Learning Stable Graphs from Multiple Environments with Selection Bias

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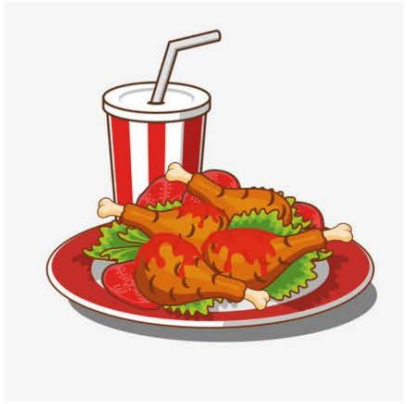
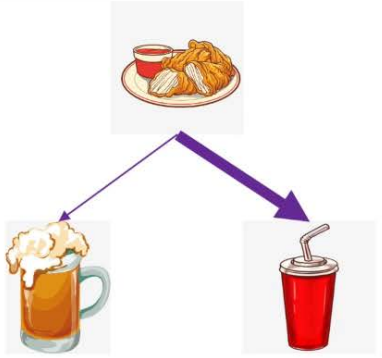
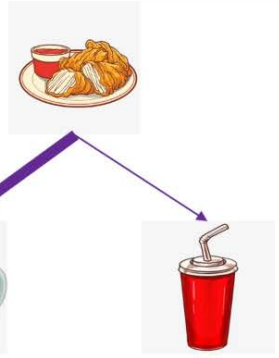
Zekun Cai 20200821

