

# The Quest for Trusted Information

Karl Aberer

**Celebrating and commemorating** 

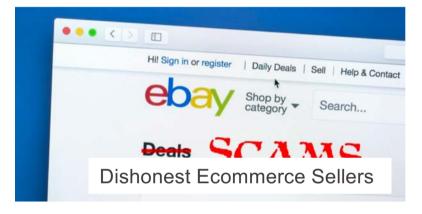
Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

21-22 February 2020

# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

# The Internet is a dangerous place









#### **EPFL** Trust

- Trust: the extent to which an agent <u>believes</u> an other agent will cooperate
  - Gain is to be shared with the other agent
  - But the agent is exposed to a risk of loss







## **Is Trust Important?**

A comparison of trust and reciprocity between France and Germany: Experimental investigation based on the investment game

Marc Willinger <sup>a</sup> A ≅, Claudia Keser <sup>b, c</sup>, Christopher Lohmann <sup>d, e</sup>, Jean-Claude Usunier <sup>f</sup>

■ Show more

https://doi.org/10.1016/S0167-4870(02)00165-4

Get rights and content

#### Abstract

We compare the results of a one-shot investment game, studied earlier by Berg et al. [Games and Economic Behavior 10 (1995) 122], for France and Germany. In this game, player A is the trustor and player B the trustee. The average level of investment is significantly larger in Germany, but the level of reciprocity is not significantly different between the two countries. This implies that German B-players earned significantly more than French B-players. Furthermore, in both countries B-players earned significantly more than A-players. Our results support Fukuyama's conjecture that the level of trust is higher in Germany than in France, a situation which can explain a higher rate of investment and a higher level of performance. However, our results also show that the increased revenue which is attributable to the higher level of trust, is not shared in a more equitable way, but essentially increases B-players' payoffs. Finally, based on an intercultural trust experiment, we show that French A subjects did not find German B subjects less trustworthy and German A subjects did not find French B subjects less trustworthy.

#### Example: eBay

- eBay reputation profiles predictive of future performance [Resnick et al., 2002]
- Prices positively correlated with the feedback [Melnik and Alm, 2002]

#### Overall profile makeup

94 positives. 91 are from unique users and count toward the final rating.

4 neutrals. 0 are from users no longer registered.

I negatives. I are from unique users and count toward the final rating.

<b>eb</b> Ƴ ID card		<u>seller01(90)</u>	
dember since Tuesday, Dec 15, 998			
Summary of Mo	st Recent Co	nments	
	Past 7 days	Past month	Past 6 mo
Positive	2	3	15
Neutral	0	0	0
Negative	0	0	0
Total	2	3	15
Bid Retractions	0	ñ	n.

# Trust Model: The way in which the trust belief is inferred

- Trust is a property of an agent A
  - i.e. label agent as trustworthy / not trustworthy
- Typical inferences could be
  - 1. If A cooperated with ME in the past, it will also cooperate with ME in the future
  - 2. If A cooperates with B then A will also cooperate with ME with high probability
- Basis of a large body of work on reputation-based trust
  - Building predictive models based on historical data (reports)
  - Signalling approach to trust management

Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

## **Reputation-based Trust**

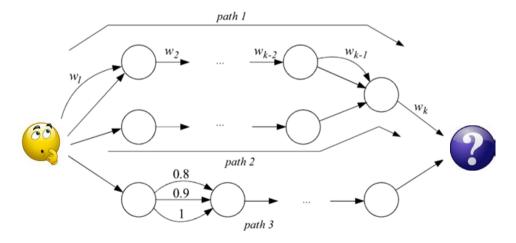
- Requires
  - 1. that we obtain reports and
  - 2. that we are able to interpret them
- Problem 1: have no reports about an unknown agent
  - Solution: share reports in a community
- Problem 2: we cannot interpret the report
  - Solution: perform inferences on sets of reports

- Entrée: Community-based Trust (Problem 1)
- Main Course: Inference on Trust Signals (Problem 2)
  - Checking consistency
  - Learning from history
- Dessert: Rationality

## Entrée: **Community-based Trust**

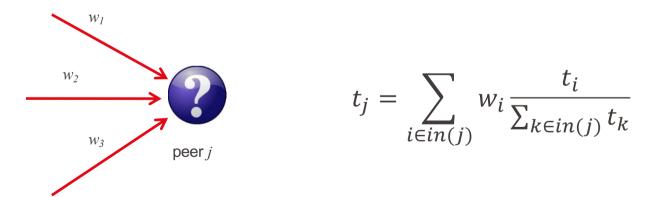
#### EPFL Model

- Original motivation: peer-to-peer systems
- Peers provide services to other peers
  - Know other peers they interacted with
  - Store feedback  $w_i$  on interactions with peer i
  - Feedback on service and reporting
  - A social network (trust graph)



# Social Networking Approach

- Compute global trust values t<sub>i</sub> for peer j
  - By aggregating feedbacks
  - Weighting by the trust in the recommender
  - Similar to PageRank computation



Xiong, Li, and Ling Liu. "Peertrust: Supporting reputation-based trust for peer-to-peer electronic communities." IEEE transactions on Knowledge and Data Engineering 16.7 (2004): 843-857.

