

# ***Building Trust in Online Rating Systems through Signal Modeling***

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Motivation  
Introduction  
System  
Algorithms  
(1) Detection  
(2) Trust in raters  
(3) Rating  
Aggregation  
Simulation  
Rating Challenge



## ***Online Feedback-based Rating Systems***

<b>Web Site</b>	<b>Category</b>	<b>Summary of reputation mechanism</b>
<i>eBay</i>	Online auction house	Buyers and sellers rate one another following transactions
<i>eLance</i>	Professional Services marketplace	Contractors rate their satisfaction with subcontractors
<i>Epinions</i>	Online opinions forum	Users write reviews about products/services; other members rate the usefulness of reviews
<i>Slashdot</i>	Online Discussion board	Postings are prioritized or filtered according to the ratings they receive from readers
<i>YouTube</i>	Multimedia broadcasting	Viewers rate the video clips
<i>Amazon</i>	Online shopping site	Shoppers rate the products

- Users submit their opinions regarding to products, services, or other users;
- Submitted opinions are analyzed, aggregated and made publicly available.

## ***An Important Problem: Unfair Ratings***

- Unfair ratings -- a **critical** factor that undermines the **reliability** of online rating systems.

### *Individual unfair ratings*

- an individual rater provides unfairly high or low ratings, resulting from raters' personality/habit, carelessness, or randomness in rating behavior.

### *Collaborative unfair ratings*

- a group of raters providing unfairly high or low ratings to boost or downgrade the overall rating of an object.

## ***Existing Solutions***

- Existing solutions
    - Clustering techniques
    - Statistically analysis
    - Endorsement-based quality estimation
    - Entropy-based detection
- All based on  
*Majority Rule*

## **A Challenging Problem: Unfair Ratings**

- **No sufficient number of ratings** → Statistical methods, such as clustering, will not work.
- **Rating values are highly discrete;** → Detecting rating is low unless tolerate a high false alarm rate;
- **With smart, collaborative unfair raters, majority rule may not hold** → Most existing schemes lost their foundation.

## ***Our Novel Idea***

- Rating values  $\rightarrow$  samples of a random process
- Fair ratings  $\rightarrow$  noise
- Unfair ratings  $\rightarrow$  signal

**Basic Idea:** Model the overall rating values using an **autoregressive (AR) signal modeling** technique, and exam the **model errors**. When the **'signal'** is presented, the model error is low.

## ***Our Contributions***

- An **algorithm** that detects suspicious ratings in the scenarios where existing techniques do not work;
- A **system** that utilizes trust models for rating aggregation and improves system reliability.

## ***Classification of Unfair Ratings***

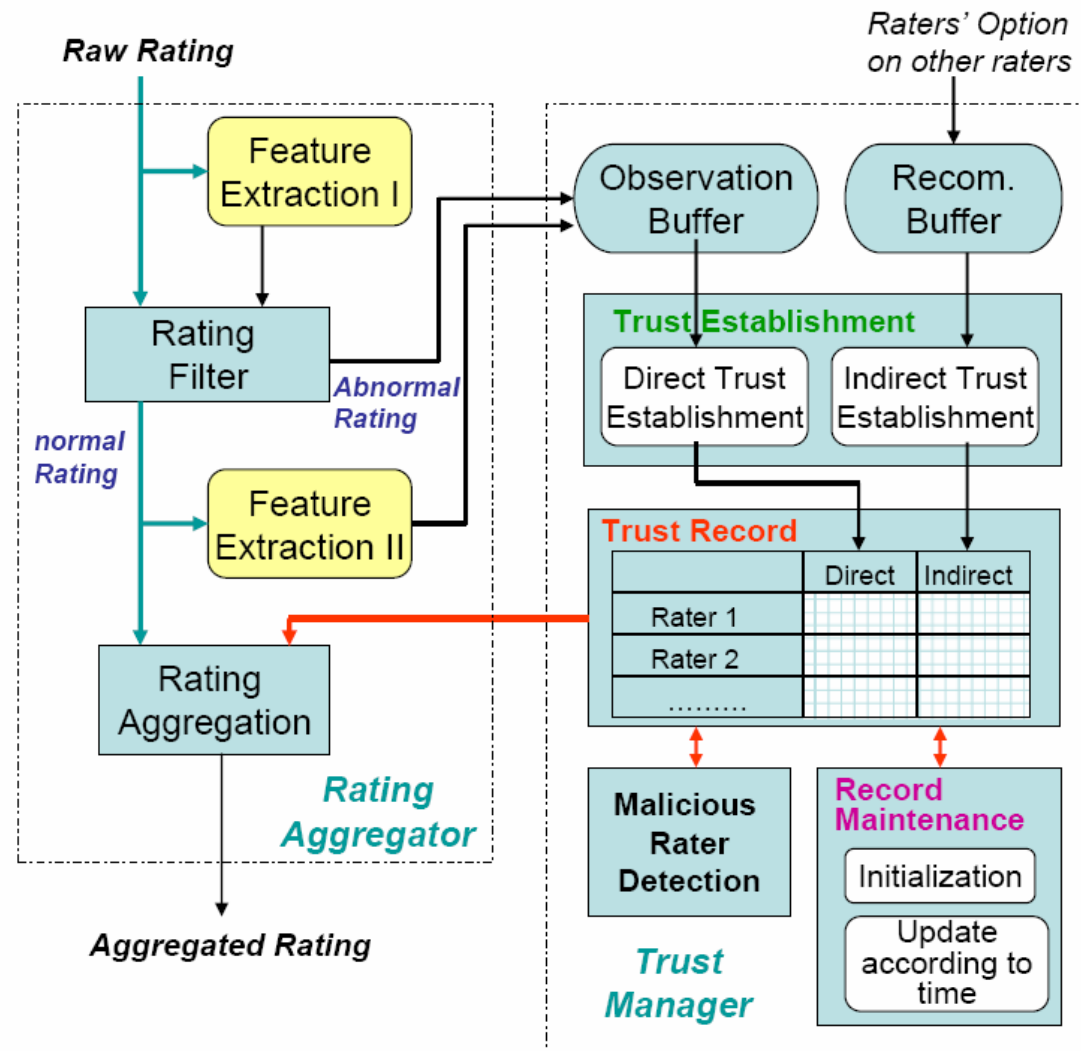
- ***Individual unfair ratings***
  - an individual rater provides unfairly high or low ratings, resulting from raters' personality/habit, careless, or randomness in rating behavior.
  
