

graph regularized matrix factorization

graph regularized MF

data: (compound i , compound j , miscibility outcome)
 $i, j \in \text{compound}$ $r \in \{0, 1\}$

M : miscibility matrix, $C \times C$, symmetric $M^T = M$, M_{ij} is miscibility outcome.

Suppose only a fraction of entries are observed:
 $\Omega_{obs} \subset \{1, \dots, C\} \times \{1, \dots, C\}$

also, each compound i has class label given by $\phi(i)$,
 protein, mutant, etc.

model: $\vec{z}_i \in \mathbb{R}^d$ low dimensional latent representation for compound i

we wish to learn these:
 $m_{ij} = \sigma(\vec{z}_i \cdot \vec{z}_j)$

with $\sigma(x) = 1/(1+e^{-x})$ the sigmoid function

$\vec{z}_i \cdot \vec{z}_j = \|\vec{z}_i\| \|\vec{z}_j\| \cos \theta$
 $\cos \theta$ is vectors point in same direction, miscible, otherwise non-miscible.

note: model as of now doesn't account for class labels.

loss:
$$\mathcal{L}(\vec{z}_1, \dots, \vec{z}_C) = - \sum_{(i,j) \in \Omega_{obs}} m_{ij} \log[\sigma(\vec{z}_i \cdot \vec{z}_j)] + (1 - m_{ij}) \log[1 - \sigma(\vec{z}_i \cdot \vec{z}_j)]$$

$$+ \lambda \sum_{(i,j)} \|\vec{z}_i - \vec{z}_j\|^2 \mathbb{I}(\phi(i) \neq \phi(j))$$

Second term is graph regularization.
 encourages compounds from same class to coalesce.
 λ hyperparam controls penalty for clones to drift away from each other.

same as making proteins fully connected graph, spectral embedding if $\lambda \rightarrow \infty$

$C = [\vec{z}_1 \dots \vec{z}_C]$ dxC matrix. Useful constraint: $CC^T = I$, why?