Corporate Technology

SIEMENS
TUHH
Technische Universität Hamburg-Harburg

Abductive Reasoning for Imperfect Information

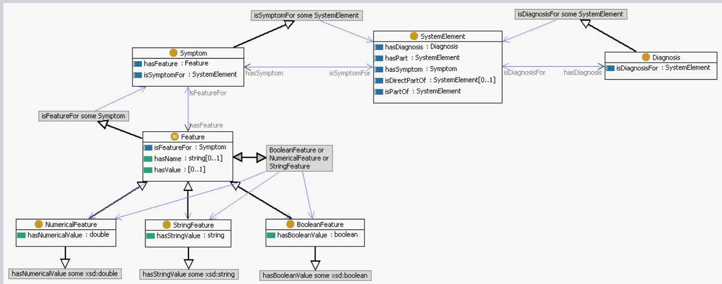
Thomas Hubauer

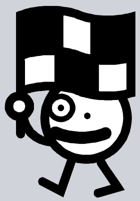
Siemens AG, CT IC 6 (Intelligent Autonomous Systems)
Hamburg University of Technology, STS (Software, Technology, and Systems)

Talk Outline

Principles
- Qualities of Information Imperfection
- Abductive Reasoning and Imperfect Information

Application to Situation Recognition
- Requirements
- Proposed Solution
  - An Ontology Pattern for Abduction-Based Situation Recognition
  - Efficient Abductive Model Evaluation





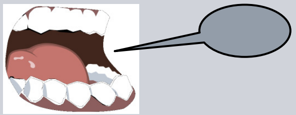
Conclusion

Qualities of Information Imperfection (1/2)

(Dubois, 2006) distinguishes 4 different types of information imperfection:

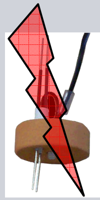
Uncertainty / Degree of Confidence

tossing a coin

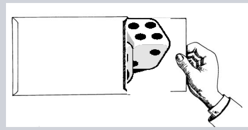


truth or lie?

Incompleteness

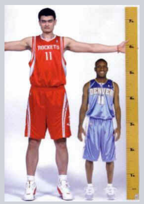


sensor malfunction



Known: score(d) = *odd*
Query: score(d) = *prime*?

Gradual Definitions



Tall(*john*) ?

Granularity

score(d) = *5*

/

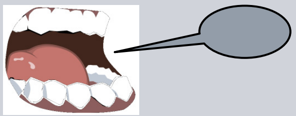
score(d) = *odd*

Qualities of Information Imperfection (2/2)

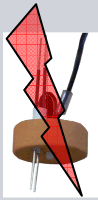
We focus on uncertainty and incompleteness
(ignoring granularity and approximating fuzziness if needed)

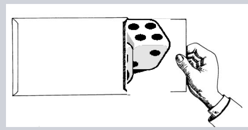
Uncertainty / Degree of Confidence


tossing a coin


truth or lie?

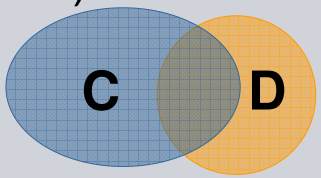
Incompleteness


sensor malfunction


Known: score(d) = *odd*
Query: score(d) = *prime*?

There are two levels of information, each subject to uncertainty:

- Factual knowledge (about instances, Abox):
  → sensor accuracy, credibility
- Terminological knowledge (about the schema, Tbox):
  → partial subsumptions between concepts



$C \sqsubseteq D$: 0.3
$D \sqsubseteq C$: 0.5

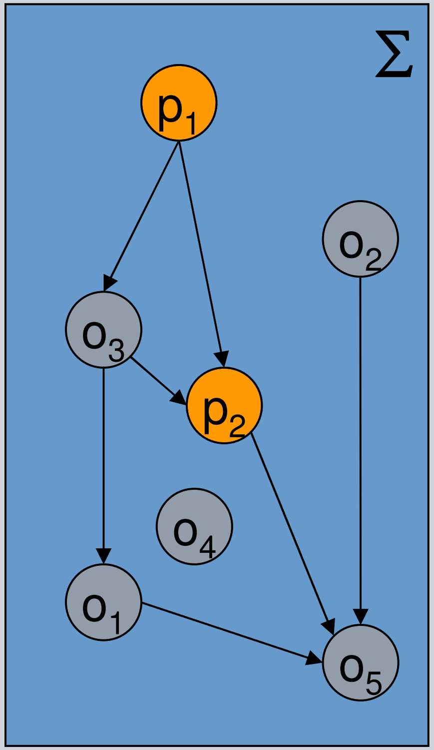
Abductive Reasoning (1/2)
Definition

Given
- a *theory* Σ of the domain of discourse
- and a set *O* of *observations* o_i (data),

find
- a set of *explanations E* (hypotheses) valid in Σ that explain the observations (i.e. $\Sigma + H \models O$).

