

Exponential Decay in Probabilistic Trust Models

Mogens Nielsen's 60th Fest

Aarhus, 4/10/09



To your sharpness of mind and kindness of heart

Vladimiro Sassone

I dag er det Mogens' fødselsdag

I dag er det Mogens' fødselsdag



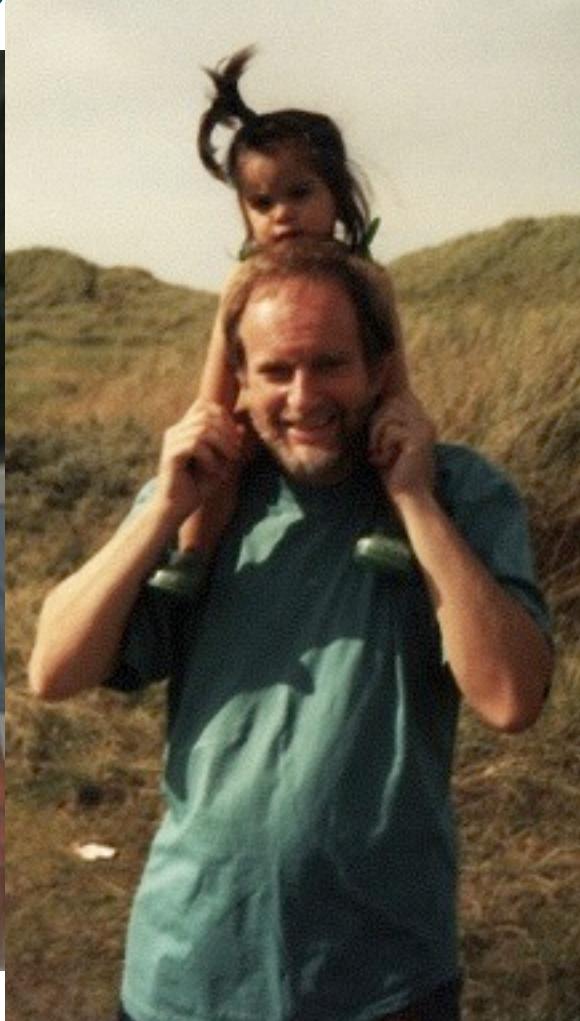
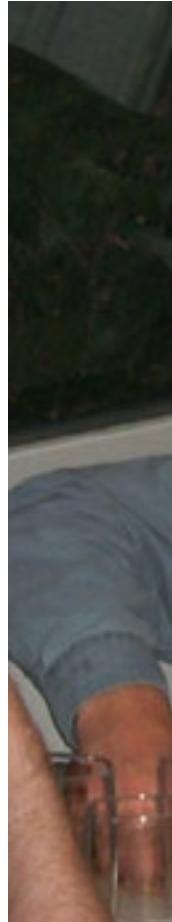
I dag er det Mogens' fødselsdag



