

# Neural Networks for Network-like structures

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# Common examples so far

- Plain features (tables)
- Image
- Text
- Time series

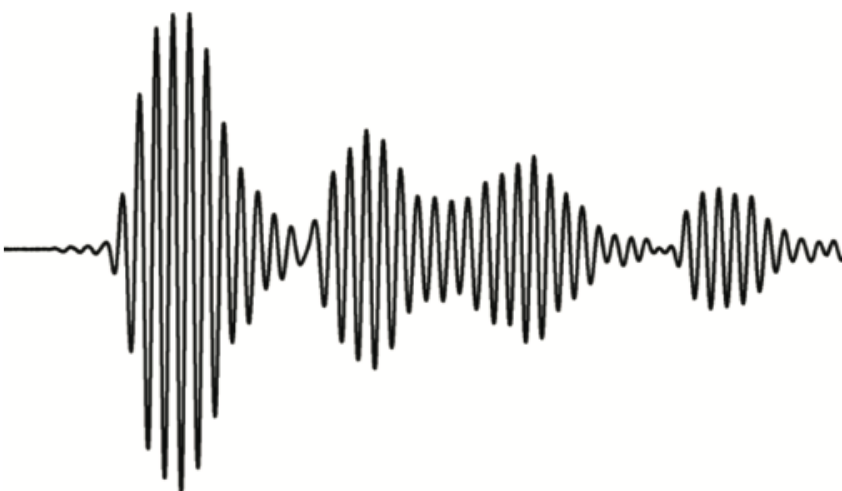
Таблица умножения в упрощенном виде

Фактически для запоминания **только 36 комбинаций** !  
Остальные либо простые (например, умножение на 1 или 10),  
либо обратимые (например  $2 \cdot 4 = 4 \cdot 2$ ).

	2	3	4	5	6	7	8	9	
2	4	6	8	10	12	14	16	18	2
3	6	9	12	15	18	21	24	27	3
4	8	12	16	20	24	28	32	36	4
5	10	15	20	25	30	35	40	45	5
6	12	18	24	30	36	42	48	54	6
7	14	21	28	35	42	49	56	63	7
8	16	24	32	40	48	56	64	72	8
9	18	27	36	45	54	63	72	81	9
	2	3	4	5	6	7	8	9	

Doubt thou the stars are fire,  
Doubt that the sun doth move,  
Doubt truth to be a liar,  
But never doubt I love...

