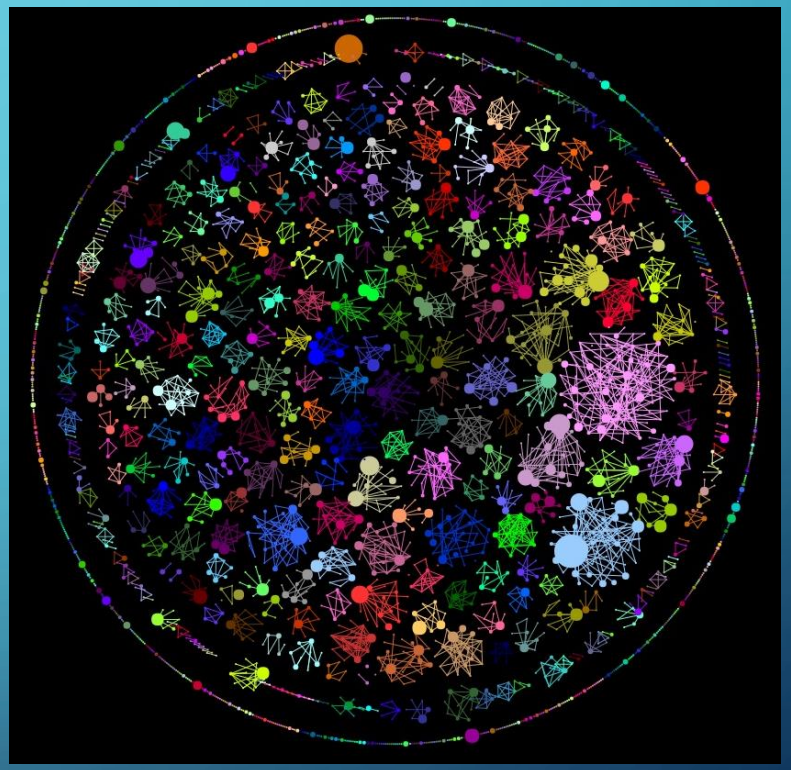
FORCEATLAS LAYOUT TYPES



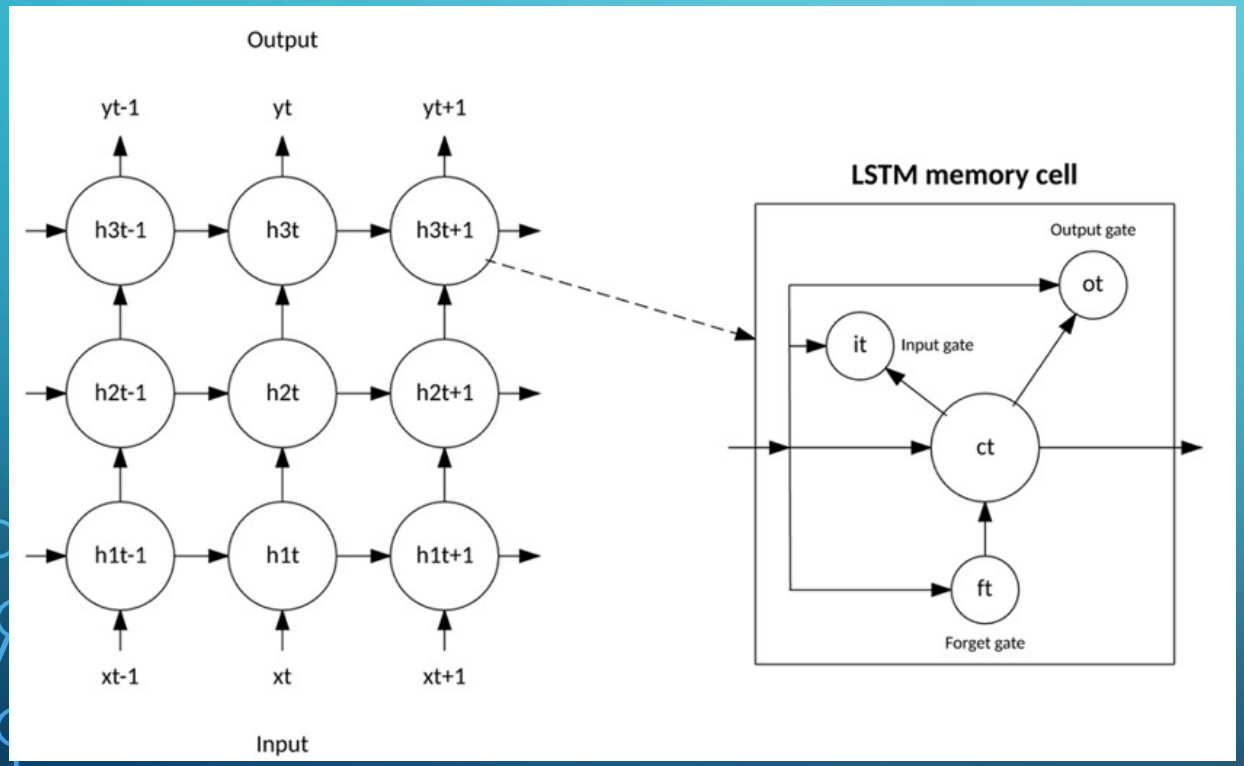
Original layout



Community based layout

BARNES-HUT TREE WITH RNN

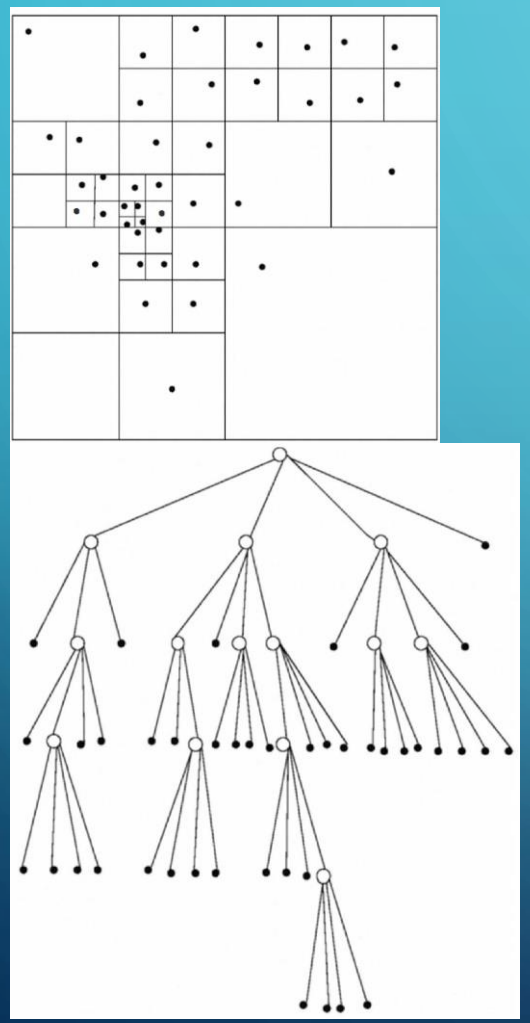
BARNES–HUT TREE WITH RNN