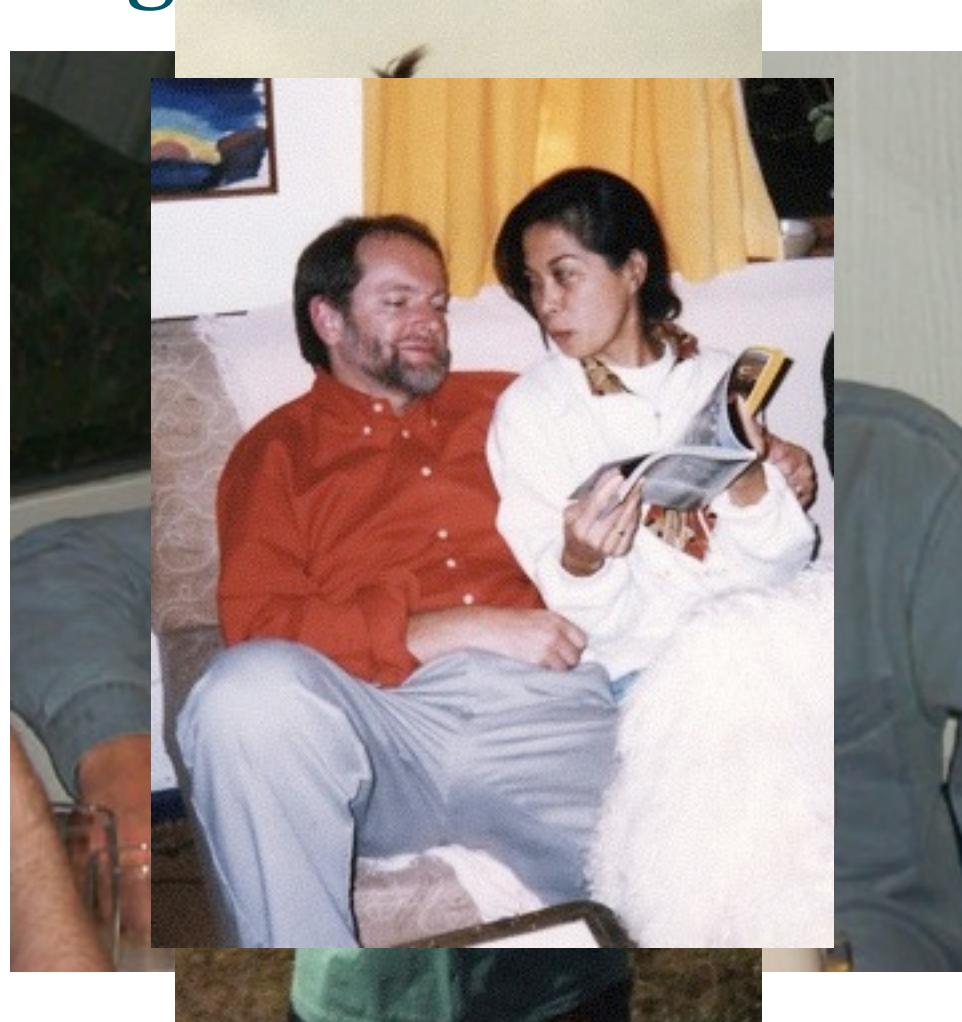
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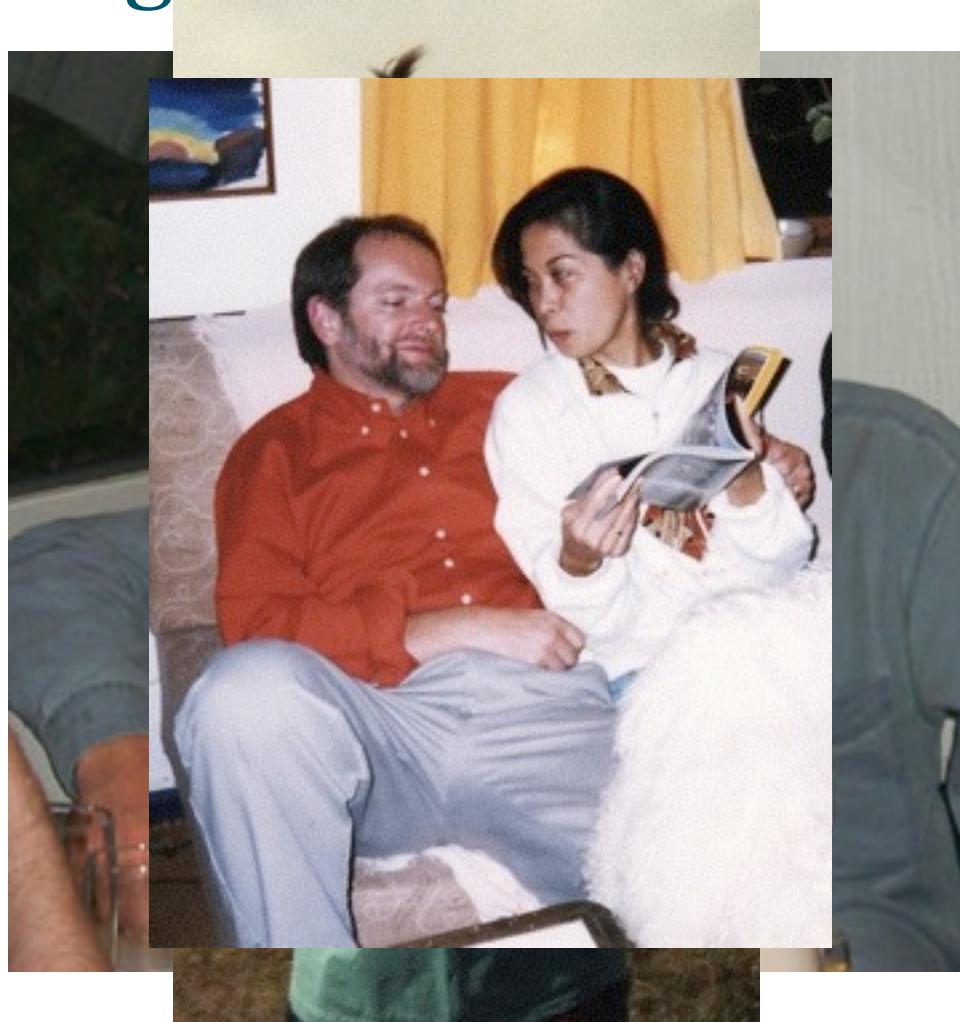