- ***Collaborative unfair ratings***
  - a group of raters providing unfairly high or low ratings to boost or downgrade the overall rating of an object.

***Strategy 1***: large bias

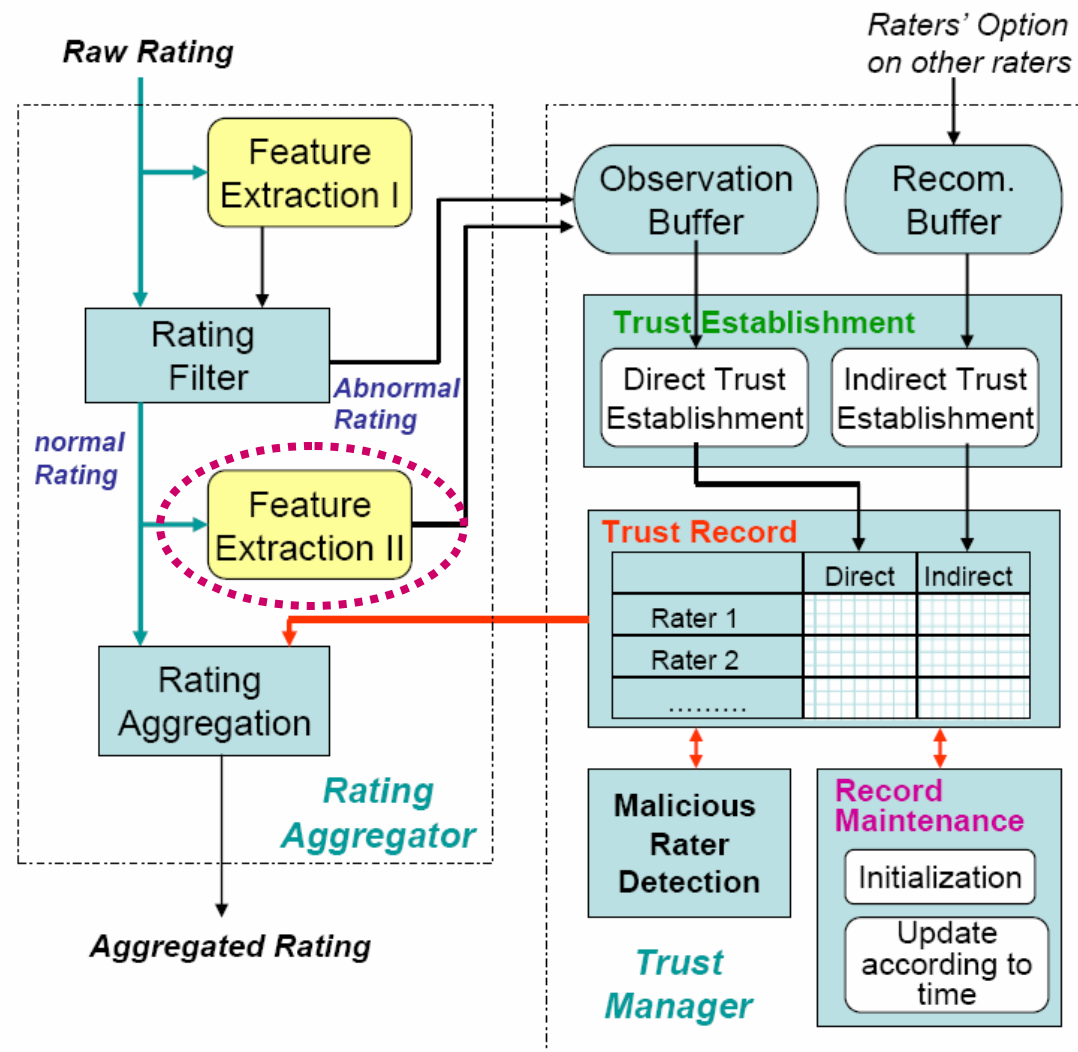
***Strategy 2***: moderate bias



# System



## Algorithm 1: Detect Suspicious Interval



## Algorithm 1



# Algorithm - 1

**Procedure 1** Detecting suspicious interval and updating raters' suspicious values

```
1: For each rater  $i$ , initialize  $L_i^{latest} = 0$ 
2: for  $k = 1 : W$  do
3:   let  $R$  denote the ratings for a certain object in the  $k^{th}$  window.
4:   find the all-pole model of the signal  $R$  using the covariance
      method [7]. In particular, given the model order  $p$ , calculate the
      model coefficients  $a = [1, a(1), \dots, a(p)]$  and normalized model
      error  $e(k)$  ( $0 < e(k) < 1$ ).
5:   if  $e(k) < threshold$  then
6:     The  $k^{th}$  window is marked as the suspicious
7:     A suspicious level is calculated as  $L(k) = scale(1 - e(k))/threshold$ ,
      where  $scale$  is scaling factor between 0 and 1.
8:     for each rating in the  $k^{th}$  window. do
9:       assume this rating is from rater  $j$ 
10:      if  $L_j^{latest} = 0$  then
11:         $C_i = C_i + L(k); L_j^{latest} = L(k);$ 
12:      else
13:        if  $L_j^{latest} > L(k)$  then
14:           $C_i = C_i + L(k) - L_j^{latest}, L_j^{latest} = L(k);$ 
15:        end if
16:      end if
17:    end for
18:  end if
19: end for
```

AR signal  
modeling



Examining  
model error



Suspicious  
level depends  
on the model  
error



## Algorithm 1

# Evaluation of Algorithm 1

- Simulation Parameters

$simu\_time = 60$	simulation time is 60 days
$arrival\_rate = 3$	rating arrival is a Poisson process with arrival rate 3
$R\_level = 11$	ratings which have 11 levels can be 0, 0.1, 0.2, ..., or 1
$quality\_start = 0.7$ $quality\_end = 0.8$	The quality of the object is 0.7 at the beginning and linearly increases to 0.8 at the end of the experiment.
$goodVar = 0.2$	The ratings from honest raters follow a Gaussian distribution with mean being the quality of the object and variance being 0.2.

