Construction and Training of Multi-Associative Graph Networks

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ECML PKDD


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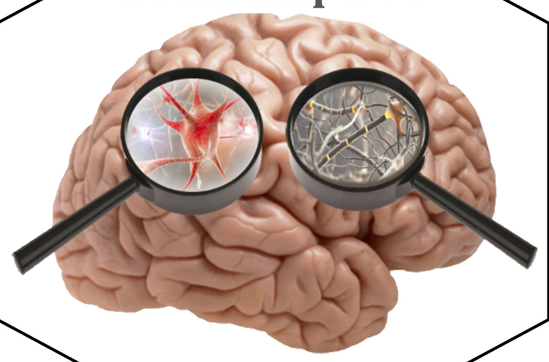
Brain inspired MAGNs



Problem Definition

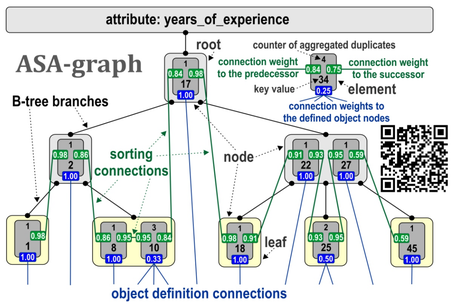
How to operate on database objects and their relations in brain-like ways using associations for classification and knowledge representation?

Aim and Objectives

1. Create a model that can represent and associate objects to recall and use them contextually for classifying or regression.
2. Develop a sparse network structure capable of representing related objects.
3. Use this network as a neural network to trigger associated objects, classes, etc.

Methodology

Associate data and objects of all tables of all DBs by:
- Aggregating duplicates and representing them by the same nodes.
- Sorting data in numerical or symbolic order to connect them in order.
- Connecting nodes representing similar values and related objects in the graph.



Similarity of two numerical values of the same attribute determines the weights between them in view of the range of all the attribute values:

$$w^{C_n}_{i,i+1} = s^{C_n}_{i,i+1} = 1 - \frac{(v^{C_n}_{i+1} - v^{C_n}_{i})}{R^{C_n}}$$

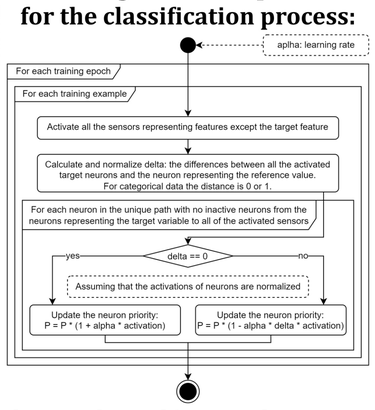
$$R^{C_n} = v^{C_n}_{max} - v^{C_n}_{min}$$

Weights between different neurons are calculated (not trained) using numbers of represented features or objects by the same nodes that behave like neurons:

$$w_{V^{C_n}_i, O^{T_m}_j} = \frac{1}{d(V^{C_n}_i)}$$

$$w_{O^{T_n}_k, O^{T_m}_j} = \frac{1}{d(O^{T_n}_k)}$$

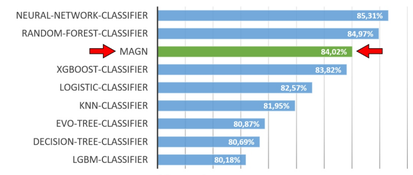
Additionally, we prioritize (adapt the soft attention) the values of some nodes according to their importance for the classification process:

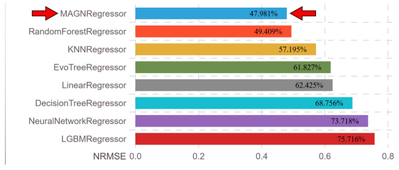


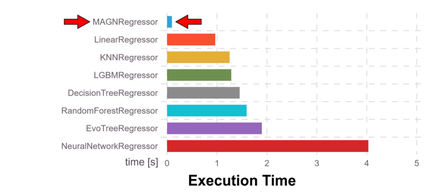
The associative transformation process transforms values, objects, and keys (relationships) of database tables into specific nodes and connections of a sparse Multi-Associative Graph Network using a simple rule.
It allows to associate data and objects of all tables of many databases creating a knowledge model about the data collected and using it for classification, regression, prediction, and other ML tasks.
Next, new nodes representing conclusions can be added.