Text



Audio signals

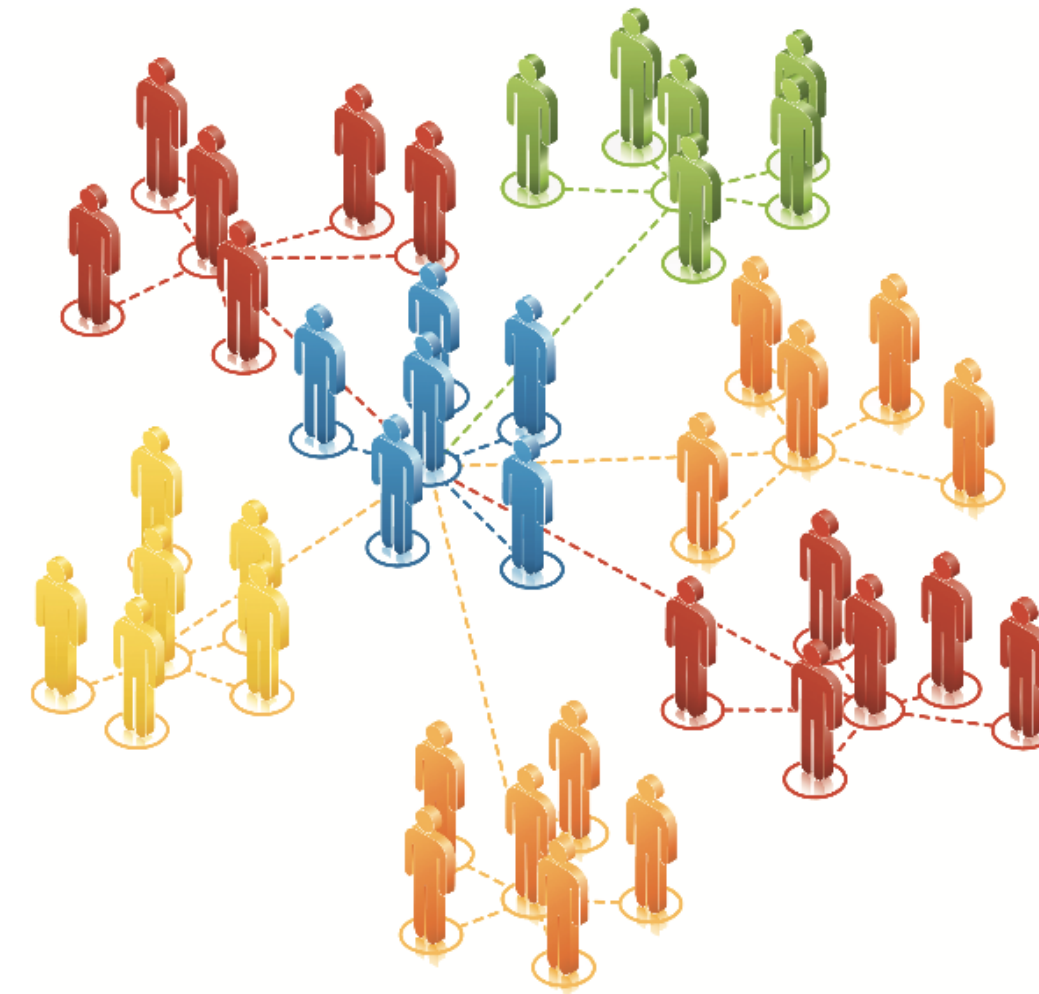


Images

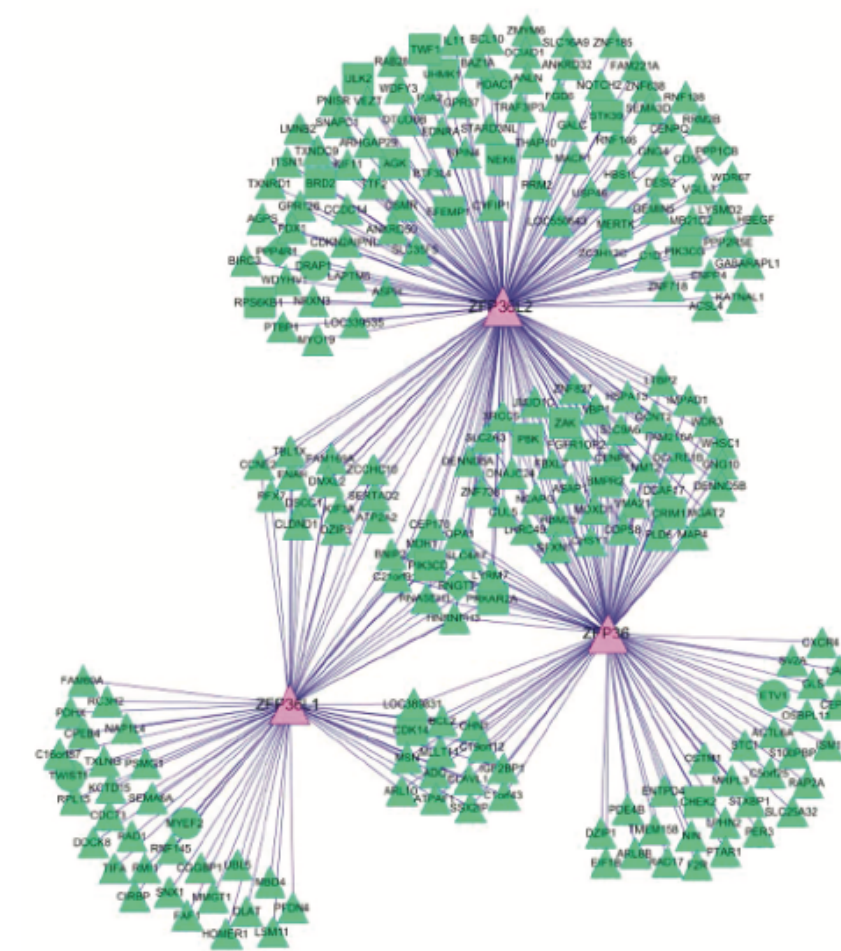


# What about those?

Geometry  
Manifolds  
Graphs