Influenced

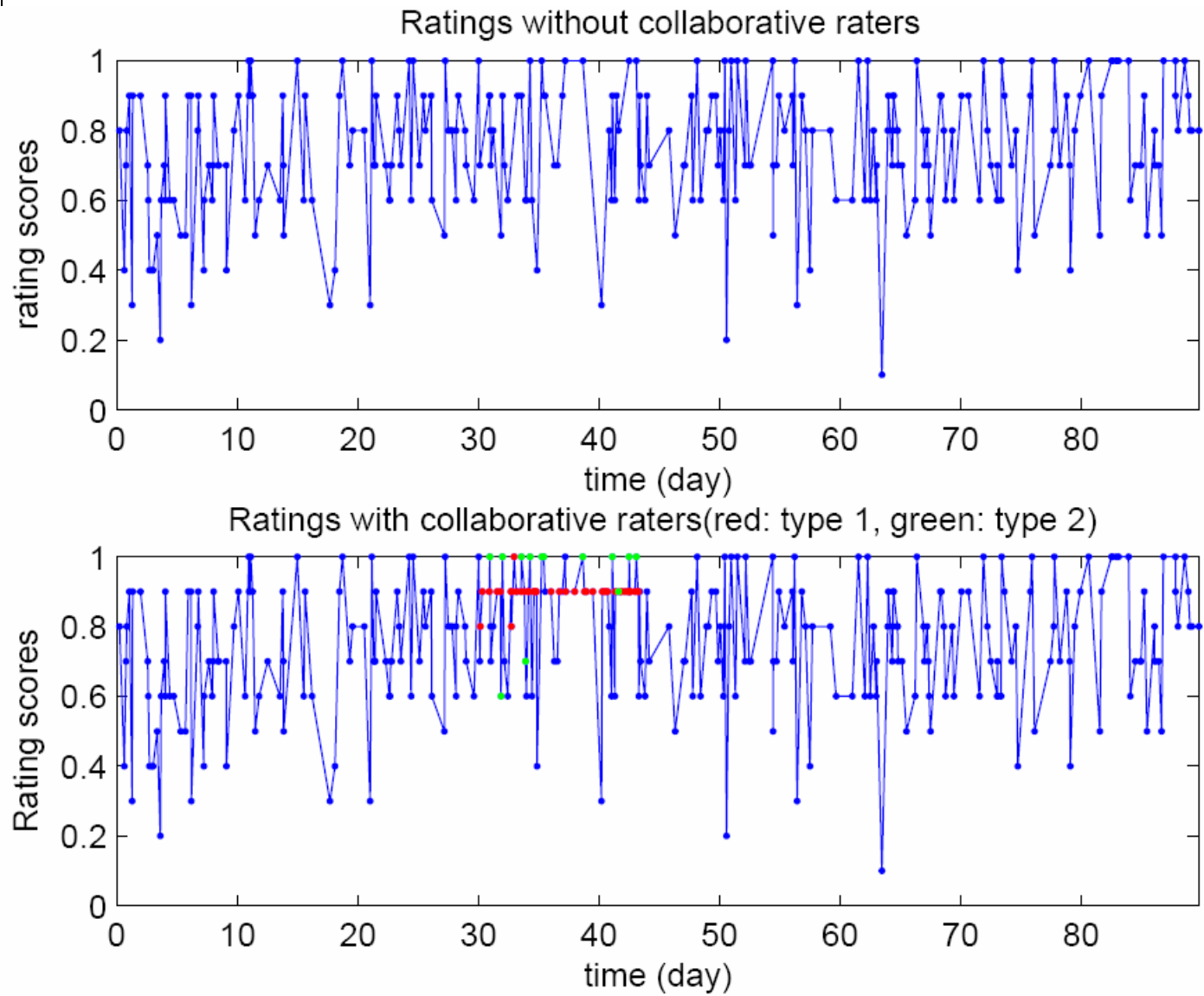


$A\_start = 30$ $A\_end = 44$	The unfair ratings arrive between day 30 and day 44
$biasshift_1 = 0.2$ $recruitpower_1 = 0.3$	during the attack interval, 30% raters increase their original ratings by 0.2
$biasshift_2 = 0.15$ $badVar = 0.02$ $recruitpower_2 = 1$	type 2 collaborative ratings, whose arrival rate is 3, follow a Gaussian distribution with variance 0.02, and mean = object quality + 0.15.

