A Weibo Bot-users Indentification Model Based on Random Forest

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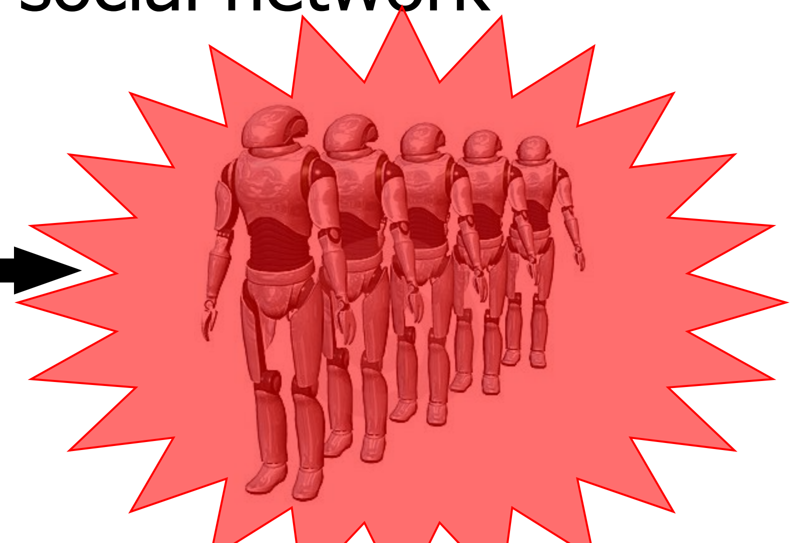
What's the Problem?

- Lower credibility on online social network

traditional water army

- manually manipulated
- easy to be distinguished
- weak targeted ability
- low efficiency