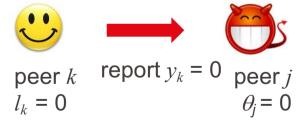
## Social Networking Assessment

- Problems solved
  - Automatic aggregation of reputation data
  - 2. Does not require central authority
  - 3. Possibility of misreporting considered
- Shortcomings
  - Costly (global) computation
  - Trust values have no further meaning but ranking
  - No distinction between propensity to provide poor service and to misreport

## Probabilistic Estimation Approach

- Assume probabilistic peer behavior, e.g.
  - P[peer j performs service honestly] =  $\theta_i$
  - P[peer k lies when reporting] = l<sub>k</sub>
- Probability of report  $y_k$  on peer j from peer k

$$P[Y_k = y_k] = \begin{cases} l_k (1 - \theta_j) + (1 - l_k)\theta_j & \text{if } y_k = 1\\ l_k \theta_j + (1 - l_k)(1 - \theta_j) & \text{if } y_k = 0 \end{cases}$$



Despotovic, Zoran, and Karl Aberer. "P2P reputation management: Probabilistic estimation vs. social networks." Computer Networks 50.4 (2006): 485-500.

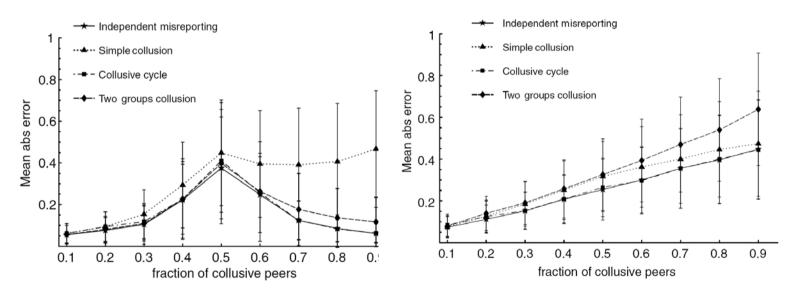
# **Probabilistic Estimation Approach**

- Maximum Likelihood Estimation
  - Determine  $l_k$  by checking reports on own performance
  - Collect all reports  $y_1, y_2, ..., y_n$  on peer j
  - Select  $\theta_j$  that maximizes the probability to obtain the observed reports

$$L(\theta_{j}) = P[Y_{1} = y_{1}]P[Y_{2} = y_{2}] \cdots P[Y_{n} = y_{n}]$$

## **Comparative Evaluation**

Precision in correctly assessing misbehavior



Maximum Likelihood Estimation

Social Networking

# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

**EPFL** 

# **Implementation Questions**

- Central or distributed storage of trust reports
  - Cost of updating and retrieving reports
- Manipulation of stored data
  - Replication

## **Main Course: Inference on Trust Signals**

## **Chapter 1: Checking Consistency**

# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

# Typical Example: Crowd-Sourcing

- Crowd-Sourcing Platform
  - · Crowd-workers label data
- Can the labels be trusted?
  - Use multiple labels to check their consistency
  - Assign trust value to crowd-workers



## **Classical Approach**

- Expectation maximization
- Iterates in two steps
  - 1. E-Step: estimate the labels from the answers of workers
  - 2. M-Step: estimate the reliability of workers from the consistency of answers

(E) step: estimate  $P(x_j = \ell)$  as

$$P(x_j = \ell) = \frac{1}{\sum_{i=1}^{N} w_i} \sum_{i=1}^{N} (w_i \mid a_i(x_j) = \ell)$$

(M) step: update the expertise  $w_i$  as

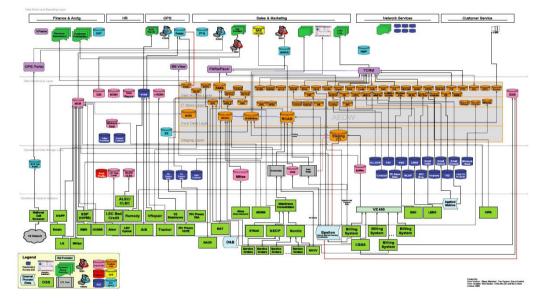
$$w_i = \frac{1}{M} \sum_{j=1}^{M} (1 \mid a_i(x_j) = \arg \max_{\ell} P(x_j = \ell))$$

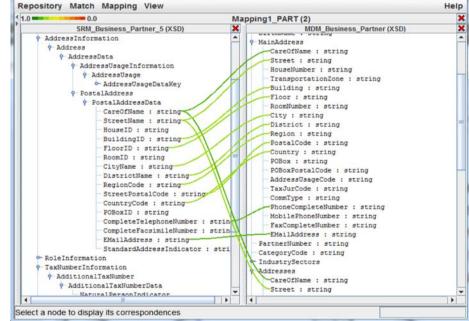
 $W_i$  expertise of worker i

M number of webpages to label

Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

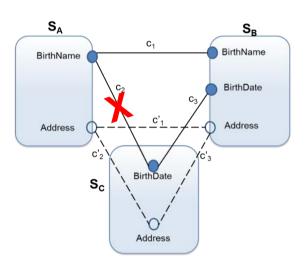
## **Data Integration**





#### **EPFL** The Problem

 Multiple database schemas to be mapped pair-wise by attribute correspondences

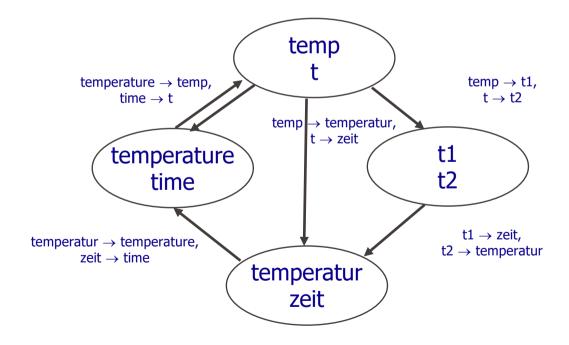


Initial mappings generated by humans or automated schema matchers

Can we trust them?

