#### 1 Question 1

In terms of training accuracy, the architecture is likely to totally overfit the training set since the expressive power of the architecture is high. Indeed, each node of the graph could have an unique representation on the latent space (for example, Z could be the adjacency matrix padded with zeros).

## 2 Question 2

We could simply gives the indicator vector for each node (node number k would have  $e_k$  as representation).

### 3 Question 3

Because the probability of each pair of nodes having an edge is independent, by denoting N(G) the number of nodes of a graph G, we simply have the formula:

$$\mathbf{E}(N(G(n,p)) = \frac{n(n-1)}{2}p$$

Indeed N(G(n,p)) follows a binomial law of parameters  $\frac{n(n-1)}{2}$  and p. Thus the variance is:

$$\mathbf{Var}(N(G(n,p)) = \frac{n(n-1)}{2}p(1-p)$$

Numerical application:

$$\mathbf{E}(N(G(15, 0.2)) = 21$$

$$\mathbf{Var}(N(G(15, 0.2)) = 16, 8$$

$$\mathbf{E}(N(G(15, 0.4)) = 42$$

$$\mathbf{Var}(N(G(15, 0.4)) = 25, 2$$

# 4 Question 4

Max:

$$\begin{split} z_{G_1} &= [0.89, 0.34, 1.31] \\ z_{G_2} &= [0.89, 0.34, 1.31] \\ z_{G_3} &= [0.89, 0.34, 1.31] \end{split}$$

Sum:

$$\begin{split} z_{G_1} &= [0.71, -0.49, 2.39] \\ z_{G_2} &= [3., 0.41, 2.] \\ z_{G_3} &= [2.31, 0, 1.] \end{split}$$

Mean:

$$\begin{split} z_{G_1} &= [0.237, -0.163, 0.797] \\ z_{G_2} &= [0.75, 0.1025, 0.5] \\ z_{G_3} &= [1.155, 0, 0.5] \end{split}$$

The most distinctive readout functions here is the sum function (the less distinctive being the max, and the mean giving the same 3rd value for the second and third graphs).

#### References