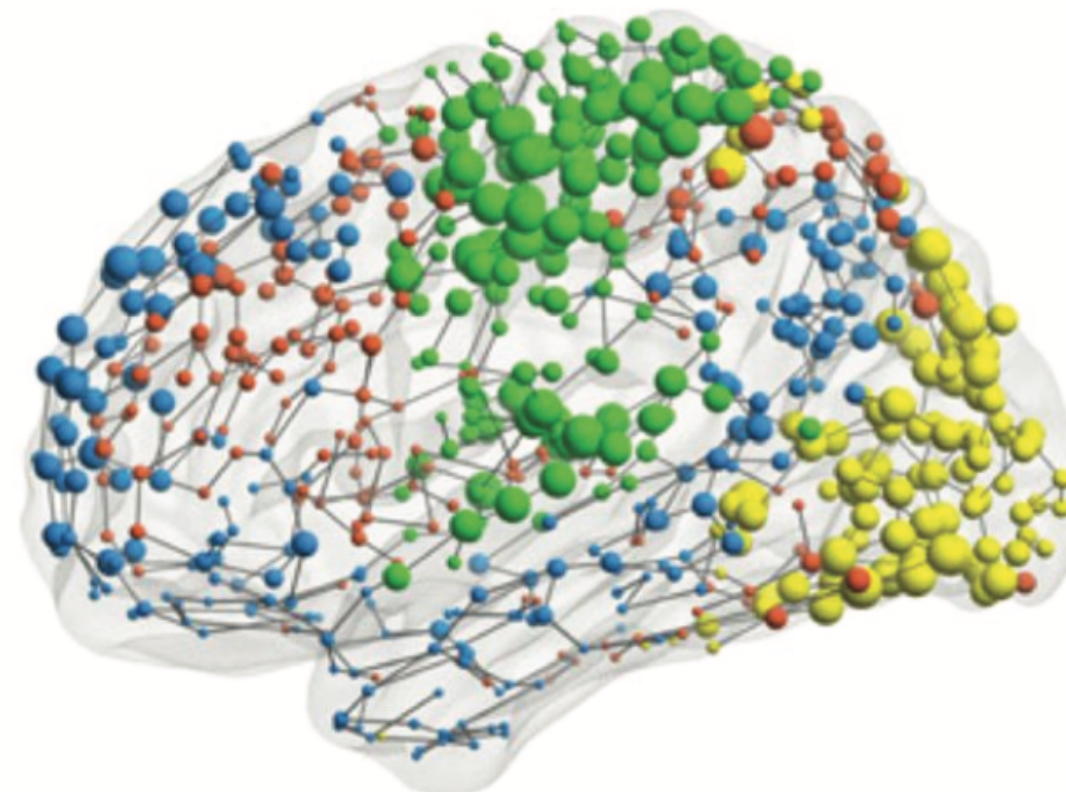


Social networks

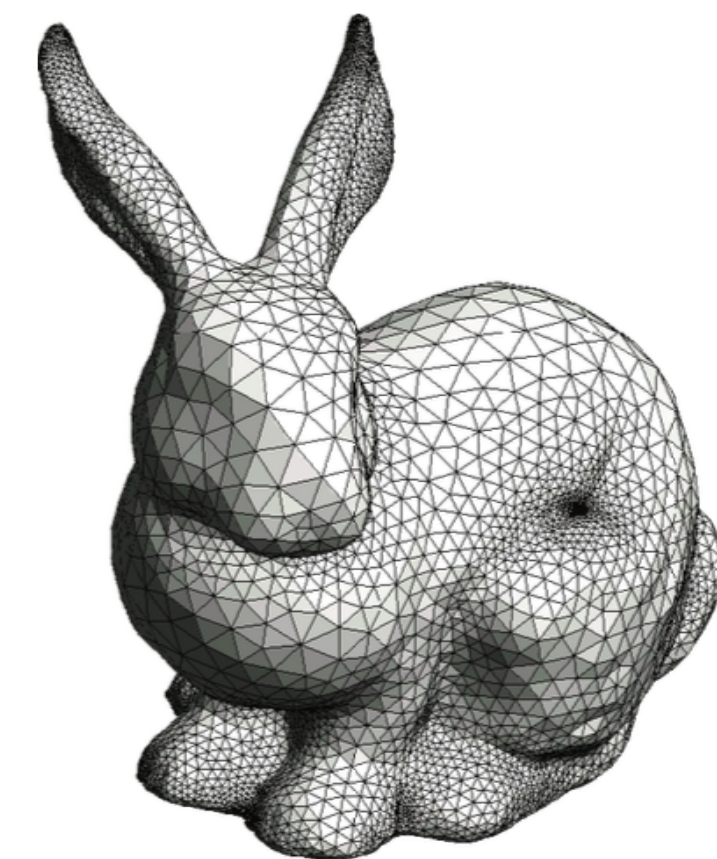


Regulatory networks

Non-euclidean distance,  
twisted connectivity



Functional networks