## **Semantic Gossiping**

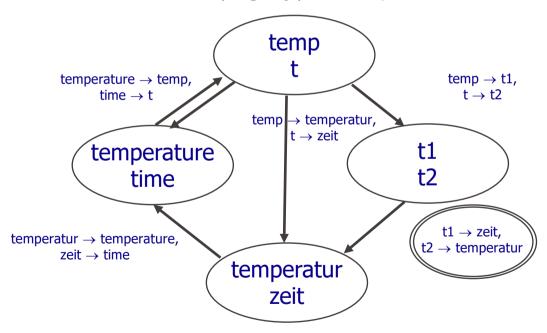
Different schemas on similar data will be related to each other





## **Erroneous Mappings**

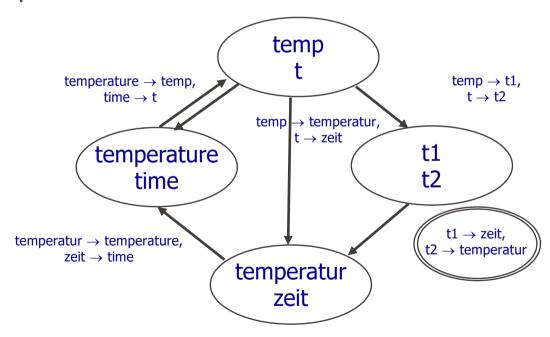
 Relationships among schemas will be either manually or automatically created: both methods are (highly) error-prone





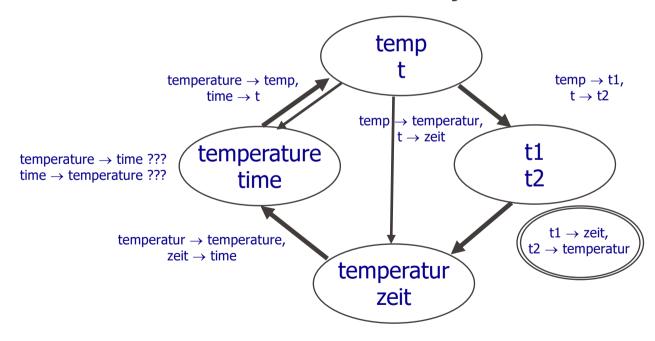
## **Erroneous Mappings**

• Problem: Is it possible to learn <u>from the network</u> about the correctness of relationships?



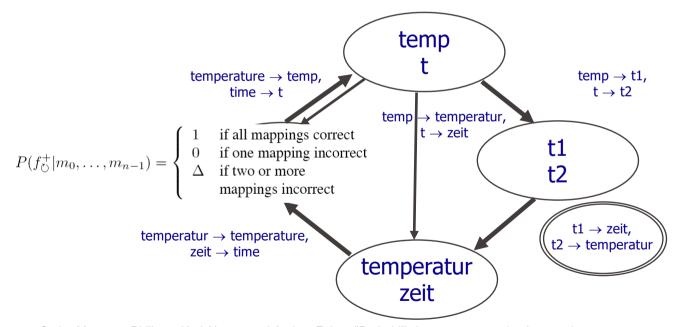
## **Erroneous Mappings**

- Mappings among concepts can be composed
  - Allows to identify redundant compositions, e.g. cycles
  - Those can be checked for consistency



## **Probabilistic Reasoning**

- Probabilistic model on the correctness of mappings m<sub>i</sub> in a cycle using feedback f<sub>i</sub> from mapping composition
  - Basis for probabilistic inference of correctness of mappings



Cudre-Mauroux, Philippe, Karl Aberer, and Andras Feher. "Probabilistic message passing in peer data management systems." 22nd International Conference on Data Engineering (ICDE'06). IEEE, 2006.