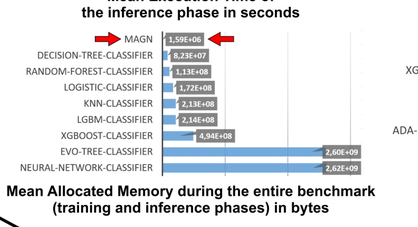
Results

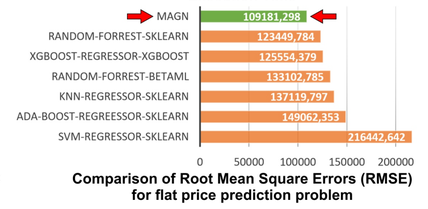
The results collected for classification and regression benchmark training datasets prove the efficiency of MAGNs:





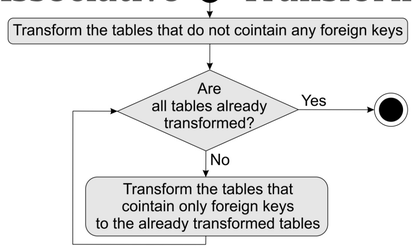


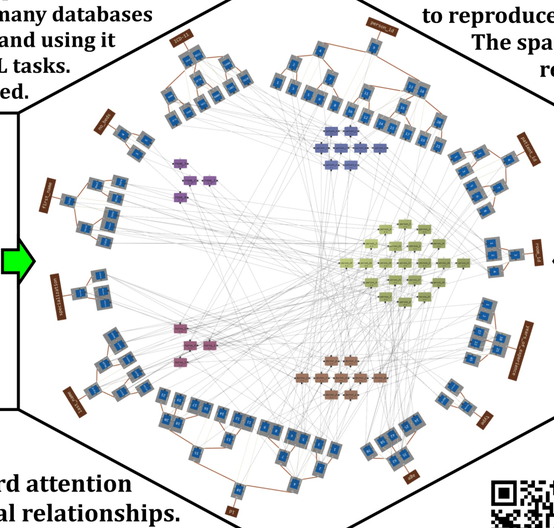




Such results were possible because MAGN structures are constructed to reproduce specific relationships of every dataset or database. The sparse connections created in the construction process reproduce real relationships supporting predictions.

Associative Transformation





Database

table: **patient**

id	person_id	room_id	ICD-11
1	9	1	['CA01', 'BA00']
2	10	1	['BD11', '2F7A']
3	11	3	['EA80']
4	13	2	['EA80', 'BA00']
5	12	4	['BD11', 'EA80']
6	15	4	['2F7A', 'BA00', 'SA10']
7	16	2	['SA10']
8	14	4	['BA00', 'EA80', 'SA11']

table: **doctor**

id	person_id	patient_id	specialization	years_of_experience
1	2	1	Surgery	25
2	1	2	Radiology	10
3	4	4	Surgery	45
4	3	5	Oncology	17
5	18	3	Patology	2
6	20		Surgery	22
7	17	7	Radiology	25
8	19	8	Surgery	10
9	21	6	Surgery	1

table: **room**

id	type	no_beds
1	PostOp	3
2	Emergency	3
3	Ward	4
4	Ward	5

table: **nurse**

id	person_id	room_id	years_of_experience
1	7	4	10
2	5	3	1
3	8	1	25
4	6	2	2

table: **person**

id	first_name	last_name	age
1	Nina	Musk	35
2	John	Smith	58
3	Evelyn	Musk	42
4	John	Bush	70
5	Evelyn	Ford	70
6	Evelyn	Woods	25
7	Sara	Bosch	62
8	Cate	Smith	35
9	Lucy	Allen	70
10	Cate	Bosch	62
11	Sara	Ford	25
12	David	Smith	42
13	John	Bosch	35
14	David	Musk	58
15	Sara	Hanks	42
16	Nina	Ford	70
17	Nina	Smith	42
18	Lucy	Bush	25
19	David	Allen	35
20	Raul	Hanks	42
21	Raul	Woods	24

Conclusions

1. Sparse associative connections work like hard attention allowing the MAGNs to focus only on essential relationships.
2. The weights reproduce the strengths of these relationships, defined by the frequency of occurrences of values and objects.
3. This strategy does not require a long-lasting training process.