3D shapes

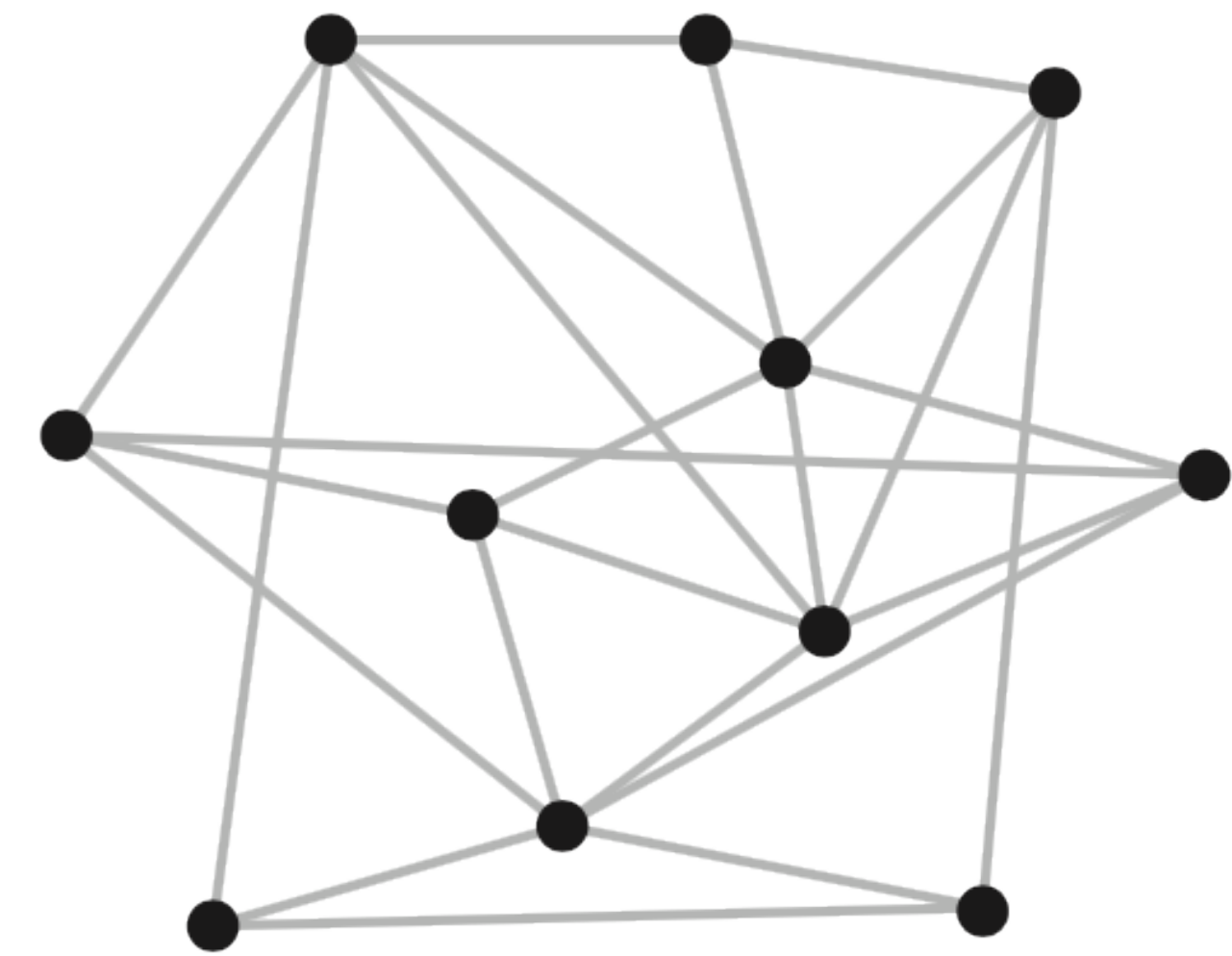
# Formalization

## Graph (structure):

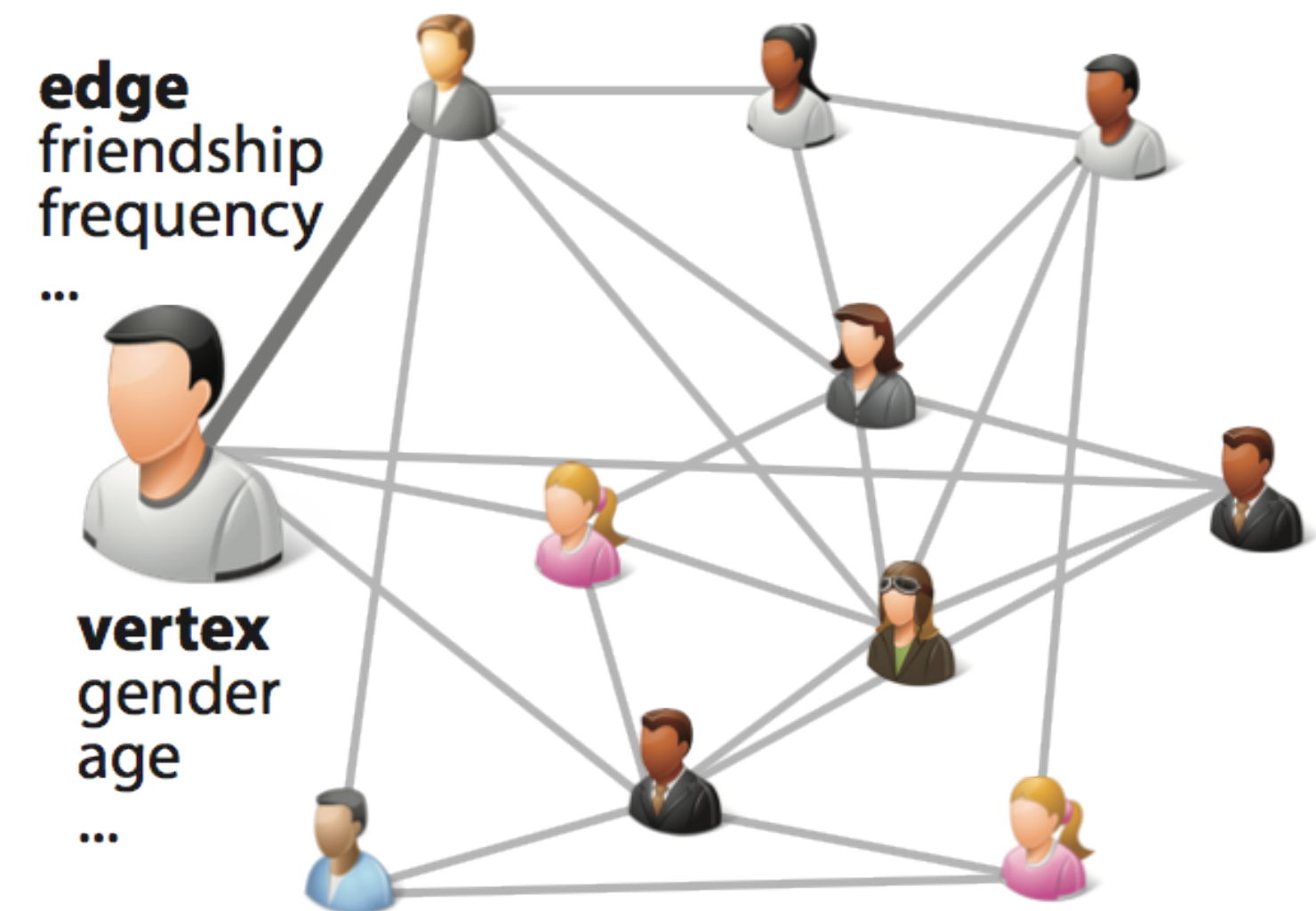
- ›  $G(V, E)$ ,  $A$  – adjacency matrix