Explanations may
- postulate missing
- and ignore observed facts.

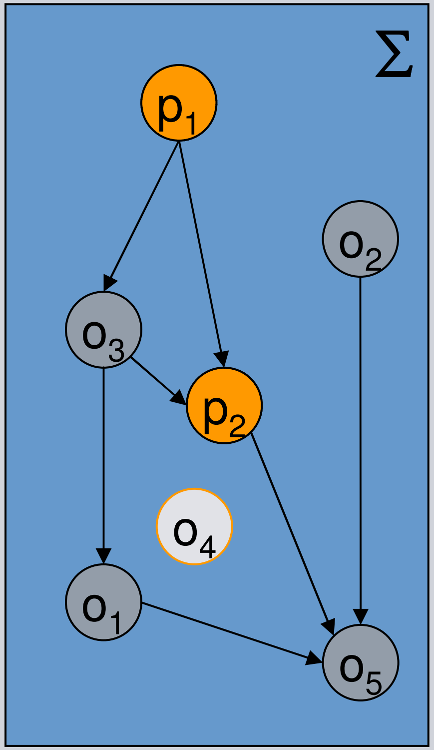
This gives abduction the flexibility to handle incomplete information.



Abductive Reasoning (2/2)
Properties

(Elsenbroich, 2006) lists some desirable properties for hypotheses:

- Consistency: $\Sigma + H \nvDash \perp$
- Relevance: $H \nvDash O$
- Explanatoriness: $\Sigma \nvDash O$; $H \nvDash O$
- Minimality: *various criteria*



Typically there is not one single hypothesis

- A preference measure can be defined to determine the best / most plausible explanation
- Using a probabilistic measure naturally integrates handling of uncertain information (c.f. partial concept subsumption)

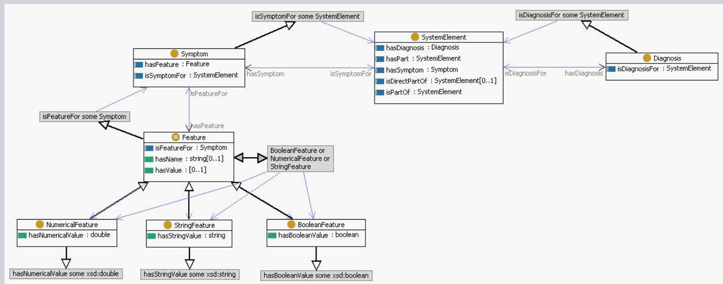
Talk Outline

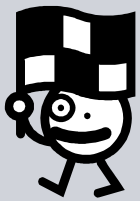
Principles

- Qualities of Information Imperfection
- Abductive Reasoning and Imperfect Information

