### Trust and Reputation Systems Part 1

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CRICOS No. 00213J

### **Tutorial overview**

- Wednesday 13 September
  - Basic trust concepts
  - Trust classes and trust semantics
  - Principles for building trust and reputation systems
    - Network architectures
    - Reputation engines (binomial)
- Thursday 14 September
  - Reputation engines (multinomial)
  - Trust computation engines
  - Commercial and online systems
  - Problems and proposed solutions
  - Concluding remarks



## Basic trust concepts





# Complexity of trust

Trust is a complex concept with multiple meanings

Concept:	Counts:	Webster's (1981)	Oxford's (1989)
Cooperation	# defs.	3	2
	# lines	14	75
Trust	# defs.	9	18
	# lines	112	633
Love	# defs.	17	28
	# lines	82	1670

Source: McKnight & Chervany 1996



### Manifestations of trust

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### Two definitions of trust

- Reliability trust
  - The **subjective probability** by which an individual, *A*, expects that another individual, *B*, performs a given action on which its welfare depends. (Gambetta 1988)
- Decision trust
  - The willingness to depend on something or somebody in a given situation with a feeling of relative security, even though negative consequences are possible. (McKnight & Chervany 1996)



### Would you trust this rope?



For what?

To climb down from the 3rd floor window of a house

The rope looks a bit old

Fire drill: No!

Real fire: Yes!



### **Computational trust**

- Most computational models assume reliability trust.
- Decision trust not often modelled
- Decision trust can be complex, and needs to take many additional factors explicitly into account, e.g. utility, risk, risk attitude, reliability.
- Examples of decision trust models:
  - Manchala (1998)
  - Josang & Lo Presti (2004)



### Manchala's Risk-Trust Matrix



# Trust and economic modelling

- Trust adds nothing new
  - (Williamson: Calculativeness, Trust and Economic Organisation, 1993)
- Many advanced economic models for decision making, based on
  - Reliability
  - Utility (subjective and objective)
  - Risk and risk attitude
  - etc.
- The original elements of computational trust modelling comes from the architectures for communicating and processing information relating to trust and decision making



### When is trust relevant?



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### Trust related phenomena

- Dependence
- Belief
- Uncertainty
- Risk
- Risk attitude
- Decision
- Dynamics
- Subjectivity





### Hormones and trust

The hormone *oxytocin* 

- is released after trusting behaviour, and
- stimulates trusting behaviour



Figure 1: OT and total amount sent by DM2

from Zak *et al.*, 2003



## Importance of trust

- Progress requires collaboration
- Potential collaboration partners must make decisions involving risk and uncertainty
- Fear of negative consequences is an obstacle for collaboration
- Trust
  - is the perception that the risk is acceptable
  - Is a catalyst for human cooperation
  - influences type and size of organizations
  - represents social capital in a community





## Trust is a relationship



- Trusting party
  - Also called
    - "relying party"
    - "trustor"
  - Is in a situation of
    - Dependence

- Trusted party
  - Also called
    - "trustee"
  - Is in a situation of
    - Power
    - Expectation to deliver



### Two sides of trust management

#### **Trusting party**

Wants to **assess** and make **decisions** w.r.t. the dependability of the trusted party for a given transaction and context

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#### **Trusted party**

Wants to **represent** and put in a **positive light** own competence, honesty, reliability and quality of service.

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assessment

### A definition of reputation

• Reputation is what is generally said or believed about a person's or thing's character or standing. (Concise Oxford Dictionary)

– (Reputation of B)= Average[Reliability Trust in B]



## Reputation and trust

### **REPUTATION**

- Public info
- Common opinion
- Not necessarily objective

#### <u>TRUST</u>

- Both private and public info
- Private info carries more weight
- Subjective
- "I trust you because of your good reputation"
- "I trust you despite your bad reputation"

### **Reputation aspects**

- Default / base rate reputation of a group's member = the group's reputation
- A group's reputation
  = average reputation of its members (not always true, one bad example can destroy ...)
- Reputation of well-known companies transfer from the real to the online world.
- Reputation of lesser known companies is built on what others say about them online
- Reputations are not a function of right or wrong, but of perception, whether correct or not.



#### We trust what we depend on



# Why is trust so popular?

- Metaphorical trust expressions
  - IT security people like metaphors:
    - E.g. firewall, honeypot, virus, Trojan horse, digital signature
  - Trust expressions serve as simple metaphors for complex security concepts, e,g., ..., *trusted code, circle of trust*, ...
- Trust has very positive connotations
  - Trust expressions are ideal as marketing slogans

# Trust expressions can be difficult to intuitively understand



#### Trust as an abstract security layer



### Trust as assumptions and primitives





## Trust and IT security

Trusted code Trustworthy computing **Trust management Trusted Computing Base** WS Trust Trusted computing **Trusted system** Trust eco-system Trust bar Trust provider **Trust negotiation Trusted Third Party** Circle of trust

# Hard v. soft security

- Security is the protection from harm
- Traditional information security:
  - Confidentiality, integrity & availability of info assets
  - Hard security
- What about deceit and poor quality services?
  - Problem is inversed, information assets can harm
  - Traditional security provides no protection
  - Trust and reputation systems provides protection
- Trust and reputation systems:

Soft security



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### Hard v. soft security

#### **Hard Security**

- Focuses on the assets and the methods to protect those assets from attackers
- Goal: to preserve the CIA properties of assets.
- Attacker agnostic

#### **Soft Security**

- Focuses on the attackers, and collaborative methods to identify and sanction them
- Goal: To stimulate quality
  assets and service providers
- User agnostic



### Trust and access control

- Access control paradigm:
  - The resource owner grants access authorisation
  - The system verifies authorisation before access
- **Trusted user** = authorised user
- **Trusted code** = code running as system
- **Untrusted code** = code running in a sandbox
- **Semitrusted code** = some more access rights
- Access authorisation can be delegated in a transitive fashion ⇒ transitive trust



### AC Conceptual diagram



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Legend PAP: Policy Administration Point

PEP: Policy Enforcement Point

PDP: Policy Decision Point



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(WS-Security terminology and architecture) http://www.oasis-open.org/specs/index.php

# Distributed access control

originally called trust management (1996)

- Idea: "Who can I trust to access my resources?"
- Access authorisation can be delegated in a distributive fashion

Trust management is supposed to be an incredibly vague and provocative term invented by Matt Blaze. I don't know whether he intended it that way, but it comes natural to him