# **Computing a Marginal for One Mapping**

• Goal: determine  $P(m_i | f_0)$ 

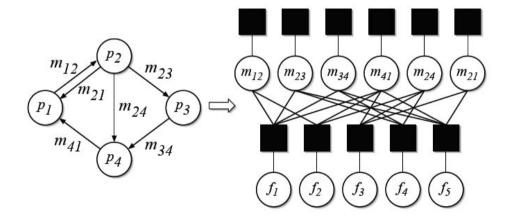
$$P(m_0 \mid f_0) = \sum_{m_3 m_4} P(m_0, m_3, m_4, f_0) P(f_0)^{-1} =$$

$$\sum_{m_3 m_4} P(m_0) P(m_3) P(m_4) P(f_0 \mid m_0, m_3, m_4) P(f_0)^{-1}$$
a priori probability known

- Maximum entropy principle: a priori probability  $P(m_i) = 0.5$
- Bayes Theorem  $P(m|f) = \frac{P(m)P(f|m)}{P(f)}$  and marginalization

#### **Correlated Feedback**

- But: feedbacks on different cycles are correlated
  - One wrong mapping will affect several cycles/paths
  - Need to express a global probabilistic model for the mapping graph



Deriving PDMS Factor-Graphs from Mapping Network

# Message Passing on Factor Graphs

General Formulation (n() neighbors in factor graph)

variable x to local factor f:

$$\mu_{x \to f}(x) = \prod_{h \in n(x) \setminus \{f\}} \mu_{h \to x}(x)$$

local factor f to variable x

$$\mu_{f \to x}(x) = \sum_{n \in \mathbb{Z}} \left( f(X) \prod_{y \in n(f) \setminus \{x\}} \mu_{y \to f}(y) \right)$$

Works correctly on trees

 Checking consistency works well if you have many redundant reports (dense feedback)

• What to do if feedback is sparse?

## **Chapter 2: Learning from History**

#### **EPFL** Fake News



#### OPINION, ANALYSIS AND DEBATE ON SECURITY ISSUES

TOPICS ↓ · ABOUT · CONTACT US

SUBSCRIBE · Q SEARCH · EN ↓

NATO Review / The "Lisa case": Germany as a target of Russian disinformation

#### The "Lisa case": Germany as a target of Russian disinformation

Stefan Meister • ## 25 July 2016

The media storm surrounding a fake story about a Russian-German girl, who had reportedly been raped by Arab migrants, was a wake up call for German political elites earlier this year. For the first time, they clearly saw the links between Russian domestic and foreign media campaigns against Germany and Russian politics at the highest level. The German government promptly advised the Federal Intelligence Service (BND) in coordination with the Foreign Office to check Russian sources of manipulation of German public opinion.

Germany's leading role in the Ukraine crisis, Angela Merkel's consequent position on sanctions against Russia and her leadership in Europe make the German government a core target of Russian disinformation.

The "Lisa case" also shows not only the failure of Germany's partnership for modernisation with Russia but also the dysfunctionality of Russia's attempts to use personal ties and informal networks to influence German decision-making and policy when it comes to the current crisis and, in particular, the person of Chancellor Merkel. While the German government remains strongly committed to keeping channels for dialogue open, we see a complete loss of trust in relations which will be very hard to rebuild in the forseeable future.



https://www.nato.int/docu/review/articles/2016/07/25/the-lisa-case-germany-as-a-target-of-russian-disinformation/index.html

### **Boosting Bad Science**

Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

By PAULA COHEN CBS NEWS May 29, 2015, 5:00 AM

## How the "chocolate diet" hoax fooled millions



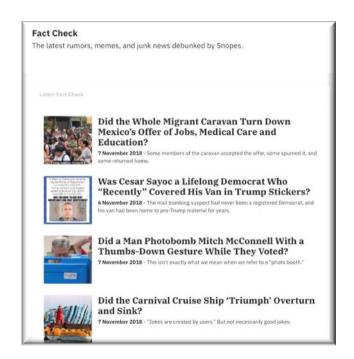
Last Updated May 29, 2015 5:23 PM EDT

Eating chocolate every day can help you lose weight? If it sounds too good to be true -- that's because the chocolate diet study that made headlines around the world last year was all an elaborate hoax.

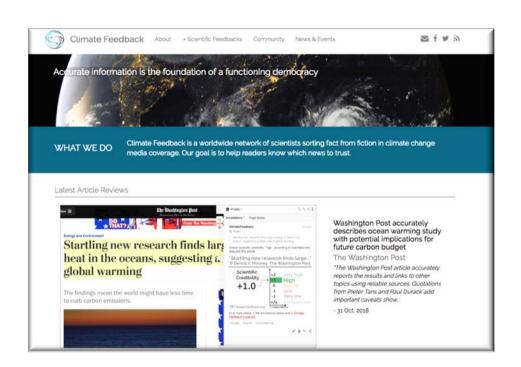
Now those responsible are going public with the story behind the bogus diet study and the media frenzy that followed. It was a carefully planned effort to expose the prevalence of junk science and unchecked, hype-driven press coverage.

## **Credibility Evaluation Today**

#### Manual fact checking by experts



General Fact Checking Sites (mostly journalists)



Specialized Science Fact Checking Sites (mostly scientists)

## **Evaluation? Automated Web Credibility**

#### Insights

- There exist features that correlate with credibility
- Combination of content and social features works best

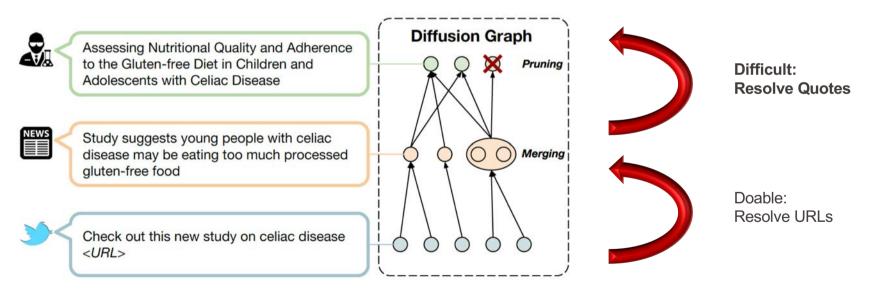
 Quality of classification depends on quality of training data = ground truth



Olteanu, A., Peshterliev, S., Liu, X., & Aberer, K. (2013, March). Web credibility: features exploration and credibility prediction. In *European conference on information retrieval* (pp. 557-568). Springer, Berlin, Heidelberg.

