

# **ML Course 2019 :Tutorial-6**

**Weizmann Institute Of Science**

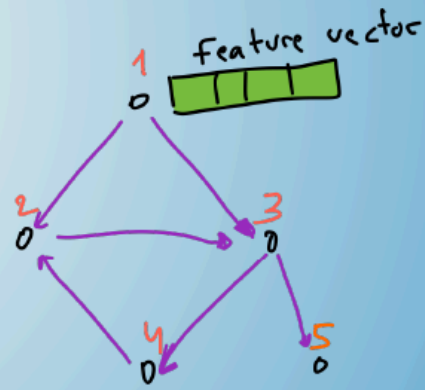
**15.05.2019**

# Introduction to graphs

nodes	
index	features
1	
2	
3	
4	
5	

edges		
index	start/end	features
1	3 → 4	
2	1 → 2	
3	4 → 2	
4	1 → 3	
5	2 → 3	
6	3 → 5	

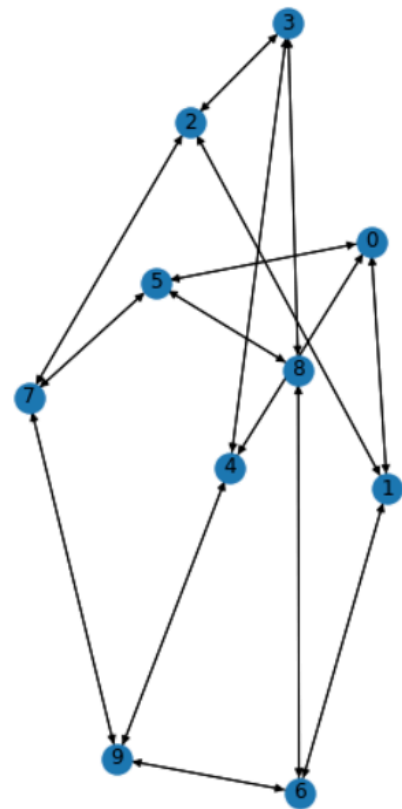
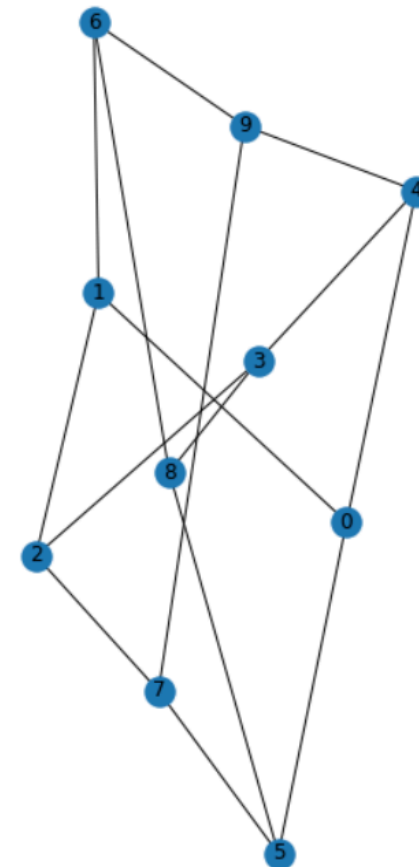
its easy for  
us to visualise



```
[ ] g_nx = nx.petersen_graph() # -- a graph with 10 vertices and 15 edges ----
    g_dgl = dgl.DGLGraph(g_nx)

import matplotlib.pyplot as plt
plt.rcParams["figure.figsize"]=10,10
plt.subplot(121)
nx.draw(g_nx, with_labels=True)
plt.subplot(122)
plt.draw(g_dgl.to_networkx(), with_labels=True)

plt.show()
```