Joan Feigenbaum, AT&T Labs



## **Trust expressions**

- Trusted computing = Computing platform with additional security hardware
- **Trustworthy computing** = Microsoft marketing slogan
- **Trust eco-system** = Microsoft marketing slogan
- **WS Trust** = WS Security standard specifying how to generate security tokens
- **Trust Bar** = Mozilla browser toolbar
- **Circle of trust** = Liberty Alliance term for group of organisations that enter into identity federation agreement
- **Trust provider** = Certificate Authority
- **Trusted Third Party** = Entity assumed to keep secrets



### Perception and reality; The subjective perspective

#### Perceived security



#### Real security is bad for e-business



- e-business revolution not possible with real security
- Thank God the Internet isn't secure



#### Perceived security is good for e-business



e-business growth needs perceived security



### The security dilemma





#### Jøsang's law of security and e-business

The potential of e-business is bounded by:

- The lack of functionality caused by real security
- The lack of trust caused by perceived insecurity





### Trust classes and semantics




# The Trust Scope

- For what something is trusted
- A particular trust scope can for example be
  - "to be a good car mechanic"
- Trust scopes can be specific or general
- Trust scopes can be related
  - i.e. if an entity is trusted for a specific scope, it can be assumed trustworthy for other scopes as well
- Hard to determine dependence between trust scopes
- Other terms used with the meaning of trust scope:
  - Trust context, Trust purpose, Subject matter



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# Classification of trust scopes

- Provision trust
  - Relying party's trust in a service, or a service provider.
- Access trust
  - Service provider's trust in entities requesting access to resources and services.
- Identity trust
  - Belief that an entity's identity is as claimed
- Delegation trust
  - Trust in a agent to make trust decisions on behalf of the relying party
- Context trust
  - Belief that the necessary systems and institutions are in place in order to support a transaction that involves risk

(Source: Grandison & Sloman)



## Combination of scope and assessment

- Scope dimension: "Specificity generality"
- Assessment dimension: "Subjectivity objectivity"

Assessment:	Scope:	Specific, vector based	General, synthesized
Subjective		Survey questionnaires	eBay, elections
Objective		Product tests	Synthesized general score from product tests, D&B rating

trust and reputation measures, with examples



# Trust mechanisms and processes



# Trust and decision making



# Extrinsic and intrinsic trust

#### **Extrinsic Factors**

- Cognitive
- Observed
- Recommendation
- Reputation
- External evidence
- Easy to manufacture

#### Intrinsic Factors

- Affective
- Experienced
- Intimate relationship
- Internalised pattern
- Take time to build
- Override extrinsic



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# A model for e-commerce trust



# Trust transitivity



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# Variants of the same trust scope

- 1. Functional trust
  - Belief in an entity's ability (and willingness) to carry out or support a specific function (the scope) on which the relying party depends
- 2. Referral trust
  - Belief in an entity's ability and willingness to recommend another entity with respect to 1).



# Trust types of the same scope

- Direct trust
  - Trust resulting from direct experience with the trusted party
- Indirect trust
  - Trust resulting from recommendation from other third parties



#### **Basic trust diversity dimensions**



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# Additional trust dimensions

- Trust measure:  $\mu$ 
  - Binary (e.g. "Trusted", "Not trusted")
  - Discrete (strong-, weak-, trust or distrust)
  - Continuous (percentage, probability, belief)
- Time: τ
  - Time stamp when trust was assessed and expressed.
    Very important as trust generally weakens with temporal distance.



# Valid transitive chains

- Every leg in the chain contains the same trust scope [ $\sigma$ ]. (It doesn't make any sense otherwise!)
- The last trust link is **direct functional** trust  $[df\sigma]$ .
- All other trust links are **direct referral** trust [ $dr\sigma$ ].





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# Trust transitivity

Trust is diluted in a transitive chain.



Computed with the discounting operator of subjective logic Graph notation: [A, D] = [A, B] : [B, C] : [C, D]Explicit notation:  $[A, D, if\sigma] = [A, B, dr\sigma] : [B, C, dr\sigma] : [C, D, df\sigma]$ 

**Trust fusion** 



Computed with the consensus operator

**Graph notation:**  $[A, D] = ([A, B] : [B, D]) \diamond ([A, C] : [C, D])$ 

# Non-distributivity of serial and parallel trust

Discounting is non-distributive on consensus.







# Indirect referral trust



# Hidden and perceived topologies

Perceived topology:

Hidden topology:



 $[A, B] : [B, E] \diamond [A, C] : [C, E]$  $\neq [A, B] : [B, D] : [D, E] \diamond [A, C] : [C, D] : [D, E]$ 

(D, E) is taken into account twice



# Indirect referral trust

(corrected)



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### PKI and trust transitivity



- Trust in public keys must be included in the analysis.
- Separate topology analysis for determining trust in each public key.



# Principles for building trust and reputation systems



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#### Difference between real and online world

	Availability and richness of evidence for trust	Efficiency in the communication and processing
Real world	Very good	Poor
IT / Online	Poor	Very good

- Communication of trust information often restricted to local community in the real world
- The online world currently provides very little reliable trust evidence



# Basis for trust and rep. systems

- Focus on the trust evidence and on the methods for collecting this information
  - Find substitutes for traditional information used in physical world
  - Create new types of evidence
  - Application specific
- Exploit the efficiency of IT and the Internet for
  - Collection of information
  - Processing
  - Dissemination



# Centralised reputation system



# Distributed reputation system





# Applications of reputation systems

- e-Auctions
- P2P networks
- Software agent communities
- Contract negotiations
- Online markets: B2C, B2B, C2C
- Web service search and selection
- Information/intelligence gathering



# Market Efficiency Experiment



Source: Bolton,Katok,Ockenfels,2002

# P2P networks

- P2P Networks: servent = server + client
- Search phase: discover resources
  - Centralised: e.g. Napster, with central directory
  - Pure distributed: Gnutella, Freenet
  - Semi-distributed: FastTrack, KaZaA, grokster, with distributed directory servers
- Download phase: get the resources
- Problems
  - Spreading malware
  - Free riding
  - Poisoning



#### Gnutella example

• Pure distributed search phase



# Reputation systems in P2P

- Purpose of Reputation systems in P2P
  - 1. Identify most reliable servents with best quality resources
  - 2. Determine which servents provide most reliable information w.r.t. 1.
- Reduces or eliminates existing problems
  - Many theoretical proposals
  - Few practical implementations



## Reputation/trust system with Gnutella

• XRep proposed by Damiani et al.