# SciLens: Evaluating Quality of Scientific News

Investigate whether scientific findings are adequately presented in science news: Analyze the news in their **context** 

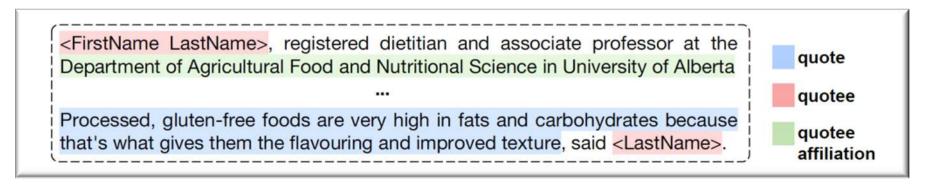


Panayiotis Smeros, Carlos Castillo, Karl Aberer: Evaluating the Quality of Scientific News Reporting from Social and Content Indicators, In *The International World Wide Web Conference 2019*.

## **Resolving Quotes**

Linking news to science articles: bootstrapping approach

- Create a set of reporting verbs ("say", "claim", "prove",...), studies ("survey", "analysis") and scientists ("researcher", "analyst")
- Extend this set with semantic similar words using word embeddings
- Identify indirect speech using NLP processing
- Build regular expression patterns over word classes



90% precision at 50% recall

## Data Collection in the Nutrition domain

Start from social media posts
then identify news,
finally find quotations of science articles

- 11'000 social media posts
- 7'500 news articles
- 1'300 papers



Most Quoted Organization per Topic

# **Quality Features**

Context	Type	Indicator			
Article	Baseline	Title [Clickbait, Subjectivity, Polarity], Article Readability, Article Word Count, Article Bylined			
Arucie	Quote-Based	#Total Quotes, #Person Quotes, #Scientific Mentions, #Weasel Quotes			
Cai litanatuma	Source Adherence	Semantic Textual Similarity			
Sci. literature	Diffusion Graph	Personalized PageRank, Betweenness, [In, Out] Degree, Alexa Rank			
Social media	Reach	#Likes, #Retweets, #Replies, #Followers, #Followees, [International News, Temporal] Coverage			
	Stance	Tweets/Replies [Stance, Subjectivity, Polarity]			

### Should You Be Taking a Curcumin or Turmeric Supplement?

A PLOS ONE study did find, however, that a combination of curcumin and tomatine, an antifungal and anticancer compound in tomatoes, inhibited cell growth of prostate cancer.

**Fitness Magazine** 

### Combination of α-Tomatine and Curcumin Inhibits Growth and Induces Apoptosis in Human Prostate Cancer Cells

Curcumin and  $\alpha$ -tomatine alone or in combination had a small inhibitory effect on the growth of non-tumorigenic prostate epithelial RWPE-1 cells.

PLOS ONE

Example: Source Adherence (semantic textual similarity feature for News article)

# **EPFL** Non-Expert Evaluation

Hypothesis: when non-experts see the quality features they can do a better assessment

Visitors per day of this news website (more visitors = more stars)

Mentions of universities and scientific portals (more mentions = more stars)

Length of the article (longer article = more stars)

Number of quotes in the article (more quotes = more stars)

Number of replies to tweets about this article) (more replies = more stars)

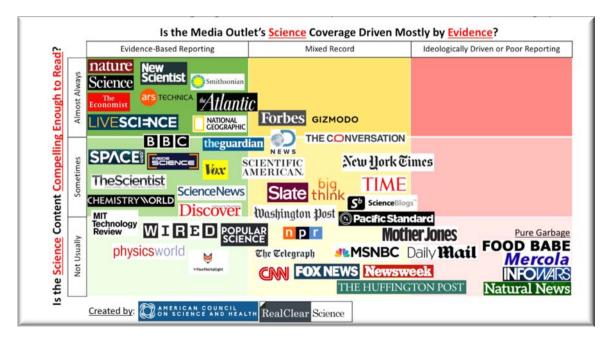
Article signed by its author (✓ = signed, ✗ = not signed)

Sentiment of the article's title (☺☺= most positive, ☺☺= most negative)

## **EPFL** Weak Supervision

Building a machine learning classifier using the quality features

- In absence of ground truth we use weak supervision
- Instead of judging the quality of articles we judge quality of outlet



Expert assessment of quality of journals

### **EPFL** Results

	Experts		Non-Experts		<b>Fully</b>
	by agreement	#	No ind.	Ind.	automated
ATC	Strong agreement	7	0.80	0.45	1.41
	Weak agreement	12	1.28	1.18	0.76
	Disagreement	1	0.40	1.30	0.00
	All articles	20	1.10	1.00	1.00
CRISPR	Strong agreement	6	1.40	1.17	1.00
	Weak agreement	10	0.86	0.76	0.67
	Disagreement	4	0.96	1.22	1.03
	All articles	20	1.96	0.96	0.85

- When displaying features to non-experts, the quality of their evaluation increases significantly
- A weakly-supervised classifier performs better than non-experts!