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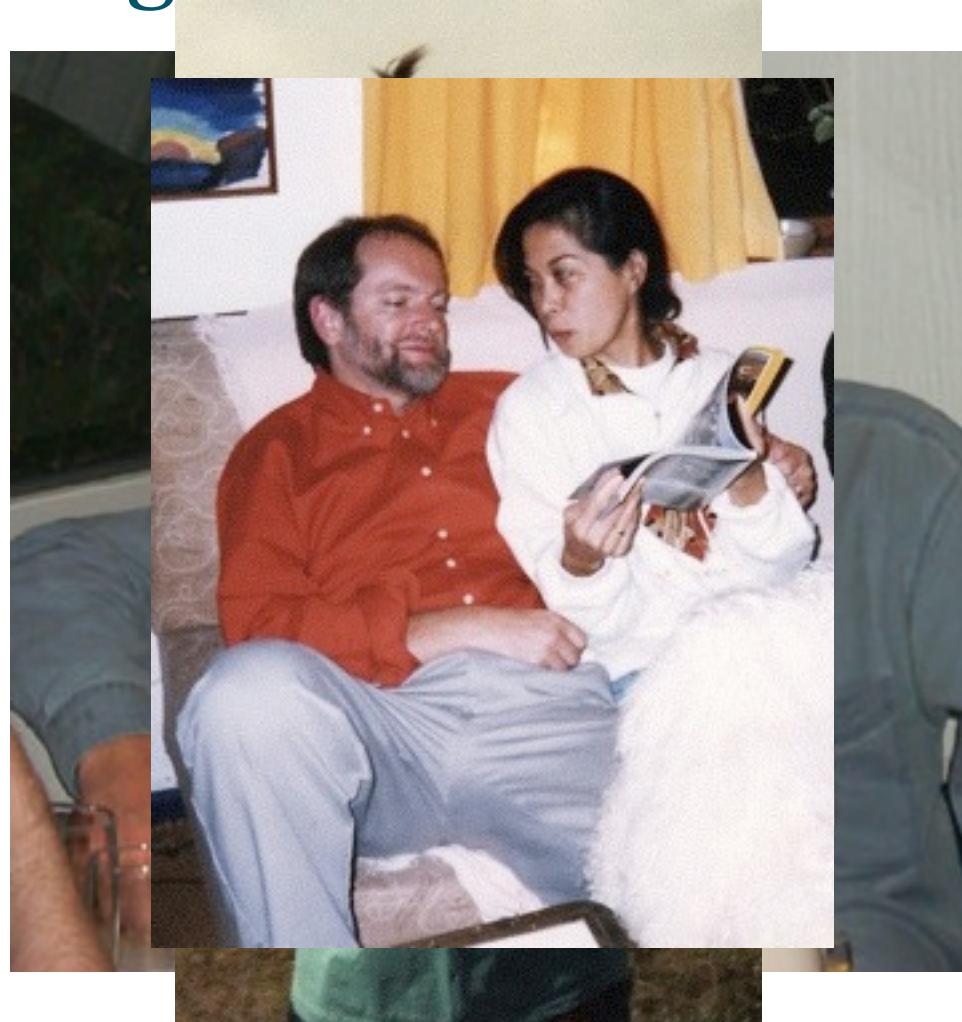
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I dag er det Mogens' fødselsdag