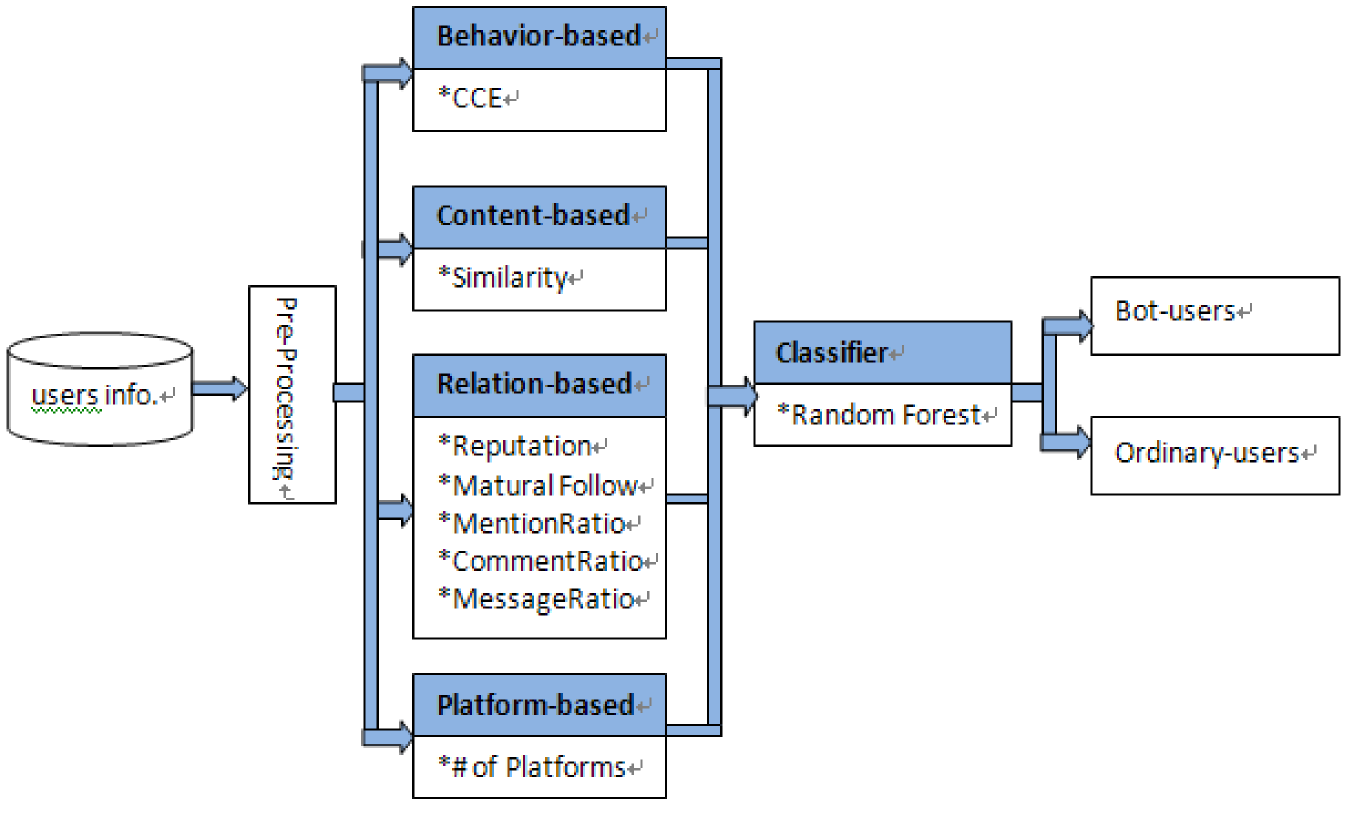


advanced bot-users

- high-level automation
- strong disguise power
- targeted ability to release
- high efficiency

Key idea

- Got after Experiencing & Analysis



Framework for bot-users indentification model

Data

- Data
  - get users from investigation & API
  - manually classify the data based on predefined rules
  - Tool: java, R

表 1 用户的基本信息表

Table 1 Typical attributions for users

属性	Id	Followers	Friends	Mutural_F	Comment	Commented	SendM	ReceiveM
说明	用户 UID	粉丝数	关注数	互粉数	评论数	被评论数	发私信数	收私信数

表 2 微博信息表

Table2 Typical attributions for Weibo

属性	MID	Time	Content	Platform
说明	微博 MID	创建时间	微博内容	发布平台

Behavior-based

- CCE(Corrected Conditional Entropy)
  - **measuing the regularity of user's behavior**
  - treat time intervals of tweet from every user as a sequence $X=\{X_i\}$

Entropy: $$H(X_1,\ldots,X_m) = E[I(x)] = -\sum_{X_1,\ldots,X_m} P(x_1,\ldots,x_m) \log P(x_1,\ldots,x_m)$$

CE: $$CE(X_m / X_{m-1}) = H(X_m / X_1,\ldots,X_{m-1}) = H(X_1,\ldots,X_m) - H(X_1,\ldots,X_{m-1})$$

CCE: $$CCE_m = CCE(X_m / X_{m-1}) = CE(X_m / X_{m-1}) + perc(X_m) \times EN(X_1)$$