Application to Situation Recognition

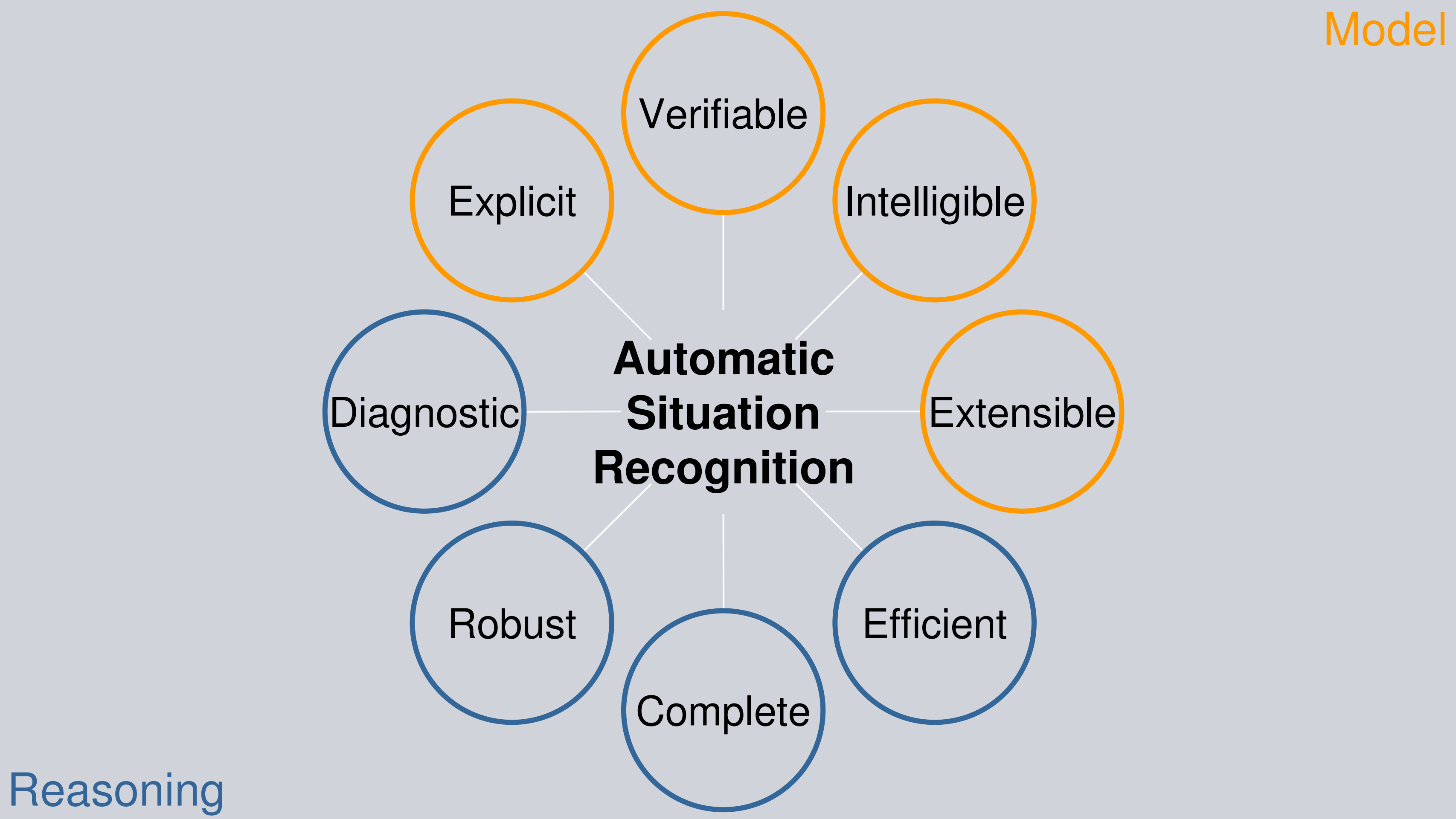
- Requirements
- Proposed Solution
  - An Ontology Pattern for Abduction-Based Situation Recognition
  - Efficient Abductive Model Evaluation