Trust in UbiCom

- Features of Ubiquitous Computing like *scalability*, *mobility*, and *incomplete information* deeply affect security requirements.
- One of the proposed approaches is to use a notion of *computational trust*, resembling the concept of trust among human beings.

- *Probabilistic models* are used to evaluate trust.
- A probabilistic model assigns a degree of confidence to a principal's ability to predict another principal's behaviour.
- Eg, the behaviour of a principal A may be defined as the probability that interaction with A yields a certain outcome (eg, success or failure).

Beta Trust Model

- The outcome of an interaction between a principal a and a partner b is either *successful* or *unsuccessful*:

$$o \in \{Succ, Fail\}$$

- The probability that a partner b interacts successfully with a is governed by the parameter θ where

$$\theta = \Pr(o = Succ)$$

Beta Trust Model

- The behaviour of the partner b represented by θ is assumed to be fixed over time.
- The estimated probability of success, $B(\text{Succ} | o)$, at time t is the expected value of θ given the sequence of outcomes $o = \{o_0, o_1, \dots, o_t\}$

$$B(\text{Succ} | o) = E[\theta | o]$$

Beta Trust Model

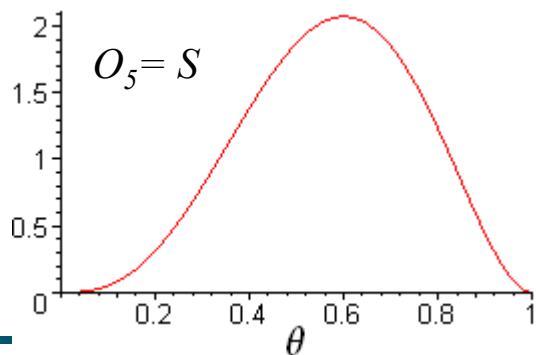
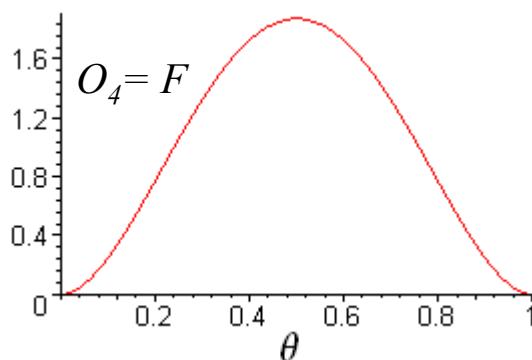
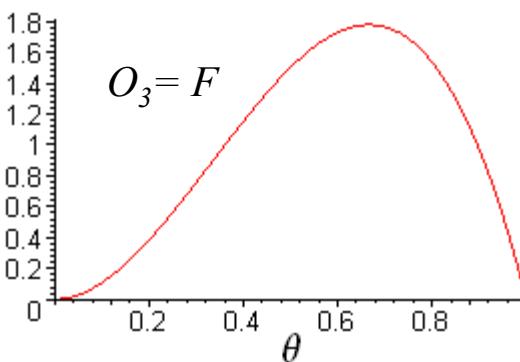
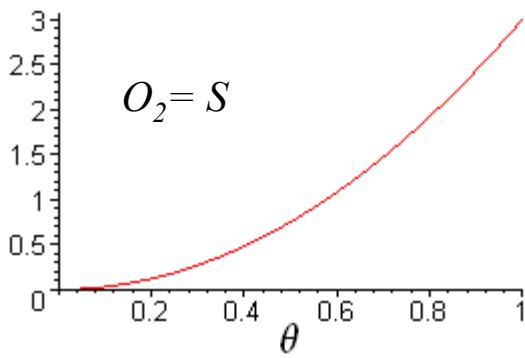
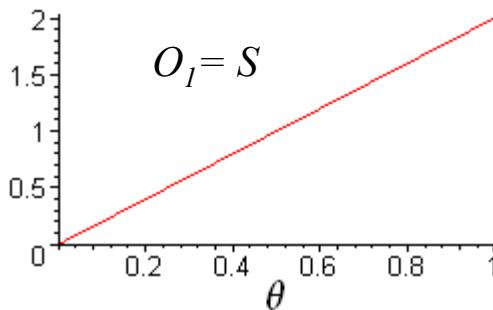
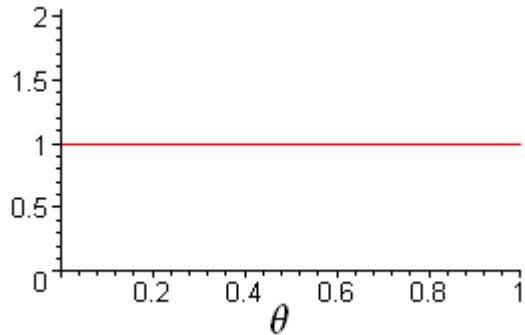
Using Bayesian inference to learn the parameter θ from observations o .