Percentage of unique sequenses

Entropy when m = 1

Final CCE_u: $$CCE_u = MIN\{CCE_2, CCE_3, \ldots, CCE_m\}$$

m: the length of the sequence

Behavior-based

- CCE

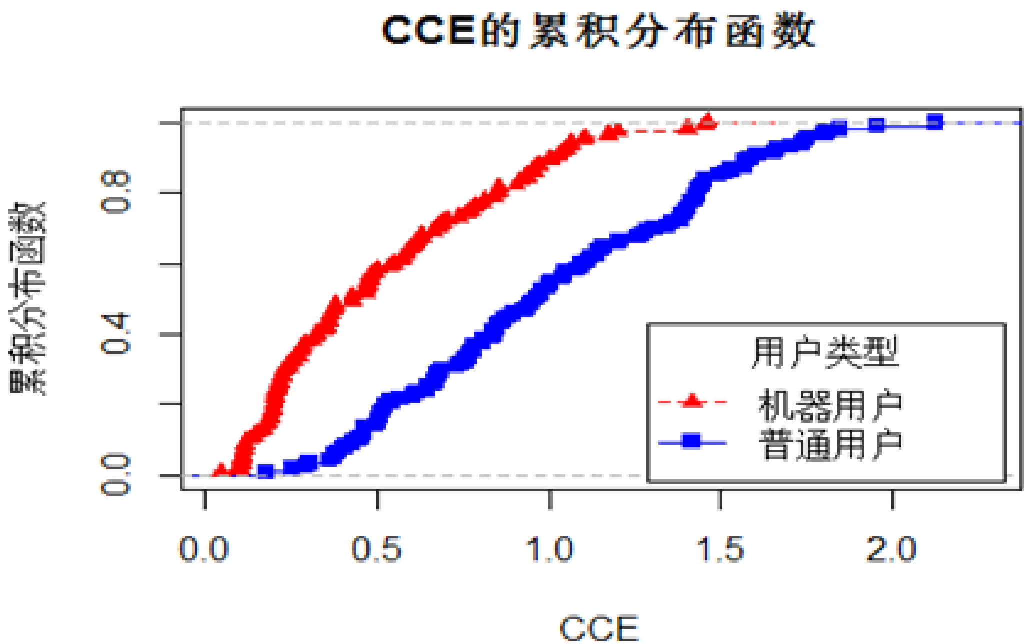


Fig. 2 Cumulative Distribution Function of CCE

Content-based

- Similarity
  - **measuring ratio of weibo with repeated content**

$$Similarity_i = \frac{IdenticalWeibo_i}{TotalWeibo_i}$$

TotalWeibo: # of all compared weibos
IdenticalWeibo: # of weibos with exactly the same content

$$Similarity_u = \frac{1}{n}\sum_{i=1}^{n} Similarity_i$$

n: # of weibos the targeted users released

Content-based

- Content-based

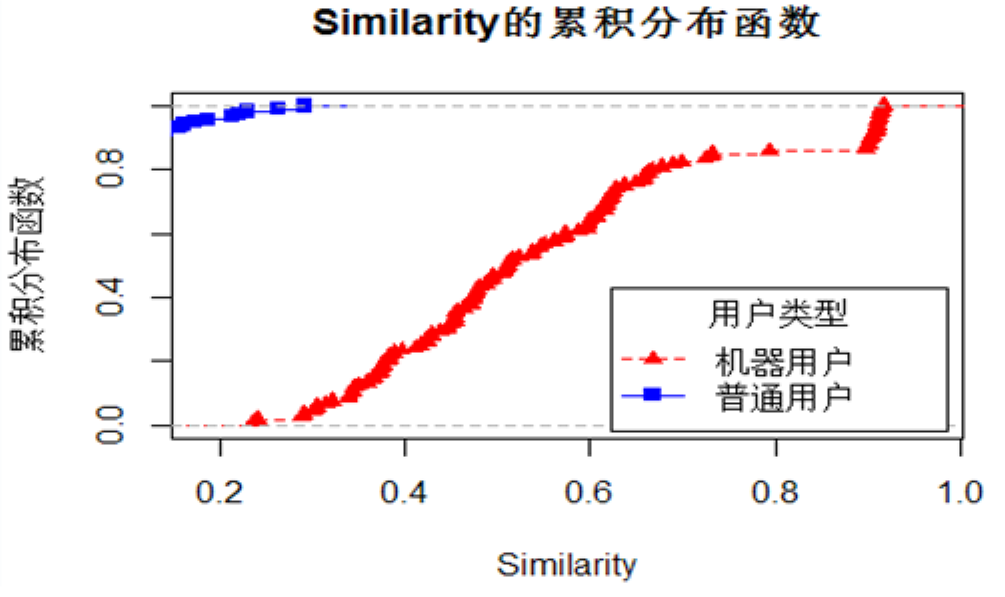


Fig. 3 Cumulative Distribution Function of Similarity

Relation-Based

- Follow: reputation & MuturalRatio
  - **measuring one-way following relationship**

