Representation Learning on Graphs and Networks (L45)
CST Part III / MPhil in ACS

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1 Primer on Graph Representations

1. Mathematical definition of graphs:
   A *graph* $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ is a collection of nodes $\mathcal{V}$ and edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$
   The edges can be represented by an *adjacency matrix*, $\mathbf{A} \in \mathbb{R}^{|\mathcal{V}| \times |\mathcal{V}|}$, such that
$$A_{uv} = \begin{cases} 1 & \text{if } (u,v) \in \mathcal{E} \\ 0 & \text{otherwise} \end{cases}$$
2. Some interesting graph types:
   - **Undirected**: $\forall u, v \in \mathcal{V}.\ (u,v) \in \mathcal{E} \iff (u,v) \in \mathcal{E}$ (i.e., $\mathbf{A}^\top = \mathbf{A}$)
   - **Weighted**: provided *edge weight* w_{uv} for every edge $(u,v) \in \mathcal{E}$
   - **Multirelational**: various *edge types*, i.e. $(u,t,v) \in \mathcal{E}$ if there exists an edge (u,v) linked by type t
   - **Heterogeneous**: various *node types*
3. Machine learning tasks on graphs by domain:
   - **Transductive**: training algorithm sees all observations, including the holdout observations
     - Task is to *propagate* labels from the training observations to the holdout observations
     - Also called *semi-supervised learning*
   - **Inductive**: training algorithm only sees the training observations during training, and only sees the holdout observations for prediction
4. Node statistics:
   - **Degree**: amount of edges the node is incident to:
   $$d_u = \sum_{v \in \mathcal{V}} A_{uv}$$
   - **Centrality**: a measure of how "central" the node is in the graph: how often do infinite random walks visit the node?
   $$d_u = \lambda^{-1} \sum_{v \in \mathcal{V}} A_{uv} e_v$$
   where $\mathbf{e} \in \mathbb{R}^{|\mathcal{V}|}$ is the largest eigenvector of $\mathbf{A}$, with corresponding eigenvalue λ
   - **Clustering coefficient**: a measure of "clusteredness": are neighbours connected amongst each other?
   $$c_u = \frac{\left|\left\{(v_1, v_2) \in \mathcal{E} \middle| v_1, v_2 \in \mathcal{N}(u)\right\}\right|}{\binom{d_u}{2}}$$
5. Graph Laplacian:
   Let $\mathbf{D}$ be the diagonal (out)-degree matrix of the graph, i.e., $D_{uu} = \sum_{v \in \mathcal{V}} A_{ij}$. Then:
   - The *unnormalised* graph Laplacian: $\mathbf{L} = \mathbf{D} - \mathbf{A}$
   - The *symmetric* graph Laplacian: $\mathbf{L}_{\text{sym}} = \mathbf{D}^{-\frac{1}{2}} \mathbf{L} \mathbf{D}^{-\frac{1}{2}} = \mathbf{I} - \mathbf{D}^{-\frac{1}{2}} \mathbf{A} \mathbf{D}^{-\frac{1}{2}}$
   - The *random walk* graph Laplacian: $\mathbf{L}_{\text{RW}} = \mathbf{D}^{-1} \mathbf{L} = \mathbf{I} - \mathbf{D}^{-1} \mathbf{A}$

   Properties:
   - For undirected graphs, $\mathbf{L}$ is *symmetric* ($\mathbf{L}^\top = \mathbf{L}$) and *positive semi-definite* ($\forall \mathbf{x} \in \mathbb{R}^{|\mathcal{V}|}.\ \mathbf{x}^\top \mathbf{L} \mathbf{x} \geq 0$)
   - For undirected graphs:
   $$\forall \mathbf{x} \in \mathbb{R}^{|\mathcal{V}|}.\ \mathbf{x}^\top \mathbf{L} \mathbf{x} = \frac{1}{2} \sum_{u \in \mathcal{V}} \sum_{v \in \mathcal{V}} A_{uv} (x_u - x_v)^2 = \sum_{(u,v) \in \mathcal{E}} (x_u - x_v)^2$$
   - $\mathbf{L}$ has $|\mathcal{V}|$ nonnegative eigenvalues: $\lambda_1 \geq \cdots \geq \lambda_{|V|} = 0$

6. Spectral clustering:
   - Two-way cut: partition the graph into $\mathcal{A} \subseteq \mathcal{V}$ and its complement $\mathcal{A}_c \subseteq \mathcal{V}$:

     $$\text{Cut}(\mathcal{A}) = \left|\left\{(u,v) \in \mathcal{E} \middle| u \in \mathcal{A} \wedge v \in \mathcal{A}_c\right\}\right|$$

     Ratio cut metric:

     $$\text{RCut}(\mathcal{A}) = \text{Cut}(\mathcal{A}) \left(\frac{1}{|\mathcal{A}|} + \frac{1}{|\mathcal{A}_c|}\right)$$

   - Minimising RCut($\mathcal{A}$):
     Let $\mathbf{a} \in \mathbb{R}^{|\mathcal{V}|}$ be a vector representing the cut $\mathcal{A}$, defined as follows:

     $$a_u = \begin{cases} \sqrt{\frac{\mathcal{A}_c}{\mathcal{A}}} & \text{if } u \in \mathcal{A} \\ -\sqrt{\frac{\mathcal{A}}{\mathcal{A}_c}} & \text{if } u \in \mathcal{A}_c \end{cases}$$

     Then

     $$\mathbf{a}^\top \mathbf{L} \mathbf{a} = \sum_{(u,v) \in \mathcal{E}} (a_u - a_v)^2 = |\mathcal{V}| \text{RCut}(\mathcal{A})$$