The random variable θ follows Beta distribution function, and therefore

$$B(\text{Succ} \mid o) = E[\theta \mid o] = \frac{m(o) + 1}{m(o) + n(o) + 2}$$

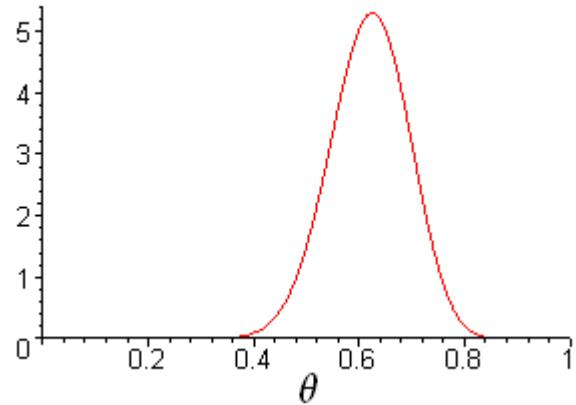
where $m(o)$ is the number of successful interactions in o and $n(o)$ that of unsuccessful ones in o .

Trust Inference Process



Trust Inference Process

The distribution of θ after 40 interactions
25 Successful and 15 Failed



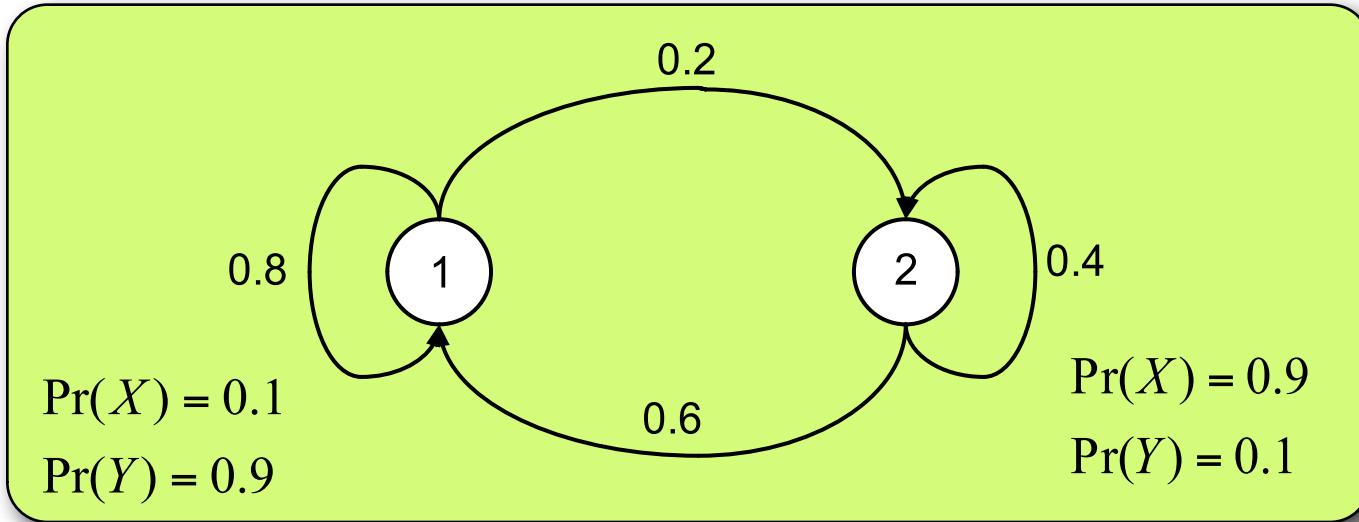
Limitation of the Beta model

- The assumption that a principal behaviour is fixed is not always realistic:
- The behaviour of a principal may depend on its internal state which may change over time.

Modelling Dynamic Behaviour

- Modelling static behaviour as a probability distribution over outcomes leads to modelling the dynamic behaviour by a *Hidden Markov Model (HMM)*.
- A single state in an HMM models the system behaviour at a particular time.

Hidden Markov Model:



$$S = \{1, 2\}$$

$$V = \{X, Y\}$$

$$A = \begin{bmatrix} 0.8 & 0.2 \\ 0.6 & 0.4 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix}$$

Beta Trust Model with Decay

- The probability distribution over outcomes changes over time.
- Old observations are given less weight (decayed) than more recent observations.
- Weights of observations are controlled by the decay factor r .