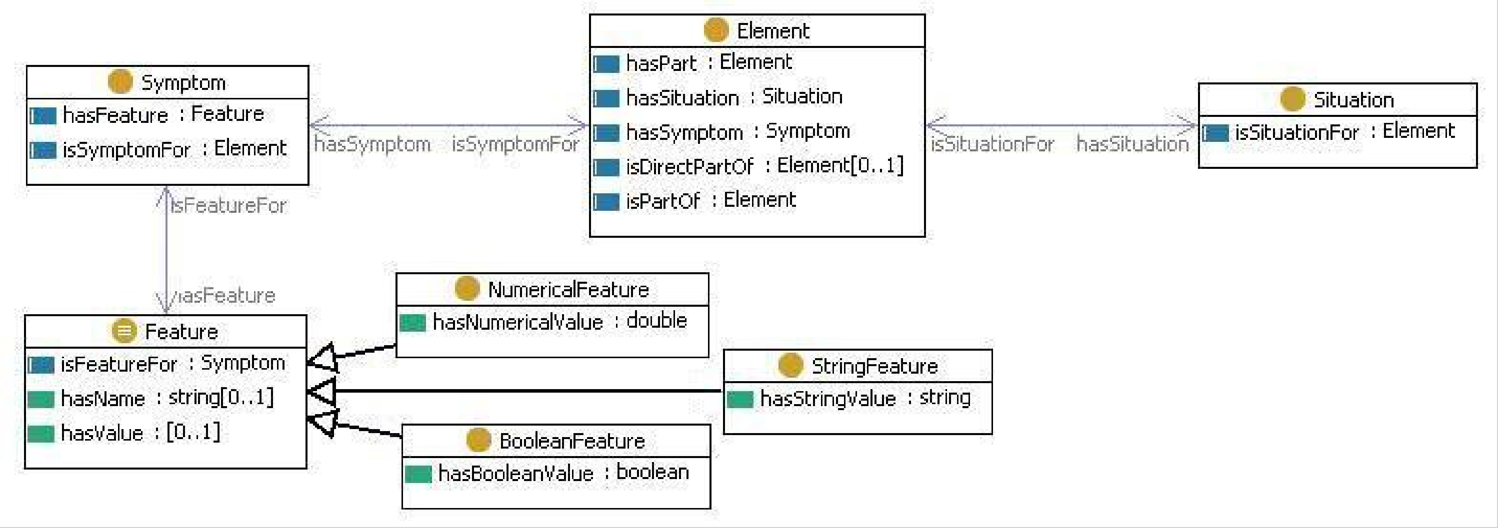


Conclusion

Requirements



Ontology-Pattern for Situation Recognition (1/2)
General Structure

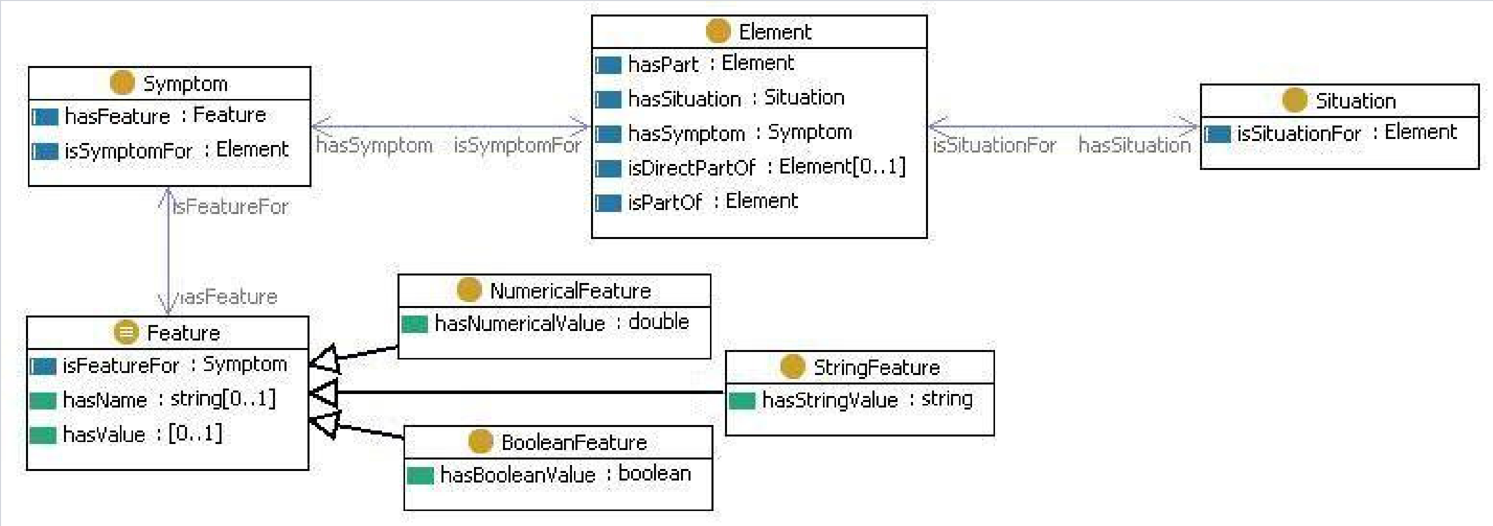


Elements

- `Feature`s can be observed directly using sensors (primitive data types)
- `Symptom`s are domain-specific interpretations of a single `Feature`
- `Element`s are the entities in a scene whose properties can be observed
- A `Situation` is the interpretation of the features of the scene elements (using an auxiliary root `Element` if necessary)

Additional integrity constraints (not shown) ensure model correctness.