Introduction

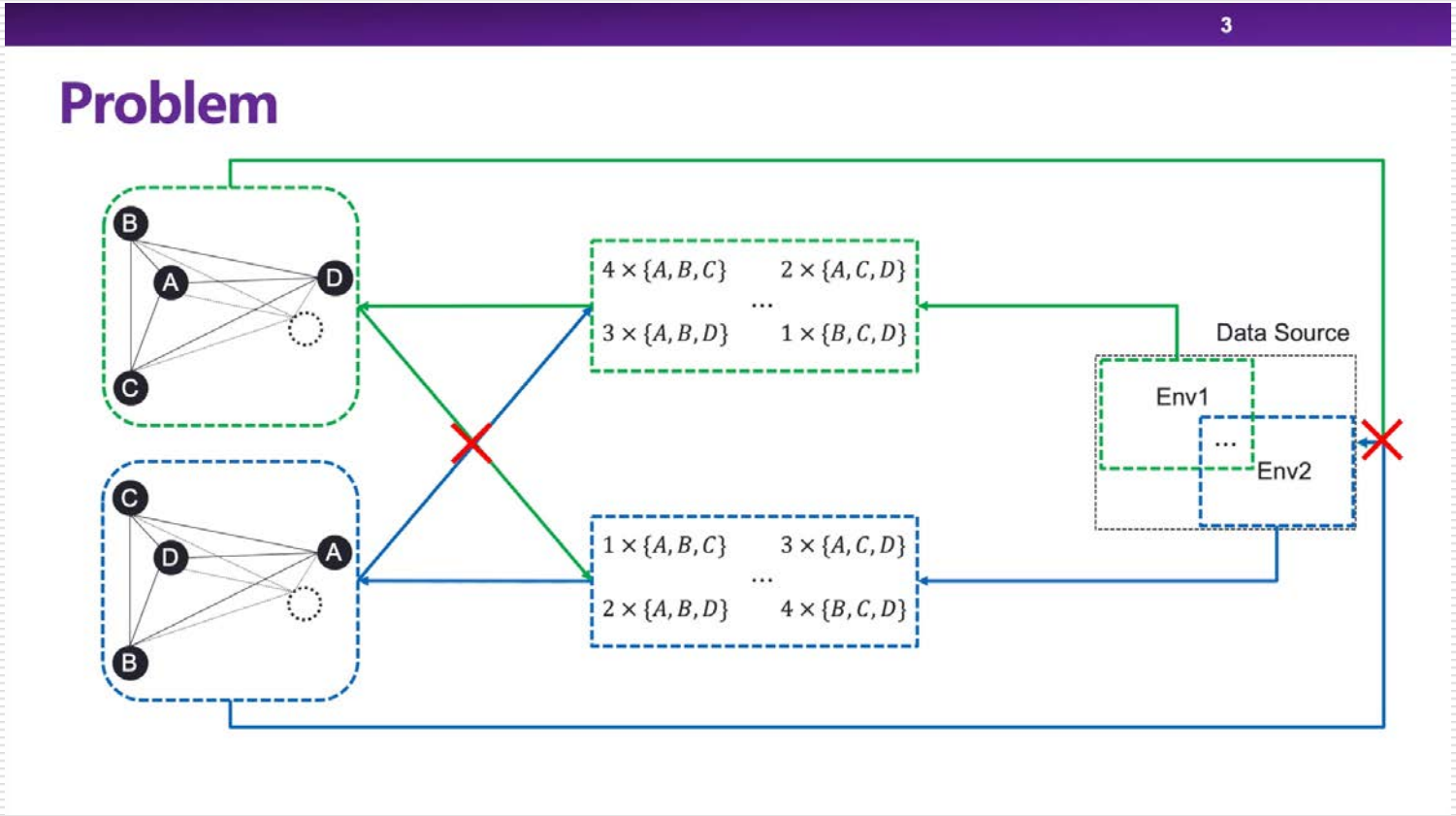
Background







Problem



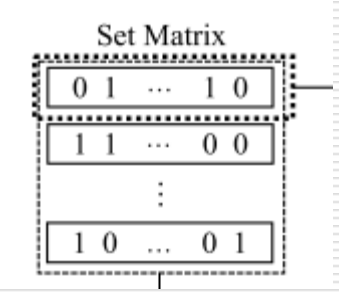
The data collection process is usually full of known or unknown sample selection biases, leading to spurious correlations among entities. (product purchasing graph: female and male; different geographical regions; long time-span)

→We need stable graph across different environments with selection bias.

The learned graph can be applied into multiple, even unknown environments and help to produce stable performances with subsequent tasks.

Concept

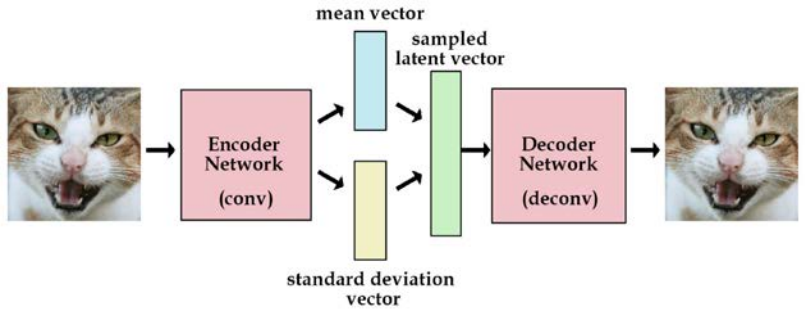
- Set data
  - a data sample is represented by a set (e.g. a shopping basket in recommendation systems)



- Elements
  - Graph nodes(e.g. products in recommendation systems)

- Environments
  - different environments are with different selection bias

- VAE（变分自编码器）
  - Deep Generative Model



$$l_i(\theta,\phi) = -E_{z\sim q\theta(z|x_i)}[log(p_\phi(x_i|z))] + KL(q_\theta(z|x_i)||p(z))$$

重建 loss+KL散度

Notations and Problem

- 给出M个不同环境的graph和set data $\{(G^{(m)}, S^{(m)})\}_{m=1}^{M}$ 我们的任务是在其之上学习出一个稳定的图结构（如图的邻接矩阵），可以在不同的环境中都有良好的效果。