### **EPFL Platform**

☐ SciLens BETA Science behind results Account ▼

This project is supported by Open Science Fund & SATW

# Pete Buttigieg's new plan targets social factors in health care

by Anjalee Khemlani, Ben Werschkul

Posted on 2019-12-03 11:00:13

Source: finance yahoo

Article url: https://finance.yahoo.com/news/a-new-pete-buttigieg-plan-targets-the-social-factors-of-health-care-110002603.html

Pete Buttigieg released a health plan on Tuesday that pushes toward universal health coverage by focusing more on the social determinants of health, in an attempt to sharpen the distinctions with other contenders for the Democratic presidential nomination.

The problem, the campaign says in its plan, is that "millions of Americans today still find their health determined by who they are or where they live." Buttigieg's proposal would have a budget of \$5 billion over 10 years, but offered vague details of how that figure was derived, or how the funding would be distributed.

scilens.epfl.ch

Submit annotation
Add a score from 1 to 10 on the following aspects.

• Factual Accuracy \*:

• Scientific Understanding \*:

• Logic Reasoning \*:

• Precision Clarity \*:

• Sources Quality \*:

• Fairness \*:

**Annotate** 

No

You have not annotated this

· Clickbait title \*:

# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

**EPFL** 

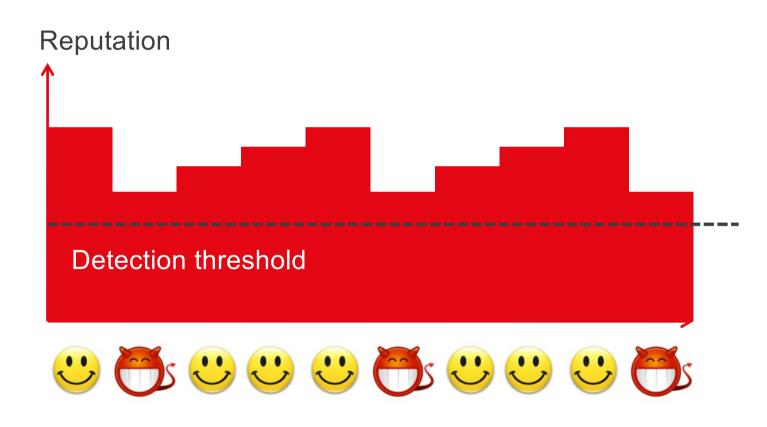
# **Dessert: Rationality**

# arl Aberer

# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

**EPFL** 

# **A Rational Agent**



Trust is not an inherent property of an agent!

# **EPFL** Rationality

- Actions of peers have associated utility
- Example: prisoners dilemma

$u_1,u_2$	Cooperate	Cheat
Cooperate	5, 5	0, 6
Cheat	6, 0	1, 1

- Main insights (2 Nobel prices)
  - One shot game: no cooperation (Nash)
  - Repeated game: cooperation tit-for-tat (Axelrod)
- Common explanation of the concept of trust

# **EPFL** The Setting

- Model (the community model)
  - Feedback  $w_i$  on peer i's service
  - Peer i has incentive to cheat: legal gain  $u_i$  < illegitimate gain  $u_i + v_i$
- Peer behavior
  - Honest peers never cheat
  - Malicious peers cheat probabilistically
  - Rational peers optimize their utility



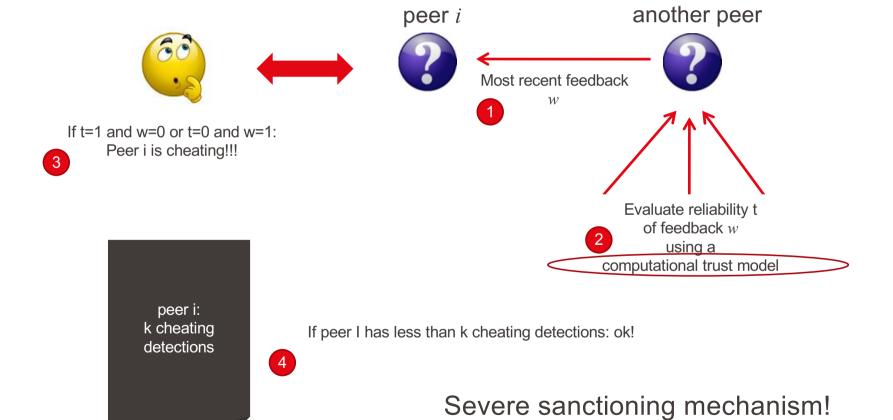




Vu, Le-Hung, and Karl Aberer. "Effective usage of computational trust models in rational environments." ACM Transactions on Autonomous and Adaptive Systems (TAAS) 6.4 (2011): 1-25.

