## Epitomic Variational Graph Autoencoder

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Overview

## Autoencoder



## Variational Autoencoder (VAE)



Graph Autoencoder (GAE)


## Variational Graph Autoencoder (VGAE)



Over-pruning

## Over-pruning in VGAE

VGAE loss function penalizes the latent dimensions/units that fail to convey enough information about the input to the decoder block.

## Unit Activity

## Intuition:

An active unit should have different values for different inputs.
Definition:

$$
A_{u}=\operatorname{Cov}_{x}\left(\mathbb{E}_{u \sim q(u \mid x)}[u]\right)
$$

A unit $u$ is considered active if $A_{u}>0.02$

## KLD \& Unit Activity in Pure VGAE - Cora Dataset




Only one out of 16 hidden units is actively encoding input information required for the reconstruction.

## VGAE Approach to Tackle Over-pruning

$$
L_{\mathrm{VGAE}}=L(A, \bar{A})+\beta D_{K L}(\mathcal{N}(\mu, \sigma) \| \mathcal{N}(0,1))
$$

- VGAE applies $\beta=\frac{1}{N}$
- Less pruning compared to pure VGAE
- Poor distribution matching $\rightarrow$ poor generativeness
- VGAE $\rightarrow$ GAE as $\beta \rightarrow 0$


## KLD \& Unit Activity in VGAE - Cora Dataset



All the hidden units are active but KL-divergence is quite high, indicating poor matching of learnt distribution with prior, consequently affecting generative ability of the model

## Effect of $\beta$ on VGAE - Cora Dataset




As $\boldsymbol{\beta}$ decreases, both number of active units and average KLD of active units increases.

Epitomic Variational Graph Autoencoder

## Epitomic VGAE (EVGAE)

- EVGAE consists of multiple sparse VGAE models, called epitomes.
- One epitome is active for each training sample.
- Latent space is shared between the epitomes.


Example of 8 epitomes in 16 dimensions. Gray and white cells refer to 1 and 0 respectively.

Epitomic VGAE (EVGAE)


$$
\prod_{j=1}^{D}(E[y, j] \mathcal{N}(0,1)+(1-E[y, j]) \delta(0))
$$

Generative Model


$$
\epsilon \sim \mathcal{N}(0,1)
$$

Inference Model

## EVGAE - Loss Function

$$
\begin{aligned}
L & =\overbrace{\mathrm{BCE}}^{L_{1}}+\overbrace{\sum_{i=1}^{N} D_{K L}\left(\operatorname{Cat}\left(\pi_{i}(\mathcal{G})\right) \| \mathcal{U}(1, M)\right)}^{L_{2}} \\
& +\underbrace{\sum_{i=1}^{N} \sum_{y_{i}} \pi_{i}(\mathcal{G}) \sum_{j=1}^{D} E\left[y_{i}, j\right] D_{K L}\left(\mathcal{N}\left(\mu_{i}^{j}(\mathcal{G}),\left(\sigma_{i}^{2}\right)^{j}(\mathcal{G})\right) \| \mathcal{N}(0,1)\right)}_{L_{3}} .
\end{aligned}
$$

## KLD \& Unit Activity in EVGAE - Cora Dataset




EVGAE achieves better distribution matching compared to VGAE, while simultaneously getting more units active.

## EVGAE vs VGAE vs Pure VGAE - Cora Dataset




EVGAE achieves better distribution matching compared to VGAE, while simultaneously getting more units active.

## Results on Link Prediction

| Method | Cora |  | Citeseer |  | PubMed |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | AUC | AP | AUC | AP | AUC | AP |
| DeepWalk | $83.1 \pm 0.01$ | $85.0 \pm 0.00$ | $80.5 \pm 0.02$ | $83.6 \pm 0.01$ | $84.4 \pm 0.00$ | $84.1 \pm 0.0$ |
| Spectral Clustering | $84.6 \pm 0.01$ | $88.5 \pm 0.00$ | $80.5 \pm 0.01$ | $85.0 \pm 0.01$ | $84.2 \pm 0.02$ | $87.8 \pm 0.01$ |
| GAE (VGAE with $\beta$ <br> $=0)$ | $91.0 \pm 0.02$ | $92.0 \pm 0.03$ | $89.5 \pm 0.04$ | $89.9 \pm 0.05$ | $96.4 \pm 0.00$ | $96.5 \pm 0.0$ |
| VGAE $\left(\beta \sim 10^{-4}-\right.$ <br> $\left.10^{-5}\right)$ | $91.4 \pm 0.01$ | $92.6 \pm 0.01$ | $90.8 \pm 0.02$ | $92.0 \pm 0.02$ | $94.4 \pm 0.02$ | $94.7 \pm 0.0$ |
| pure VGAE $(\beta=1)$ | $79.44 \pm 0.03$ | $80.51 \pm 0.02$ | $77.08 \pm 0.03$ | $79.07 \pm 0.02$ | $82.79 \pm 0.01$ | $83.88 \pm 0.01$ |
| EVGAE $(\beta=1)$ | $\mathbf{9 2 . 9 6} \pm \mathbf{0 . 0 2}$ | $\mathbf{9 3 . 5 8} \pm \mathbf{0 . 0 3}$ | $\mathbf{9 1 . 5 5} \pm \mathbf{0 . 0 3}$ | $\mathbf{9 3 . 2 4} \pm \mathbf{0 . 0 2}$ | $\mathbf{9 6 . 8 0} \pm \mathbf{0 . 0 1}$ | $\mathbf{9 6 . 9 1} \pm \mathbf{0 . 0 2}$ |

## Thanks!