$$Reputation_u = \frac{Followers_u}{Friends_n + Followers_u}$$

  - **measuring bidirectional following relationship**

$$MutualRatio_u = \frac{Mutual\_F_u}{Friends_n + Followers_u - Mutual\_F_u}$$

Relation-Based

- Relation-based

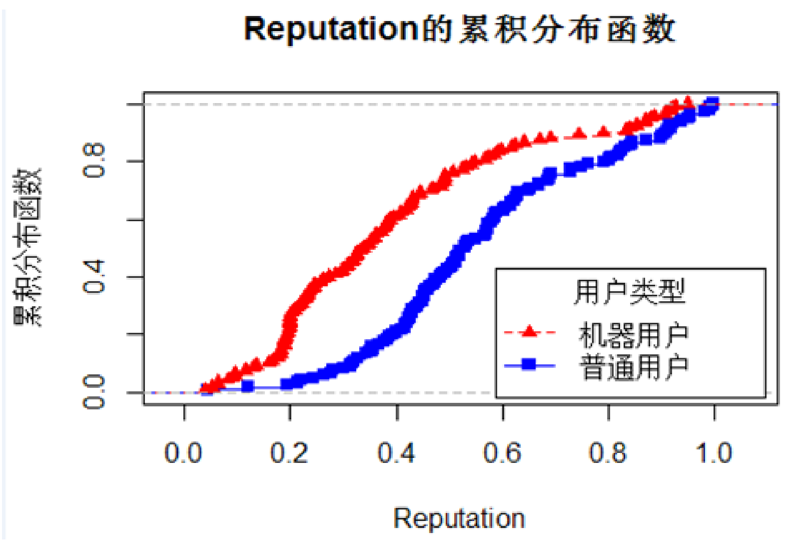


Fig. 4 Cumulative Distribution Function of Reputation

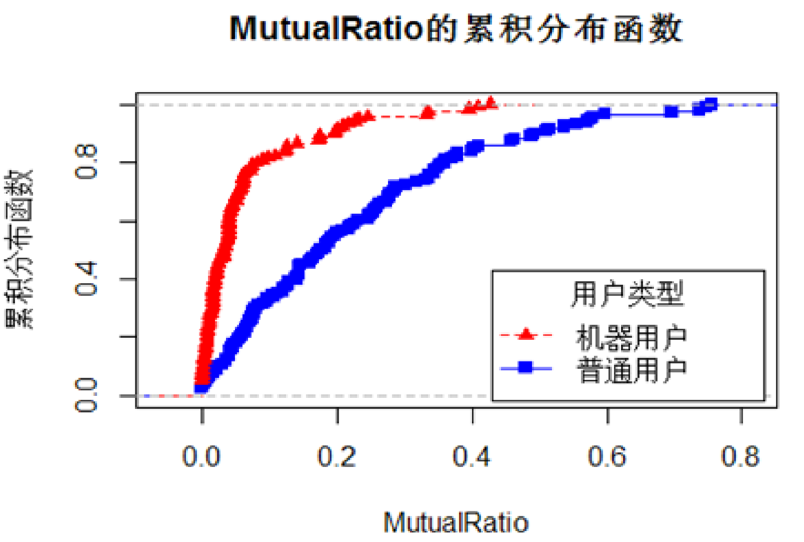


Fig. 5 Cumulative Distribution Function of MutualRatio

Relation-Based

- MentionRatio
  - **measuring ratio of mentions in all weibos**

$$MentionRatio_u = \frac{Mention_u}{TotalWeibo_u}$$

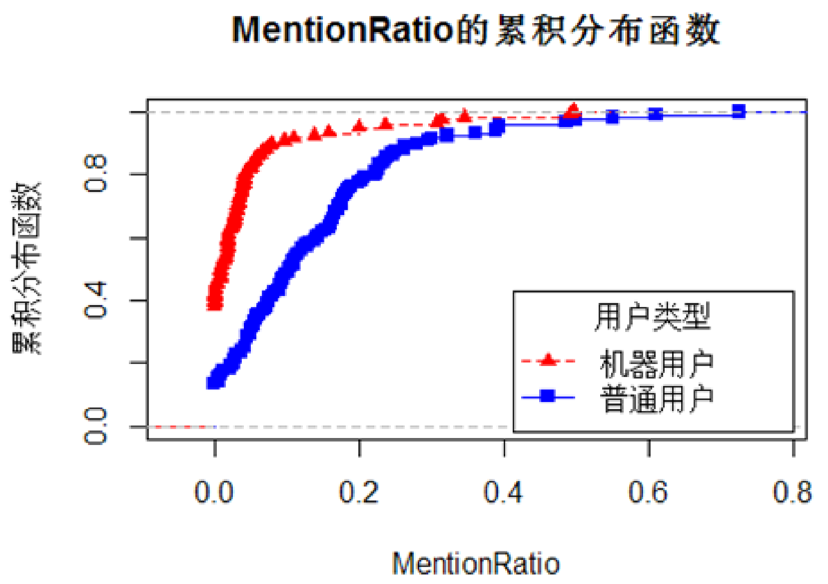


Fig. 6 Cumulative Distribution Function of MentionRatio

Relation-Based

- CommentRatio
  - **measuring difference between # of comments made and comments received**