# Trust and reputation computation engines

- Summation or average
- Bayesian models
- Discrete models
- Belief models
- Fuzzy models
- Flow models



# Summation and average

- Summation
  - Reputation score =  $\Sigma$ (positive)  $\Sigma$ (negative)
  - E.g. eBay
- Average
  - Reputation score =  $\Sigma$ (ratings)/N(ratings)
  - E.g. Epinions
- Can be combined with sliding time windows
- Simple to understand
- Can give false impression of reputation



# **Bayesian Reputation Systems**

- Theoretically sound rating algorithm.
- Binomial and multinomial models.
- Rating possibilities:
  - any range,
  - combination,
  - discounting,
  - longevity,
  - weight ~ transaction value.



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# **Binomial model**

Based on the Beta PDF

$$f(p \mid \alpha, \beta) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} p^{\alpha - 1} (1 - p)^{\beta - 1} \qquad 0 \le p \le 0 \qquad \alpha, \beta > 0$$

• Probability expectation:

$$\mathrm{E}(p) = \frac{\alpha}{\alpha + \beta}$$

• The Beta PDF naturally expresses the probability of binary events.



# Beta PDF of Binary Events

Define:  $\begin{cases} \alpha = r+1 & \text{where:} \\ \beta = s+1 & r,s \ge 0 \end{cases}$ 

*r*: positive observations

s: negative observations

Example: uniform density




### **Binomial reputation score**

• Based on probability expectation of Beta-PDF.

$$Sc(Z) = \frac{r_{\text{base}} + \sum r(Z)}{r_{\text{base}} + s_{\text{base}} + \sum r(Z) + \sum s(Z)} \quad \text{, where: } S(Z) \in [0.1]$$

- Sc(Z) : reputation score of Z
- $-\Sigma r(Z)$  : positive evidence sum.
- $\Sigma s(Z)$  : negative evidence sum.
- $-r_{\text{base}}$ ,  $s_{\text{base}}$ : default base rate parameters.

Limitation: Unable to reflect polarised ratings!



## Computing binomial reputation over time with longevity factor

- $R_i$ : accumulated positive evidence at time *i*
- $S_i$ : accumulated negative evidence at time *i*
- r : positive evidence during 1 time period
- *s* : negative evidence during 1 time period
- $\lambda$  : longevity factor in range [0,1]
- $R_{i+1} = \lambda \cdot R_i + r$ : Recursive updating algorithm
- $S_{i+1} = \lambda \cdot S_i + s$ : Recursive updating algorithm

• 
$$Sc_i(Z) = \frac{r_{base} + R_i(Z)}{r_{base} + s_{base} + R_i(Z) + S_i(Z)}$$
: Score at time period *i*  
• Typically,  $r_{base} = 1$ ,  $s_{base} = 1$ 

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#### Score evolution with different longevity

Period 1-25: Positive rating, r = 1, s = 0Period 26-50: Negative rating, r = 0, s = 1



## e-Market Simulation

- Buyers:
  - Vary risk aversion
  - Provide ratings
- Sellers:
  - Vary honesty and price
  - Have reputation score
- Sellers and buyers seek to maximise own profit



#### Seller honesty with fixed reputation



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#### Seller honesty and reputation with $\lambda$ =1



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#### Seller honesty and reputation with $\lambda$ =0.99



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## **Observations from simulation**

- A market without reputation system will degenerate
- A market with a reputation system that never forgets will degenerate
- A market with a reputation system that gradually forgets old behaviour can have stable quality.



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### Trust and Reputation Systems Part 2

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#### Answer to question about convergence

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Answer	Hello Audun,
	If you work out some of the values the algorithm gives:
	$ \begin{array}{l} R(0) = 0 \\ R(1) = 0k + 1 = 1 \\ R(2) = 1k + 1 = k + 1 \\ R(3) = k(k + 1) + 1 = k^{n}2 + k + 1 \\ R(4) = k(k^{n}2 + k + 1) + 1 = k^{n}3 + k^{n}2 + k + 1 \\ \end{array} $ $ \begin{array}{l} Y ou \ can \ see \ this \ is \ just \ a \ geometric \ series \ c^{n} \ is \ equal \ to \ 1/(1 - c) \ if \ -1 < c < 1. \ lt \\ diverges \ for \ all \ other \ values \ of \ c. \\ \end{array} $ $ \begin{array}{l} In \ the \ case \ of \ your \ algorithm \ you \ have \ 0 < k < 1, \ so \ calculated \ to \ infinity \ the \ algorithm \ will \ convege \\ at \ 1/(1 - k). \\ So \ R(infinity) = 1/(1 - k). \end{array} $
	Suzanne.
	Rate the Expert Ask a Follow-Up
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## Convergence values

• For an infinite series of positive ratings r = 1, s = 0

$$- R_{\infty} = 1/(1-\lambda)$$

- 
$$S_{\infty} = 0$$
  
- Score converges to  $Sc(Z) = \frac{2-\lambda}{3-2\lambda}$  (with  $r_{\text{base}} = s_{\text{base}} = 1$ )

• For an infinite series of negative ratings r = 0, s = 1

$$- R_{\infty} = 0$$

- 
$$S_{\infty} = 1/(1-\lambda)$$
  
- Score converges to  $Sc(Z) = \frac{1-\lambda}{3-2\lambda}$  (with  $r_{\text{base}} = s_{\text{base}} = 1$ )

### **Rating Suzanne**

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### Suzanne's reputation score

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## Multinomial Bayesian reputation

- Problems with binomial reputation systems
  - Can only take binary ratings (positive, negative)
  - Can not represent polarised ratings
- Multinomial reputation systems
  - Can have any number of rating levels
  - Can represent polarised ratings



## Multinomial reputation example

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## Multinomial Bayesian model

• Dirichlet PDF (probability density function)

$$f(\vec{p} \mid \vec{r}, \vec{a}) = \frac{\Gamma\left(\sum_{j=1}^{l} \left(r(x_j) + Ca(x_j)\right)\right)}{\prod_{j=1}^{l} \Gamma\left(r(x_j) + Ca(x_j)\right)} \prod_{j=1}^{l} p(x_j)^{r(x_j) + Ca(x_j) - 1}$$

- $\vec{p}$ : multinomial probability vector
- $\vec{r}$ : multinomial evidence vector
- $\vec{a}$ : multinomial base rate vector
- $x_j$ : event

#### Example: ternary state space



• Additivity requires:  $p(t_1) + p(t_2) + p(t_3) = 1$ 

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## Prior ternary Dirichlet PDF

Example:

Urn with balls of 3 different colours. Ternary *a priori* probability density.

