知识图谱

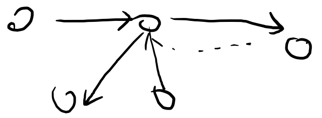
(1) 基于行为构建图；
(2) 引入先验信息：知识图谱、Ripple Net work.
(3) 图神经网络：

链路：o → o → o → o （线性链）
↓
graph（退化）

⇓
item2Vec
⇑
word2Vec

历史行为 → ~~grap~~ Real Graph.

item1、item2, ... itemj



~~实体~~
安徽省 ---- 黄山市
四川省

先验 — 知识

图嵌入：Graph Embedding
⇓
item2Vec

action sequence

o o o o

入口 item2item

u2 i ai item to item

1、DeepWalk：Random walk.

u1: D C A B F
u2: E F A B m
u3: Z D H G A B

u2ai
i2ai
u2i2ai

u2u2ai

item
相关性：文章 tw

LINE:

一阶相似度、二阶相似度.

order1: 0.

order2:

经验分布: $\hat{p}_1(v_i, v_j) = \frac{w_{ij}}{W}$

$p_1(v_i, v_j) = \sigma(\vec{u}_i^T \vec{u}_j) = \frac{1}{1+\exp(-\vec{u}_i^T \vec{u}_j)}$

⇓

顶点 (item → item Embedding)　　$u = (u_1, u_2, \cdots u_n)$

记: $v_i : u_i$, $v_j : u_j$

$$\begin{cases} \hat{p}_1(v_i, v_j) = \frac{w_{ij}}{W} \\ p_1(v_i, v_j) = \frac{1}{1+\exp(-\vec{u}_i^T \vec{u}_j)} \end{cases}$$

⇒ KL 散度.
⇓
衡量两个分布的 distance.

$KL \geq 0$　　$KL(p \| q) \neq KL(q \| p)$

$KL(\hat{p}_1(v_i, v_j) \| p_1(v_i, v_j))$ → minimize

def of KL: 交叉熵. Label

$KL(p \| q) = \sum p \log \frac{p}{q} = \sum p\log p - p \log q$　　LR

$= \int p \log \frac{p}{q}$　　$p\log q \neq q \log p$　　constant

KL散度 = 交叉熵 − 熵

minimize $KL(\hat{p}_1(v_i, v_j) \| p_1(v_i, v_j))$

$= \sum \hat{p}_1(v_i, v_j) \log \frac{\hat{p}_1(v_i, v_j)}{p_1(v_i, v_j)}$

$= \sum \frac{w_{ij}}{W} \left(\log \frac{w_{ij}}{W} - \frac{1}{1+\exp(-\vec{u}_i^T \vec{u}_j)}\right)$

$= \sum \frac{w_{ij}}{W} \log \frac{w_{ij}}{W} - \left(\sum \frac{w_{ij}}{W} \frac{1}{1+\exp(-\vec{u}_i^T \vec{u}_j)}\right)$

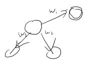
⇓
Constant

$\triangleq \text{argminimize} - \sum \frac{w_{ij}}{W} \cdot \frac{1}{1+\exp(-\vec{u}_i^T \vec{u}_j)}$

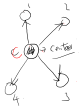
$\triangleq \text{argmin} - \sum \frac{w_{ij}}{W} p_1(v_i, v_j)$

$u_{t+1} = u_t - \eta \cdot \frac{\partial J}{\partial u_j}$

$\frac{\partial J}{\partial u_j}$



二阶相似度: 具体 def.



经验分布: $\hat{p}_2(v_j | v_i) = \frac{w_{ij}}{d_i}$

$p_2(v_j | v_i) =$

$p_2(3 | c) = \frac{\exp(-\vec{u}_3^T u_c)}{\sum_{(1,2,3,4) \in C} \exp(-\vec{u}_k^T u_c)}$

minimize $KL(\hat{p}_2(v_j | v_i) \| p_2(v_j | v_i))$

$u^* = \text{argmin } KL(\hat{p}_2(v_j | v_i) \| p_2(v_j | v_i))$

$= \text{argmin} \sum \hat{p}_2(v_j | v_i) \log \frac{\hat{p}_2(v_j | v_i)}{p_2(v_j | v_i)}$

$= \text{argmin} \left[\sum \hat{p}_2(\cdot) \log \hat{p}_2(\cdot) - \sum \hat{p}_2(\cdot) \log p_2(v_j | v_i)\right]$

⇓
constant

$\text{argmin} - \sum \hat{p}_2(v_j | v_i) \cdot \log p_2(v_j | v_i)$

⇓
u

u^*

⇓

$\frac{\partial J}{\partial u} =$

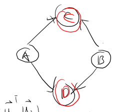
∂J

$u_t = u_{t-1} - \eta \cdot \frac{\partial J}{\partial u}$

LINE:

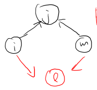
1. 一阶、二阶　2、所处环境相似的节点，他们所对应的 embedding vector 应该也是相近的.

A.B 相近



$P_2(v_j|v_i) = \frac{\exp(\vec{u}_j^{\,T} \vec{u}_i)}{\sum(\cdot|\vec{u}_i)}$ ⇒ softmax　负采样 ⇓ softmax

$P_2(v_j|v_m) = \frac{\exp(\vec{u}_j^{\,T} u_m)}{\sum(\cdot|\vec{u}_m)}$



$P_2(e|i)$
$P_2(e|m)$

□ → embedding

商品：类别、价格.

文章：一级分、二级分、lda、关键词.

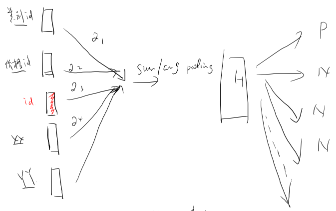
side information → side info 信息.

user　item → 一级分类、关键词.

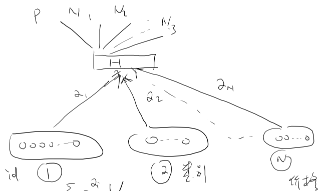
item2vec、Graph embedding 之 deepwalk ✓

node2vec、LINE ✓

GES Model: → side info

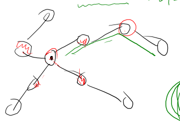


阿里：EGES　2：需要学习.



$$H = \frac{\sum_i e^{a_i} \cdot V_i}{\sum_i e^{a_i}}$$

deepwalk.　Node2Vec { BFS. DFS. }　p. q



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