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

- 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

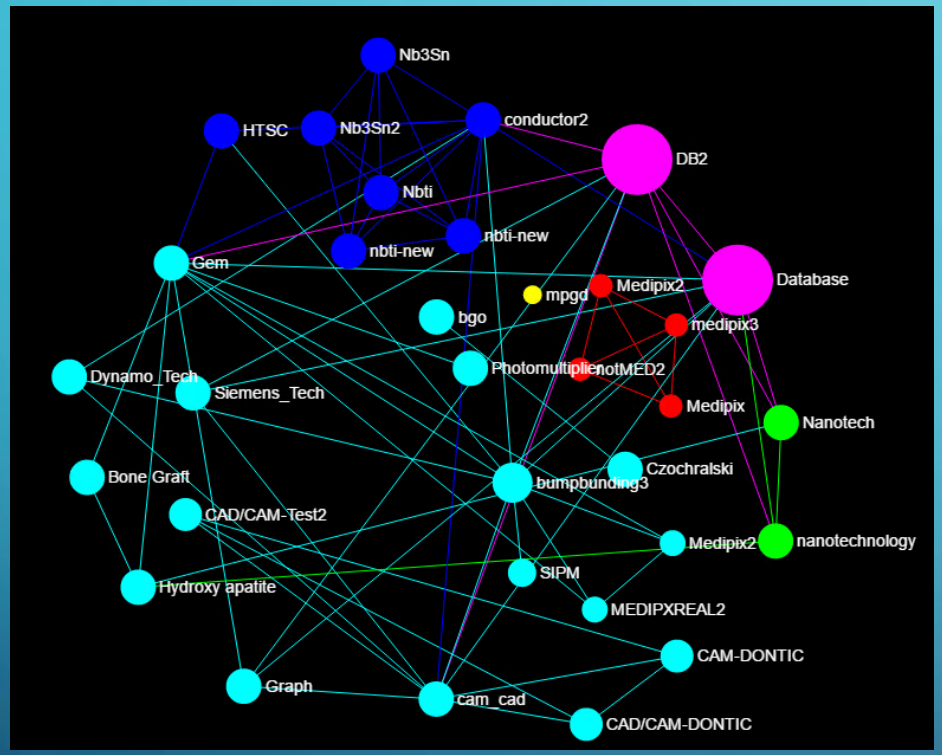
t, x, y, old_n_1, old_n_2, old_n_3, …, old_n_N, new_n_1, new_n_2, …, new_n_N