## Features (data):

- › Vertex (node) features
- › Edge features



Domain structure



Data on a domain



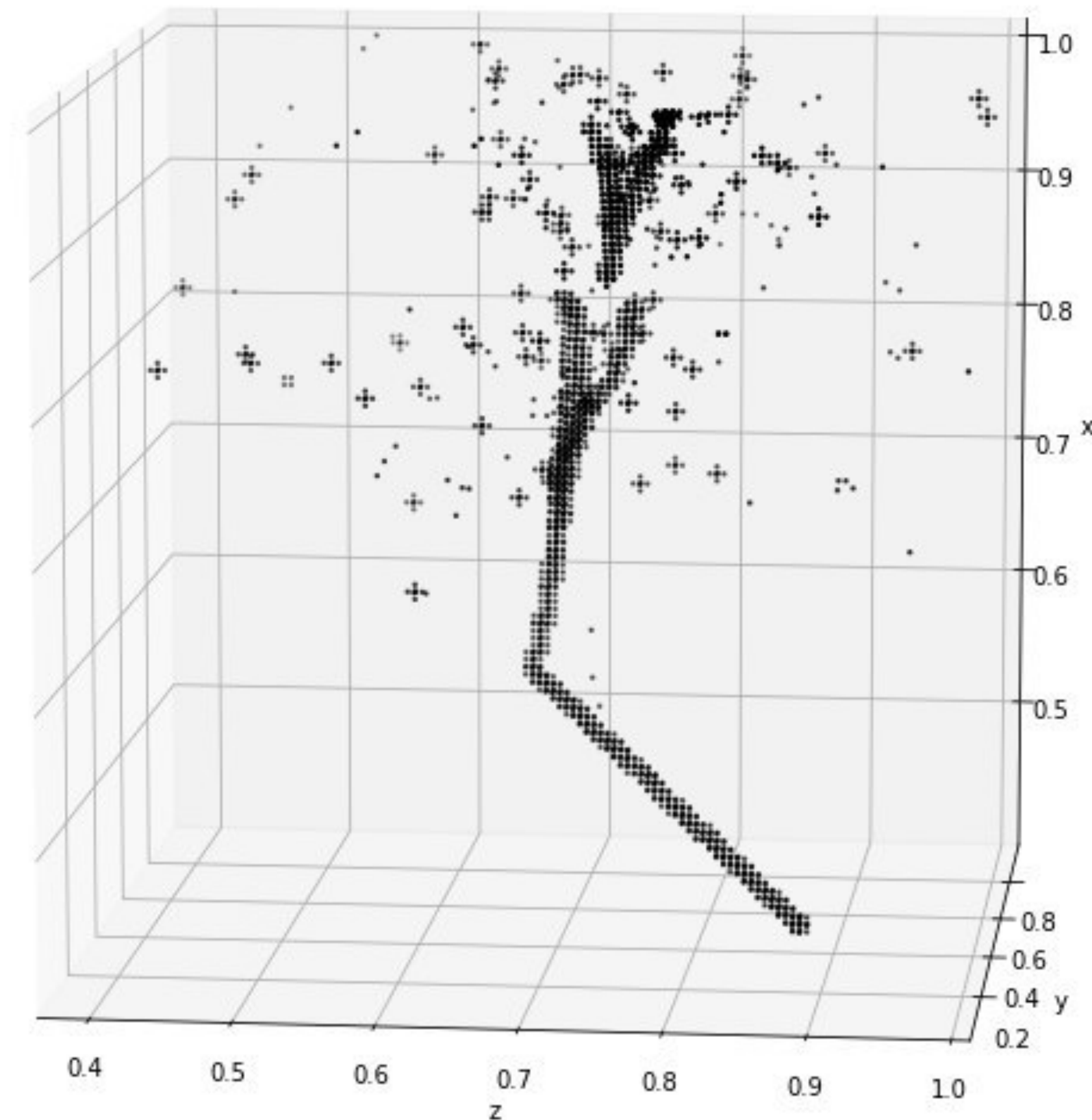
# From hits to graph

## K-nearest neighbors, euclidean distance

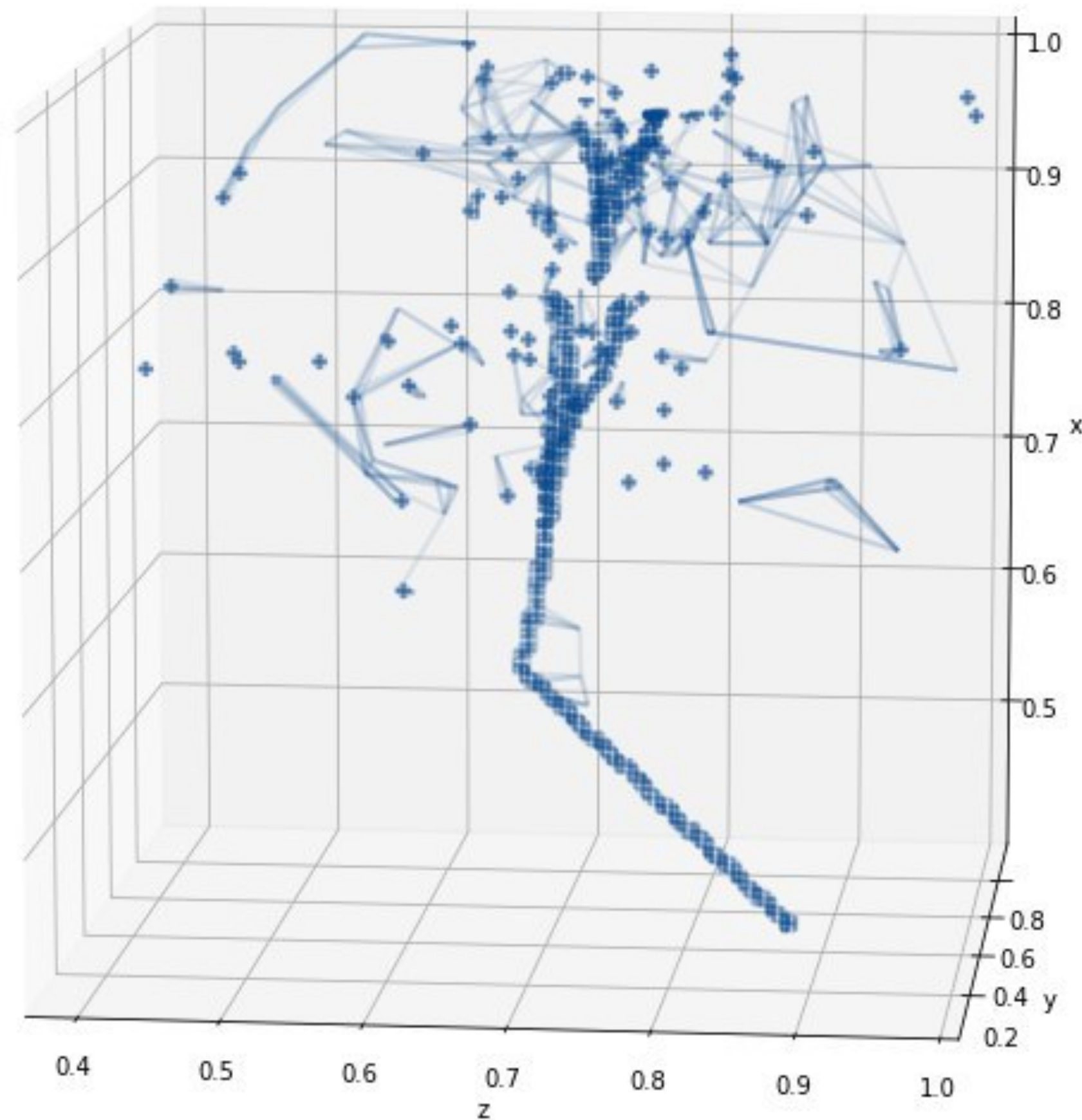
