从 KDDCUP2012 看微博好友推荐

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背景

- KDDCUP2012
- 腾讯微博
- 1st-0.4265 undergrads@ 数据和知识管理实验室 @ 上海交大
- 2st-0.41874 盛大研究院

Outline

- 训练数据格式
- 超越矩阵分解模型
- 其他方法
- 实验分析

KDDCUP 2012 Track1

- 目标: 用户好友推荐, MAP@3

KDDCUP 2012 Track1

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- datasets:
  1. 训练集:(UserId)(ItemId)(Result)(Unix-timestamp)
  2. 其他信息:
     - Profile: (UserId)(Year-of-birth)(Gender)(Number-of-tweet)(Tag-Ids)
     - item: (ItemId)(Item-Category)(Item-Keyword)
     - user-action: (UserId)(Action-Destination-UserId)(Number-of-at-action)(Number-of-retweet)(Number-of-comment)

矩阵分解模型 (SVD/SVD++)

$$\hat{r}_{ui} = (\sum_{c \in C(u)} \alpha_c^{(u)} \mathbf{p}_c)^T (\sum_{c \in C(i)} \beta_c^{(i)} \mathbf{q}_c) + \sum_{c \in C(u,i)} \gamma_c^{(u,i)} g_c \tag{1}$$

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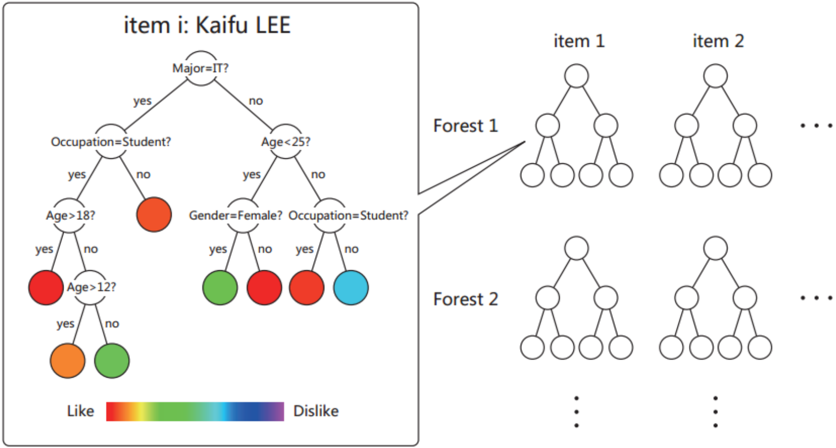
- $\theta = \{\mathbf{p}, \mathbf{q}, g\}$. 模型参数, 随机梯度下降
- $\alpha_c^{(u)}$ 用户特征 (user features), tags, keywords, 社交网络
- $\beta_c^{(i)}$ item features, 分类, 网络
- $\gamma_c^{(u,i)}$ 公共特征, user, item 间的交互

Additive Forest

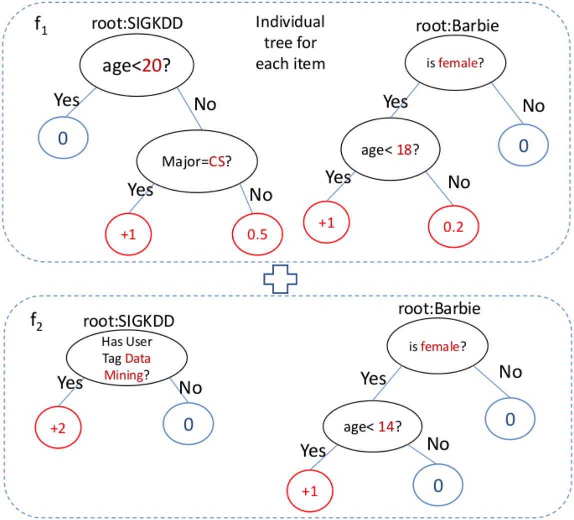
$$\hat{r}_{ui} = \sum_{s=1}^{S} f_{s,root(i,s)}(x_u) \tag{2}$$

- x_u 用户 u 的特性
- $f_{s,root(i,s)}$ 用回归树定义的函数
- 采用梯度提升法学习

Additive Forest



Additive Forest 实例



矩阵分解模型 vs Additive Forest

	矩阵分解	Additive Forest
稀疏矩阵处理	非常好	一般
不同信息整合	线性组合	非线性组合
对连续值的处理	人为划分	自动产生划分

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- 两种模型都各有各自的特点
- 结合他们的特点对提高精度至关重要