- 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



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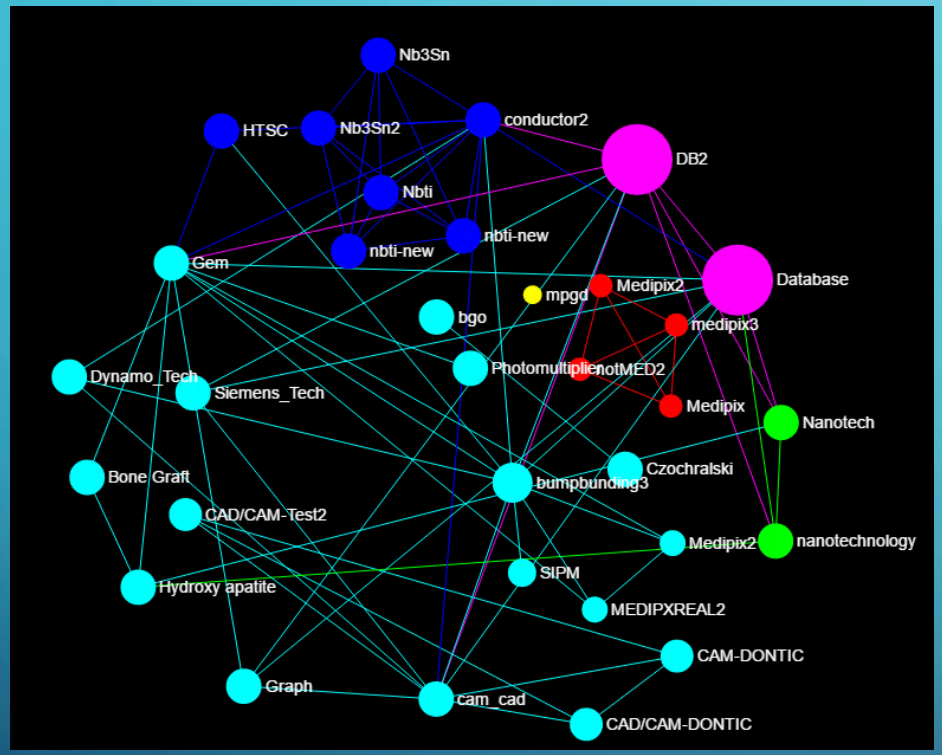
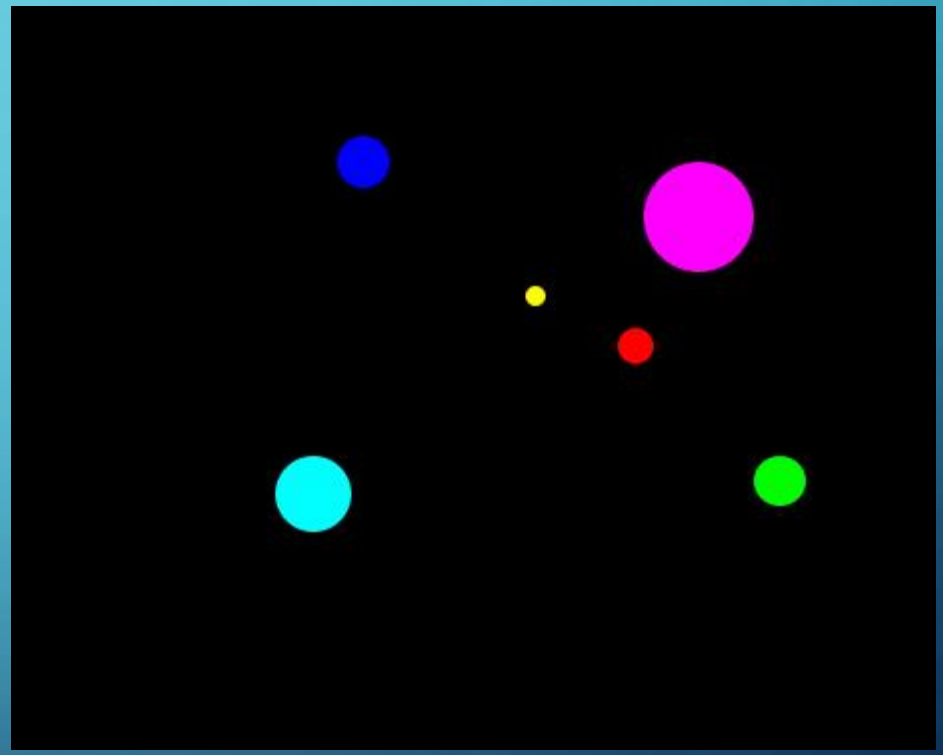
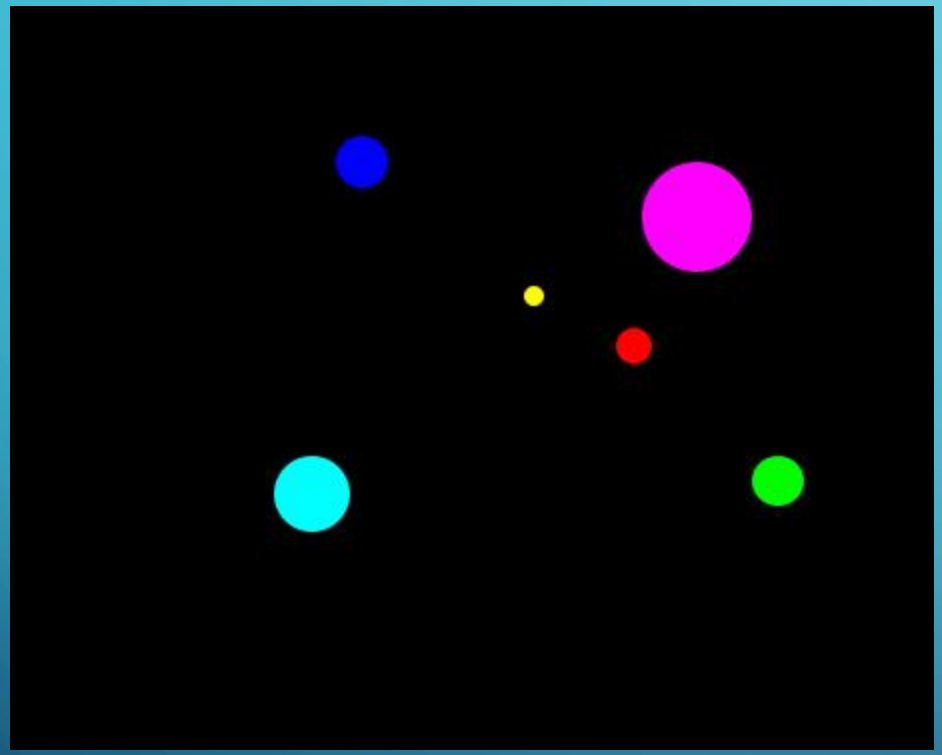