- t1: Red
- t2: Yellow
- t3: Black



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#### Example posterior ternary Dirichlet PDF

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Density

A posteriori probability density after picking:

- 6 red balls (t1)
- 1 yellow ball (t2)
- 1 black ball (t3)



#### Example posterior ternary Dirichlet PDF

Density

A posteriori probability density after picking:

- 20 red balls (t1)
- 20 yellow balls (t2)
- 20 black balls (t3)



#### Example posterior ternary Dirichlet PDF

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Density

A posteriori probability density after picking:

- 20 red balls (t1)
- 20 yellow balls (t2)
- 50 black balls (t3)



#### Score of ordered set of outcomes

 Density functions do not naturally represent the reputation score on an ordered set of rating levels

– e.g. Set of {Mediocre, Bad, Average, Good, Excellent}

- Rating levels can be represented as a set of different outcomes
- Probability expectation of each rating level can be represented separately



### Multinomial reputation score

•The multinomial reputation score can be defined equal to the Dirichlet-PDF probability expectation

$$E(p(L_j) | \vec{r}, \vec{a}) = \frac{r(L_j) + C \cdot a(L_j)}{C + \sum_{j=1}^{l} r(L_j)} \quad \text{Proba. expect}$$

- $\vec{r}$ : Multinomial evidence vector
- $\vec{a}$ : Multinomial base rate vector
- C = 2
- *l* : Number of rating levels
- $L_j$ : particular rating level

 $Sc(L_j) = E(p(L_j) | \vec{r}, \vec{a})$ : Multinomial reputation score

## Initial reputation score

Example with l = 5 discrete rating levels:

- 1) mediocre, 2) bad, 3) average, 4) good, 5) excellent
  - Initial uniform reputation score before any ratings have been received.

Base rate  $a(x_i) = 0.2$ 

Can represent polarised ratings!



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### Reputation score of polarise ratings

As before, 5 discrete levels:

1) very bad, 2) bad, 3) average, 4) good, 5) very good



Non-polarised reputation score after 10 average ratings



Polarised reputation score after 5 very bad and 5 very good ratings



## Computing multinomial reputation over time with fixed base rate

- $\vec{R}_i$ : accumulated evidence at time *i*
- $\vec{r}$  : evidence collected during 1 time period.
- $\lambda$  : longevity factor
- $\vec{R}_{i+1} = \lambda \cdot \vec{R}_i + \vec{r}$  : Recursive updating algorithm • $Sc_i(L_j) = E_i(p(L_j) | \vec{R}_i, \vec{a})$  : Score at time period *i*



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## Score evolution over time with fixed base rate

Five discrete rating levels:

- 1. Mediocre
- 2. Bad,
- 3. Average,
- 4. Good,
- 5. Excellent

Longevity  $\lambda$ = 0.9

Base rate a(x)=0.2

Periods 1-5: Mediocre

Periods 6-10: Excellent





## Score evolution over time with fixed base rate





## Dynamic base rate as function of average reputation score

- New members should get a base rate equal to the average reputation score of the community
- Same for existing members
- Let M denote the whole community
- $\vec{a}_{i+1} = \vec{E}_i(M)$  : Dynamic base rate at time period *i*+1
- Dynamic base rate is thus updated each period
- $Sc_i(L_j) = E_i(p(L_j) | \vec{R}_i, \vec{a}_i)$  : Score with dynamic base rate
- Max and min reputation score become independent of the longevity factor  $\boldsymbol{\lambda}$



## Score evolution over time with dynamic base rate

Longevity  $\lambda = 0.9$ Base rate  $a_{i+1}(Lj) = E_i(Lj)$ Periods 1-10: Mediocre 0.8 Periods 11-50: Excellent 0.6 Score 0.4 50 43 0.2 36 The max and min reputation 29 22 Period scores are 0 and 1 respectively, 15 and are independent of the  $\infty$ Lev longevity factor  $\lambda$ . el

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### Point Estimate Reputation Score

- Sometimes useful to have a single-valued score
- Translate multinomial score to point-estimate score
- *l* : number of different rating levels
- *j* : particular rating level

• 
$$v(L_j) = \frac{j-1}{l-1}$$
 : Point value for each rating level

• 
$$\sigma = \sum_{j=1}^{l} v(L_j) \cdot Sc(L_j)$$
 : Point estimate

## Multinomial score and point estimate with dynamic base rate

- Level values:
- $v(L_1) = 0$  $-v(L_2)=0.25$  $- v(L_3) = 0.5$  $- v(L_4) = 0.75$ 0.8  $- v(L_5) = 1$ 0.6 Score •  $s=\sigma=$  point estimate 0.4 • Longevity  $\lambda = 0.9$ 49 4 • Base rate  $a_{i+1}(L_i) = E_i(L_i)$ 0.2 33 25 Period Periods 1-10: Mediocre N • Periods 11-50: Excellent L+s

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## Score and point estimate with 5 consecutive uniform rating periods

Longevity  $\lambda = 0.9$ Base rate  $a_{i+1}(Lj) = E_i(Lj)$ Periods 1-10: Mediocre 0.8 Periods 11-20: Bad 0.6 Periods 21-30: Medium Score Periods 31-40: Good 0.4 50 Periods 41-50: Excellent 43 0.2 36 29 Period 22 15 •s= $\sigma$ = point estimate  $\infty$ 

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## **Discrete models**

- Discrete measures
  - "Very trustworthy", "trustworthy", "untrustworthy"
- Computation
  - Heuristic formula, or lookup tables
- Simple to understand
- Qualitative
- Theoretically misguided



## **Belief models**

- Assumes a trust scope  $\sigma$
- Two semantic variants of each trust scope
  - Fuctional: Trust *x* for scope σ
     (e.g. "to be a good mechanic")
  - Referral: Trust *x* to refer or recommend someone/thing for scope *σ* (*e.g. "to be a good at recommending mechanics*)
- Two topological types
  - Direct: Trust as a result of direct experience
  - Indirect: Trust as a result of second hand evidence



# Computing Trust with Subjective Logic

- Generalization of binary logic and probability calculus.
- Trust represented as binomial opinion:  $\omega_x^A = (b, d, u, a)$

- in range [0,1]

- *b*: belief
- d: disbelief
- *u*: uncertainty
- *a*: base rate
- Where: b + d + u = 1
- Expectation value:  $E(\omega) = b + au$
- Explicit belief ownership.