$$CommentRatio_u = \frac{Comment_u}{Commented_u}$$

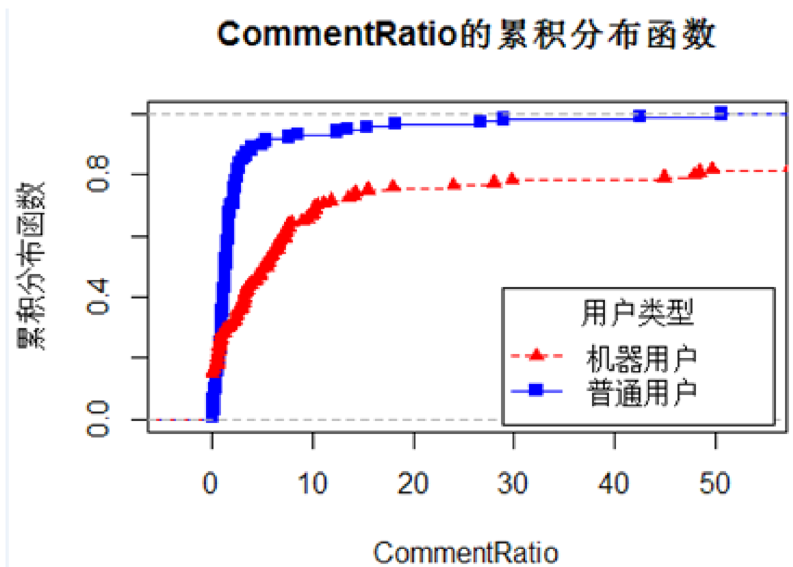


Fig. 7 Cumulative Distribution Function of CommentRatio

Relation-Based

- MessageRatio
  - **measuring ratio of sending messages**

$$Message_u = \frac{SendM_u}{SendM_u + ReceiveM_u}$$

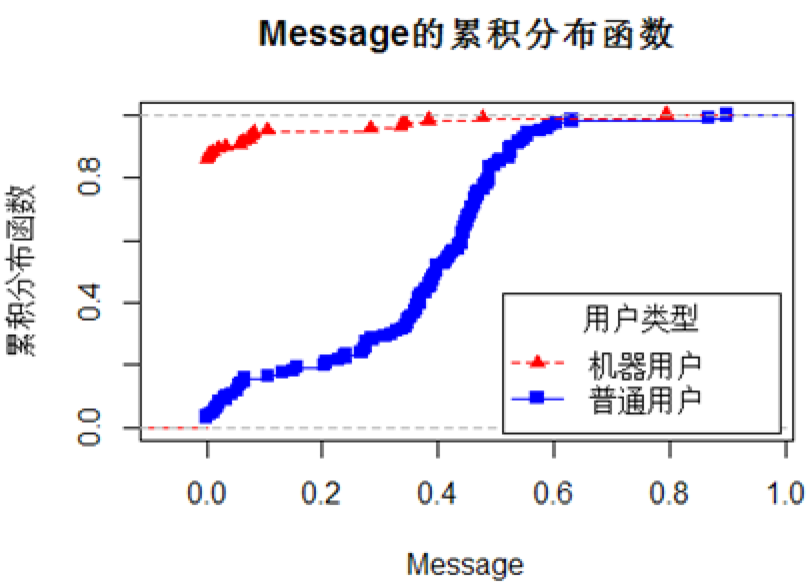


Fig. 8 Cumulative Distribution Function of Messages

Platform-based

- NumOfPlatform
  - **measuring the diversity in platform**

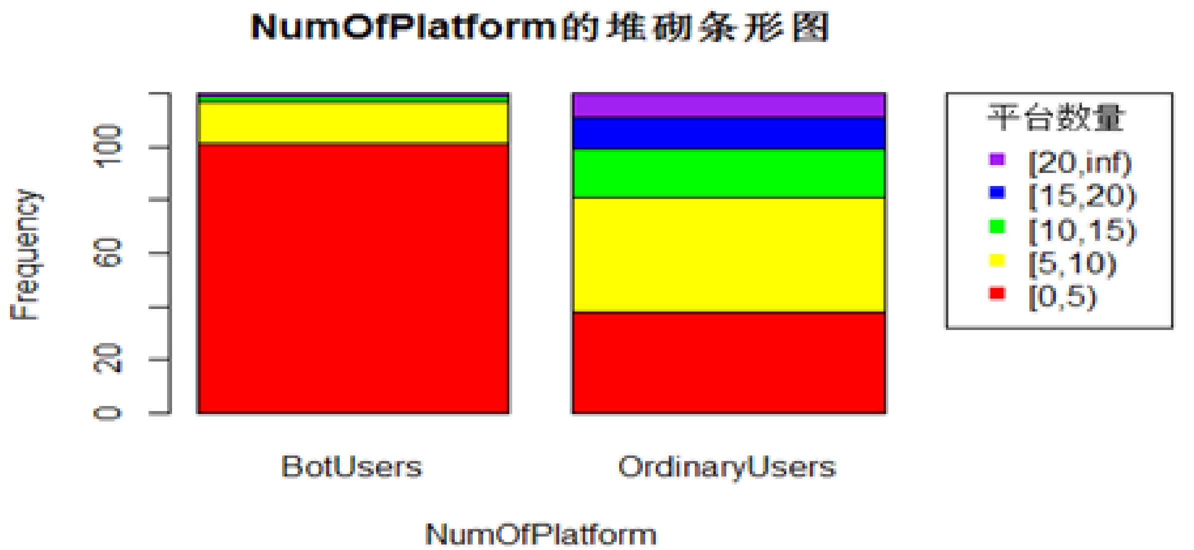


Fig. 9 Bar graph of platform number

Classifier

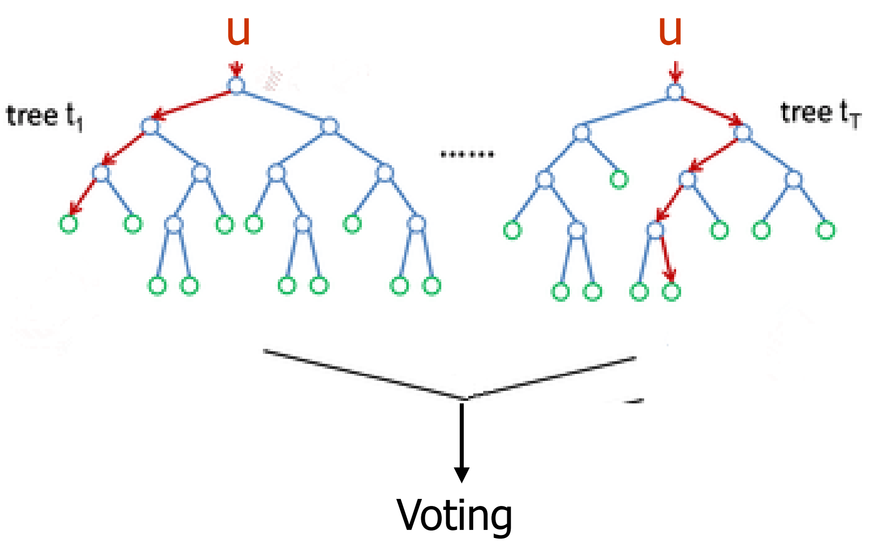
- Re-expound Problem

$$u\{CCE_u, \text{Similarity}_u, Reputation_u, Mutural_u, MentionRatio_u, CommentRatio_u, Message_u, NumOfPlatform_u\} \xrightarrow{classify} \{Bot, Ordinary\}$$

- Reasons for choosing Random Forest
  - not sensitive to correlation
  - not sensitive to outlier
  - easily get the importance of every feature

Classifier

- Random Forest
  - random features
  - random samples



Classification

- test the efficience

Table The prediction results for test data

Results	Ordinary-users(30)	Ordinary-users(120)	Ordinary-users(240)
Precision	0.967	0.935	0.935
Recall	0.967	0.967	0.967