BARNES-HUT TREE WITH RNN



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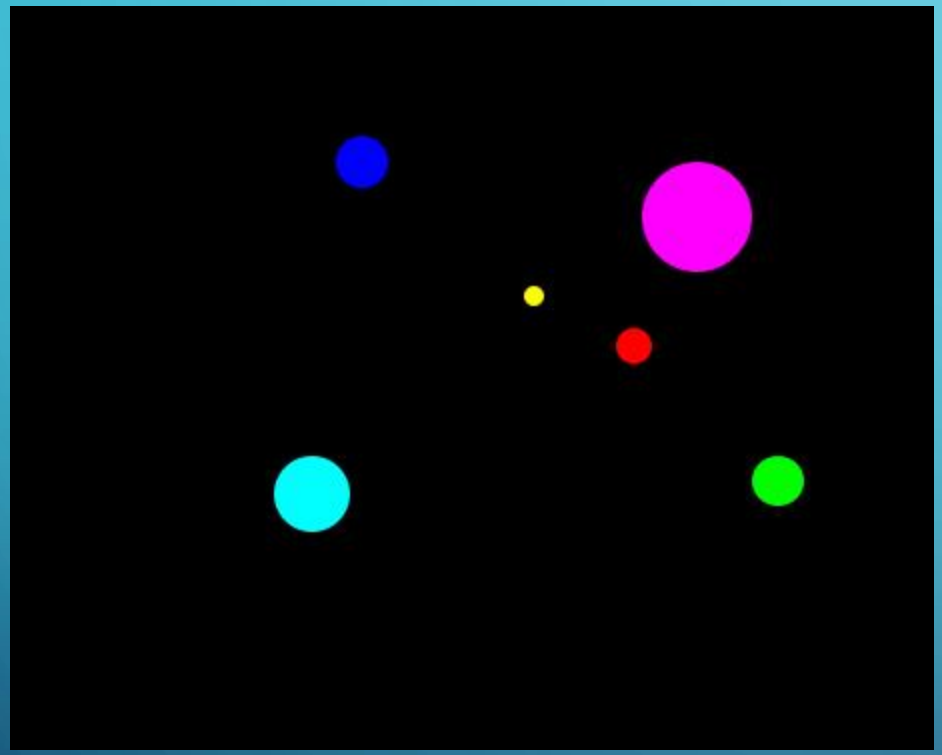