#### Subjective logic operators 1

Opinion operator name	Opinion operator symbol	Logic operator symbol	Logic operator name
Addition	+	U	UNION
Subtraction	-	١	DIFFERENCE
Complement	٦	X	NOT
Expectation	E(x)	n.a.	n.a.
Multiplication	•	$\wedge$	AND
Division	/	$\overline{\}$	UN-AND
Comultiplication	Ц	$\vee$	OR
Codivision	Π	$\overline{\vee}$	UN-OR



# Subjective logic operators 2

Opinion operator name	Opinion operator symbol	Logic operator symbol	Logic operator name
Discounting	$\otimes$	• •	TRANSITIVITY
Consensus	$\oplus$	$\diamond$	FUSION
Conditional deduction	Ø	I	DEDUCTION (Modus Ponens)
Conditional abduction	0	Π	ABDUCTION (Modus Tollens)



#### Simple Trust Network Demo

Four entities, labelled A, B, C and D have opinios about each other represented as points in triangles. Entity A is trying to form an opinion about D, and receives opinions from B and C as to the trustworthiness of D. Furthermore, A has his own opinions about the trustworthiness of B and C.



Left-click and drag opinion points to set opinion values. Entity A combines these opinions using the <u>Subjective Logic Operators</u> to derive his own opinion about **D**, as shown by the bottom opinion triangle. In detail, entity A *discounts* **B**'s opinion about **D** by his opinion about **B**, and does similarly for C. Finally, he combines the two discounted opinions using the *consensus* operator in order to determine his opinion about **D**. Right-click on the opinion triangles to see the exact values of each opinion. Opinion values can also be visualised using three-coloured rectangles.



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#### Simplifying complex trust networks

• Trust graphs can contain dependent paths, e.g.:



• One path can be removed to produce e.g.:





#### Building series-parallel graphs

- Trust graph analysis with subjective logic requires independent paths
  - called series-parallel graphs
- Constructed with series compositions and parallel compositions



a) Directed series composition



b) Directed parallel composition



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#### Method for building independent graphs

- 1. Determine all possible paths from relying party to trusted party through initial graph
- 2. Rank all paths on trust confidence/certainty
- 3. Build series-parallel graph by
  - including paths one-by-one according to rank
  - rejecting paths that can not be included with series-parallel composition

Resulting graph contains no dependent paths

can be directly analysed with subjective logic



#### Series-parallel trust graph examples



 $[A,F] = ([A,B]:[B,C]:[C,F]) \diamond ([A,D]:[D,E]:[E,F]) \text{ graph expr.}$  $\omega_F^A = (\omega_B^A \otimes \omega_C^B \otimes \omega_C^C) \oplus (\omega_D^A \otimes \omega_E^D \otimes \omega_E^D) \text{ SL expr.}$ 



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 $[A,F] = ((([A,B]:[B,D]) \diamond ([A,C]:[C,D])) : [D,F])) \diamond ([A,E]:[E,F])$  $\omega_F^A = (((\omega_B^A \otimes \omega_D^B) \oplus (\omega_C^A \otimes \omega_D^C)) \otimes \omega_F^D) \oplus (\omega_E^A \otimes \omega_F^E)$ 



 $[A,G] = ((([A,B] : ([B,D]:[D,F]) \diamond ([B,E]:[E,F])) \diamond ([A,C]:[C,F])) : [F,G]) \diamond [A,G]$  $\omega_G^A = (((\omega_B^A \otimes (\omega_D^B \otimes \omega_F^D) \oplus (\omega_E^B \otimes \omega_F^E)) \oplus (\omega_C^A \otimes \omega_F^C)) \otimes \omega_G^F) \oplus \omega_G^A$ 

#### Flow models

- Transitive iteration through graph
- Loops and arbitrarily long paths
- Source of trust can be distributed
  - evenly, e.g. early version of PageRank
  - discretely, e.g. current PageRank, EigenTrust
- Sum of trust over all parties can be
  - constant, e.g. PageRank, so one party's increase comes at the cost of another party's decrease
  - function network size, e.g. EigenTrust



# Proposed and Commercial trust and reputation systems





# EigenTrust algorithm

- Decision support for P2P networks
- Individual experience recorded
- Based on
  - Normalised local trust scores made public
  - Iterative transitivity to compute global trust
- No negative ratings
- Sum of trust scores in community increases with number of members
- EigenTrust is a reputation system



# EigenTrust visualisation

- Local satisfaction score: s<sub>ij</sub> = sat(i,j) unsat(i,j)
- Normalised local trust score:  $c_{ij} = \max(s_{ij}, 0) / \sum \max(s_{ij}, 0)$
- Iterative computation of trust score:  $t_{ik} = \Sigma c_{ij} \cdot c_{jk}$
- Iterative vector  $t_i = C^n \cdot c_i$  converges to Eigenvector of C.
  - where C is the matrix of all local trust scores



# Google's PageRank

- Purpose to provide quality search results
- Based on:
  - Number of incoming links, weighted by the
  - PageRank of the sites behind incoming links
- Hyperlinks interpreted as positive ratings.
- No negative ratings.
- Random surfer model.
- PageRank is a reputation system



# PageRank visualisation

•R(*A*) = (1-*d*)/N(Web) +  $d \Sigma R(\text{prev}(A))/N(\text{next}(\text{prev}(A)))$ •Damping factor  $d \approx 0.85$ • $\Sigma R(A) \approx 1$ , i.e. R(*A*) is the probability of the random surfer •PageRank(*A*) = *I* + log<sub>≈10</sub> R(*A*), where *I* ≈ 11



#### Link spam and "nofollow"

- Survival of e-commerce sites depends on rank
- Possible to increase rank with link spam
  - consists of putting URLs to own Web site in wikis (publicly editable Web sites) and in postings to public discussion groups
- The "nofollow" tag, introduced in 2005, instructs Web crawlers not to follow a link
  - <a href=http://some-spammer-website.com rel="nofollow">Link</a>
- Wikis and discussion groups now enforce that all URLs have "nofollow", thereby solving the link spam problem



#### Negative side-effects of "nofollow"

- Outgoing URLs causes rank leak
- Many webmasters misuse "nofollow" to avoid leaking Web ranking
- Undermines basis for original PageRank algorithm
- Alternative info sources required for ranking Web pages
  - Toolbars
  - Reputation systems