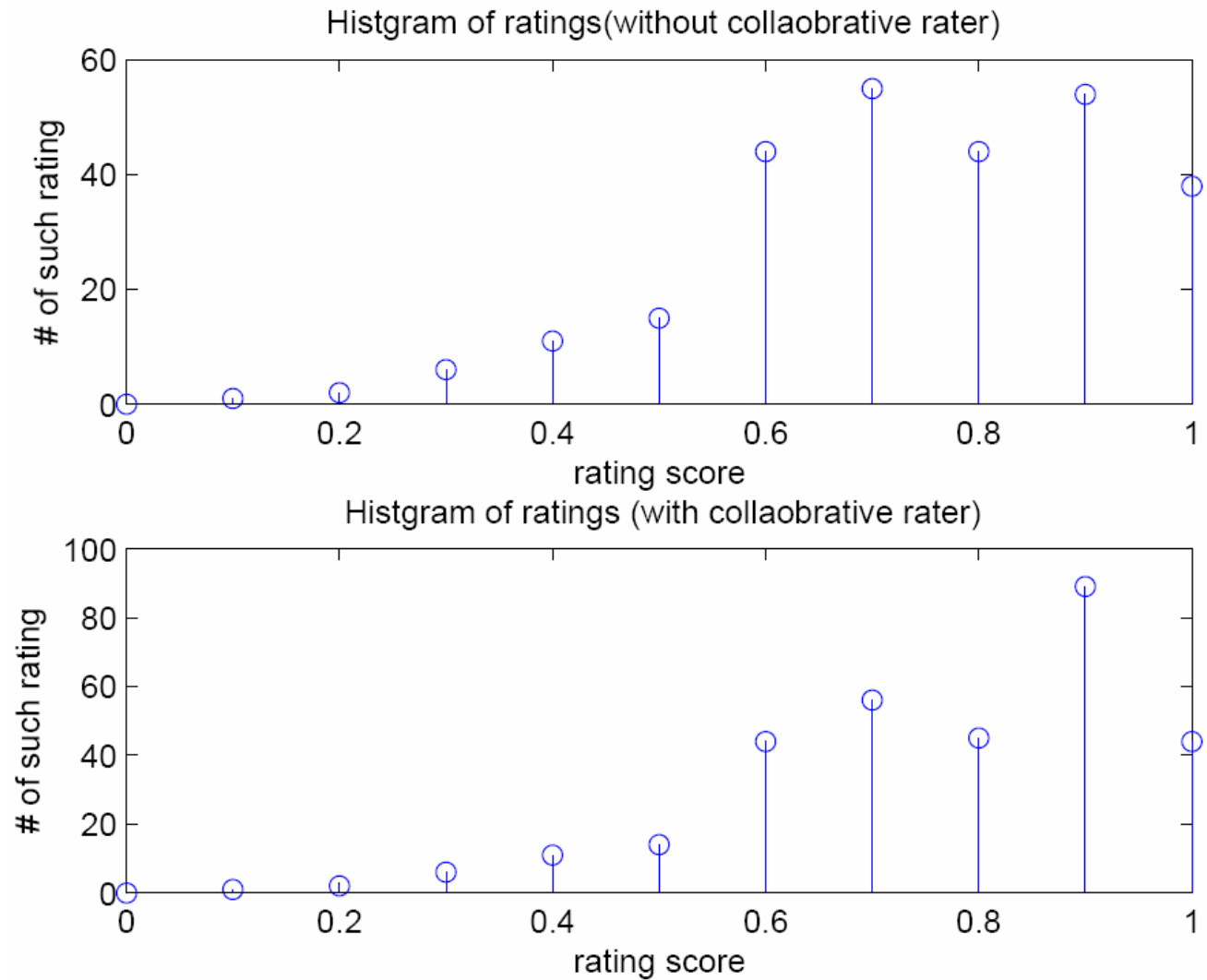
Recruited



## *Raw Ratings*

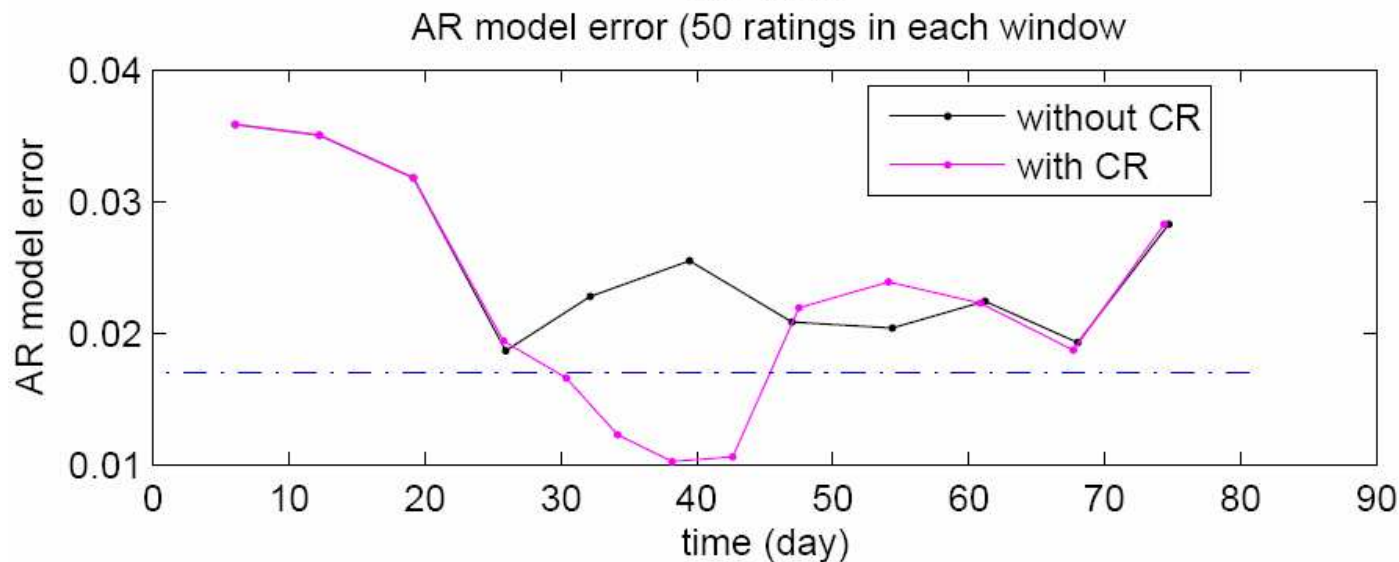
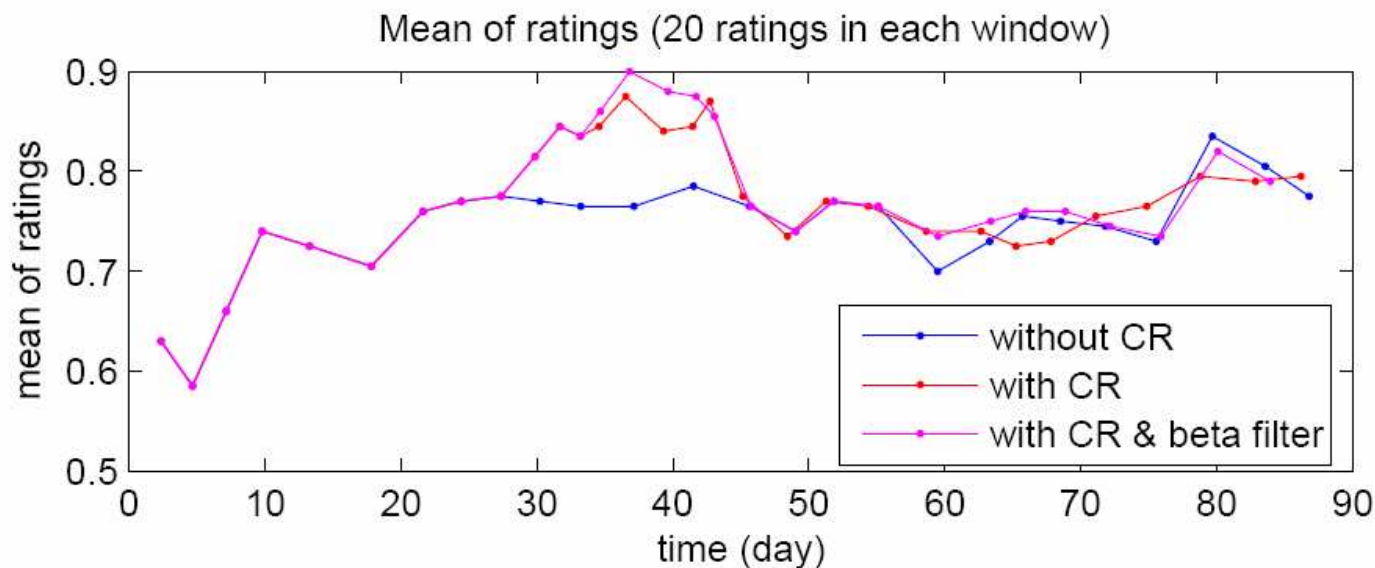