- Method
  - 由于环境的不同，不同环境的图结构以及节点的条件概率分布也不同

$$P^{(m)}(I_k|\mathbf{s}) = h(G^{(m)}, I_k, \mathbf{s}).$$

  - 没有数据偏见的图结构和概率分布，应该是所有环境的随机选择。

$$P_S(I_k|\mathbf{s}) = \sum_{m=1}^{M} \frac{P^{(m)}(I_k|\mathbf{s})}{M}.$$

  - 因此，若一个图结构满足稳定图结构，应该满足上面的非偏见条件概率分布
    →我们需要把图结构原始的参数空间(邻接矩阵)变为概率空间，然后在概率空间优化。

METHOD

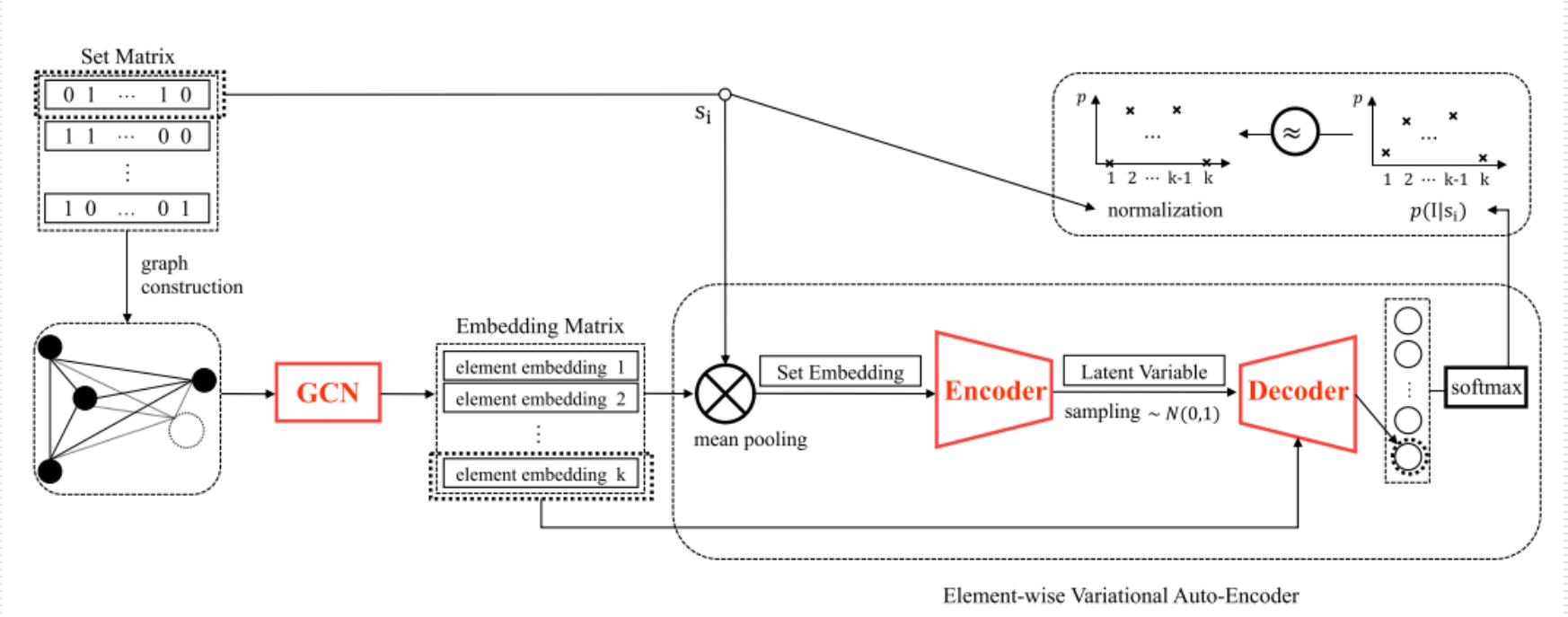
1. Graph Based Set Generation

- Model the function h()
  - GCN学习node的表示得到node的embedding matrix
  - 使用embedding matrix对set编码得到set embedding
  - 将set embedding输入到VAE，得到条件概率分布

$$\mathbf{x}_k^{(l+1)} = \sigma\Big(\sum_{j \in N_k} \hat{\mathbf{D}}^{-\frac{1}{2}}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-\frac{1}{2}}\mathbf{x}_j^{(l)}\mathbf{W}^{(l)} + \mathbf{b}^{(l)}\Big),$$

$$\frac{\mathbf{s}_i^{(m)} \cdot \mathbf{X}^{(m)}}{\mathbf{s}_i^{(m)} \cdot \mathbf{1}},$$