Classification

- importance

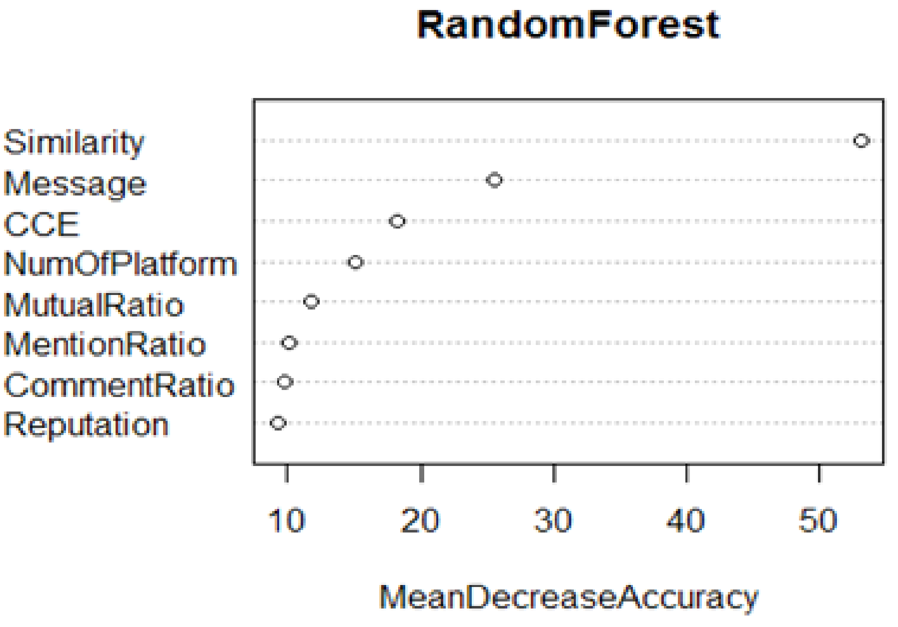


Fig. 9 The mean decrease accuracy of each feature

Summary

- Contributions
  - specificly analyse the features of bot-users in Weibo
  - a novel method to distinguish bot-users from ordinary ones
  - an empirical study of the method's effectiveness

- Future work
  - Considering the semantic features
  - Adding Graphic techniques
  - Extending in others areas, like forum, E-commence websites
  - …

Thank you !

Scenario Experience

offer registered accounts

ask to spread fake infomation

bot-users


Angela的日记本
一句话介绍一下自己吧，让别人更了解你
我的主页
我的相册
管理中心
142
关注
18
粉丝
28
微博
教育背景
最高学历
请选择
目前专业
专业分类
专业
确认
忽略
全部
搜索我的微博
想一想我居然没吃过炸酱面，不知道正宗的是什么样，不过我也不喜欢吃那种可吃可不吃的面食，今天吃了一碗东北人做的，味道不好极了，决定以后还是吃拌面的好，要不吃完了还得吃个馕补充......人有悲欢离合，馕有阴晴圆缺。
4月8日 20:02 来自 微博 weibo.com
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想一想我居然没吃过炸酱面，不知道正宗的是

bcgfxdvxc

想一想我居然没吃过炸酱面，不知道正宗的是什么样，不过我也不喜欢吃那种可吃可不吃的面食，今天吃了一碗东北人做的，味道不好极了，决定以后还是吃拌面的好，要不吃完了还得吃个馕补充……人有悲欢离合，馕有阴晴圆缺。

11月22日22:39 来自 微博 weibo.com

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_鲵毖江夏

想一想我居然没吃过炸酱面，不知道正宗的是什么样，不过我也不喜欢吃那种可吃可不吃的面食，今天吃了一碗东北人做的，味道不好极了，决定以后还是吃拌面的好，要不吃完了还得吃个馕补充……人有悲欢离合，馕有阴晴圆缺。

11月22日12:17 来自 微博 weibo.com

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wo野吖頭

想一想我居然没吃过炸酱面，不知道正宗的是什么样，不过我也不喜欢吃那种可吃可不吃的面食，今天吃了一碗东北人做的，味道不好极了，决定以后还是吃拌面的好，要不吃完了还得吃个馕补充……人有悲欢离合，馕有阴晴圆缺。