## ***Majority Rule won't work***

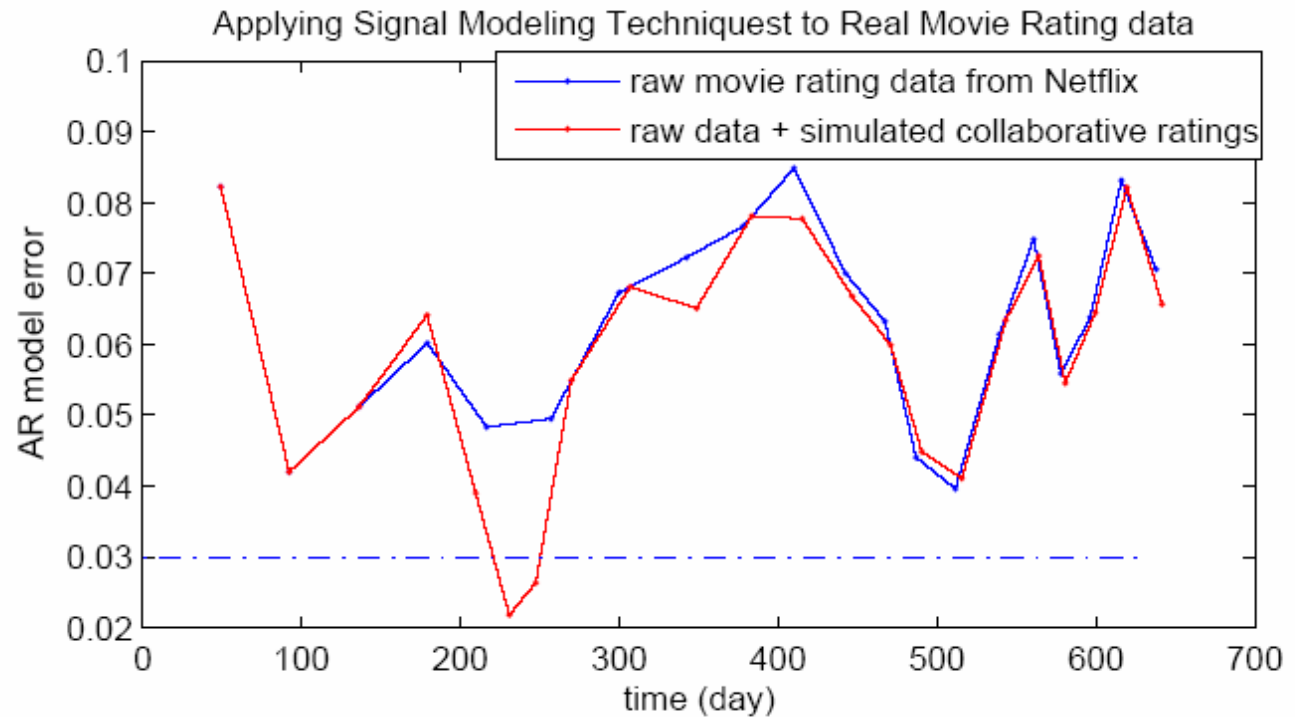


## ***Our Algorithm Worked !***

Detection Ratio = 0.782;  
False Alarm Ratio = 0.06.



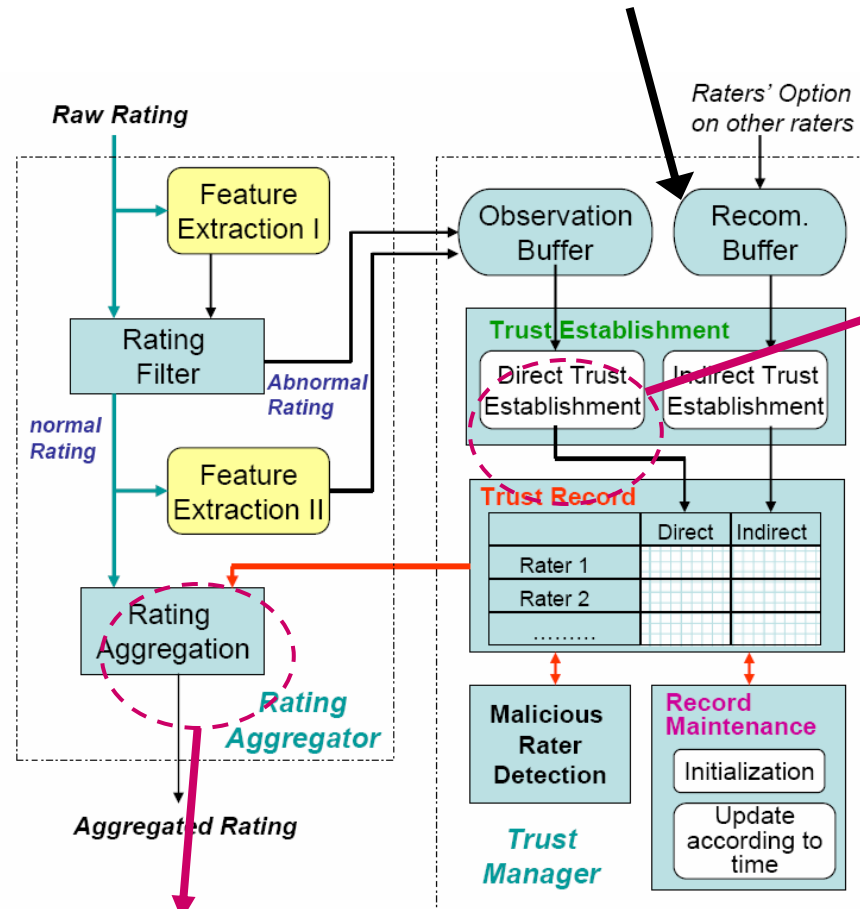
## ***Our algorithm worked for real-world data***



Model errors for original data and data with collaborative ratings. (Dinosaur Planet, 2003.)