Commercial Deployment

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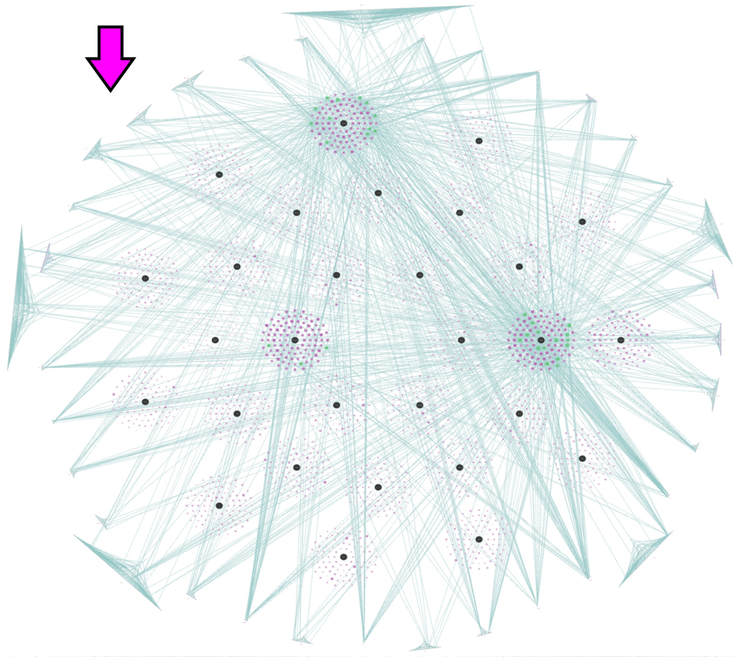
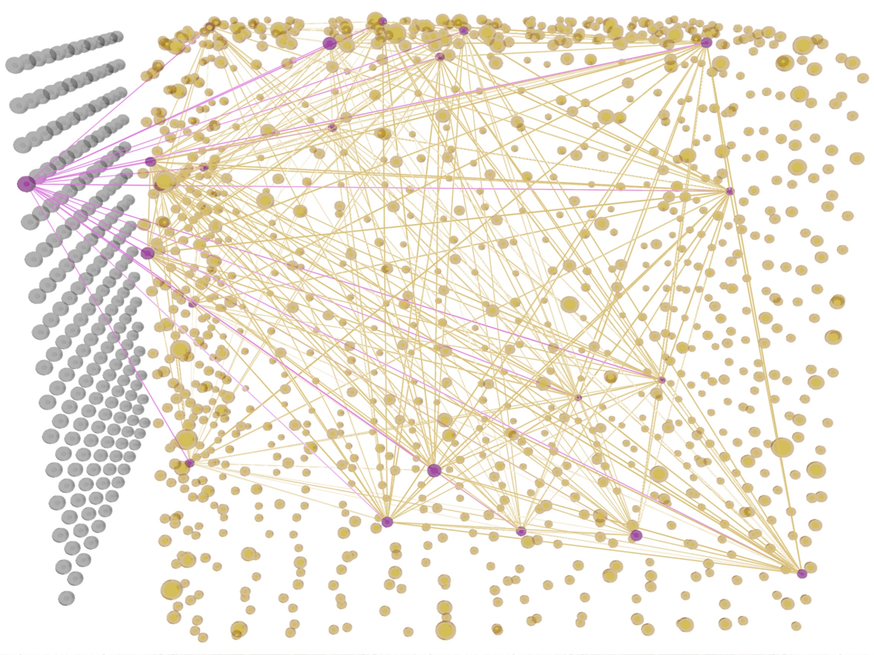
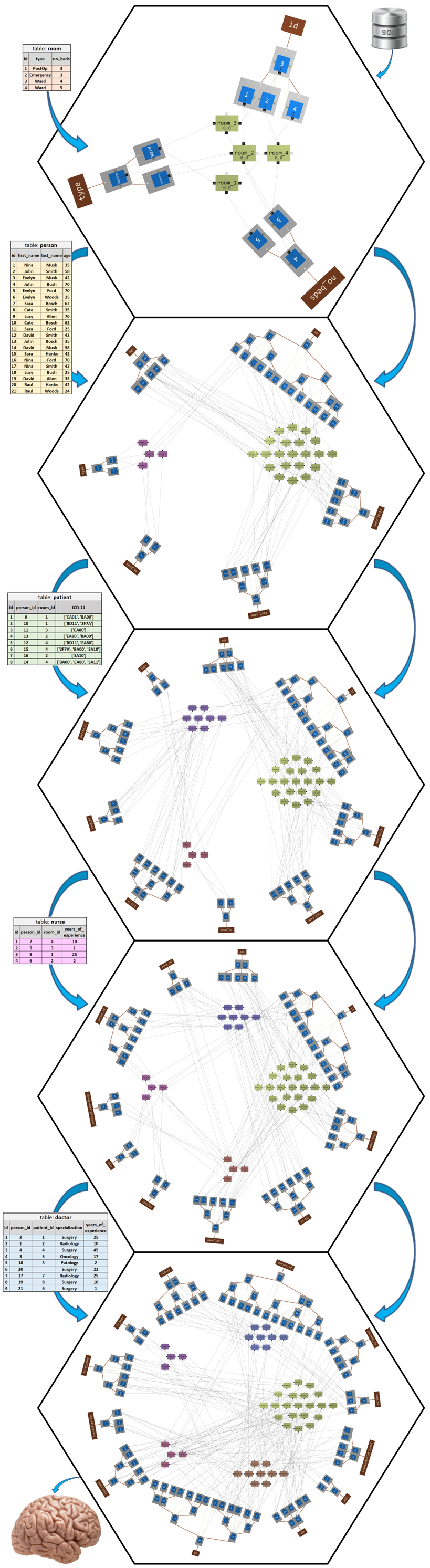




Associative Transformation



References

Adrian Horzyk, Daniel Bulanda, and Janusz A. Starzyk, Construction and Training of Multi-Associative Graph Networks, Proc. of 2023 European Conference on Machine Learning (ECML PKDD 2023), Part III, LNCS 14171, Chapter 17, Springer, 2023.

A. Horzyk, D. Bulanda, J. A. Starzyk, ASA-graphs for Efficient Data Representation and Processing, International Journal of Applied Mathematics and Computer Science (AMCS), Vol. 30, No. 4, 2020, pp. 717 - 731, DOI: 10.34768/amcs-2020-0053