Beta Trust Model with Decay

Given a decay factor $0 \leq r < 1$ and an observation sequence $o = \{o_L, \dots, o_1, o_0\}$, where o_0 is the last outcome, o_1 is the previous outcome, and so on, then

$$B_r(\text{Succ}|O) = \frac{m_r(O) + 1}{m_r(O) + n_r(O) + 2} \quad , \quad B_r(\text{Fail}|O) = \frac{n_r(O) + 1}{m_r(O) + n_r(O) + 2}$$

Where

$$m_r(O) = \sum_{i=0}^L r^i \delta_i(\text{Succ}) \quad , \quad n_r(O) = \sum_{i=0}^L r^i \delta_i(\text{Fail})$$

And

$$\delta_i(\text{Succ}) = \begin{cases} 1 & \text{if } o_i = \text{Succ} \\ 0 & \text{otherwise} \end{cases} \quad , \quad \delta_i(\text{Fail}) = \begin{cases} 1 & \text{if } o_i = \text{Fail} \\ 0 & \text{otherwise} \end{cases}$$

How good is the model ?

- Given a dynamic system modelled by an HMM λ we define Beta estimation error as follows

$$\text{Error}(\lambda, r) = E \left[(B(\text{Succ} | o) - \alpha)^2 \right]$$

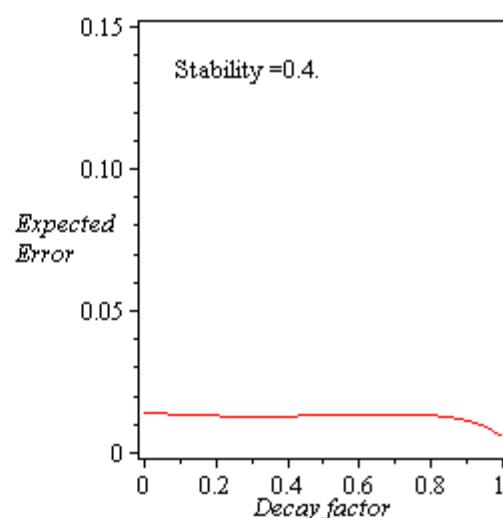
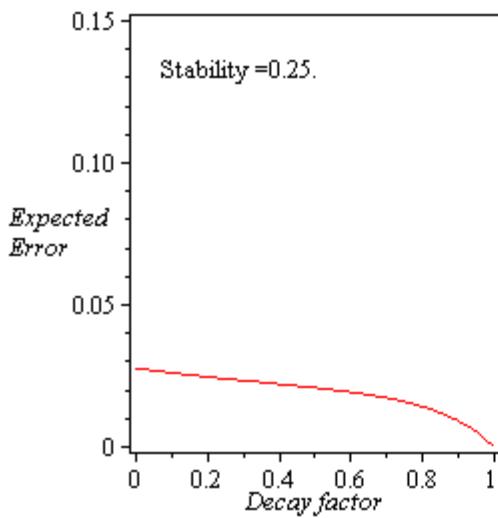
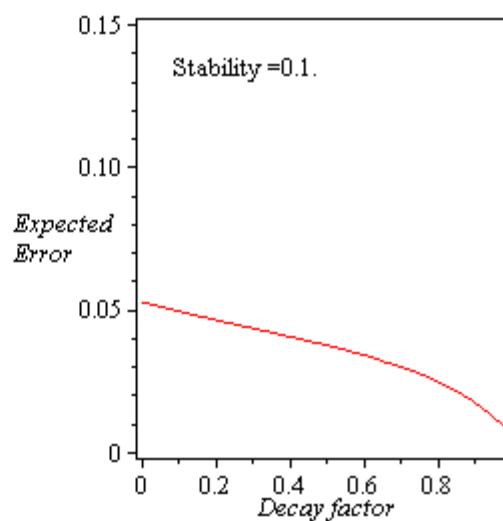
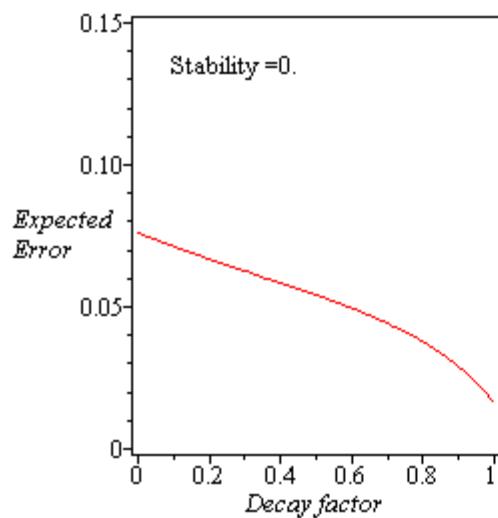
where r is the decay factor, and α is the real probability that next outcome is Success