$$P^{(m)}(I_k|\mathbf{s}_i^{(m)}),$$

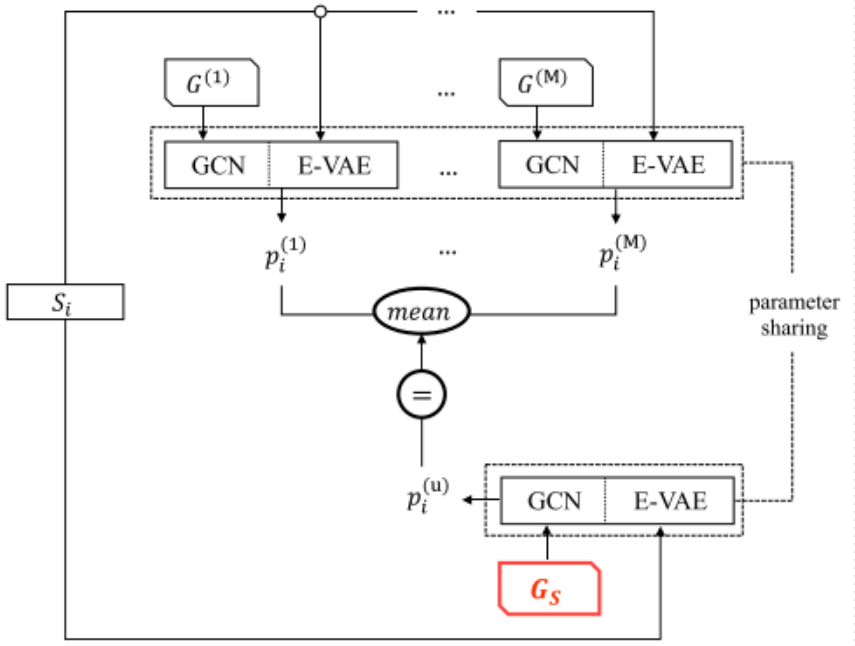


METHOD

2. Stable Graph Learning

- 使用训练好的GCN和VAE得到set在每个环境的条件概率分布 $\{P^{(m)}(I_k|\mathbf{s})\}_{m=1}^{M}$
- 初始化稳定图结构G_S，将set输入得到稳定图中的条件概率分布 $P_S(\mathbf{I}|\mathbf{s}_i^{(m)})$
- 优化G_S使得稳定图条件概率等于每个环境的概率分布的均值

$$\mathcal{L}_{rf} = ||P_S(\mathbf{I}|\mathbf{s}_i^{(m)}) - \sum_{j=1}^{M} \frac{P^{(j)}(\mathbf{I}|\mathbf{s}_i^{(m)})}{M}||_2$$



EXPERIMENT

- Baselines and Data
  - 由每个环境生成自己的图结构 $\{G^{(m)}\}_{m=1}^{M}$
  - 将上面所有的图求平均 $G_A = \sum_{m=1}^{M} \frac{G^{(m)}}{M}$
  - 将所有环境的数据拼接到一起生成图结构 G_C
  - 本研究提出的稳定图结构 G_S

  - Cloud Theme Click Dataset
    - 淘宝APP中云主题场景的用户点击日志
    - more than 4 million purchase histories of users for one month

EXPERIMENT

Real Data Experiment

- 根据purchasing behavior prediction判断不同图结构的好坏
- 依据是否经常购买流行商品/用户性别换把整个数据集划分成两个不同的环境

	Mean ACC	STD	Env1:Env2=0:10	1:9	2:8	3:7	4:6	5:5	6:4	7:3	8:2	9:1	10:0
$G^{(1)}$	12.93%	**0.0050**	13.54%	13.42%	13.62%	12.62%	13.49%	12.87%	12.92%	12.81%	12.16%	12.17%	12.62%
$G^{(2)}$	15.96%	0.0485	23.12%	22.21%	20.64%	18.83%	17.91%	16.11%	14.04%	13.67%	11.62%	9.46%	7.56%
G_A	18.09%	0.0347	23.21%	22.74%	21.76%	19.68%	19.46%	17.71%	16.68%	16.87%	14.98%	13.34%	12.57%
G_C	16.15%	0.0310	20.50%	20.57%	19.23%	17.49%	17.47%	16.08%	14.79%	15.24%	13.26%	11.78%	11.23%
G_S	**18.64%**	**0.0288**	22.90%	22.44%	21.81%	19.71%	19.98%	18.53%	17.31%	17.57%	15.91%	14.68%	14.22%

Table 4: Purchasing behavior prediction with exposure bias using item embeddings learnt from commodity network. The environment 1 consists of shopping logs mainly with unpopular items and env 2 consists of logs mainly with popular items.

	Mean ACC	STD	Env1:Env2=0:10	1:9	2:8	3:7	4:6	5:5	6:4	7:3	8:2	9:1	10:0
$G^{(1)}$	17.69%	0.0148	15.85%	16.03%	16.44%	16.64%	16.94%	16.67%	18.22%	18.87%	18.87%	19.99%	20.03%
$G^{(2)}$	17.46%	**0.0063**	16.86%	16.97%	16.56%	16.87%	17.17%	18.16%	16.99%	18.07%	18.10%	18.09%	18.27%
G_A	18.51%	0.0132	16.79%	16.94%	17.24%	17.60%	17.94%	18.50%	18.24%	19.78%	19.43%	20.46%	20.70%
G_C	18.56%	0.0127	16.84%	16.97%	17.34%	17.63%	17.81%	18.68%	18.94%	19.50%	19.53%	20.33%	20.62%
G_S	**20.17%**	**0.0092**	19.09%	19.01%	19.14%	19.51%	19.77%	20.02%	20.29%	20.84%	21.02%	21.62%	21.53%

Table 5: Purchasing behavior prediction in different gender groups using item embeddings learnt from commodity network. The environment 1 consists of shopping logs of females and env 2 consists of logs of males.