- Motivation
- Introduction
- System
- Algorithms
- (1) Detection
- (2) Trust in raters

# Trust Manager



2. Calculating trust in raters

3. Find a good trust model for rating aggregation

## ***Trust in Raters***

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(2) Trust in raters

$n$  : total number of ratings provided by this rater

$n_f$  : the number of ratings that are filtered out

$n_s$  : the number of ratings that are in suspicious interval

$C_i$  : the suspicious level,  $i = 1, 2, \dots, n_s$

$b$  : scaling factor between 0 and 1

$$F = n_f + b \sum_{i=1}^{n_s} C_i$$

$$S = n - n_f - n_s$$

$$\text{TrustValue} = (S + 1) / (S + F + 2)$$

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(3) Rating

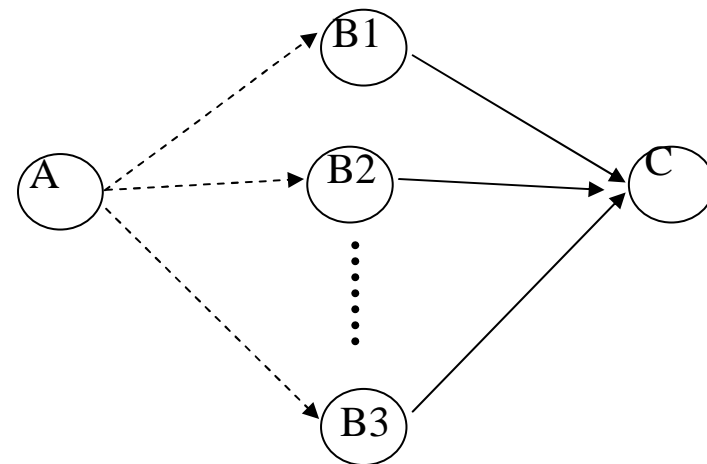
Aggregation



# Rating Aggregation

## Trust Relationship {A: B, task}

- {rater: product, have a certain quality} – Rating Value
- {system: rater, provide fair ratings} – Trust in Raters
- {system: product, having a certain quality} – aggregated ratings.



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## ***A Good Trust Model***

- We have compared four popular trust models.
  - Simple averaging
  - Beta function based aggregation, without trust.
  - **Modified weighted average**

$$R_{ag} = \frac{1}{\sum_{i:i \in R} \max(T_i - 0.5, 0)} \sum_{i:i \in R} \max(T_i - 0.5, 0) \cdot r_i$$

