OPTET
DELFT PLENARY MEETING

AUEB
Network Economics
and Services Group.
Costas Kalogiros , Michalis Kanakakis

Trust Computational Model in Dynamic Context

Bayesian Inference based on Beta p.d.f.

- Static: Observation equally weighted on estimation process.
  - Beta (α,β) : Increase the α/β parameter if acceptable / unacceptable observation.

- Dynamic: More recent observations have a higher weight → the impact of observations in distant past asymptotically vanishes.
  - Beta (α,β) : Update both parameters after each observation. **s=1/0 if acceptable / unacceptable**

$$\alpha := u\alpha + s \qquad \beta := u\beta + (1 - s) \qquad u < 1$$

- **Trade-off**:

  Static: (+) provides a more accurate estimation in cases of unchanged trustworthiness.

  (-) needs a great number of observations to capture a possible change.

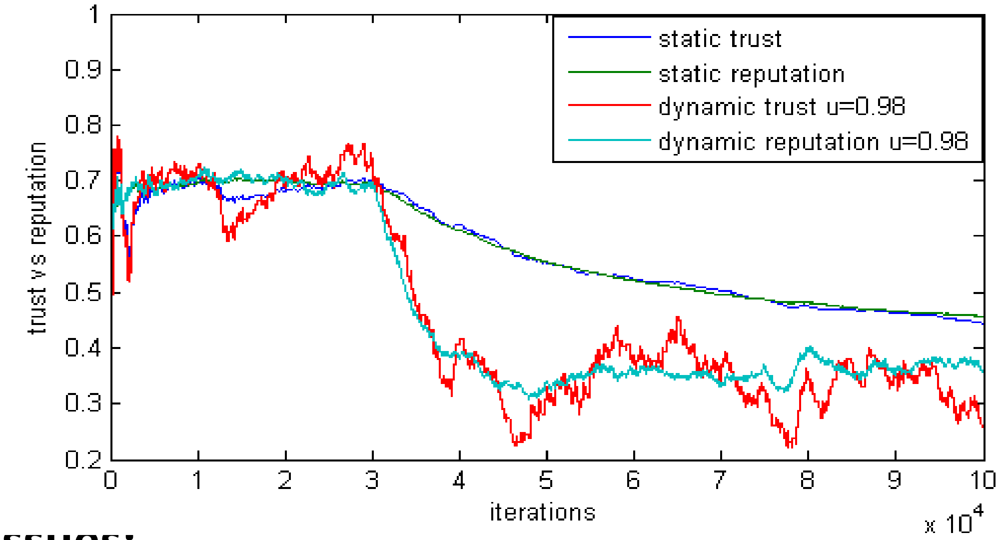
  Dynamic: (+) captures faster any possible changes in trustworthiness

  (-) suffers from oscillations around the estimated value.

- **Involving Marketplace :** Combine personal estimation and referrals from others.

First Simulation Results

- ❑ Trustworthiness changes form 0.7 → 0.35 at iteration 30K.
- ❑ Expected tradeoff appears between the two approaches.



- **Further issues:**
  1) Trustworthiness of the marketplace mechanism → reject inaccurate referrals.
  2) Define the cost effective approach w.r.t priors and the number of iterations.
  3) Define the optimal policy for the detection of a change in trustworthiness (window of last observations).

Comparing Centralized vs Ad-hoc Trust Computational Models(1/2)

- The actual trustworthiness of a control is "**μ**".

- Each agent has a **subjective estimation** for the trustworthiness of the control, based on **past "isolated"** observations :
  - Probability distribution function (Bayesian inference – Beta p.d.f.)
  - A point estimation (mean of Beta p.d.f.)
  - The average value of point estimations is "μ".

- The agents are connected in a society. Each agent places weighted trust on neighbors, denoted by a row stochastic matrix (**normalization**).

- Studying how energy providers adopt controls for dealing with threats by "*learning from their neighbors*".

- **Adding Marketplace →** most accurate estimation for "**μ**" (certificates).

