AN ITERATIVE ALGORITHM FOR TRUST AND REPUTATION MANAGEMENT

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References:

- 1. Ayday, E.; Hanseung Lee; Fekri, F., "An iterative algorithm for trust and reputation management," Information Theory, 2009. ISIT 2009. IEEE International Symposium on, vol., no., pp.2051,2055, June 28 2009-July 3 2009
- 2. Ayday, E.; Hanseung Lee; Fekri, F., "Trust management and adversary detection for delay tolerant networks," MILITARY COMMUNICATIONS
 CONFERENCE, 2010 MILCOM 2010 , vol., no., pp.1788,1793, Oct. 31 2010-Nov. 3 2010
- 3. Ayday, E.; Fekri, F., "Iterative Trust and Reputation Management Using Belief Propagation," Dependable and Secure Computing, IEEE Transactions on , vol.9, no.3, pp.375,386, May-June 2012

ITRM (iterative trust reputation mechanism)

Background:

 In the environments of online communities, web services, ad-hoc networks, P2P computing and e-commerce communities, the recipient of the service has no choice but to rely on the reputation of the service provider based on the latter's prior performance.

Goals:

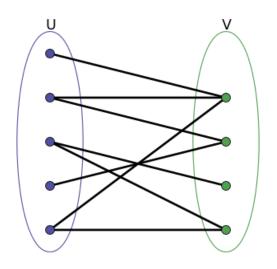
 The scheme is robust in filtering out the peers who provide unreliable ratings.

Adversary:

- Bad-mouthing: malicious raters collude and attack the service providers with the highest reputation by giving low ratings
- Ballot-stuffing: malicious raters collude to increase the reputation value of peers with low reputations

Bipartite Graph

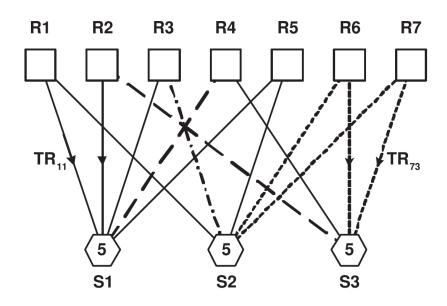
• In the <u>mathematical</u> field of <u>graph theory</u>, a **bipartite graph** (or **bigraph**) is a <u>graph</u> whose <u>vertices</u> can be divided into two <u>disjoint sets</u> U and V such that every <u>edge</u> connects a vertex in U to one in V.





Illustrative example of ITRM

Every check-vertex has some opinion of what the value of each bitvertex should be.



$$TR_j^{\nu} = \frac{\sum_{i \in A} R_i \times WR_{ij}^{\nu}}{\sum_{i \in A} R_i \times w_{ij}(t)}$$

1
Check vertices(rater-peer)

$$WR_{ij} = w_{ij} \bullet TR_{ij}$$

$$w_{ij} = \lambda^{t-t_{ij}}$$
 Age-factor



Then, we compute the inconsistency factor of each check-vertex *i*, using values of bit vertex, B is the set of bit-vertex which *i* has connect to

$$C_{i}^{\nu} = \left[1 / \sum_{j \in B} \hat{\lambda}^{t-t_{ij}} \right] \sum_{j \in B} d(TR_{ij}^{\nu-1}, TR_{j}^{\nu-1})$$

d(,) is the distance metric used to measure the inconsistency

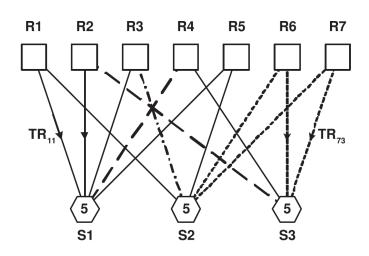
$$d(TR_{ij}^{\nu-1}, TR_j^{\nu-1}) = |TR_{ij}^{\nu-1} - TR_j^{\nu-1}|\hat{\lambda}^{t-t_{ij}}|$$

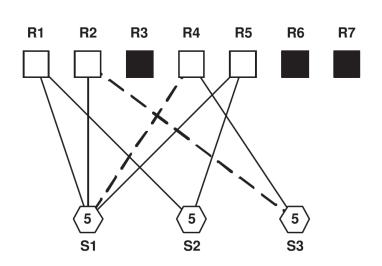
Check vertex i with highest inconsistency, place it in the blacklist if the inconsistency is greater than threshold τ

The iteration stops if there is no vertex with inconsistency greater than τ



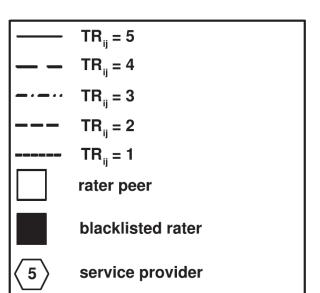
Example







$$TR_i = 5$$



Iteration	TR ₁	TR ₂	TR ₃	
0	4.8	3	2.75	
1	4.8	3.5	3.33	
2	4.8	4.33	4.5	
3	4.75	5	4.5	

Iteration	C1	C2	СЗ	C4	C 5	C6	C 7
0	1.1	.72	.10	1.52	1.1	1.87	1.87
1	.85	.43	.35	1.23	.85	2.42	-
2	.43	.35	.77	.65	.43	-	-
3	.12	.38	-	.63	.12	-	-



From the example, we can see:

- 1. ITRM gives better estimation of TR_j 's compared to the weighted averaging method (corresponded to the zero iteration)
- 2. Rater 3, although honest, is also blacklisted at the third iteration, it's reasonable when a honest but faulty rater's rating have a large deviation from the other honest raters.