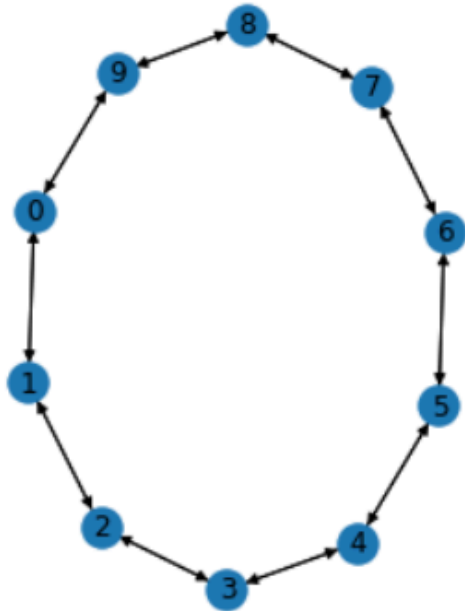


Each edge has a starting and an ending node

# Different kind of graphs



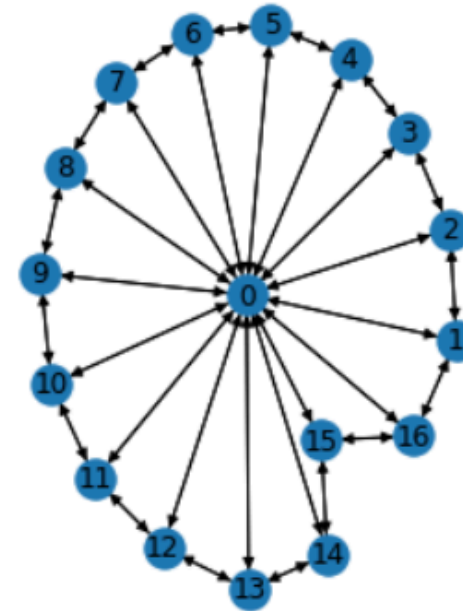
Class: 0, cycle graph



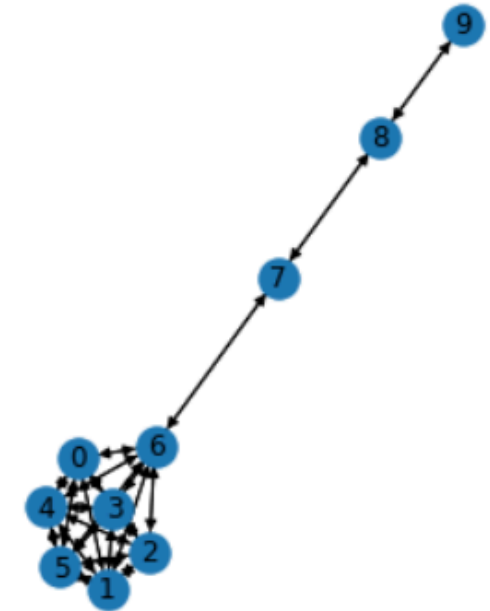
Class: 1, star graph



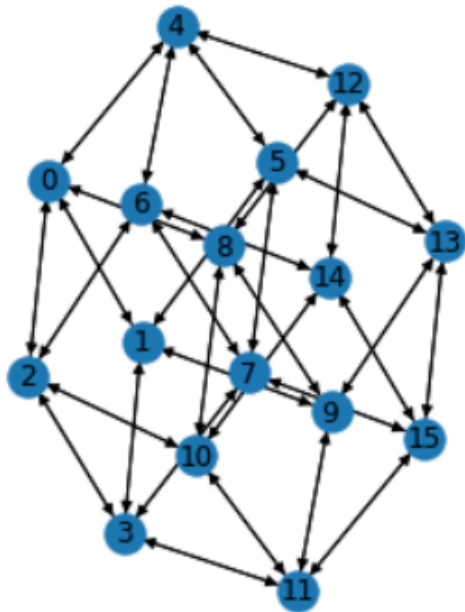
Class: 2, wheel graph



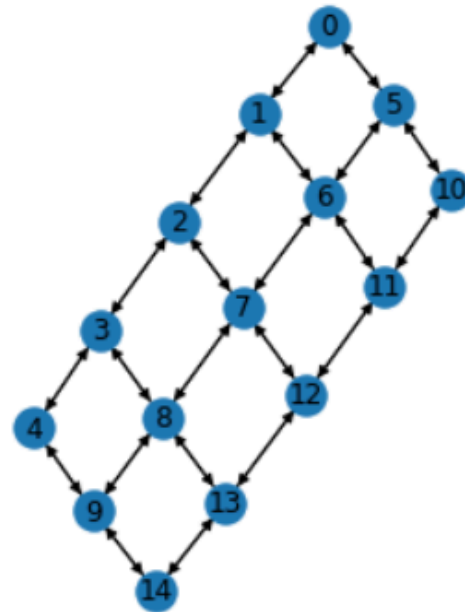