Comparing Centralized vs Ad-hoc Trust Computational Models (2/2)

<u>Research Issues</u>

- At ach iteration:
  - Each agent revises the personal estimation.
  - The update equals a linear combination of personal and neighbors' estimations.

- Research Issues: **Consensus** & **Cost**
  1) Conditions in graph for converging to the same value (could be the wrong one…).
  2) Conditions in graph for converging to the same, **true** value: "**μ**".
  3) How to insert the **marketplace** in the graph, s.t. the new consensus is closer to "**μ**"?
     - Redefine the trust matrix.
  4) How should the **marketplace** influence the beliefs of agents, consensus → "**μ**"?
     - Consider a cost per unit of influence.

Marketplace: The need for imposing minimum contribution schemes (1/2)

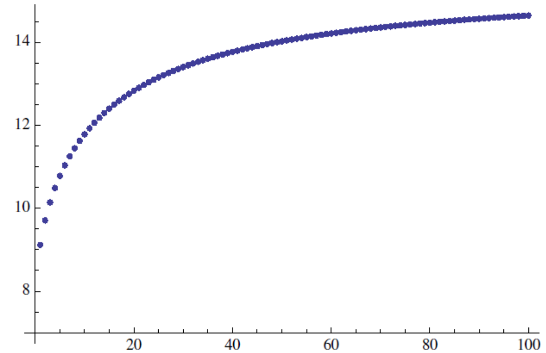
- Incentive problem
  - Free riding: service providers don’t have the incentive to upload certificates to the Marketplace
- Consequences

- Proposed solution: impose a fixed minimum contribution to each provider → set of certificates is a *public good*
  - Incentive-compatible
  - Maximizes the social welfare
  - Simple to be enforced

Marketplace: The need for imposing minimum contribution schemes (2/2)

- 2 substitute components are available:
  - Comp1 with known TW, e.g., mean μ′
  - Comp2 with a prior estimate of TW, e.g., $\mu \sim N[\mu_0, \sigma_0^2]$

- The benefit of providers from having n extra evidences of Comp2 is
  - concave if μ>μ'
  - convex if μ<μ'



(a) For $\sigma = 100$

- Approach:
  - Each provider truthfully announces its utility (as a function of the public good size)
  - Mechanism computes personalised minimum contribution levels

Optimal contracts as economic controls (1/2)

A portion of elderly people is expected to have low trust in PERS → more calls for support → inappropriate service usage (e.g., the HU5.2: FalseServiceUsage threat) → increased cost for AAL provider & poor performance for rest users

The theory of optimal contracts can help an AAL provider in designing contracts for each user category, so that:

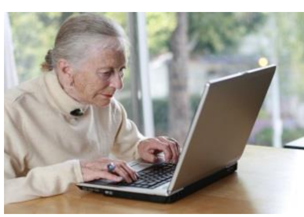
- AAL provider maximizes its profits (second best), while
- each buyer has the incentive to choose the contract for its category

Users can be of 2 types based on their trust in PERS. Users' i utility is: $\theta_i v(q) - T$

- θ_i: preferences of user type i (e.g., anxiety)
- v(q): value from placing q calls to the operator
- T: payment asked by operator

High trust in PERS

θ_H



$\theta_H < \theta_L$

Low trust in PERS

θ_L

q_H

q_L

Marginal cost of serving a call: C>0

Alarm call center operator has a belief that a person asking for service will be of:

- Low trust type: P_L
- High Trust type : $P_H=1-P_L$

Optimal contracts as economic controls (2/2)

- Benchmark case: If operator knows the type of the user asking for service it can make a “take or leave it” offer (first-best) that would make the user indifferent (net benefit=0)

- In case of information asymmetry the operator maximizes its expected profit by:
  – offering a set of contracts (T_H, q_H), (T_L, q_L)
  – and allowing users to select the most appropriate
  – Low-Trust user benefits from information asymmetry and achieves net benefit >0, while net benefit of High-Trust user=0

- Future work:
  – extend the model by including more than one service to the alarm call centre operator and
  – define contracts that incentivize service recipients to use the service more wisely (moral hazard model).