Ontology-Pattern for Situation Recognition (2/2)
Pattern Application by Subclassing



- A concrete `Situation` is defined by the `Symptom`s of its relevant `Element`s:

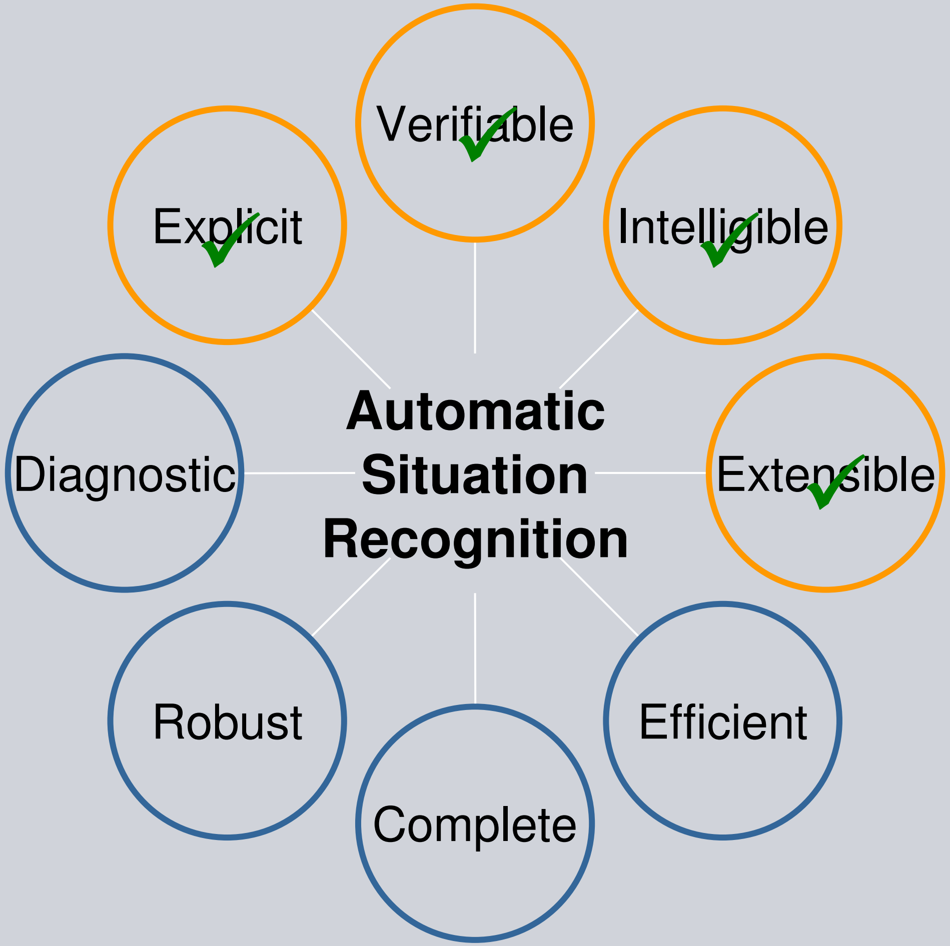
```
owl:equivalentClass
syd:isDiagnosisFor some (
(syd:hasPart some (SD611_Einspeisungsmodul and (syd:hasSymptom some Symptom_Allgemeiner-Zustand_Defekt)))
and (syd:hasPart some (SD611_Regelungsbaugruppe and (syd:hasSymptom some Symptom_Trafo_Defekt)))
and (syd:hasPart some (SD611_Netzdrossel and (syd:hasSymptom some Symptom_Temperature_Increased)))
and (syd:hasPart some (Motor1FT and (syd:hasSymptom some Symptom_Erdschluss)))
)
```

- The notion of `Symptom`s makes `Situation`s independent from non-logical features (such as concrete domains):

```
owl:equivalentClass
syd:hasFeature some (Temperatur and (syd:hasNumericalValue all xsd:double[>50]))
```