     Minimising $\mathbf{a}^\top \mathbf{L} \mathbf{a}$ corresponds to minimising RCut($\mathcal{A}$) (NP-hard as the constraint is discrete)
   - Relaxing: minimise $\mathbf{a}^\top \mathbf{L} \mathbf{a}$ subject to $\mathbf{a} \perp \mathbf{1}$ and $||\mathbf{a}||^2 = |\mathcal{V}|$
     Rayleigh–Ritz Theorem: The solution is exactly the second-smallest eigenvector of $\mathbf{L}$
     To obtain the cut, place u into $\mathcal{A}$ or $\mathcal{A}_c$ depending on the sign of a_u
   - Can be generalised to k-clustering

2 Permutation Invariance and Equivariance

1. Informal definitions:
   - **Permutation invariance**: applying a permutation matrix does not modify the result
   - **Permutation equivariance**: transformation preserves the node order
   - **Locality**: signal remains stable under slight deformations of the domain
2. Setup:
   - **Node feature matrix**: $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1 & \cdots & \mathbf{x}_{|\mathcal{V}|} \end{bmatrix}^\top \in \mathbb{R}^{|\mathcal{V}| \times k}$, where $\mathbf{x}_i \in \mathbb{R}^k$ is the features of node i
   - **(1-hop) neighbourhood** of node i: $\mathcal{N}_i = \left\{j \middle| (i,j) \in \mathcal{E} \vee (j,i) \in \mathcal{E}\right\}$
   - **Neighbourhood features**: $\mathbf{X}_{\mathcal{N}_i} = \{\{\mathbf{x}_j | j \in \mathcal{N}_i\}\}$
   - **Permutation matrix**: a $|\mathcal{V}| \times |\mathcal{V}|$ binary matrix that has exactly one entry of 1 in every row and column, and 0s elsewhere: $\mathbf{P} = \begin{bmatrix} \mathbf{e}_{\pi(1)} & \cdots & \mathbf{e}_{\pi(|\mathcal{V}|)} \end{bmatrix}^\top$
3. Learning on sets:
   - $f(\mathbf{X})$ is *permutation invariant* if for all permutation matrices $\mathbf{P}$: $f(\mathbf{P}\mathbf{X}) = f(\mathbf{X})$
   - $\boldsymbol{F}(\mathbf{X})$ is *permutataion equivariant* if for all permutation matrices $\mathbf{P}$: $\boldsymbol{F}(\mathbf{P}\mathbf{X}) = \mathbf{P}\boldsymbol{F}(\mathbf{X})$
   - Locality on sets: transform every node in isolation, through a shared function ψ: $\mathbf{h}_i = \psi(\mathbf{x}_i)$
     Stacking $\mathbf{h}_i$ into a matrix yields $\mathbf{H} = \boldsymbol{F}(\mathbf{X})$:

     $$\boldsymbol{F}(\mathbf{X}) = \begin{bmatrix} — & \psi(\mathbf{x}_1) & — \\ & \vdots & \\ — & \psi(\mathbf{x}_{|\mathcal{V}|}) & — \end{bmatrix}$$

   - Deep Sets (Zaheer *et al.*, NIPS 2017):

     $$f(\mathbf{X}) = \phi\left(\bigoplus_{i \in \mathcal{V}} \psi(\mathbf{x}_i)\right)$$

     Universality of Deep Sets: any permutation invariant model can be expressed as a Deep Sets

4. Learning on graphs:
   - $f(\mathbf{X})$ is *permutation invariant* if for all permutation matrices $\mathbf{P}$: $f(\mathbf{PX}, \mathbf{PAP}^\top) = f(\mathbf{X}, \mathbf{A})$
   - $\boldsymbol{F}(\mathbf{X})$ is *permutataion equivariant* if for all permutation matrices $\mathbf{P}$: $\boldsymbol{F}(\mathbf{PX}, \mathbf{PAP}^\top) = \mathbf{P}\boldsymbol{F}(\mathbf{X}, \mathbf{A})$
   - Locality on graphs: apply a local function ϕ over all neighbourhoods:

$$\boldsymbol{F}(\mathbf{X}, \mathbf{A}) = \begin{bmatrix} — & \phi(\mathbf{x}_1, \mathbf{X}_{\mathcal{N}_1}) & — \\ & \vdots & \\ — & \phi(\mathbf{x}_{|\mathcal{V}|}, \mathbf{X}_{\mathcal{N}_{|\mathcal{V}|}}) & — \end{bmatrix}$$

   To ensure permutation equivariance, it is sufficient that ϕ is permutation invariant in $\mathbf{X}_{\mathcal{N}_i}$

3 Graph Neural Networks

Appendix: Mathematical Notations

a	A scalar (integer or real)
$\mathbf{a}$	A vector
$\mathbf{A}$	A matrix
$\mathcal{A}$ or $\{\cdot\}$	A set
$\{\{\cdot\}\}$	A multiset
$\lvert\mathcal{A}\rvert$	Cardinality of set $\mathcal{A}$
$\mathbb{R}$	The set of real numbers
a_i	Element i of vector $\mathbf{a}$, with indexing starting at 1
A_{ij}	Element i, j of matrix $\mathbf{A}$, with indexing starting at 1
f	A function
$\boldsymbol{F}$	A matrix-valued function
π	A permutation
$\phi, \psi, \cdots$	Learnable functions (e.g., MLPs)
$\oplus$	A permutation-invariant operator (e.g., sum, mean, min, max)