# **Sanctioning**

Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary



# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

# **Computational Trust Model**

- May use several information sources
  - past performance of sellers, trusted sources, own belief on environment's vulnerability, relations between peers, ratings from other agents
- May use variety of statistical models/heuristics
  - probabilistic approaches, e.g. EM, collaborative filtering, clustering of ratings, etc.
- Accuracy measure (known to peers)
  - P[est+| real-] < ε, P[est | real+] < ε</li>

# Trust Accuracy vs. Cooperation

**Theorem**: if computational trust model <u>sufficiently accurate</u> and gains are <u>bounded</u> rational peers cooperate in all but the last  $\Delta$  transactions.

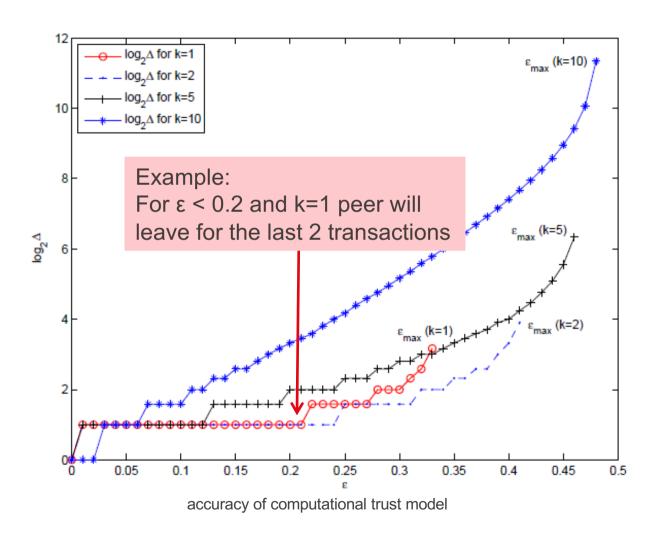
Bounded gains  $(u*\leq u\leq u^*, v*\leq v\leq v^*)$ 

$$\Delta = \max\{1, \lceil \frac{\ln\left[1 - \frac{v^* \varepsilon^k}{u_*((1-\varepsilon)^k - \varepsilon^k)}\right]}{\ln\left(1 - \varepsilon^k\right)} \rceil\}$$

$$\varepsilon < \varepsilon_{max}(k) = 1/(1 + \sqrt[k]{1 + v^*/u_*})$$

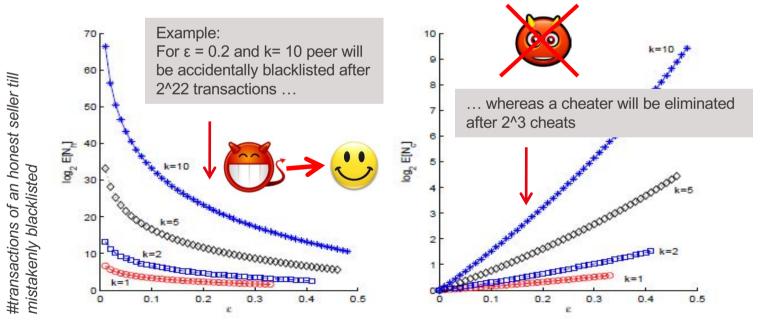
# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

# Incentive to Leave $(\Delta)$



# **Emergence of Cooperation**

- Cooperation is enforced if peers stay infinitely or long enough given  $\varepsilon$  sufficiently small
  - resilient against rating manipulation
  - · malicious peers are eliminated



#cheats of a malicious seller till being eliminated

**EPFL** 

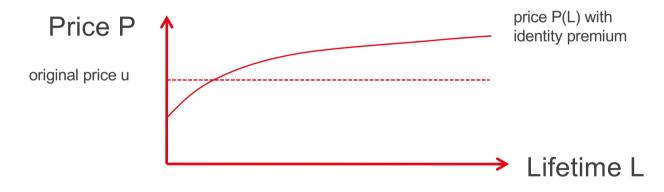
# How to Prevent Whitewashing?

- If peers that have been sanctioned can return with a new identity, this mechanism will not work
- Idea in Ebay: sellers that stay longer in the system ask for higher prices
  - · Makes it unattractive to leave the system for whitewashing
  - Clients on eBay are willing to pay higher prices for reliable seller [Resnick 2006]
- Does it work?

# **Identity Premium**

$$P(L) = u (1 - \Phi) + f(L)$$

- L lifetime of seller
- f(0) = 0, f monotonically increasing
- 0 < Φ < 1, initial price below original price u



Vu, Le-Hung, Jie Zhang, and Karl Aberer. "Using identity premium for honesty enforcement and whitewashing prevention." Computational Intelligence 30.4 (2014): 771-797.

# **Cooperation Enforcement**

Theorem: If the identity cost is <u>sufficiently small</u> there exists an <u>identity</u> <u>premium function</u> such that a rational provider will cooperate in every but the last interaction.

- Bound on identity cost and premium depends on
  - Accuracy of dishonesty detector
  - Potential cheating gain
  - Initial price

THEOREM 1. Given the provider selection protocol  $S_k = \langle \mathcal{R}, k \rangle$  where the dishonesty detector  $\mathcal{R}$  has the misclassification errors  $\alpha, \beta$  upper-bounded by  $\varepsilon < 0.5$ .