Class: 3, lollipop graph



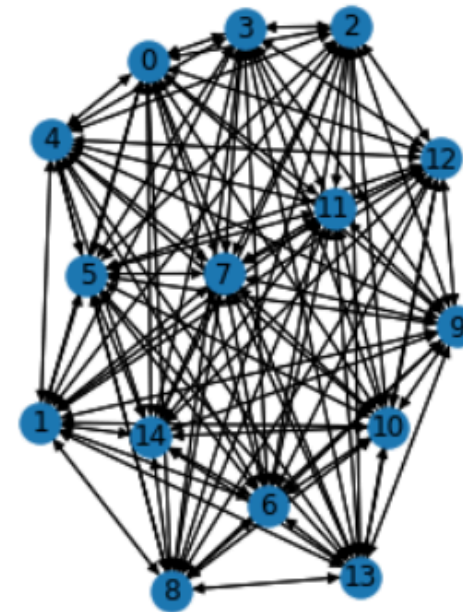
Class: 4, hypercube graph



Class: 5, grid graph



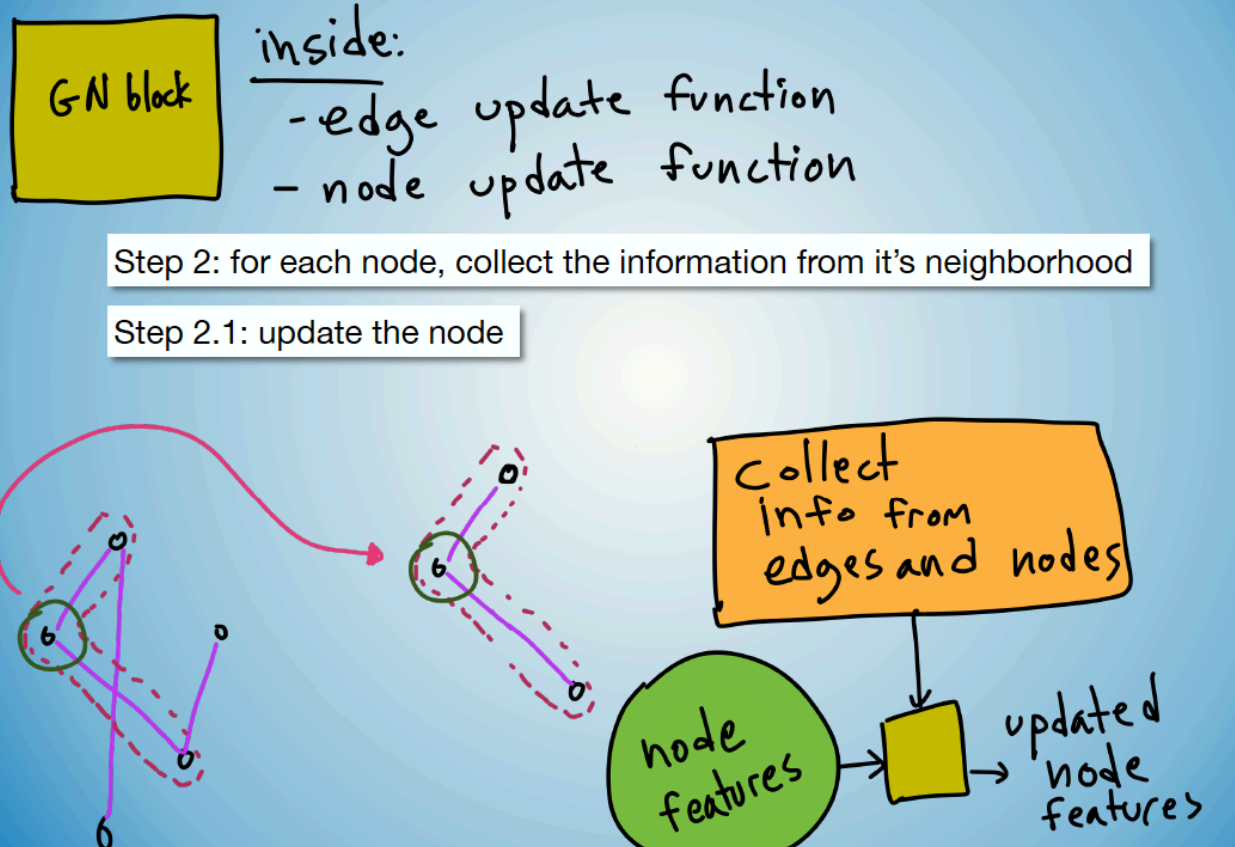
Class: 6, clique graph



Class: 7, circular ladder graph



# Message passing : updating nodes



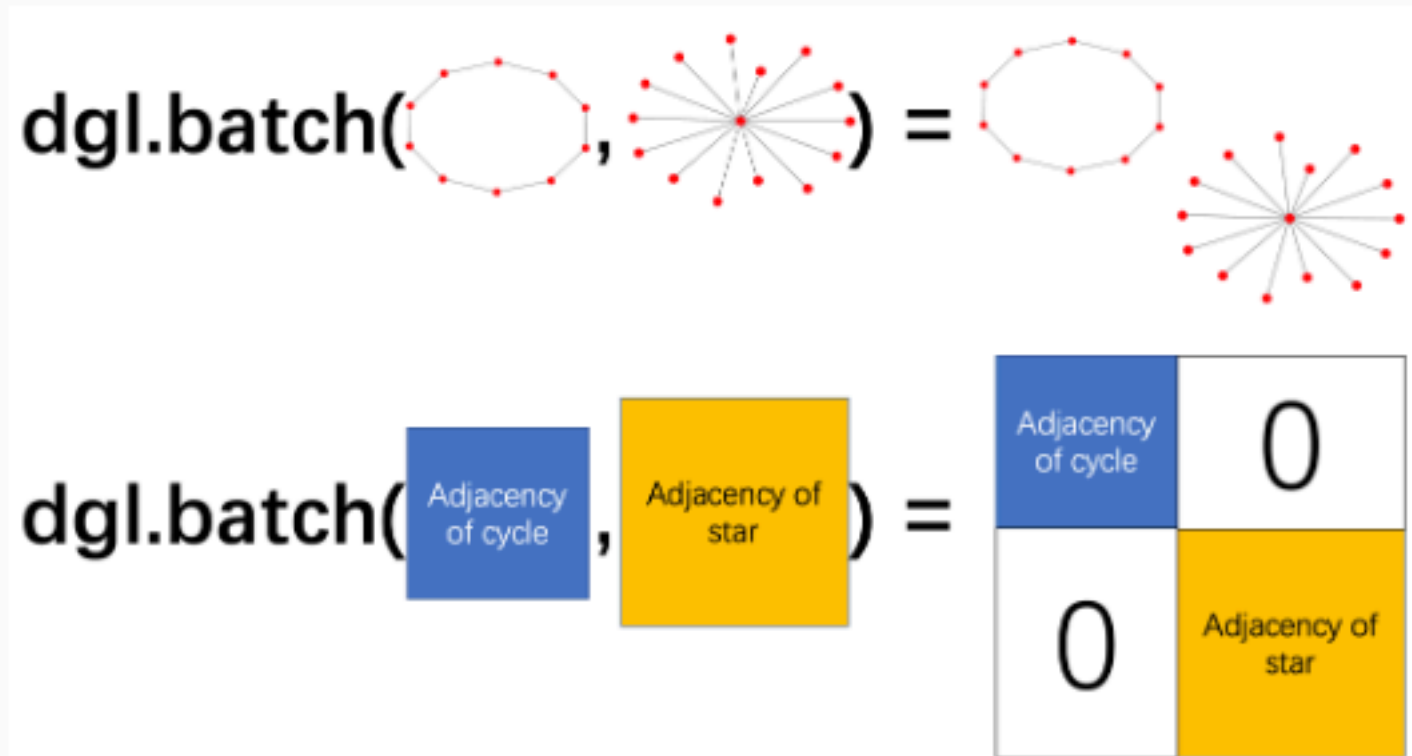
```
[41] def simple_reduce(nodes):  
    print(nodes.mailbox['message'])  
    mean_over_mailbox = torch.mean(nodes.mailbox['message'].type(torch.FloatTensor), 1)  
    return {'new_feature': mean_over_mailbox}  
  
graph.register_reduce_func(simple_reduce)  
  
for node_i in range(len(graph.nodes())):  
    graph.recv(v=node_i)  
  
print(graph.ndata)
```

