## Machine Learning for Graphs and Sequential Data Exercise Sheet 13

## **Graphs: Semi-Supervised Learning**

## Label Propagation

**Problem 1:** The goal in Label Propagation is to find a labeling  $\mathbf{y} \in \{0,1\}^N$  that minimizes the energy  $\min_{\mathbf{y}} \frac{1}{2} \sum_{ij} \mathbf{w}_{ij} (y_i - y_j)^2$  subject to  $y_i = \hat{y}_i \ \forall i \in S$  where the set of nodes V has been partitioned into the labeled nodes S and the unlabeled nodes U,  $w_{ij} \geq 0$  is the non-negative edge weight and  $\hat{y}_i$  are the observed labels.

Following from the first observation regarding the Laplacian, the minimization problem can be rewritten and then relaxed to  $\min_{\boldsymbol{y} \in \mathbb{R}^N} \boldsymbol{y}^T \boldsymbol{L} \boldsymbol{y}$  subject to the same constraints. Show that the closed form solution is

$$\boldsymbol{y}_U = -\boldsymbol{L}_{UU}^{-1} \cdot \boldsymbol{L}_{US} \cdot \hat{\boldsymbol{y}}_S$$

where w.l.o.g. we assume that the Laplacian matrix is partitioned into blocks for labeled and unlabeled nodes as

$$m{L} = egin{pmatrix} m{L}_{SS} & m{L}_{SU} \ m{L}_{US} & m{L}_{UU} \end{pmatrix}.$$

## **PPNP**

**Problem 2:** The iterative equation of PPNP is given by

$$\boldsymbol{H}^{(l+1)} = (1 - \alpha)\hat{\boldsymbol{A}}\boldsymbol{H}^{(l)} + \alpha\boldsymbol{H}^{(0)}$$

where  $\hat{A} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}}$  is the propagation matrix. Derive the closed form solution for infinitely many propagation steps.

*Hint*: If we have for a matrix T that all its eigenvalues  $\lambda$  are strictly between -1 and 1, an equivalent matrix formulation of the geometric series formula holds and

$$\sum_{k=0}^{\infty} \mathbf{T}^k = (\mathbf{I} - \mathbf{T})^{-1}.$$

Hint: The eigenvalues  $\lambda_i$  of the normalized Laplacian  $L = I + D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$  are  $0 \le \lambda_i \le 2$ .