- › Iterate by hits
  1. Find K closest hits for each hit
  2. Connect with edges

## Radius graph, euclidean distance

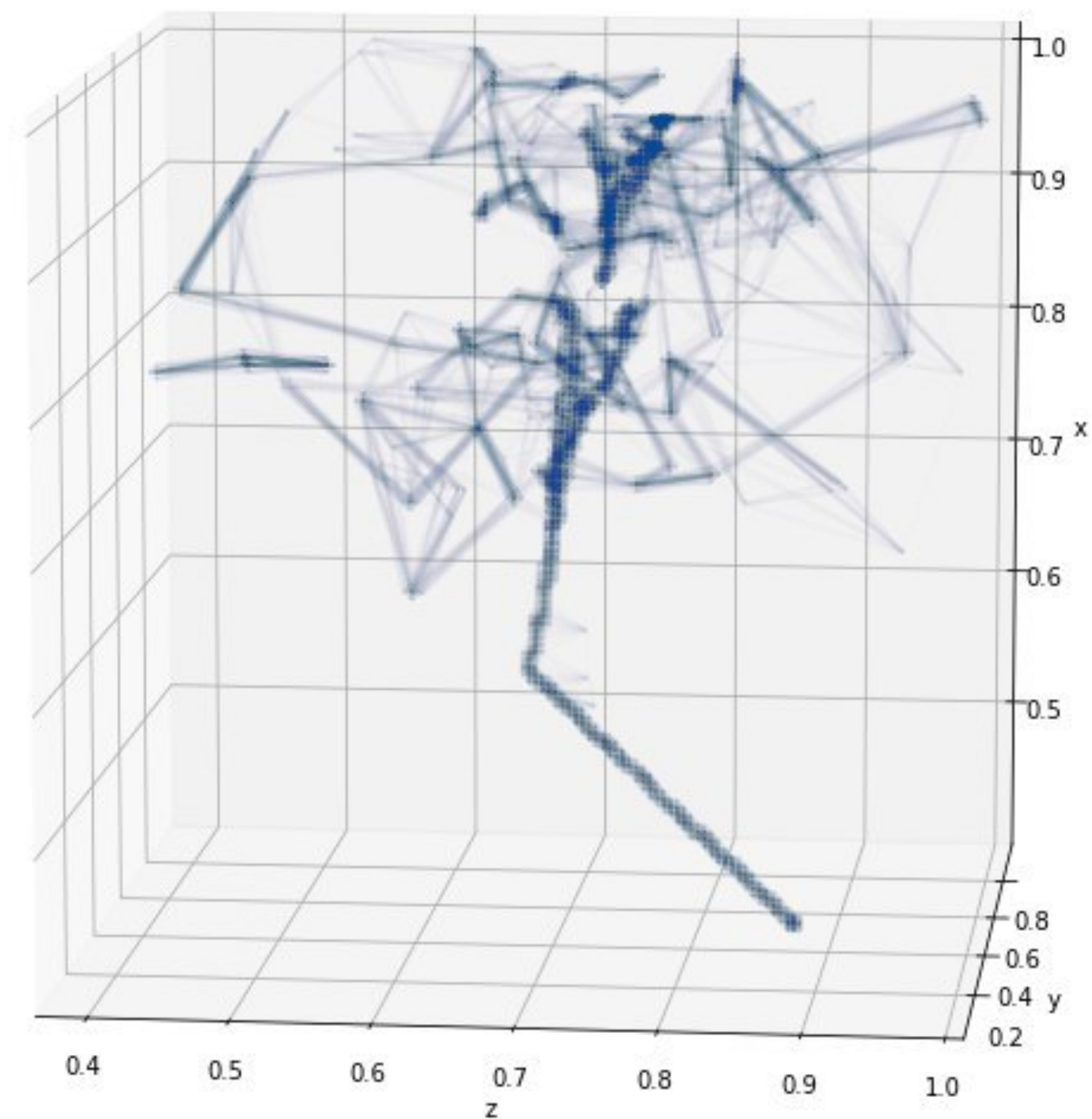
- › Iterate by hits
  1. Find nodes within given radius and connect with an edge