Consider any rational provider with N services to sell. Let  $u_* \le u_i \le u^*$ , i = 1, ..., N be the original prices of the services sold by the provider in the i-th transaction. Suppose that the pricing scheme  $\underline{P}(\phi, f)$  is used, it follows that:

(i) If the identity cost ξ is small, the following identity premium ensures that cooperation
is always the best response strategy of the provider in any transaction i = 1,..., N - 1,
for any 0 < ο < < 1:</li>

$$f(L) = \sum_{i=1}^{L} \lambda^{L-i} (\lambda u_i (1 - \phi_i) - \xi/\gamma) \text{ for } L > 0$$
 (2)

(ii) For λ ≠ 1 and providers sell services of the same standard price u<sub>i</sub> = 1, φ<sub>i</sub> = φ, i = 1,..., N, if the identity cost ξ < ξ<sub>0</sub> = γλ(1 - φ), the following identity premium function is sufficient to enforce cooperation for a provider in selling every but the last service:

$$f(L) = ((1 - \phi)\lambda - \xi/\gamma)\frac{1 - \lambda^{L}}{1 - \lambda} \text{ for } L > 0$$
 (3)

For  $\lambda = 1$ , the identity premium function becomes

$$f(L) = L(1 - \phi - \xi/\gamma) \text{ for } L > 0 \qquad (4)$$

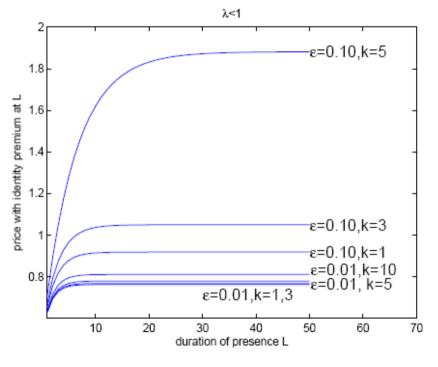
(iii) Let  $N_h$  be the number of transactions a fully cooperative (honest) provider can participate till it is mistakenly blacklisted, and let  $N_c$  be the number of bad transactions an intentionally malicious provider can benefit from defecting until eliminated from the system, respectively. We have  $E[N_h] > 1/\varepsilon^k$  and  $E[N_c] < 1/(1-\varepsilon)^k$ .

The results (i,ii,iii) hold even in presence of strategic manipulation of ratings by agents.

# Conference on Erwin Engeler's 90th birthday and Ernst Specker's centenary

**EPFL** 

# **Example**



Limit price above original price: Acceptable to buyers?

### Inefficiency?

Limit price below original price: Acceptable to sellers?

- original price u=1
- cheating gain 50% of original price
- Initial price 0.5 ( $\Phi = 0.5$ )

# Eliminating Inefficiency

- If the cheating gain is sufficiently small and the dishonesty detector is sufficiently accurate the price remains bounded and can approach any limit price by properly choosing Φ
  - Thus for a finite number of services this inefficiency can be eliminated
  - For infinite number it can be kept extremely small (order of provisioning a few services)
- Rationale to accept the scheme
  - Providers: without premium no trade at all
  - Consumers: no risk if providers are rational (provably)

# **Summary**

- Establishing trust is a fundamental challenge in information systems
- After 20 years of work related to trust, what can we say?
  - There is not a single model of trust or universal trust mechanism
    - Assumptions
    - Context
    - Availability of data
    - Identity
  - Establishing trust remains a never ending challenge

### EPFL

# **Acknowledgements**



Zoran Despotovic Principal Engineer Huawei



Philippe Cudre-Mauroux Associate Professor University Fribourg



Le-Hung Vu R&D Engineer NextThink



Alexandra Olteanu F Social Good Fellow IBM Watson Research Center



Panayiotis Smeros
PhD Student
EPFL

### **EPFL** References

- [Li et al 2004] Xiong, Li, and Ling Liu. "Peertrust: Supporting reputation-based trust for peer-to-peer electronic communities." IEEE transactions on Knowledge and Data Engineering 16.7 (2004): 843-857.
- [Despotovic et al 2004] Despotovic, Zoran, and Karl Aberer. "P2P reputation management: Probabilistic estimation vs. social networks." Computer Networks 50.4 (2006): 485-500.
- [Cudre-Mauroux et al, 2006] Cudre-Mauroux, Philippe, Karl Aberer, and Andras Feher. "Probabilistic message passing in peer data management systems." 22nd International Conference on Data Engineering (ICDE'06). IEEE, 2006.
- [Vu et al 2011] Vu, Le-Hung, and Karl Aberer. "Effective usage of computational trust models in rational environments." ACM Transactions on Autonomous and Adaptive Systems (TAAS) 6.4 (2011): 1-25.
- [Olteanu et al 2013] Olteanu, Alexandra, et al. "Web credibility: Features exploration and credibility prediction." European conference on information retrieval. Springer, Berlin, Heidelberg, 2013.
- [Vu et al 2014] Vu, Le-Hung, Jie Zhang, and Karl Aberer. "Using identity premium for honesty enforcement and whitewashing prevention." Computational Intelligence 30.4 (2014): 771-797.
- [Smeros et al 2019] Panayiotis Smeros, Carlos Castillo, Karl Aberer: Evaluating the Quality of Scientific News Reporting from Social and Content Indicators, In The International World Wide Web Conference 2019.