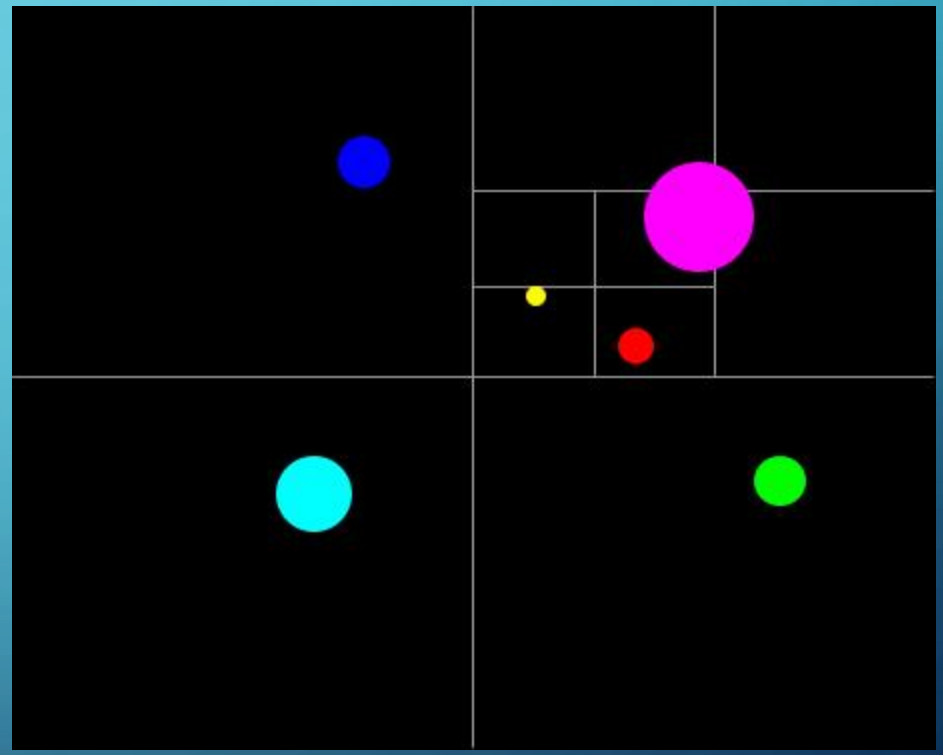
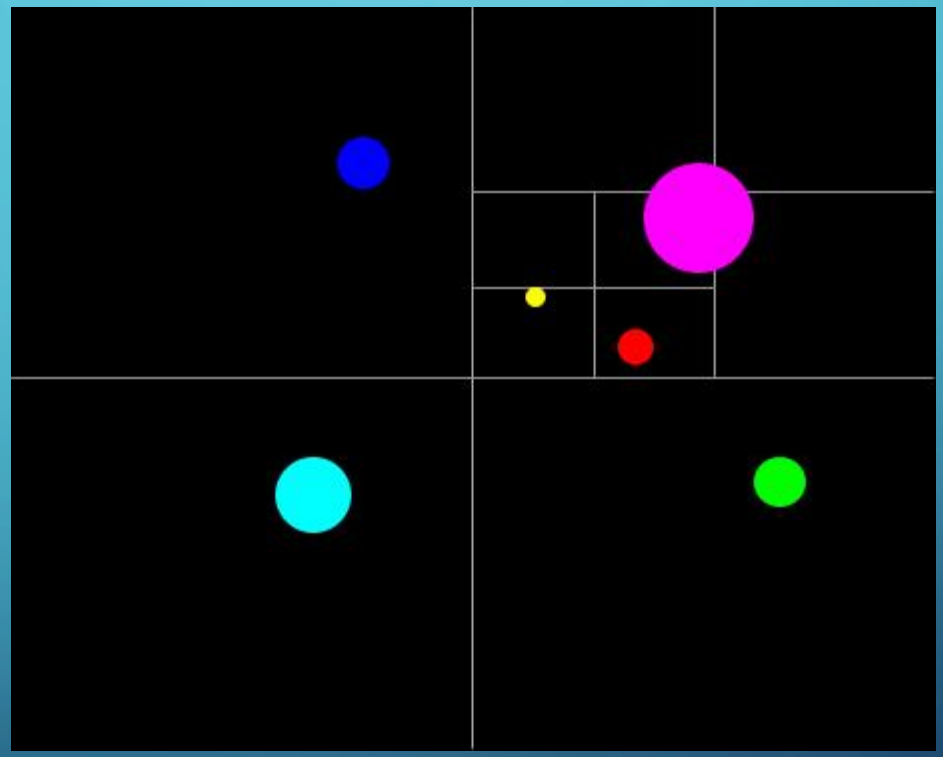