# After graph-ication



Neighbors = 5



Neighbors = 20

# Neural Networks over graph

■ We want to learn some structural patterns in nodes adjacency (connectivity), that correlate with labels we want to predict for every node.

■ Connectivity patterns correspond to some structure in adjacency matrix. How can we reveal it using neural network?

■ Let's assume that labels we want to predict correlate with certain computable function over incoming/outgoing edges of each node

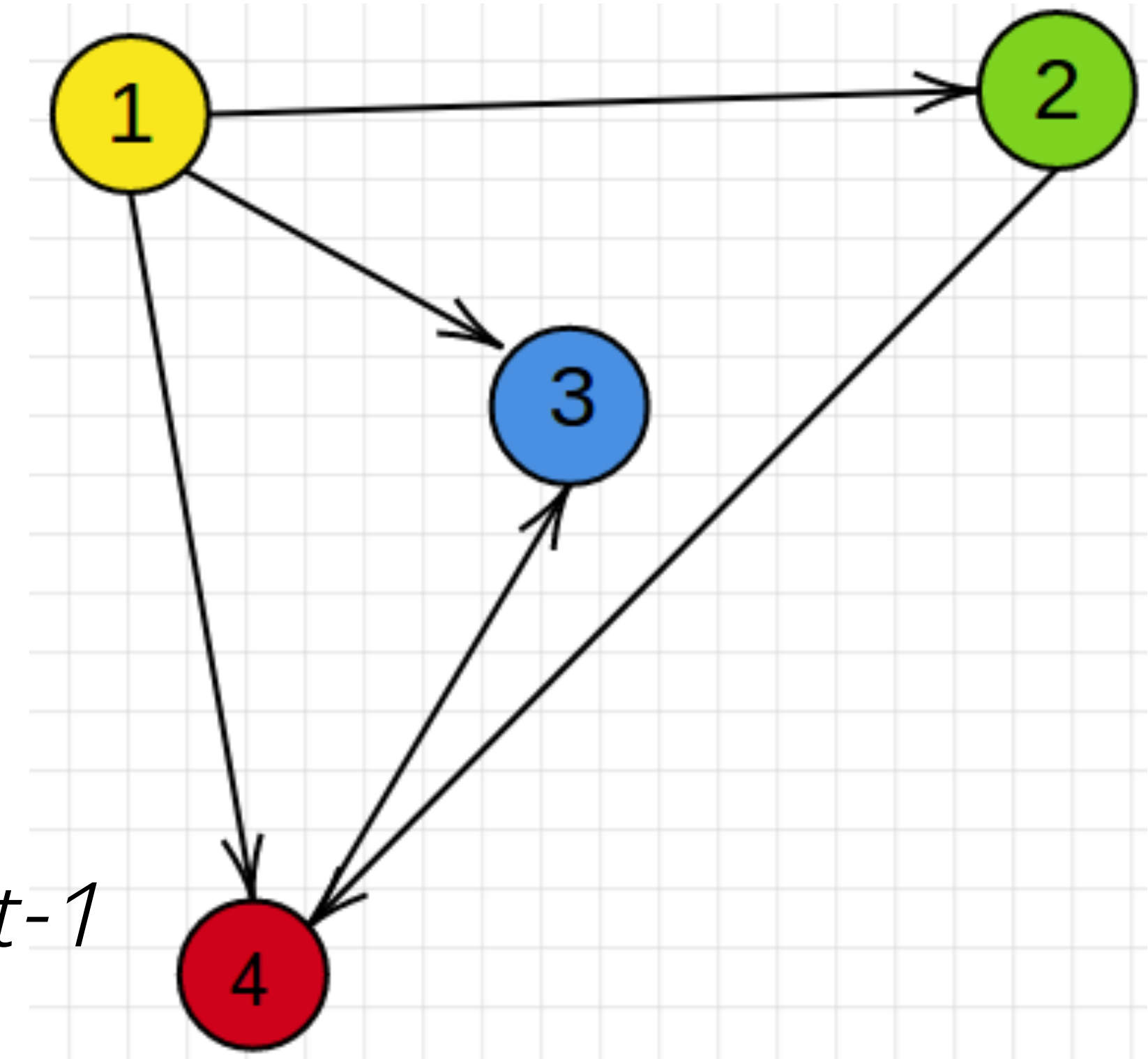


# Message Passing Neural Networks

We want to predict label for each node

Let's assume the following :