# The future of Web page ranking

- 1990s: No ranking, random order (Altavista)
  - Boolean selection criteria possible
- 1998: Random surfer model
  - Based on PageRank algorithm
- 2005: Intentional surfer model
  - Based on Toolbar feedback
- 2008: Critical surfer model
  - Based on reputation systems



# Random surfer model

- Assumes a monkey that randomly clicks on Web links.
- The monkey is the random surfer.
- Ranking = probability of monkey accessing a given page
- PageRank algorithm is the basis for this model



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# Intentional surfer model

- Assumes people who actually surf the Web
- Ranking = probability of people accessing a given page
- Difficult to obtain global information about how often a page is actually accessed.
- Browser toolbar provides source of info



#### Browser toolbar architecture





#### Evidence from toolbars and spyware



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# Critical surfer model

- People sometimes access a Web site even though they don't approve of its content
  - e.g. IT security researcher investigating phishing sites
- Critical surfer model depends on people rating Web pages
- Ranking = probability of people accessing a given page, weighted by its reputation score



#### Critical surfer model implementation





#### Web Sites with reputation systems

- Auction sites:
  - www.ebay.com
  - auctions.yahoo.com
- Expert sites
  - www.expertcentral.com
  - www.askme.com
- Product review sites
  - www.epinions.com
  - www.amazon.com
- e-commerce
  - www.bizrate.com
  - www.virtualratings.com

- Article postings
  - www.slashdot.com
  - www.everything2.org
- Education
  - us.ratemyteachers.com
  - www.virtualratings.com

#### • Entertainment

- www.citysearch.com
- www.imdb.com
- radio.weblogs.com

# The eBay Feedback Forum

- Centralised reputation system
- Ratings:
  - Buyers and sellers rate each other, 50% 60% times
  - positive, negative, neutral, + short comment
- Score =  $\Sigma$  positive  $\Sigma$  negative
- Time windows
- Surprisingly positive ratings, only 1% negative
- Correlation between seller and buyer ratings
- Many empirical studies
- Purpose: to control the quality of market



#### Example eBay member's profile

Ele Edit Yew Fgvorites Iools Help   Back + O + O + O + O + O + O + O + O + O +	🚰 eBay Member Profile for kevin.	2981 - Mici	rosoft Internet Explorer			
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home       pay       register       services       site map       Stat new search       Search         Buy       Sell       My eBay       Community       Help       Advanced Search         Hellol Sign in or register.       Newree By       Image: Part of the search       Search         Image:       Member Profile:       Kevin2981 (1438 *)       * Search       Member Profile         Member Swho left a positive:       1438       * Search       Month       6 Months       12 Months         Members who left a negative:       1918       Image: Past Past Month       Member Search       9 Month         All positive feedback received:       1918       Image: Past Past Month       1807       1897       9 Met 10 Favorite Sellers         Learn about what these numbers mean       Bid Retractions (Past 6 months): 0       Members       Contact Member         Feedback Received       From Sellers       Left for Others       2092 feedback received by kevin2981 (21 mutually withdrawn)       Page 3 of 84	Address 🙆 bay.com/ws/eBayISAPI.dll?V	ewFeedback8	&userid=kevin2981&items=25&page=3&fi	ompage=-1&iid=49	990172667&de=off 🔽 🋃 Go 🛛 Links 🎽	
Buy       Sell       My eBay       Community       Help       Advanced Search         Hellol Sign in or register.       Powered By IBM         Image:       Powered By IBM         Feedback Score:       1438         Positive Feedback:       96.1%         Members who left a positive:       1498         Members who left a positive:       1498         Members who left a positive:       1498         Image:       Positive 638       1807       1897         Image:       Bid Retractions (Past 6 months): 0       Co		e   pay   reg	<u>iister   services   site map</u>	Start	new search Search	
Hellol Sign in or register.       Powered By IEM         Imme > Community > Feedback Forum > Member Profile         Member Profile: kevin2981 (1438 ★ ) * Serrer         Feedback Score:       1438 96.1%         Members who left a positive:       1438 96.1%         Members who left a positive:       1498 00         All positive feedback received:       1916         Learn about what these numbers mean.       Bid Retractions (Past 6 months): 0       Month 12         Feedback Received       From Buyers       From Sellers       Left for Others         2092 feedback received by kevin2981 (21 mutually withdrawn)       Page 3 of 84       Page 3 of 84		Sell	My eBay Community He	lp	Advanced Search	
Items > Community > Feedback Forum > Member Profile         Member Profile: kevin2981 (1438 ★) * Serer         Member Score:       1438 96.1%         Members who left a positive:       1498 10         Members who left a negative:       61         All positive feedback received:       1916         Learn about what these numbers mean.       Bid Retractions (Past 6 months): 0       Members 0         Feedback Received       From Buyers       From Sellers       Left for Others         2092 feedback received by kevin2981 (21 mutually withdrawn)       Page 3 of 84       Page 3 of 84	Hello!	<u>Sign in</u> or <u>re</u>	egister.		Powered By	
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#### Example eBay feedback comments

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	) very pleased	Buyer	customtrim ( 43 🛠 )	May-02-05 18:13	<u>4987590016</u>	^
Œ	) will use agaid and again and again	Buyer	customtrim (43 😭)	May-02-05 18:13	<u>4987594247</u>	
3	) your the man	Buyer	customtrim (43 😭)	May-02-05 18:13	<u>4987649864</u>	
Œ	wow fast delivery & nice watches	Buyer	customtrim (43 😭)	May-02-05 18:11	<u>4987589950</u>	
6	Picture very misleading, dial don't actually work, could do better at wal-mart	Buyer	<u>dcree33</u> ( <u>4</u> )	May-02-05 18:03	<u>4984600746</u>	
G	) Great Product, Fast Shipment, & Excellent Seller	Buyer	<u>chad29212</u> ( <u>15</u> 😭)	May-02-05 17:56	<u>4987445224</u>	
0	) Thanks	Buyer	debbie5555kids (2)	May-02-05 17:48	<u>4984641973</u>	≡
G	Good product. Thanks very much	Buyer	<u>baek1988s</u> ( <u>10</u> 🛠)	May-02-05 17:03	<u>4975524351</u>	
6	really nice looking watch, thanks	Buyer	pinkannalu (2) 🕌	May-02-05 16:33	<u>4987611180</u>	
G	It was not watch in photo	Buyer	pinkannalu (2) 🕍	May-02-05 16:01	<u>4987607848</u>	
C	) The item looks good.	Buyer	<u>crislucero22</u> ( <u>10</u> 😭)	May-02-05 15:23	<u>4984646460</u>	
6	NOT ALL FUNCTIONS ON WATCH WORKS. WONT BUY FROM AGAIN.	Buyer	<u>billabong270</u> ( <u>18</u> 😭)	May-02-05 15:14	<u>4984789713</u>	
6	Horrible ebayer. Never received item and never got money back. FFFFF	Buyer	<u>r13dub</u> ( <u>23</u> 😭)	May-02-05 14:21	<u>4980643615</u>	~
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e				🥥 In	ternet	