Raters' trustworthiness

Beta distribution:

prior to first time-slot, for each rater-peer i, the R_i value is set to 0.5 ($\alpha_i = 1$ and $\beta_i = 1$).

If rater-peer is blacklisted, R_i is decreased by setting:

$$\beta_i(t+1) = \lambda \beta_i(t) + (C_i + 1 - \tau)^{\delta}$$

Otherwise, R_i is increased by setting:

$$\alpha_i(t+1) = \lambda \alpha_i(t) + 1$$



How to choose the threshold τ ?

τ-eliminate-optimal scheme:

we declare a reputation scheme to be τ -eliminate-optimal if it can eliminate all the malicious raters whose inconsistency exceeds the threshold τ .

Lemma 1: Let Θ_j be the number of unique raters for the j^{th} SP. Then, a sufficient condition for the inconsistency C_i , at the first iteration, to exceed the threshold τ for all malicious raters is given by

$$\sum_{r \in \Lambda} \Psi_r \ge (\hat{b}m + b\tau) \tag{2}$$

Here, $\Psi_r = \frac{mX + n\Theta_r\lambda^Q}{X + \Theta_r\lambda^Q}$ for $r \in \Lambda$, where Λ is the index set of the set Γ .

Given $C_i \ge \tau$ for a malicious rater i, for a τ -eliminate-optimal scheme, we require that the inconsistency of the malicious rater exceeds the inconsistencies of all of the honest raters.



How to choose the threshold τ ?

Lemma 2: $(\tau\text{-eliminate-optimal condition})$: Let d_t be the total number of outgoing edges from an honest rater in t elapsed time-slots. Then, provided that Lemma 1 is met, ITRM would be a τ -eliminate-optimal scheme if the condition

$$\frac{\mu}{d_t} > 1 - \frac{\Theta \lambda^Q \Delta}{D} \tag{3}$$

is satisfied with high probability at the t^{th} time-slot.



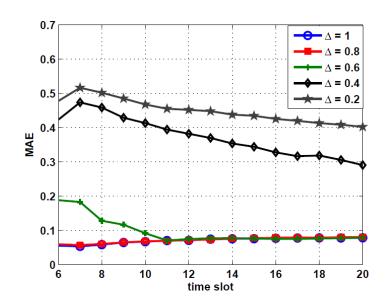
Parameters

DNumber of malicious raters HNumber of honest raters NNumber of service providers Rating given by an honest rater mRating given by a malicious rater nTotal number of malicious rates TR_{ij} per a victim SP XdTotal number of newly generated outgoing edges, per time-slot, by an honest rater bTotal number of newly generated outgoing edges, per time-slot, by a malicious rater Total number of newly generated attacking edges, per time-slot, by a malicious rater b/b (i.e., fraction of attacking edges per time-slot) Total number of un-attacked SPs rated by an honest rater μ



Simulation

$$MAE = |TR_j - \overline{TR_j}|$$
 Where $\overline{TR_j}$ is the actual value of the reputation



W=D/(D+H)=0.1 (10% malicious peers)

Fig. 3: MAE performance of ITRM versus time for bad mouthing when W = 0.10 and varying Δ



Simulation

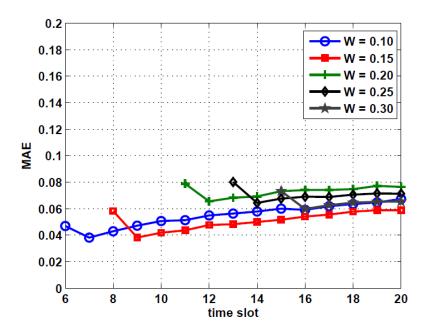


Fig. 4: MAE performance of ITRM versus time for bad mouthing and varying ${\cal W}$



Simulation(comparisons)

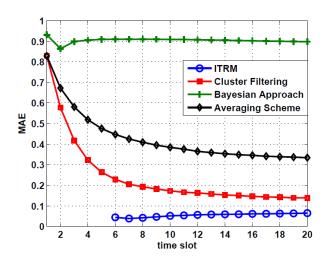


Fig. 5: MAE performance of various schemes for bad-mouthing when $W=0.10\,$

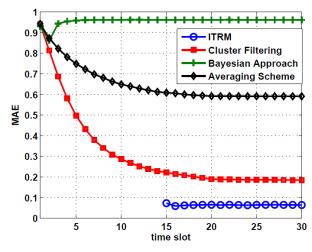


Fig. 6: MAE performance of various schemes for bad-mouthing when $W=0.30\,$



Discussion:

1. How to establish a distributed model?

2. What if the malicious raters turn good?

3. New comer attack?

