

## EE-559 Deep learning – Practice 6, Students’ questions

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A question is denoted by **Q**; the corresponding answer is denoted by **A**. The questions-related exercises are marked by their numbers in Practice\_6.pdf and Practice\_6.ipynb documents.

### Graph Neural Networks

**Q: What is the purpose of the ‘message()’ method in Pytorch Geometric and how is it linked to message passing?**

**A:** The `message()` method of the `MessagePassing` class computes the message that a node  $i$  sends to another node  $j$  during the message passing phase. When all messages to  $j$  from its neighbours are computed, these are aggregated, for example by summing them, using the method `aggregate()`. The purpose of aggregation is to combine all the messages from the neighbours into a message of fixed size, regardless of the number of neighbours. The resulting message is then used to update the hidden state of node  $j$  according to the method `update()`. These methods are tightly linked to the theoretical framework of message passing described in Bishop’s Deep Learning book (slightly different from the original formulation of Gilmer, 2017), where the function `Aggregate` includes both the computation of the  $i$ -th message (method `message()`) and the aggregation of all neighbours messages (method `aggregate()`).

**Q: Why iterating over the `DataLoader` object gives different outputs in Pytorch and Pytorch Geometric?**

**A:** Pytorch Geometric is designed to work with graphs, for which a predictive model typically needs several inputs: the adjacency matrix of the graph, the node-level features, the edge-level features and the graph-level features. Since these inputs have different shapes, they cannot be combined into a single tensor `X_train` (or `X_val`, or `X_test`) as you have instead seen in the previous labs working with 1D/2D/3D datasets. For this reason, the datasets used in Pytorch Geometric – and for extension the `DataLoaders` built from these datasets – are usually organised into `Data` objects, which are similar to dictionaries: given a `Data` object `data`, you can access different objects inside it as `data.x` (node features), `data.edge_index` (adjacency matrix in COO format), `data.y` (labels), etc. Iterating over a data loader built in this way will therefore return a single `Data` object instead of two tensors `X_train`, `y_train`.

**Q: If two nodes in a graph are connected does it mean they are similar?**

**A:** No, it only means that there is a certain relationship or link between them. For example, in a social network graph a connection between two users might mean friendship or following.

**Q: What does a grid graph represent?**

**A:** A grid graph is simply a graph where nodes are placed on a grid and connected to nodes that are horizontally, vertically and potentially diagonally adjacent. The grid graph in the notebook of Practice 6, used to demonstrate the functioning of message passing for a colouring task, was chosen just for its simplicity. In practical applications however, grid graphs are widely used for example for navigation problems in robotics or for fluid dynamics simulations.

**Q:** In 6.3, for the **conv1** layer, what is **num\_node\_features**? Where can I get its value?

**A:** **num\_node\_features** represents the number of features per node in the data. You can get its value from the dataset using **dataset.num\_node\_features**. To make the GCN model more flexible, you can modify the **\_\_init\_\_** method to accept **num\_node\_features** as a parameter instead of accessing it directly from the dataset. This allows the model to work with different datasets without modification.