#### Reputation extortion on eBay

- Serious sellers
  - want satisfied customers
  - don't want negative feedback
- Dissatisfied buyers can contact seller before giving negative feedback
- Threat of negative feedback can work better in customer's favour than actual negative feedback
- Proves that reputation systems work



## AllExperts

- Free advice from volunteer experts
- Ratings given on scale [1,10] for
  - Knowledgeable, Clarity of response, Timeliness and Politeness
- Score = average of ratings
- Most experts have scores ≈ 10
- Business model:
  - Low profile advertisement
  - Prestige to volunteer experts





xample AllExperts

#### Advogato open-source community

- Community of programmers
- Hierarchic flow model reputation system
- Flow capacities assigned as a function of distance from root seed
- Computation based on Ford-Fulkerson algorithm for flow through graphs
- Recommendations as
  - Apprentice, journeyer, or master
- Purpose: give prestige to members







# Epinions product review site

- Reviews consumer products
- Product ratings
  - in range 1 5 stars
  - Score = average of product ratings
- Review ratings
  - Not helpful, somewhat helpful, helpful, very helpful
  - Review score = average of review ratings
- Reviewer status
  - Member, advisor, top reviewer, category lead
- Income share program
  - Gives cash to reviewers with high number of very helpful reviews



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# Example Epinions product reviews

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Compare Prices and Read Rev	iews on Sony Cyber-Shot DSC-P100 Digital Camera at Epinions.com - M 💶 🕻	]
File Edit View Favorites Tools	Help Search 🌟 Favorites 🧐 🎯 - 🌺 🔯 - 🧲 🦓	
Address 🔄 http://www.epinions.com/pr	r-Sony_DSC-P100_Digital_Camera/display_~reviews 🛛 🕑 Go Li	nks
Read Reviews Showing 1-15 of 23 reviews	Page 1 <u>2</u> - <u>View all</u> <u>Next</u>	
Sort by <u>Product Rating</u>	Sort by <u>Review Date</u>	
Product Rating: ★★★☆☆ Ease of Use: Durability: Battery Life: Photo Quality: Shutter Lag	A Good Compromise Between Size and Features by green-z, Jun 25 '04 Pros: Pocketable size, nice pictures. Cons: No mixed auto/manual mode, poor ergonomics, uses expensive Memory Sticks. I've been a Canon fan since my first digital camera, a PowerShot S20, back in 2000. That 3 megapixel (MP) camera was a real gem of technology way back then. But new models advance and in early 2003 I upgraded to a slick 5 MP Powershot S50. It has Read the full review	
Product Rating: ***** Ease of Use: Durability: Battery Life: Photo Quality: Shutter Lag	The DSC-P100 is such a GREAT camera! by markneustadt, Jun 23 '04 Pros: InfoLithium Battery included, 5.1 Megapixels, PictBridge Technology, FAST FAST FAST!! Cons: Proprietary USB interface on the camera end, Proprietary battery As the owner of a Sony DSC-P50 digital camera, we've been very happy with the quality of Sony cameras. It was with dismay that we began to get frustrated by the slow recharge time of the old camera. Plus, if I had known how much fun digital photography	>
ê)	Internet	-
iversity for the <b>real</b> world	® CRICOS No. 00213J	4


## Amazon

- Online book store, with reviews by members
  - Book review in prose
  - Book ratings: 1 5 stars
  - Book score = average of book ratings
- Review ratings
  - Helpful or not helpful
  - Reviewer score =  $\Sigma$  helpful ratings
- Reviewer status
  - #1, top 10, top 50, top 100, top 500, top 1000
  - To be the #1 reviewer, you must read more books than any living person could do.





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# Slashdot

- "News for nerds" message board
- Article postings, at Shlasdot's discretion
- Comments to articles posted by members
- Comment moderation by members
  - Positive: insightful, interesting, informative funny, underrated
  - Negative: offtopic, flamebait, troll, redundant, overrated
  - Comment score  $\approx \Sigma$  positive(Karma)  $\Sigma$  negative(Karma),
  - Moderation by members with high Karma carries more weight
- Comment viewing filtered by score
- Member Karma

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- Terrible, bad, neutral, positive, good, excellent
- Based on moderation of comments.
- Metamoderation, to combat unfair moderation
  - Rate the moderations: fair, unfair, neutral
  - Affects Karma of member who gave the moderation
- Arbitrary moderation by Shlashdot staff
- Purpose: Directing massive collaborative moderation effort

## Hierarchic reputation architecture

Shlashdot type

QUT



# **Example Slashdot posting**



	Microsoft to Sh	hare 'Spare' Tech with Startups - Microsoft Internet Explorer				
	<u>File E</u> dit <u>V</u> iew I	Favorites Iools Help				
	🌀 Back 🔹 🕥	) 👻 😰 🏠 🔎 Search 🤺 Favorites 🤣 😥 - 嫨 🖾 - 📙 🖄				
	Address 🙆 http://sla	lashdot.org/comments.pl?sid=148528&cid=12447626&pid=12447626&threshold=2&mode=thread&commentsort=0&op=Chan( 💌 💽 Go 🛛 Li	inks <sup>:</sup>			
	Login Why Login2	Microsoft to Share 'Spare' Tech with Startups   Log in/Create an Account   Top   93 comments   Search Discussion	2			
	Why Subscribe?	Threshold: 2: 40 comments 💌 Threaded 💉 Oldest First 💽 Change Reply	L			
	Sections					
	<u>Main</u>	The Fine Finit: The following comments are owned by whoever posted them. We are not responsible for them in any way. New motto: "It just doesn't work " (Score: 5 Funny)				
	Apache Apple	by localroger (258128) on Thursday May 05, @09:14PM (#12447626)				
	AskSlashdot	(http://www.kuro5hin.org/prime-intellect/index.html)				
	5 mare Books	Otherwise, wouldn't it be integrated into Windows by now?				
	BSD	[Reply to This]				
	1 more Developers	Starting Score: 1 point				
	1 more	Moderation +3				
	Games	100% Funny				
)	13 more Hardware	Extra 'Funny' Modifier 0				
ا ر	3 more	Karma-Bonus Modifier +1				
	Interviews IT	Total Score: 5				
	2 more	Re:New motto: "It just doesn't work." (Score:4, Insightful)				
-	Linux	by <u>smchris (464899)</u> on Thursday May 05, @09:31PM ( <u>#12447750</u> )	ı			
	Politics	Basically.				
-	Science	No loss, possible win. If somebody does build upon it successfully, they can get the novel warm glow of saving				
_	<u>YRO</u>	that the tech "originated" at Microsoft.	I			
5	2 more	[Reply to This   Parent ]				
く	Help	It works too well (Score:2)				
ノ	FAQ	by <u>appleLaserWriter (91994)</u> on Thursday May 05, @09:48PM ( <u>#12447844</u> )	L			
	Bugs	More likely is that it works too well, and the Windows group doesn't want it because it will make them look bad.				
	Stories	[Reply to This   Parent ]				
UT	e	🔮 Internet				
	a university for	CRICOS No. 00213J	10			

