

# Interactive Visual Pattern Search on Graph Data via Graph Representation Learning

(Comprehensive Summary)

Suvi Varshney \*

## I. Objective

The paper aims to support interactive graph pattern search by providing a visual analytics framework using graph representational learning. They utilize existing *Graph Neural Networks (GNNs)* for subgraph creation, decision, and node alignment, essentially converting them to high dimensional fixed length vectors. This allows their methods to scale the search as the graph scales. In *GNNs*, they propose a novel, **NeuroAlign** method for node alignment. The visual implementation of their system, **GraphQ**, is able to provide query and result modification through visual interaction.

## II. Contributions

The outline of the contributions are:

- 1) They come up with a visual analytics system for human-in-the-loop, example-based graph pattern search using graph representational learning.
- 2) Node-alignment is done through a novel approach, **NeuroAlign**, which they claim is 10-100 x faster than the baseline combination algorithms.
- 3) The framework is implemented is called **GraphQ**, which provides an interactive query display supporting modification based on visual results.

## III. VIS Designs / Techniques Used

GraphQ consists of 5 major parts:

- 1) Query editing panel which represents the subparts of the query and their interrelation to each other using a graph. Here we can modify the query.
- 2) Query result panel displaying an overview of all the sub-graphs which are the result of a query and the user-selected sub-graph in detail.
- 3) A statistics and filtering panel helps the user to visualize the statistics of the query results using scatterplots, bar-graphs, and tabular format.
- 4) A toggle switch panel to enable/disable fuzzy matching and to highlight/unhighlight the matches.
- 5) A popup window to compare the structure of the query and the structure of the matched graphs visually.

## IV. ML Methods Used

The graph matching problem is solved by two *GNN* frameworks, **NeuroMatch** and the novel **NeuroAlign**. **NeuroMatch** decomposes the query and the graph into several subregions for an effective search. **NeuroAlign** is used to improve node alignment, by working on fixed-length embeddings. The output from the **NeuroAlign** is passed to a multi-layer perceptron which takes a pair of embeddings and returns a similarity score. This is also useful when the user wants to perform a fuzzy match in addition to an exact match.

## V. Strengths

- 1) The authors encode the topology and nodes of a graph into fixed-length vectors. Then the graph search essentially is a high dimension vector comparison problem, much cheaper to solve.
- 2) To achieve an efficient node-alignment, they propose novel **NeuroAlign**, which is 10-100 x faster than combination algorithms and 19-29% more accurate than existing deep learning graph search algorithms.
- 3) **GraphQ** helps the user to visually interact with the query structure and the results and to modify them using visual assistance.

## VI. Shortcomings

- 1) **NeuroAlign** currently isolates only isolates subgraphs isomorphic to the query in a single graph. However, in practice, we have multidimensional graphs, where more than one subgraph can match the query.
- 2) **NeuroMatch**, an integral part of **GraphQ**, is often slow in large, densely connected graphs. This problem amplifies when it has to search all the subgraphs even when they are not an exact match.
- 3) The algorithm is only available for undirected graph since the current backbone of *GNN* do not support directed graphs.

## VII. Future Work

The authors plan to extend the application to index-based search in graph databases, searching on the index embeddings to achieve sub-linear time performance. Further, this implementation could also be extended to highly dense social media networks and 3D point clouds.

## VIII. Question for Discussion

As we have seen in many visualization projects focusing on interactive graph searching algorithms, they focus on the path taken to discover relevant nodes. Will such a visualization be helpful? Will it help to debug complex queries?

---

\*MS in CS at UC Davis, ID: 920256895, suvarshney@ucdavis.edu