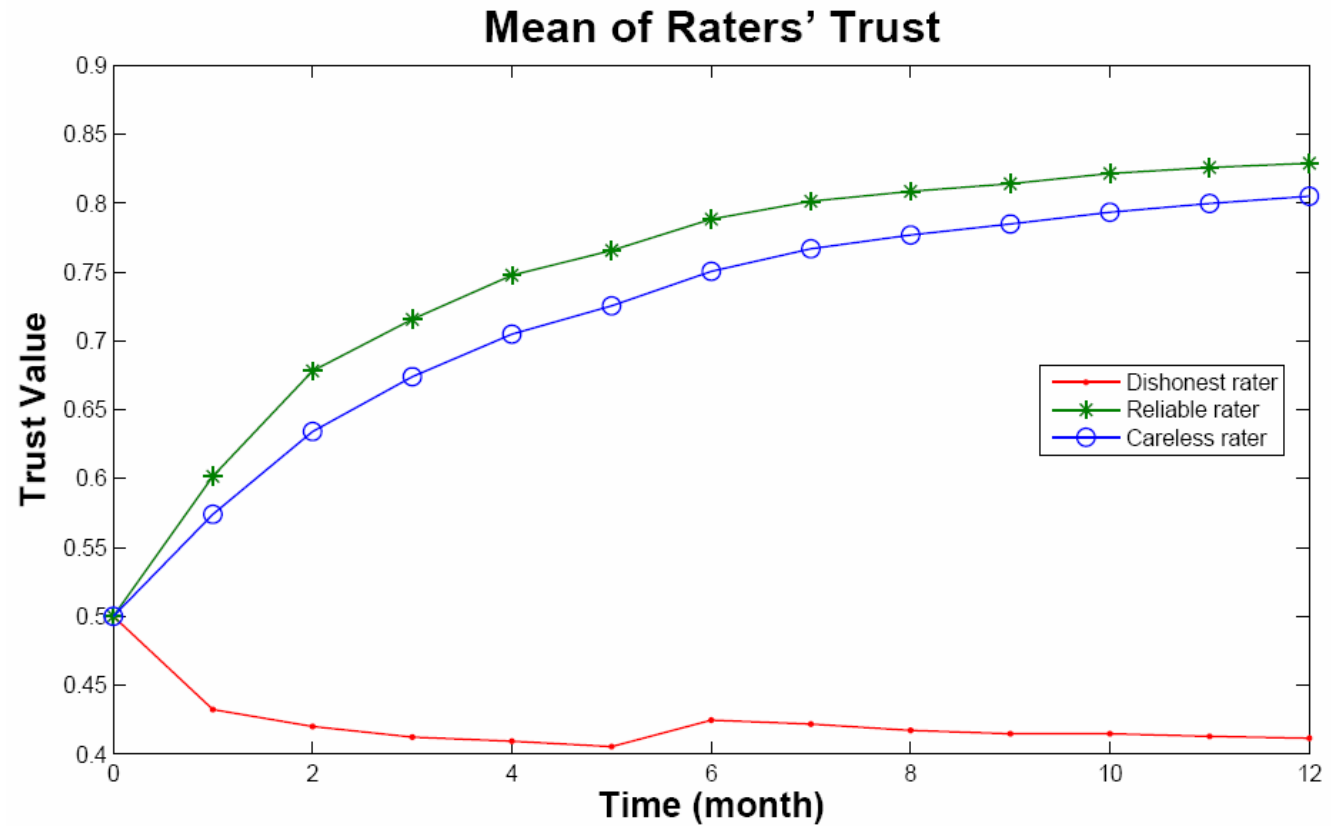
- Beta-function based trust model

## ***System Performance Setup***

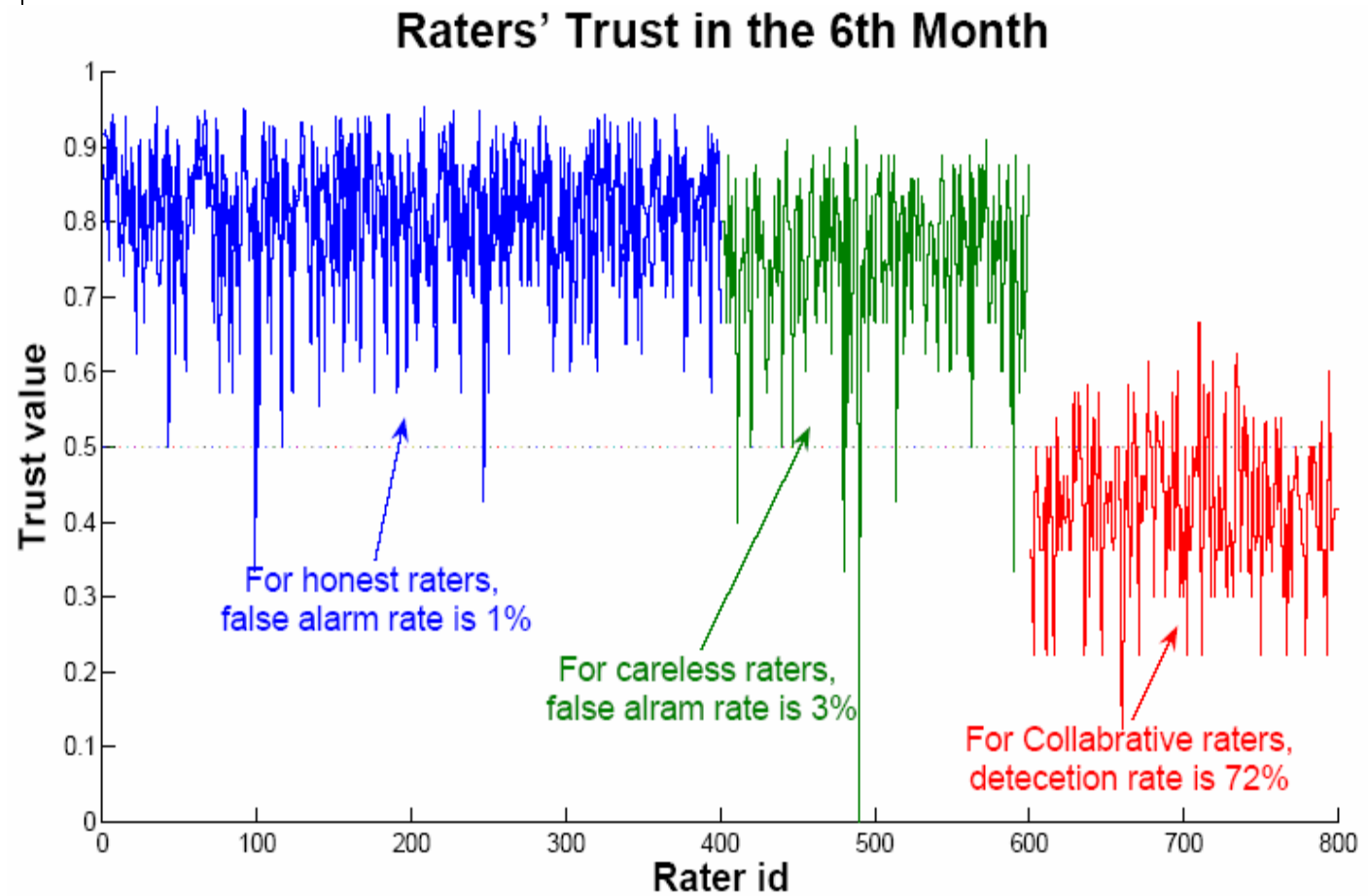
- The rating scores have 10 levels
- 400 are reliable raters, 200 are careless raters and 200 are potential collaborative unfair raters. ( $good\_var = 0.2$ ;  $careless\_var = 0.3$ )
- collaborative rater
  - If recruited: *with a higher probability to rate*;
  - If not recruited: behave as a reliable rater, but with lower probability to rate.
- Rating 60 products during 360 days. In each month (30 days), the owner of 1 product recruit collaborative raters, who rate in 10 days.
- The quality of the products is assumed to be uniformly distributed between 0.4 and 0.6.