- › Each *node* has a *state* (node features) at time  $t$
- › Each *edge* has a *state* (edge features) at time  $t$
- › *Message* is a **function** of source node state and edge state at  $t-1$
- › Node state is a **function** of incoming messages at  $t-1$
- › Node *label* is a **function** of its state at  $t$  (readout)





# Trivial Example

Step 0: pick random node states  $h_i^0$

Step 1. Messages pass node state:

$$m_{13} = h_1^0, m_{43} = h_4^0$$

Step 2. Messages are aggregated:

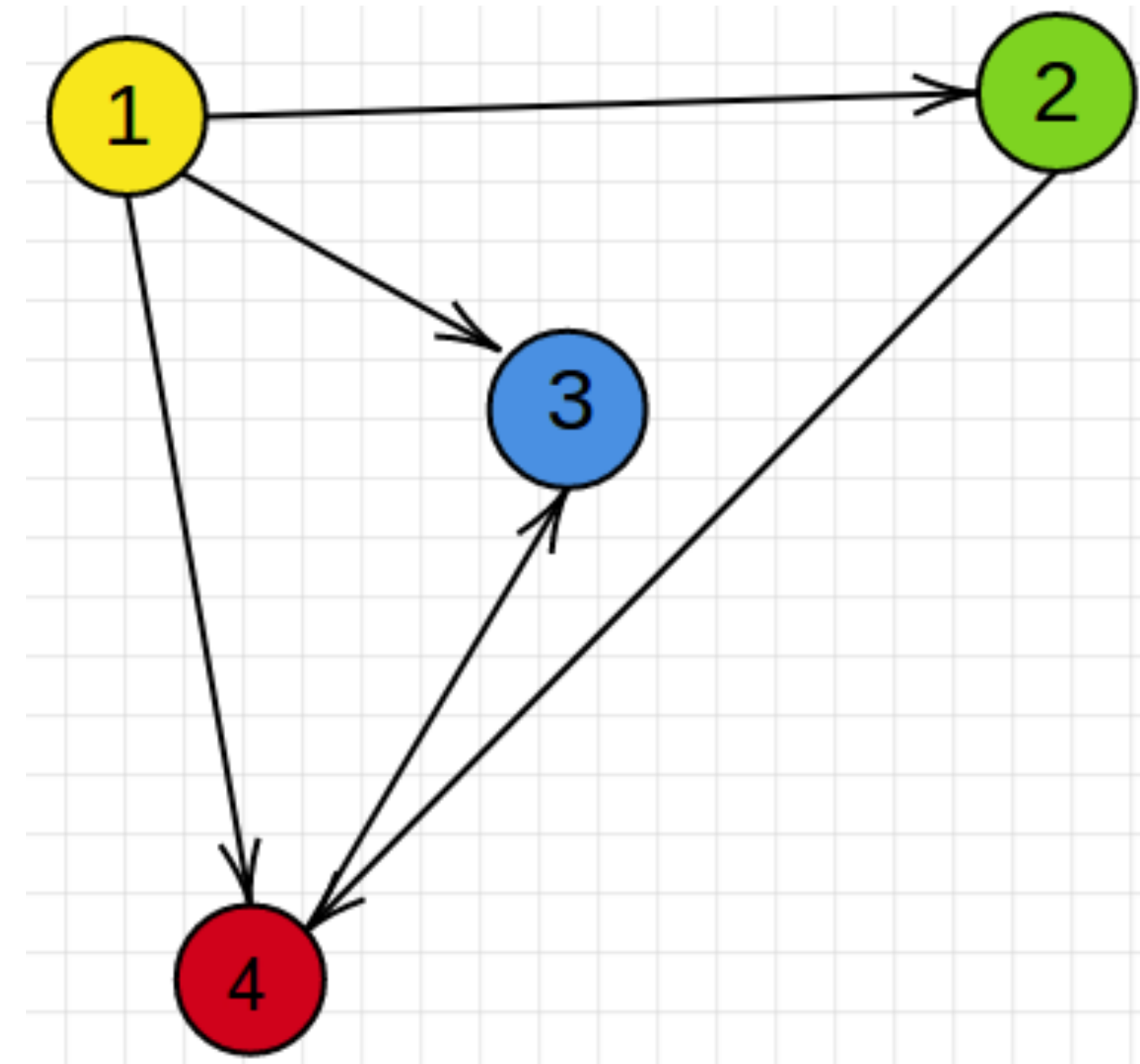
$$M_3 = (m_{13} + m_{43})/2$$

Step 3. Node updates its state:

$$h_3^1 = (h_3^0 + M_3)/2$$

Step 4. Estimate prediction (readout):

$$R_3 = ||h_3^1||$$



# Starter Kit MPNN baseline





# Ideas for improvement



Clustering algorithm type, parameters

Depth of messages (number of steps)

State updater and message passer can have longer memory GRU/LSTM

Use batches of events

Different optimizers / learning rates

Data augmentation

# References

Plot event as a graph:

<https://gist.github.com/SchattenGenie/28204a1135c3b7bca06162b7b2adf073>

Neural Message Passing for Quantum Chemistry, arXiv:1704.01212,

Neural Message Passing for Jet Physics,

[https://orbi.uliege.be/bitstream/2268/226446/1/nips\\_dlps\\_2017\\_29.pdf](https://orbi.uliege.be/bitstream/2268/226446/1/nips_dlps_2017_29.pdf)

<http://geometricdeeplearning.com>



# Backup



