

Intelligent Information Dissemination in Collaborative, Context-Aware Environments Korbinian Frank, Matthias Röckl, and <u>Tom Pfeifer</u> 21/03/11, MUCS 11, Seattle, USA



- The Need for Intelligent Information Dissemination
- ✓ Plugging Different Inference Modules with Bayeslets
- - Determination of the Net Expected Utility
 - ➤ A Probability Based Utility Function
 - ➤ A Decision Based Utility Function
- ✓ Application for Cooperative Adaptive Cruise Control
 - Position Dissemination Frequency (Probability Based Utility)
 - ➤ Acceleration or Deceleration (Decision Based Utility)

Conclusion



- ➤ The Need for Intelligent Information Dissemination
- ✓ Plugging Different Inference Modules with Bayeslets
- ✓ Utility Determination
- ➤ Application for Cooperative Adaptive Cruise Control
- ➤ Conclusion



The Need for Intelligent Information Dissemination Motivation

- ✓ Assistance systems have to recognise the current situation. E.g.:
 - ✓ Stress situations at work
- Only when situations are known, countermeasures can be taken







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The Need for Intelligent Information Dissemination Motivation

- ✓ Such situations have to be inferred as they cannot be sensed directly
- In ubiquitous systems, all information could in theory be shared from millions and billions of sensors
 - ✓ every new car has hundreds of sensors, more than 50 CPUs
 - ✓ Innumerable stress factors, often caused by others and their situation
- ✓ Information however always connected to cost for:

 - ✓ Processing
- ✓ Resources in ubiquitous systems however are limited
 - Network Bandwidth
 - ✓ Computing power and memory in mobile smart devices



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Plugging Different Inference Modules with Bayeslets Application Background

- ✓ Bayesian Networks are a powerful means for context and situation inference
- To cope with frequently changing availability of information sources, the concept of "Bayeslets" makes them pluggable



- Every plugged information source causes costs (inference time, network bandwidth)
- → Need for an intelligent way to decide if an available information source is needed



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Utility Determination

Determination of the Net Expected Utility

- ✓ Decision for connection based on the *utility* of the additional information
- ✓ Utility *U* of an additional piece of evidence *y*: U(X : y) = U(X | y) - U(X)
- ✓ X is subject to uncertainty → calculation of the *Expected Utility* (*EU*) gain by summing over all states weighted by their probability of occurrence $EU(X : y) = EU(X | y) EU(X) = \sum U(x | y)P(x | y) \sum U(x)P(x)$
- Considering that Y is unknown before transmission and existing knowledge c: $EU(X : Y) = EU(X | Y) - EU(X) = \sum_{x \in X} \sum_{y \in Y} U(x | y)P(x | y)P(y) - \sum_{x \in X} U(x)P(x)$ (1)

$$EU(X:Y|c) = \sum_{x \in X} \sum_{y \in Y} U(x|y,c) P(x|y,c) P(y,c) - \sum_{x \in X} U(x|c) P(x|c)$$
(2)

- ✓ Considering the costs of new information with the Net Expected Utility (NetEU): NetEU(X:Y | c) = EU(X:Y | c) C(Y)(3)
- \rightarrow Decision on usage of information Y, where threshold t is a constant:



Utility Determination A Probability Based Utility Function

- Utility of a random variable increases with certainty about it
- ✓ Increase can be modelled with any monotonous increasing function
- → Shannon used the binary logarithm for the *Mutual Information* I(X:Y)

$$U(x \mid y) = \log_2 P(x \mid y) \Longrightarrow EU(X : Y) = I(X : Y)$$

✓ Calculation based on the (conditional) Entropy H(X), H(X/Y), where $E_X(f)$ is the expectation function of function f over X

$$I(X:Y) = \sum_{x \in X} \sum_{y \in Y} \log_2 P(x \mid y) P(x \mid y) P(y) - \sum_{x \in X} \log_2 P(x) P(x) =$$

= $E_{X,Y} (\log_2 P(X \mid Y)) - E_X (\log_2 P(X)) = -H(X \mid Y) + H(X)$



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Utility Determination A Decision Based Utility Function

- ✓ Uncertainty reduction is not an end in itself, aim is the optimum outcome!
- → Definition:

An action *a* is a function attaching a consequence to each state of the world.

- → An instance of the expected utility is the Maximum Expected Utility (MEU) MEU(X | Y) = max_{a∈A} EU(X | Y, a) = max_{a∈A} $\sum_{x∈Y} U(x)P(x | a, Y)$
- ✓ If used in equ. (1), EU(X : Y) is equivalent to the Value of Information (VoI): EU(X : Y) = MEU(X | Y) - MEU(X) = VoI(X, Y)
- ✓ An extension of Bayesian Networks models Utility functions and Decisions:





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Application for Cooperative Adaptive Cruise Control Position Dissemination Frequency (Probability Based Utility)

Experiment 1:

- → a car drives along a road
- 3 sensors (GNSS, odometer, compass) 3 Bayeslets
- **\checkmark** Sensors are erroneous, update rate 10 Hz
- ✓ Case 1: "zig-zag" road:
 - → I = EU increases after bends
- → Case 2: straight road
 - **\checkmark** GNSS updates with only 0.4 Hz
 - → I = EU increases when new measurements are available





Case 1



Application for Cooperative Adaptive Cruise Control Acceleration or Deceleration (Decision Based Utility)

Experiment 2:

- → radar sensor: is preceding car on same lane?
- ✓ Same info available from V2V communication
- Dependencies are modelled in a Decision Network (right)
- Given no information, Radar is more valuable
- → Given Radar = center
 → V2V still adds value

Attention:

- → depending on actual value: Radar=left → VoI(V2V) = 0
- Transmission costs are still neglected here!

left center righ YVI MILD) left center righ Radar Lateral V2V Lateral 0.6 0.05 0.15 left 0.8 0.1 0 0.25 0.9 Measuremen Measurement 0.25 center 0.2 0.8 0.15 0.05 0 riaht 0.1 Contro coelevare 11.1 coelerate 0.3 Rada V2V 18% Evidence Evidence enter64% iaht richt C Radar Lateral Measur o 1/29 Lateral Measur • VZV Lateral Measure V2V Lateral Measure Zadar are Radar Lateral Measur left 27% 20% 0% left 21% eft 100% center 100% center 100% center47% center40% eanter 59% center 0% right 27% Information of Information /alue of Informatio 0.11 0.10 ъ 0.07 Value Value 0 0 n V2V V2V Radar V2V Radar Radar

Longitudinal

Control

accelerate

terelerat

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0.75*Safety+0.25*Efficiency

Utility

left

0.33

0.33

0.33

acc dec acc dec acc dec

Utility

Lateral

Distance

Efficiency

P(LD)

center

right

left

Safety

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Conclusion

- Sound theory on intelligent, content based information dissemination
- ✓ Both approaches are applicable to real world problems
- Saving bandwidth and inference time
- ✓ Preference for one or the other method depends on
 - Available information about utility and costs to be modelled: more complex, but also flexible in decision based approach
 - ✓ Problem statement: decision between different options Y_1 and Y_2 in probability based approach only possible after normalisation
- Next step: testing of both approaches in practical experience