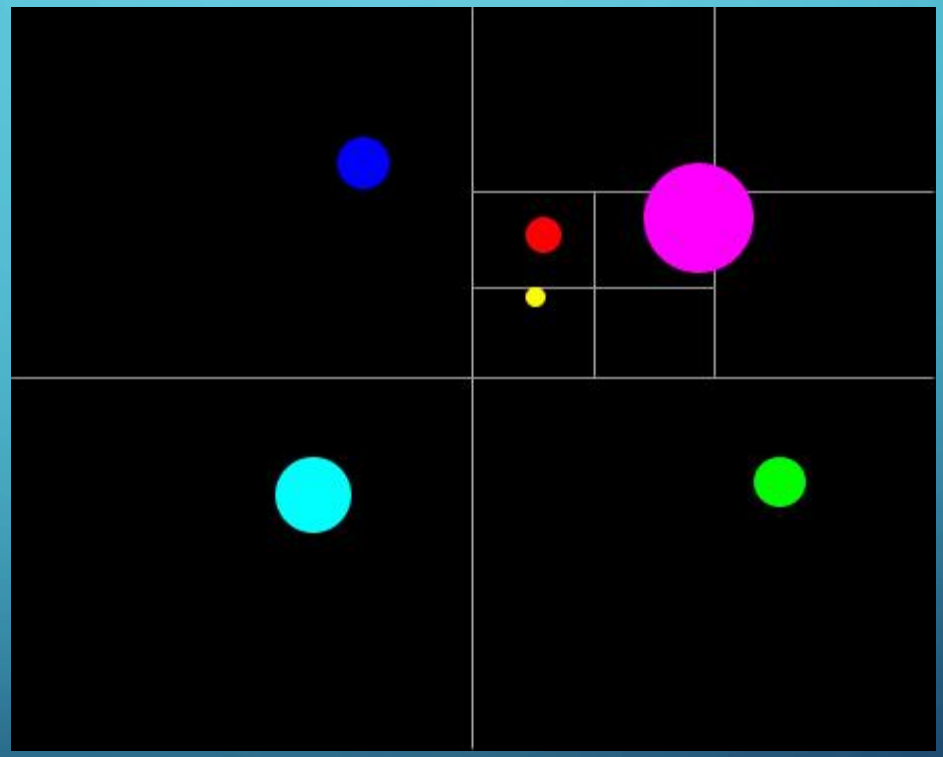
BARNES-HUT TREE WITH RNN

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



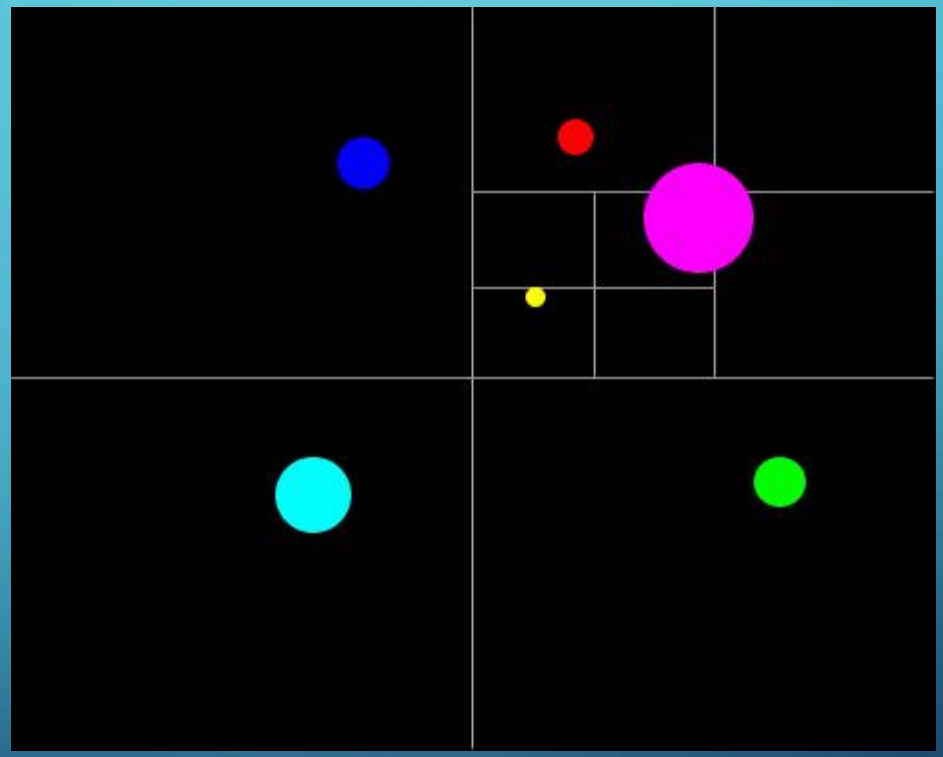
BARNES-HUT TREE WITH RNN

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



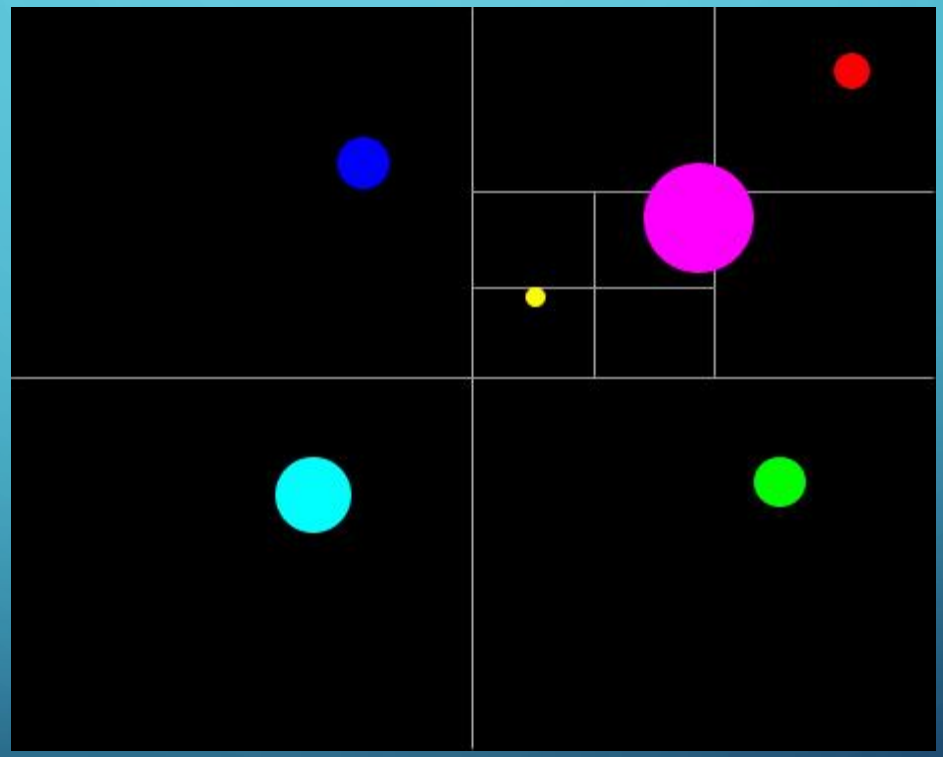
BARNES-HUT TREE WITH RNN

