## University of Bergen Department of Informatics

# Solving Maximum Weighted Matching problem using Graph Neural Networks

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# UNIVERSITETET I BERGEN Det matematisk-naturvitenskapelige fakultet

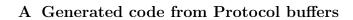
December, 2023

| Abstract  In this work we tried to train a Graph Neural Network (GNN) to solve a popular problem |
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## Introduction

This chapter is dedicated to the general introduction of the problem at hand and previous work and research that is relevant for this project.

Machine Learning (ML) and Neural Networks have shown to be extremely potent and versatile in solving vast variety of problems across different fields. One research field that has been popular and challenging in the last few years is Combinatorial Optimization (CO). CO includes problems such as Maximum Independent Set (MIS) and Maximum Weighted Matching (MWM). Such problems can be viewed in the context of graphs. GNN is a subclass of Neural Networks designed specifically for solving problems related to graphs, but there are many problems that have not yet been solved efficiently with GNNs. This work attemps to find out whether a GNN can be worth using for solving MWM

## 1.1 Background

Many researches have been done related to GNNs in the past years and some of them have shown mixed results. Lorenzo Brusca and Lars C. P. M. Quaedvlieg et al. [1] showed a self-training GNN for MIS

## 1.2 Project structure

The rest of this document has the following structure:

- 1. Approach
- 2. Training
- 3. Results
- 4. Conclusion

#### 1.2.1 Listings

You can do listings, like in Listing 1.1

Listing 1.1: Look at this cool listing. Find the rest in Appendix A.1

```
1 $ java -jar myAwesomeCode.jar
```

You can also do language highlighting for instance with Golang: And in line 6 of Listing 1.2 you can see that we can ref to lines in listings.

Listing 1.2: Hello world in Golang

```
package main
import "fmt"

func main() {
   fmt.Println("hello world")
}
```

#### 1.2.2 Figures

Example of a centred figure

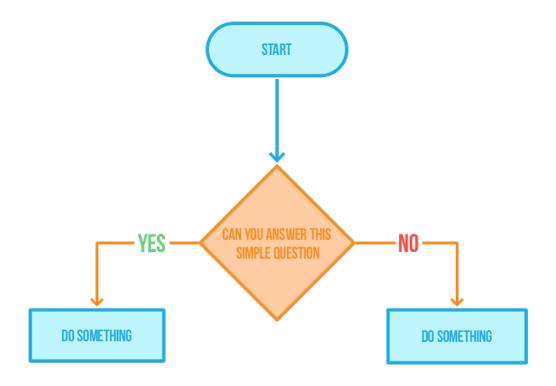


Figure 1.1: Caption for flowchart

Credit: Acme company makes everything https://acme.com/

#### **1.2.3** Tables

We can also do tables. Protip: use https://www.tablesgenerator.com/ for generating tables.

Table 1.1: Caption of table

| Title1 | Title2 | Title3 |
|--------|--------|--------|
| data1  | data2  | data3  |

## 1.2.4 Git

Git is fun, use it!

## Approach

This chapter focuses on describing which approaches were chosen for the task at hand and why.

To reiterate the current problem is to find out if GNN can compete at solving the MWM problem compared to other options such as greedy algorithm.

Before properly describing the choices made for approaching this problem, it is worth going through basic concepts of GNNs and neural networks in general. It is common to think of neural networks as of a black box where you give some data to this box and it gives back an answer. In this case the data is a graph consisting of vertices connected by edges that have weights and the expected answer should be pairs of vertices that were matched together. This is however not as straight forward as the more common examples of classification where each data item needs to be classified.

#### 2.1 Line graph approach

Line graph approach was the first attempt at using a simple GNN, which later turned out to be too time consuming for larger graphs to be worth further expriements. It did however give some usefull insight as well as a showed to be a proof of concept. In the context of graphs line graph is a complement of the original graph that turns each edge to a vertex and connects the vertices is they shared a vertex in the original graph.

Example of a graph and its line graph convertion

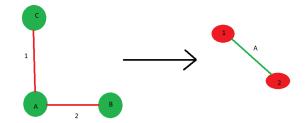


Figure 2.1: Original graph (left) and its line graph (right)

Credit: my paint skills

## 2.2 Edge classification approach

The usual thing to do is for each pair of vertices that are conneced by an edge, ask the model if this pair should be a part of the matching. In other words model is classifying an edge.

#### 2.3 Result Validation

How good a solving method for MWM is can be evaluated by:

- 1. Time how long an algorithm took to produce an answer.
- 2. Correctness is the answer correct. In case of MWM the total weight aquired would be the measurement of how correct the solution is. It is unlikely that GNN can find an optimal solution for more complex problems so it is reasonable to look at how close GNN comes to the optimal solution.
- 3. Memory how much memory is needed. However in this project there is less of a focus on memory

## Graph Neural Network

ML has become a powerfull tool for solving a wide variety of problems. One such field that has been particulary challenging is CO.

#### 3.1 Difference from normal neural network

Why it works better for graphs

# Training

ML has become a powerfull tool for solving a wide variety of problems. One such field that has been particulary challenging is CO.

## 4.1 Data

What data was used for training

## Results

ML has become a powerfull tool for solving a wide variety of problems. One such field that has been particulary challenging is CO.

## 5.1 Performance on unseen data

How well the final model solves the matching problem

## Conclusion

ML has become a powerfull tool for solving a wide variety of problems. One such field that has been particulary challenging is CO.

## 6.1 Future work

Results show that this approach

# Glossary

Git is a Version Control System (VCS) for tracking changes in computer files and coordinating work on those files among multiple people.

# List of Acronyms and Abbreviations

 ${\bf CO}\,$  Combinatorial Optimization.

**GNN** Graph Neural Network.

MIS Maximum Indepndent Set.

ML Machine Learning.

 $\mathbf{MWM}$  Maximum Weighted Matching.

 $\mathbf{VCS}$  Version Control System.

# **Bibliography**

[1] Lorenzo Brusca, Lars C. P. M. Quaedvlieg, Stratis Skoulakis, Grigorios G Chrysos, and Volkan Cevher. Maximum independent set: Self-training through dynamic programming, 2023.

## Appendix A

## Generated code from Protocol buffers

Listing A.1: Source code of something

System.out.println("Hello Mars");