# System Performance Evaluation

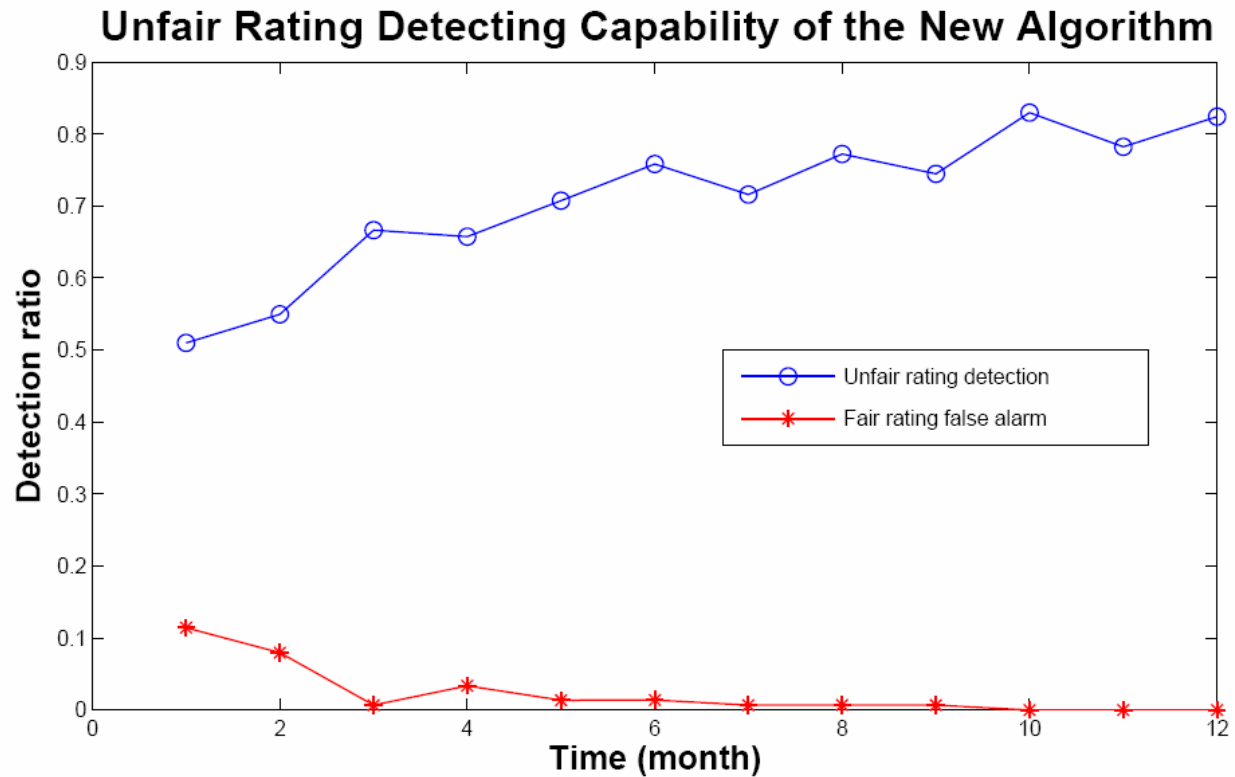
- Mean of Rater's Trust



- Trust Values

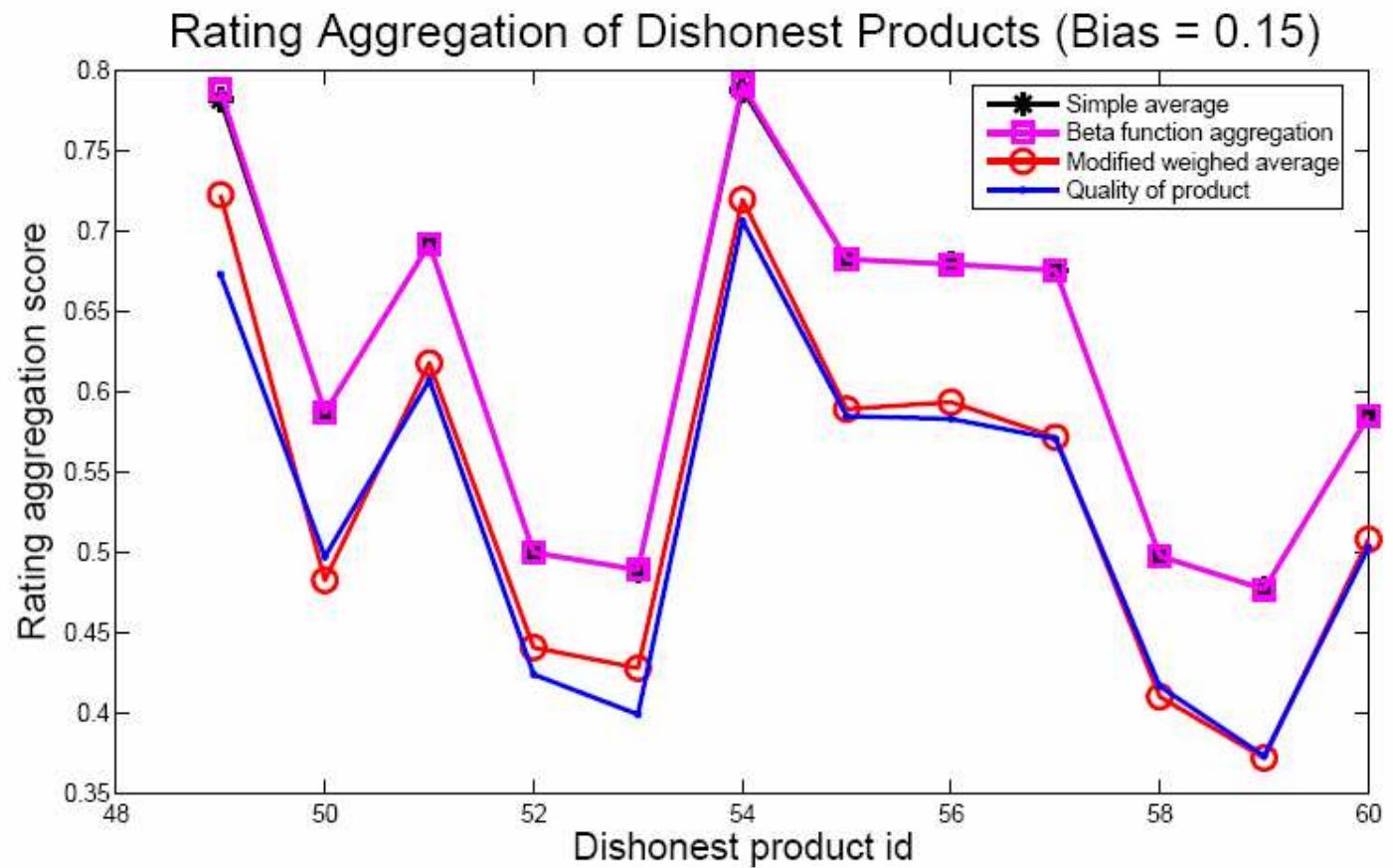


- Unfair rating detection ratio



No existing schemes are able to detect collaborative unfair raters that does not introduce a large bias and overpower honest raters in certain time intervals

- Aggregated Rating



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Trust-based  
Reliable Rating  
Aggregation

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Simulation

Rating Challenge



## ***Rating Challenge***

- Real online rating data for 9 flat panel TVs.
- Participants control 50 biased raters.
- The participants' goal is to boost the ratings of two products and reduce the ratings of another two products.
- The successfulness of the participants' attack is determined by the overall manipulation power.
- The participants that can generate the largest MP value win the competition.

**[www.etanlab.com/rating](http://www.etanlab.com/rating)**