11月22日00:02 来自 微博 weibo.com

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孤独LV行者
天下皆白唯我独黑
+ 关注
私信
他的主页
他的相册
激光切割，水冷设计，配备单芯单PCB卡皇GeForce GTX TITAN SLI，顶级性能同时保证主机稳定性。真土豪，不解释！http://t.cn/zRp6X2D
2013-11-4 17:39 来自 微博 weibo.com
收藏
转发
评论
90
关注
1232
粉丝
5090
微博
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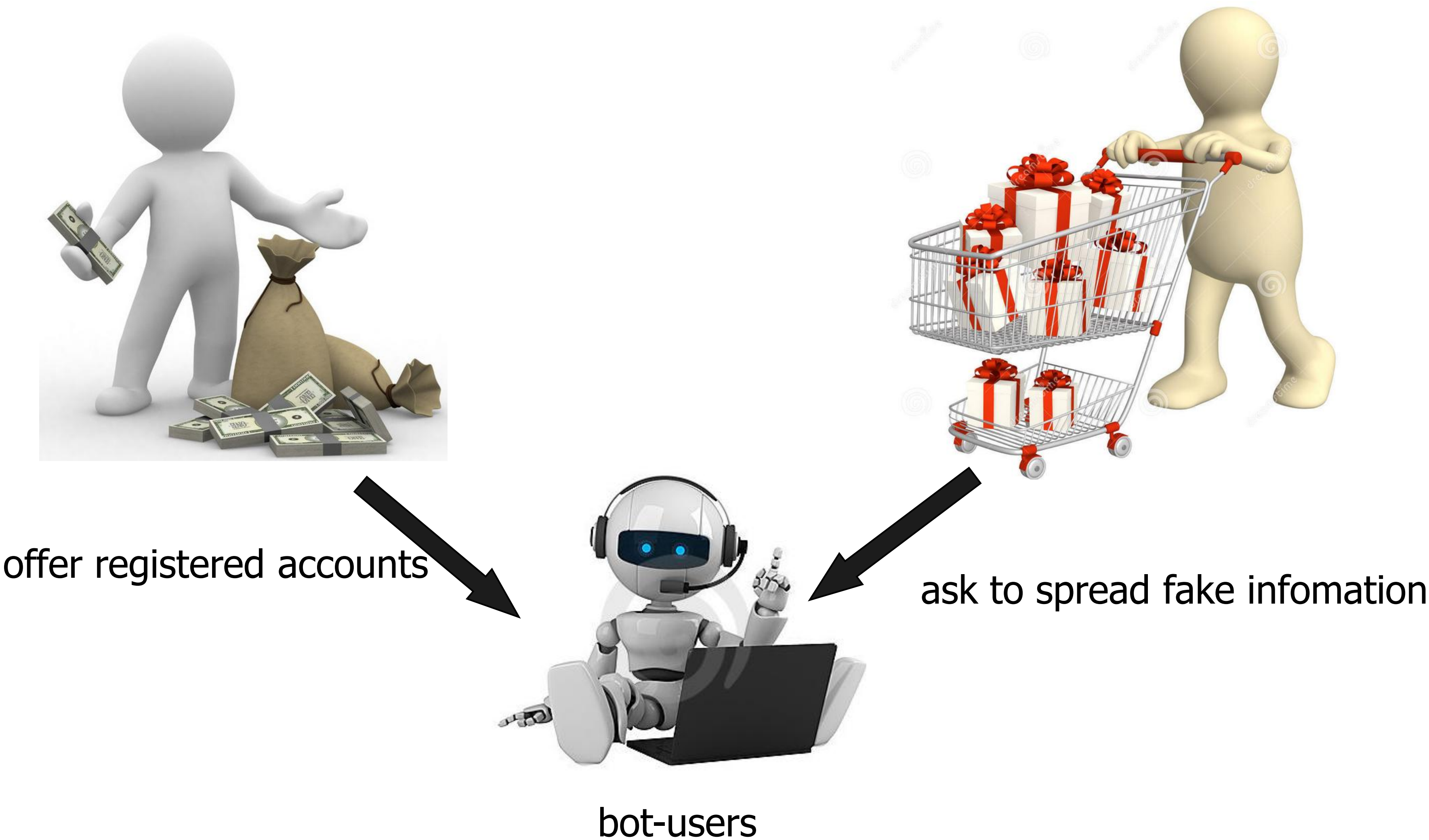
Related Work

- Water army
  - Has been well studied
  - Detect water army usually throuth URL, name, etc.
- Bot-users
  - hasn't been widely studied
  - mainly focus on the tweet
- Difference between Weibo and Tweet
  - forms: more diversive, including pics, videos, etc.
  - topics: more entertainment, while mainly news in tweet
  - behavior: higher frequence

Still requires further improvements !

Scenario Experience



Scenario Experience

offer registered accounts

ask to spread fake infomation

bot-users

Classification

- test the efficience

Table 2 The prediction results for test data1

识别结果	机器用户（30 名）	普通用户（30 名）	普通用户（120 名）	普通用户（240 名）
机器用户	29	1	2	2
普通用户	1	29	118	238