System Stability

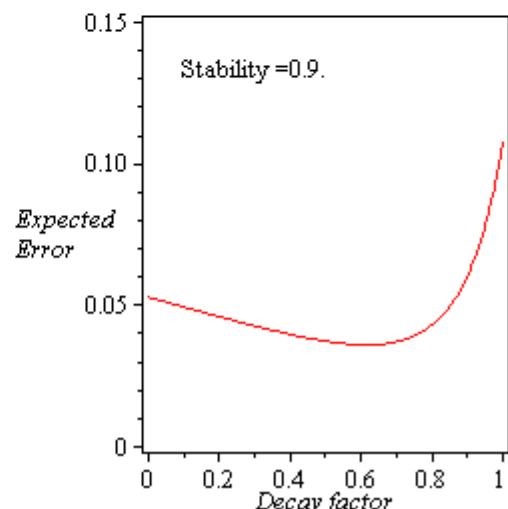
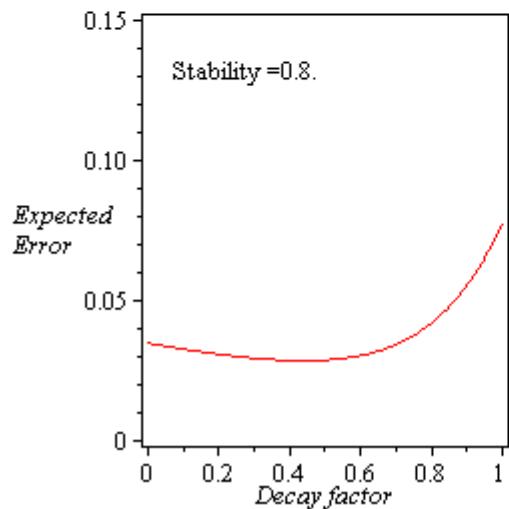
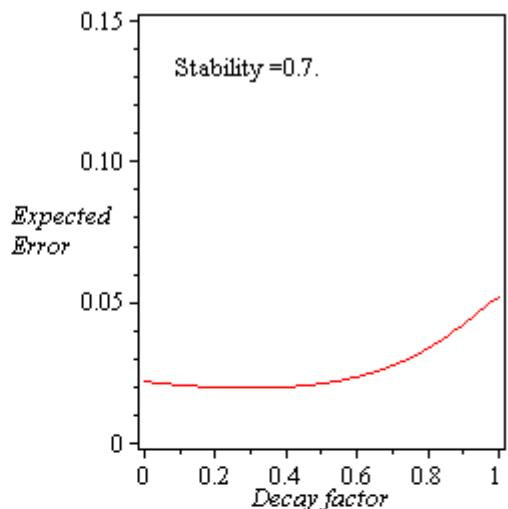
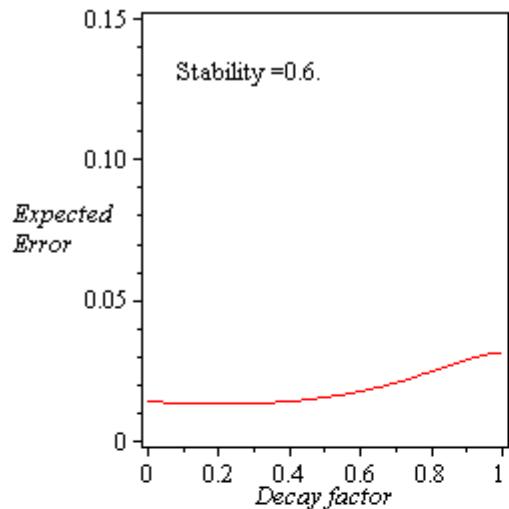
- *System stability* is the expected probability of the HMM remaining in the same state.
- Consider the system modelled by HMM:

$$A_\lambda = \begin{bmatrix} s & \frac{1-s}{3} & \frac{1-s}{3} & \frac{1-s}{3} \\ \frac{1-s}{3} & s & \frac{1-s}{3} & \frac{1-s}{3} \\ \frac{1-s}{3} & \frac{1-s}{3} & s & \frac{1-s}{3} \\ \frac{1-s}{3} & \frac{1-s}{3} & \frac{1-s}{3} & s \end{bmatrix} \quad \Theta_\lambda = \begin{bmatrix} 1.0 \\ 0.7 \\ 0.3 \\ 0.0 \end{bmatrix}$$