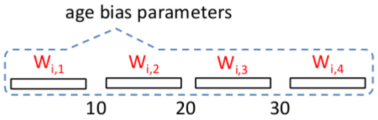
矩阵分解模型 vs Additive Forest

矩阵分解模型 vs Additive Forest

矩阵分解模型

$$\hat{r}_{ui} = p_u^T q_i + W_{i,ag(u)} \qquad (3)$$

- $ag(u)$ 年龄划分索引
- 需要实现人为划分



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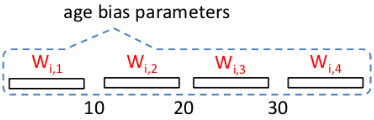
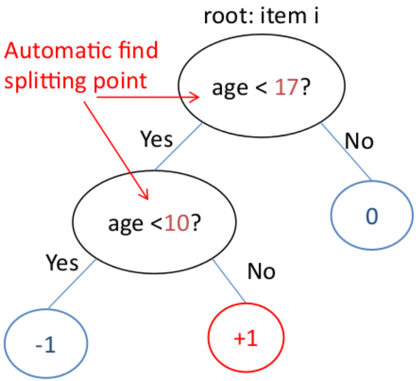


Additive Forest



社交网络

$$\hat{r}_{ui} = \left(\frac{1}{\sqrt{|F(u)|}} \sum_{j \in F(u)} \mathbf{p}_j\right)^T \mathbf{q}_i + b_i \tag{4}$$

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- $F(u)$ user u follow 的好友
- 模拟其好友对其影响

关键词和 Tag

- 分类信息对用户的预测有影响
- 影响无法无法计量

关键词和 Tag

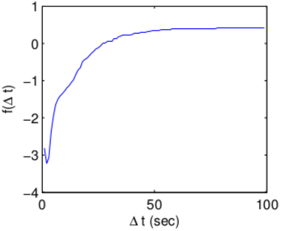
- 分类信息对用户的预测有影响
- 影响无法无法计量
- 作为潜在因素 (SVD++)

$$\mathbf{p}'_u = \mathbf{p}_u + \frac{1}{||w_u||_2} \sum_{j \in K(u)} w_{u,j} \mathbf{y}_j \tag{5}$$

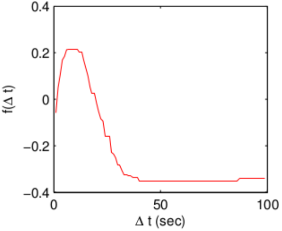
- $K(u)$ 用户 u 的 keywords or tags
- $w_{u,j}$ 特征的权重

用户序列模式 (User Sequential Patterns)

- 推测用户点击趋势



(a) $\Delta t = t_{next} - t_{curr}$



(b) $\Delta t = t_{curr} - t_{prev}$

用户序列模式 (User Sequential Patterns)

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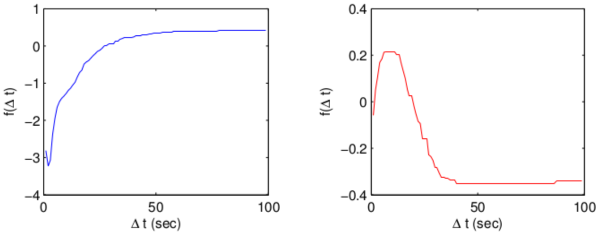

(a) $\Delta t = t_{next} - t_{curr}$ (b) $\Delta t = t_{curr} - t_{prev}$

$$\hat{r}'_{ui}(t) = \hat{r}_{ui} + f(\triangle t), f(\triangle t) = \sum_{s=1}^{S} f_s(\triangle t) \tag{6}$$

实验结果

ID	model	public	private	Δ_{public}	$\Delta_{private}$
1	item bias	34.6%	34.0%		
2	1 + user follow/action	36.7%	35.8%	2.1%	1.8%
3	2 + user age/gender	38.0%	37.2%	1.3%	1.4%
4	3 + user tag/keyword	38.5%	37.6%	0.5%	0.4%
5	4 + item taxonomy	38.7%	37.8%	0.2%	0.2%
6	5 + time-aware model	39.0%	37.9%	0.3%	0.1%
7	6 + age/gender(forest)	39.1%	38.0%	0.1%	0.1%
8	7 + sequential patterns	44.2%	42.7%	5.1%	4.7%

Table: MAP@3 of different methods

引用

[Tianqi Chen, Linpeng Tan, QIn Liu and so on,2012]
ACM
Combining Factorization Model and Additive Forest for Collaborative Followee Recommendation, 2004

[Yehuda Koren, 2008]
Factorization Meets the Neighborhood: a Multifaceted Collborative Filtering Model, 2008

Thank You, Questions?