Red node advancing



BARNES-HUT TREE WITH RNN

Red node advancing to final position

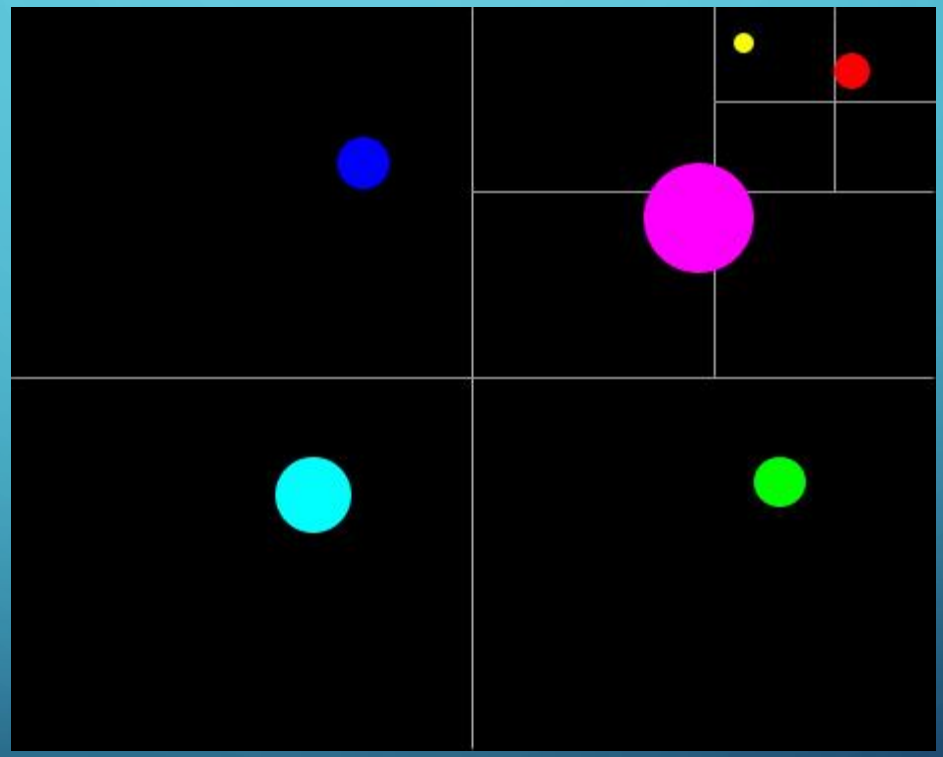


BARNES-HUT TREE WITH RNN

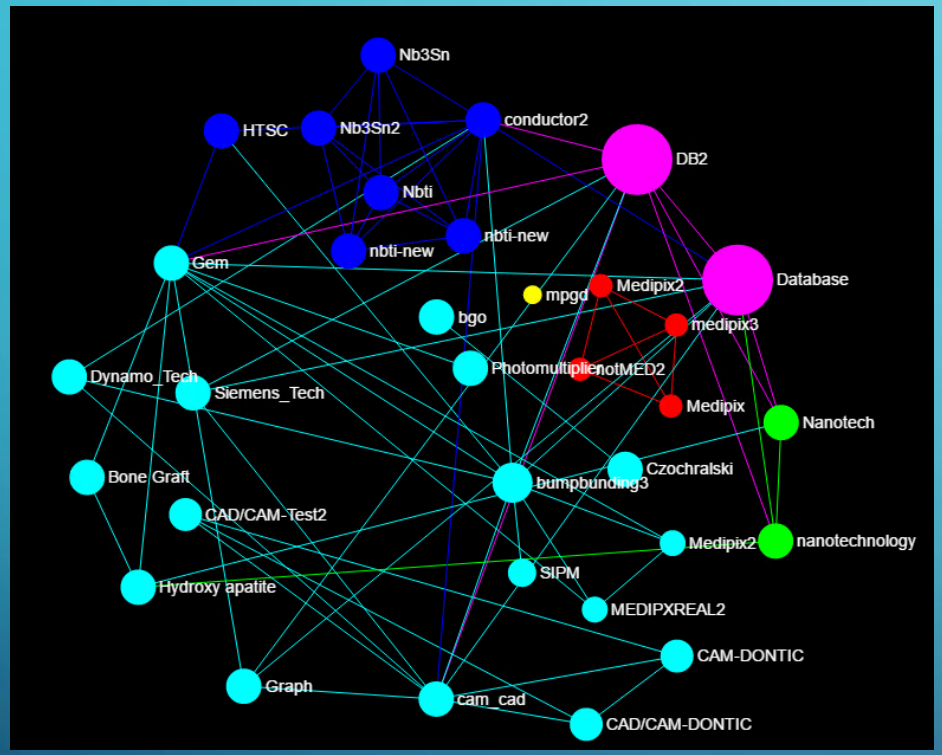
- States stored for one node (Medipix)
- Train a model for Medipix
- The model will move the node through the regions