# Forming the graph mini-batches

Graphs are sparse objects (different graphs have different shapes) .  
We need a collate function to form the batches of graphs

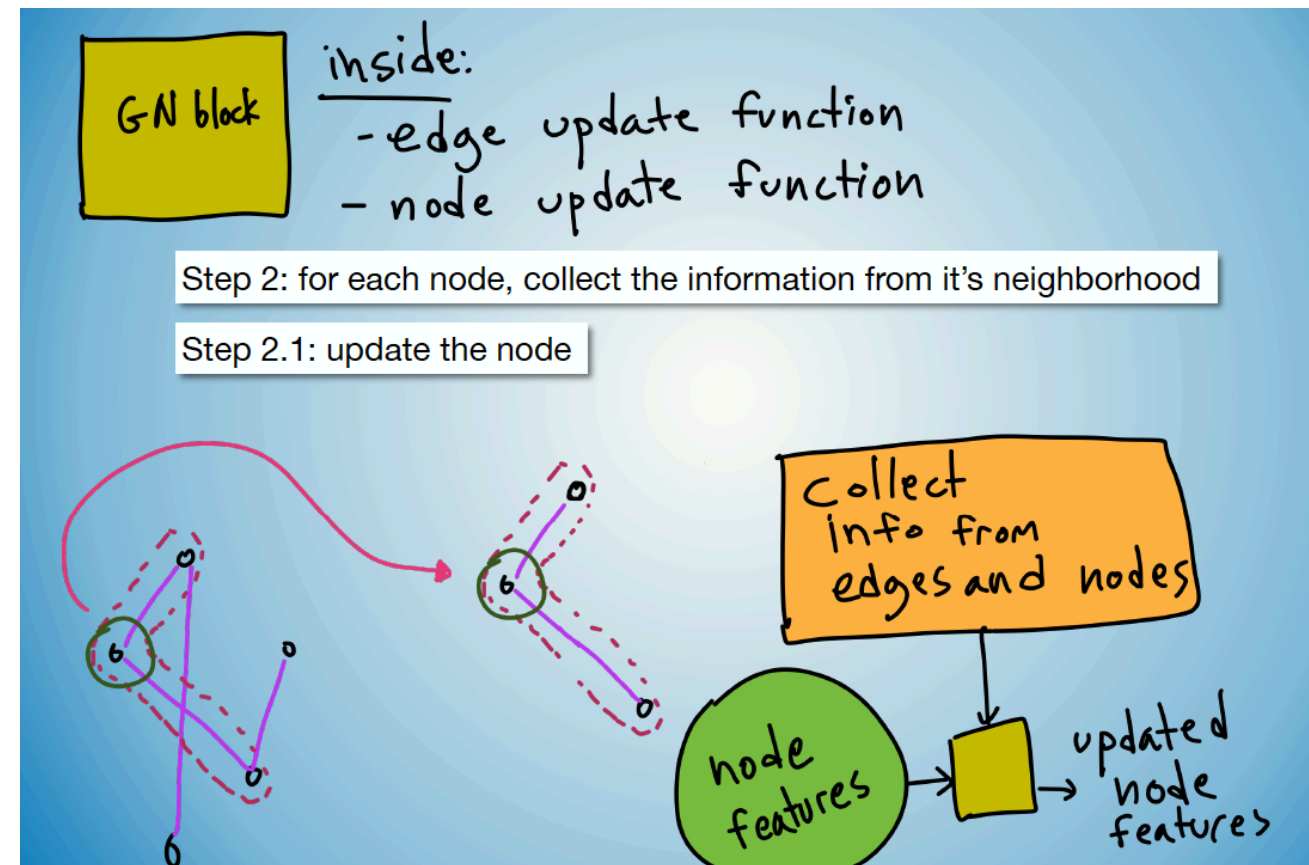
```
[43] def collate(samples):  
    # The input `samples` is a list of pairs  
    # (graph, label).  
    graphs, labels = map(list, zip(*samples))  
    batched_graph = dgl.batch(graphs) # --- the batch function creates the minibatch out of sparse graphs --- #  
    return batched_graph, torch.tensor(labels)
```

