Other Topics You May Also Agree or Disagree: Modeling Inter-Topic Preferences using Tweets and Matrix Factorization

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1引言:本文贡献

• 最先进行inter-topic用户偏好的研究

• 可以准确的预测缺失的用户-话题偏好

• 隐向量能成功编码inter-话题偏好

1引言

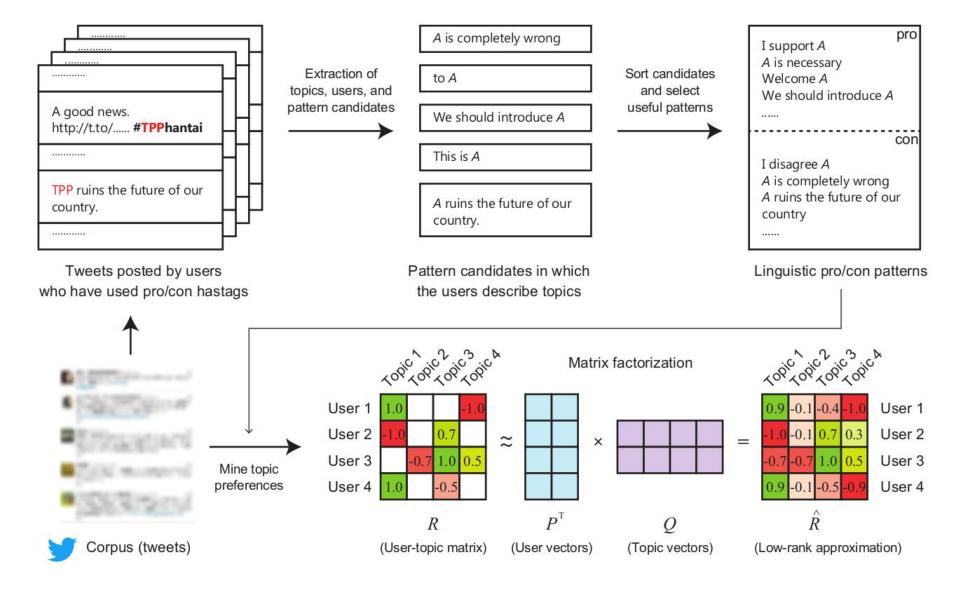


Figure 1: An overview of this study.

2 挖掘用户话题偏好

• 使用语言模式提取元组(u,t,v) , 其中u表示用户 , t表示话题 , v表示是否同意 $\{1,-1\}$ 。

• 当一个推特信息与一条语言模式(如 \underline{t} is necessary)匹配时, 认为用户u 认同话题。

2.1 挖掘语言模式

- 使用预料中含有情感、情绪、讽刺的标签,如 #immigrantWelcome #StopAbortion等。
- 使用正则表达来匹配正负标签,如 "#(.+)sansei" "#(.+)hantai"等。
- 在匹配到标签中的正(负)话题后,从文中挖掘语言模式。
- 由于会出现许多类似"this is A"或"to A"等无用模式,对模式按照使用次数降序排序,对出现次数较多的无用模式人工筛选。

2.2 挖掘话题偏好实例

- 使用语言模式提取实例(u,t,v)。
- When a sentence in a tweet whose author is user u matches one of the pro patterns (e.g., "t is necessary") and the topic t is included in the set of target topics T, we recognize this as an instance of (u, t, +1).
- When a sentence matches one of the con patterns (e.g., "I don't want t") and the topic t is included in the set of target topics T, we recognize this as an instance of (u, t, -1).

3矩阵分解

• 用户对话题的评分 $r_{u,t} = \frac{\#(u,t,+1) - \#(u,t,-1)}{\#(u,t,+1) + \#(u,t,-1)}$

$$\min_{P,Q} \sum_{(u,t) \in R} \left((r_{u,t} - \boldsymbol{p}_u^{\mathsf{T}} \boldsymbol{q}_t)^2 \right.$$

$$+\lambda_P \|oldsymbol{p}_u\|^2 + \lambda_Q \|oldsymbol{q}_t\|^2 \bigg).$$

4 评价:确定隐向量维度参数k

• 使用均方误差 $RMSE = \sqrt{\frac{\sum_{(u,t) \in R} (\boldsymbol{p}_u^\intercal \boldsymbol{q}_t - r_{u,t})^2}{N}}.$

• 不同维度对比

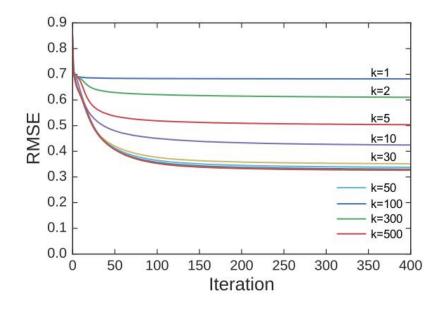


Figure 2: Reconstruction error (RMSE) of matrix factorization with different k.

4 评价:对比Majority baseline

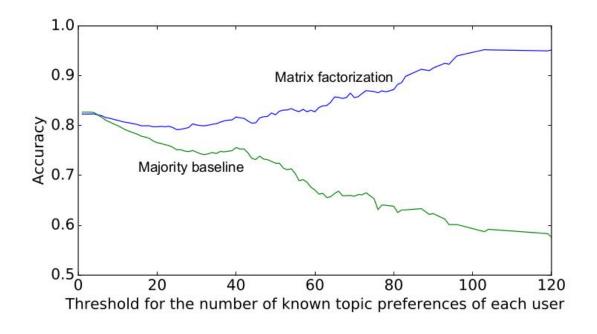


Figure 3: Prediction accuracy when changing the threshold for the number of known topic preferences of each user.

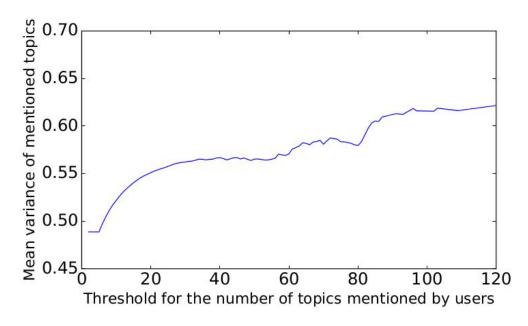


Figure 4: Mean variance of preference values of self-declared topics when changing the threshold for the number of self-declared topics.

5 总结

• 提出了一种建模用户话题偏好的新颖方法。

• 设计了语言模式来识别"支持"和"反对"评论。

• 建立矩阵分解的模型来预测缺失信息。