Example Slashdot comments

🕙 localroger - S	lashdot User - Microsoft Internet Explorer			
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3 more	localroger's Latest 24 of 490 Co	mments		
Interviews IT	Subject	Datestamp	Replies Score	
2 more	Window into the Abyss	Thursday May 05, @09:27PM	2	
Linux	New motto: "It just doesn't work."	Thursday May 05, @09:14PM	5 5, Funny	
1 more Politics		attached to <u>Microsoft to Sha</u>	re 'Spare' Tech with Star	tups
Science	<u>Oops, wrong Stella</u>	Sunday May 01, @09:46PM	2	
1 more		attached	to <u>When Lofar Meets S</u>	tella
2 more	Finally, some common sense	Saturday April 30, @11:01AM	1 5, Insightf	ul
		attached to <u>NASA Preparing Man</u>	ned Hubble Service Mis	sior
Help	So at last	*Saturday April 02, @12:06AM	1 -1, Troll	
<u>Bugs</u>		attached to <u>Scientist</u>	s Weigh Smallest Mass	<u>Eve</u>
	Who defines "close?"	*Friday January 28, @01:42PM	32	
Stories Old Stories	•	attached to <u>Norwegian Student Ordered to</u>	Pay for Hyperlinks to M	usi
Old Polls	Oddly enough re: Cyndi Lauper	*Tuesday January 25, @11:43PM	2	
<u>Topics</u> Hall of Fame		attached to <u>Could TNG Stu</u>	nt Casting Save 'Enterpr	ise"
Submit Story	He's lucky he got the real microphone to work	*Friday January 21, @10:44PM	3, Informa	ativ
About		attached to <u>Build Your</u>	Own Rotary-Dial Cell Pl	<u>ion</u>
Supporters	The new Inactive Desktop?	*Thursday January 13, @10:33PM	2 2	
<u>Code</u> Awards		attached to <u>Windows Longhorn to make Gra</u>	aphics Cards more Impo	rtan
11110100	I second the Basic Stamp	*Monday January 03, @06:21PM	2	
Services	•	attached to <u>Introdu</u>	cing Children to Comput	ers
PriceGrabber	On the fourth day of Christmas	*Friday December 24, @10:46AM	1 2	
Product Guide		attached to <u>Four New Unpatch</u>	ned Windows Vulnerabi	litie:
Tech Jobs	a-men	*Thursday November 25, @12:49PM	2	
	This is what I do	*Thursday November 25, @12:42PM	5, Informa	ative
ē			🥥 Internet	

Example Slashdot

## Problems and proposed solutions



**FOSAD 2006** 



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# **Reputation System Challenges**

- Ad hoc computation
- Collusion
- Unfair ratings
- Change of identity
- No incentive to provide ratings
- Hard to elicit negative feedback
- Discrimination
- Is past performance = future performance ?



#### Reputation systems as attack instruments

- Dependence on reputation systems makes it necessary to assess their reliability
- Strategic manipulation of reputation systems can harm the entities through reputation destruction
- Robustness of reputation systems requires hard security
  - Authentication
  - Anonymity
  - Rating tokens
  - etc.



# What about subjective taste?

- Recommender systems based on collaborative filtering
  - Assumes different taste
  - Identifies like-minded with same taste
  - Recommender systems
- Reputation System
  - Assumes consistent quality judgement
  - Sanctions poor quality
  - "Collaborative Sanctioning System"



#### Collaborative filtering



### Recommender systems in practice

Date: 4 Sep 2006 03:33:48 -0700 From: Amazon.com <store-news@amazon.com> To: a.josang@qut.edu.au Subject: Amazon.com recommends The CISSP Prep Guide: Gold Edition and more

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# Combining recommender and trust systems

- Reputation systems can be used to determine trust relationships
  - Little purpose of getting trust recommendations about Microsoft products from Linux freaks
- Trust recommendation based on collaborative filtering



#### Collaborative filtering and transitive trust



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# Yhprum's Law

(systems that shouldn't work sometimes do)

- People provide ratings despite having no rational incentive to do so.
  - Helps others, but not self
  - Can create competition over scarce resource
- Negative ratings are hard to elicit.
- Relatively easy to mount attacks against existing reputation systems.
- A reputation system works when people can relate to it
- Supports community building



# Countermeasures against attacks

- Sound computation engines
- Authentication/security
  - Prevents change of identity
- Statistical filtering, and discounting
  - To prevent unfair ratings, discrimination and collusion
- Anonymity
  - To prevent fear of retaliation
- Benefits / special offers
  - To provide incentive



# **Concluding remarks 1**

- Very primitive commercial systems
  - It is important that users can relate to the systems
  - Community building is an important factor, in addition to enhancing market quality
- Many different proposed theoretic systems
  - Little coherence among researchers
  - Pioneering period
  - No one system is optimal in for all applications



## Concluding remarks 2

- Challenging to make systems robust against attacks
  - Limits the potential of reputation systems
  - Requires hard security
- Benefits of trust management
  - Complements traditional security mechanisms
  - Provides incentive for good behaviour
  - Sanctions bad behaviour
  - Increases the quality of online markets and communities



# References

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  - http://www.fit.qut.edu.au/~josang/papers/Jos2007-multirepu.pdf
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