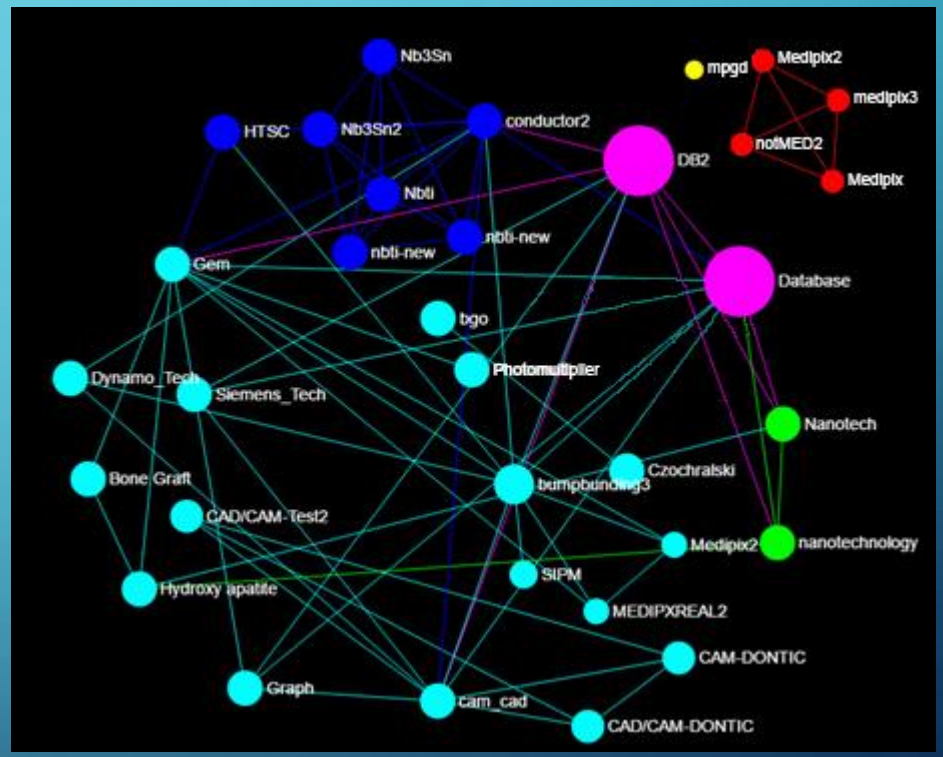
BARNES-HUT TREE WITH RNN

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



BARNES–HUT TREE WITH RNN





FUTURE WORK

- Collecting more user interaction data
- Testing on more complex graphs
- Integrating the model into the system

THANK YOU