

1 Question 1

The window parameter w controls the scale of graph structure captured by DeepWalk by defining how far apart two nodes can be in a random walk and still be treated as contextual neighbors. For small w , only immediate neighbors contribute to the objective, leading to embeddings that emphasize local connectivity and fine-grained graph structure. For large w , nodes that are farther apart along the walk are paired, which captures more global relationships and community-level structure but may blur local distinctions by combining heterogeneous contexts.

2 Question 2

The two embedding matrices are equivalent up to an orthogonal transformation. Specifically, $X_2 = X_1 R$ with $R = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$, corresponding to a reflection across one coordinate axis. This illustrates that DeepWalk embeddings are not unique and are defined only up to rotations and reflections of the embedding space.

3 Question 3

We write a single GNN layer as

$$\text{GNN}(A, X) = f(\hat{A}XW), \quad \hat{A} = \tilde{D}^{-1/2}(A + I)\tilde{D}^{-1/2},$$

where f is applied elementwise (e.g. ReLU).

Let P be a permutation matrix and define

$$A' = PAP^\top, \quad X' = PX.$$

Then

$$\tilde{A}' = A' + I = PAP^\top + I = P(A + I)P^\top = P\tilde{A}P^\top.$$

Let $\mathbf{1}$ be the all-ones vector. The degree matrix satisfies

$$\tilde{D} = \text{diag}(\tilde{A}\mathbf{1}), \quad \tilde{D}' = \text{diag}(\tilde{A}'\mathbf{1}) = \text{diag}(P\tilde{A}P^\top\mathbf{1}) = \text{diag}(P\tilde{A}\mathbf{1}) = P\tilde{D}P^\top.$$

Since P is a permutation matrix and \tilde{D} is diagonal,

$$(\tilde{D}')^{-1/2} = (P\tilde{D}P^\top)^{-1/2} = P\tilde{D}^{-1/2}P^\top.$$

Hence the normalized adjacency after permutation is

$$\hat{A}' = (\tilde{D}')^{-1/2}\tilde{A}'(\tilde{D}')^{-1/2} = P\tilde{D}^{-1/2}\tilde{A}\tilde{D}^{-1/2}P^\top = P\hat{A}P^\top.$$

Now

$$\text{GNN}(PAP^\top, PX) = f(\hat{A}'X'W) = f(P\hat{A}P^\top PXW) = f(P\hat{A}XW).$$

Since f is applied elementwise (rowwise), it commutes with the permutation:

$$f(PY) = Pf(Y) \quad \text{for all } Y.$$

Therefore

$$\text{GNN}(PAP^\top, PX) = Pf(\hat{A}XW) = P\text{GNN}(A, X),$$

which proves permutation equivariance.

4 Question 4

1. u is an eigenvector of \hat{A} with eigenvalue 1.

Let $\tilde{A} = A + I$ and $\tilde{D} = \text{diag}(\tilde{d}_1, \dots, \tilde{d}_n)$ with $\tilde{d}_i = \sum_j \tilde{A}_{ij}$. The normalized adjacency is

$$\hat{A} = \tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2}.$$

Define $u \in \mathbb{R}^n$ by $u_i = \sqrt{\tilde{d}_i}$. Then

$$(\hat{A}u)_i = \sum_j \tilde{D}_{ii}^{-1/2} \tilde{A}_{ij} \tilde{D}_{jj}^{-1/2} u_j = \frac{1}{\sqrt{\tilde{d}_i}} \sum_j \tilde{A}_{ij} \frac{1}{\sqrt{\tilde{d}_j}} \sqrt{\tilde{d}_j} = \frac{1}{\sqrt{\tilde{d}_i}} \sum_j \tilde{A}_{ij} = \frac{\tilde{d}_i}{\sqrt{\tilde{d}_i}} = \sqrt{\tilde{d}_i} = u_i.$$

Hence $\hat{A}u = u$, i.e. u is an eigenvector with eigenvalue $\lambda = 1$.

2. Limit of $Z^{(k)}$ as $k \rightarrow \infty$.

Since the graph is connected and non-bipartite, \hat{A} is symmetric with eigenvalues $1 = \lambda_1 > |\lambda_2| \geq \dots \geq |\lambda_n|$ and an orthonormal basis of eigenvectors q_1, \dots, q_n with $q_1 \propto u$. Write the spectral decomposition

$$\hat{A} = Q \Lambda Q^\top, \quad Q = [q_1 \dots q_n], \quad \Lambda = \text{diag}(\lambda_1, \dots, \lambda_n).$$

Then

$$\hat{A}^k = Q \Lambda^k Q^\top \xrightarrow{k \rightarrow \infty} Q \text{diag}(1, 0, \dots, 0) Q^\top = q_1 q_1^\top.$$

Thus

$$Z^{(k)} = \hat{A}^k XW \xrightarrow{k \rightarrow \infty} (q_1 q_1^\top) XW = q_1 (q_1^\top XW),$$

so every node embedding becomes a scalar multiple of the same global vector $v := q_1^\top XW$.

3. Why nodes with the same degree become indistinguishable.

The first eigenvector q_1 is proportional to u , hence $q_{1,i} \propto \sqrt{\tilde{d}_i}$. In the limit, the representation of node i is

$$Z_i^{(\infty)} = q_{1,i} v,$$

which depends on i only through $\sqrt{\tilde{d}_i}$. Therefore, any two nodes with the same degree (same \tilde{d}_i) have identical limiting representations, regardless of their initial features X , illustrating oversmoothing.

References