**dgl.batch()** function puts the sparse graphs in one mini-batch





# The GN block



```
class GN_block(nn.Module):
    def __init__(self, in_feats, out_feats, activation):
        super(GN_block, self).__init__()
        self.apply_mod = NodeApplyModule(in_feats, out_feats, activation)

    def forward(self, g, feature):
        # Initialize the node features with h.
        g.ndata['h'] = feature
        g.update_all(msg, reduce)
        g.apply_nodes(func=self.apply_mod)
        return g.ndata.pop('h')
```

# The GN block individual steps

**Step1 : Replace a node feature by average of neighboring node features**

```
def reduce(nodes):  
    """Take an average over all neighbor node features hu and use it to  
    overwrite the original node feature."""  
    accum = torch.mean(nodes.mailbox['m'], 1)  
    return {'h': accum}
```

**Step2 : Update the node features by passing through a linear layer + activation**

```
class NodeApplyModule(nn.Module):  
    """Update the node feature hv with ReLU(Whv+b)."""  
    def __init__(self, in_feats, out_feats, activation):  
        super(NodeApplyModule, self).__init__()  
        self.linear = nn.Linear(in_feats, out_feats)  
        self.activation = activation  
  
    def forward(self, node):  
        h = self.linear(node.data['h'])  
        h = self.activation(h)  
        return {'h': h}
```

**Step3 : GN block = assigning features → updating nodes + edges → apply activation**

```
class GN_block(nn.Module):  
    def __init__(self, in_feats, out_feats, activation):  
        super(GN_block, self).__init__()  
        self.apply_mod = NodeApplyModule(in_feats, out_feats, activation)  
  
    def forward(self, g, feature):  
        # Initialize the node features with h.  
        g.ndata['h'] = feature  
        g.update_all(msg, reduce)  
        g.apply_nodes(func=self.apply_mod)  
        return g.ndata.pop('h')
```

# The classifier

```
import torch.nn.functional as F

class Classifier(nn.Module):
    def __init__(self, in_dim, hidden_dim, n_classes):
        super(Classifier, self).__init__()

        self.layers = nn.ModuleList([
            GN_block(in_dim, hidden_dim, F.relu),
            GN_block(hidden_dim, hidden_dim, F.relu)])
        self.classify = nn.Linear(hidden_dim, n_classes)

    def forward(self, g):
        # For undirected graphs, in_degree is the same as
        # out_degree.
        h = g.in_degrees().view(-1, 1).float()
        h = h.cuda() # --- converting to gpu ---- #

        for conv in self.layers:
            h = conv(g, h)
            g.ndata['h'] = h
        hg = dgl.mean_nodes(g, 'h')
        return self.classify(hg)
```