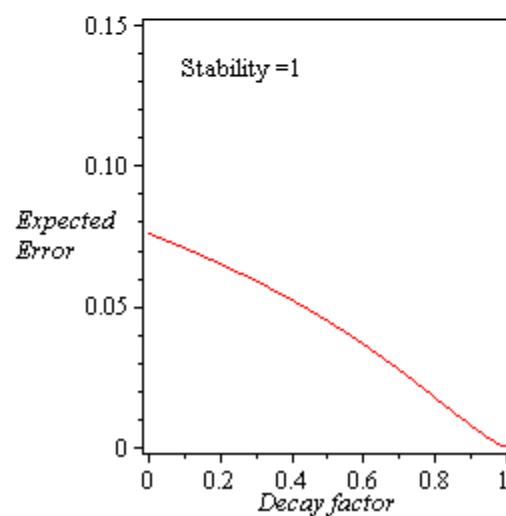
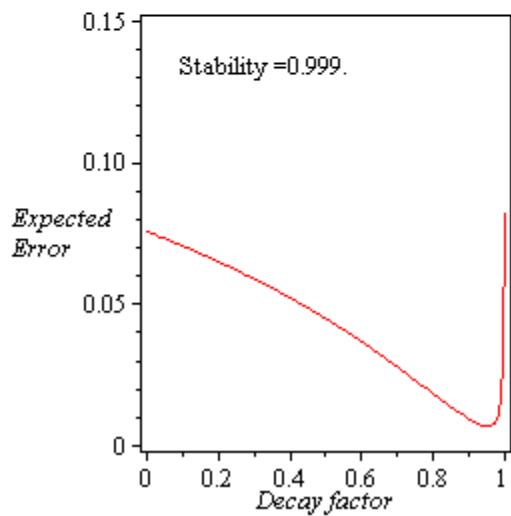
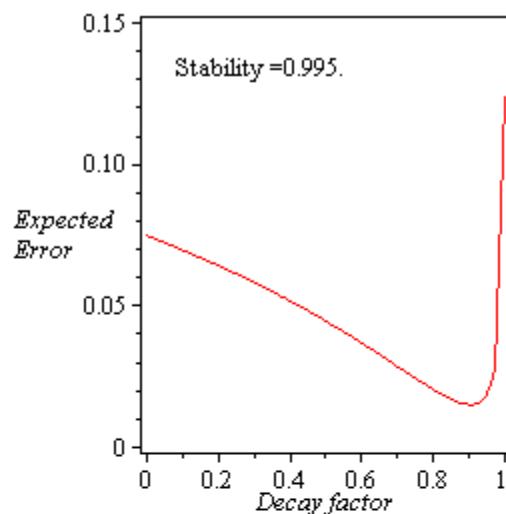
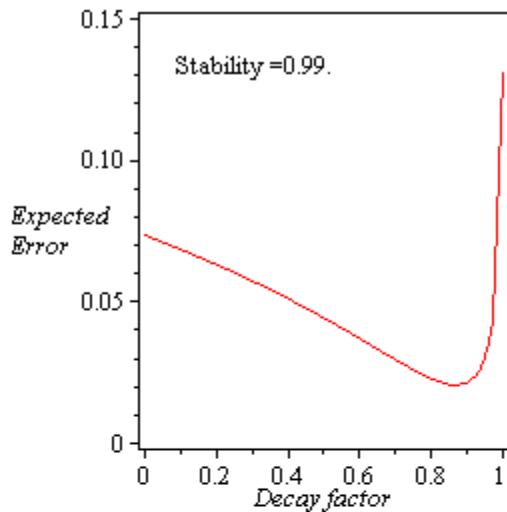
Unstable System



Stable System



Very Stable System



Conclusion

- Traditional Beta trust models are unable of coping with dynamic behaviour systems.
- Using a decay scheme enhances Beta estimation in cases where the system is very stable.
- Beta estimation error is subject to choosing the optimal value of decay which depends on the system parameters.

Current and Future Work

- Investigate using HMM as a trust model instead of using existing Beta models [FAST 2009 with MN]
- Handling Reputation problems
 - Modelling reputation reports
 - Combining reputation reports to update trust
 - Evaluating confidence in the evaluated trust