Requirements Revisited

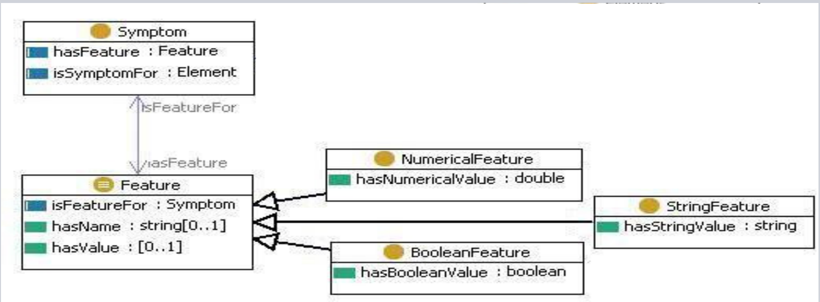
Logic-based pattern



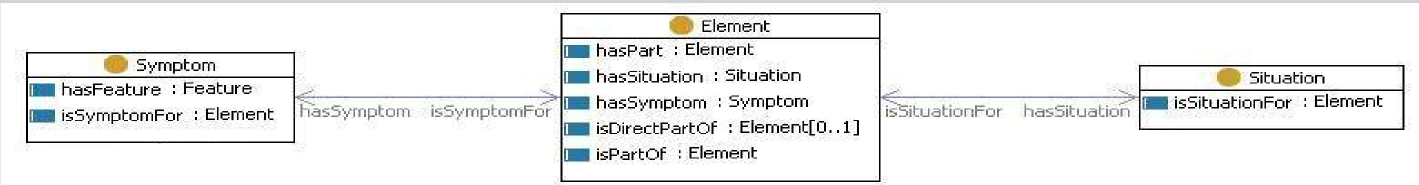
Evaluating the Model (1/4)
Situation Determination

We use abductive reasoning to derive high-level interpretations (`Situation`s) that explain the low-level observations (`Feature`s):

- Following the ideas presented in (Möller, 2008), we realize abduction as backward-chaining rule-based reasoning, where the rules can be generated automatically from the Ontology (and DL-safe rules)
- For technical reasons (tool-support), we chose a 2-step process:
  - First, we use datatype reasoning to derive `Symptom`s from `Feature`s



  - The second, abductive step may then ignore datatype reasoning



Evaluating the Model (2/4)
Ideas on Preference Measures

SIEMENS
TUHH
Technische Universität Hamburg-Harburg

Principle of Consilience

"A good explanation provides reason for the observations"

Measures based on reasoning-steps

- Partial subsumptions
- Penalties for inventing instances, ignoring observations, …
- The taxonomy provides information on the "closeness" of concepts which can be used to determine penalties

Measures based on the explanation

- Description Length

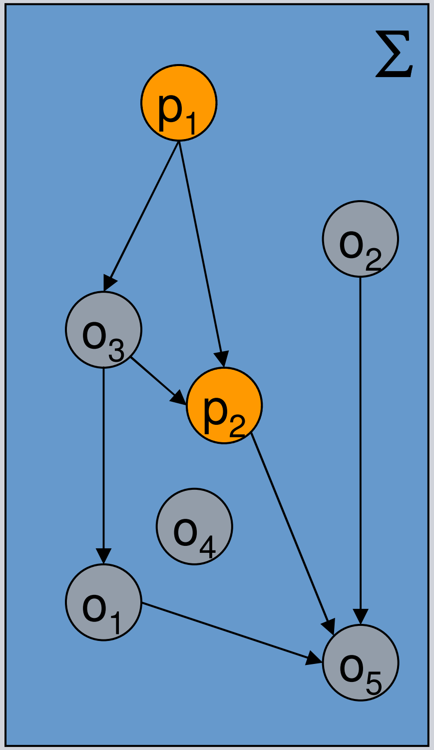
Evaluating the Model (3/4)
Explanations for Information Gathering

Hypotheses contain information on missing data:
H_1 = { A(x), R(x,y) , B(x), C(y) }
H_2 = { A(x), R(x,y) , D(x), E(y) }

This can be exploited to determine sets of distinguishing features:
→ $D_{1;2}$ = { B(x) ↔ D(x); C(y) ↔ E(y) }

Hypothesis plausibility along with information gathering cost allows to determine utility of tests

Allows for feedback to user or sensor layer



Evaluating the Model (4/4)
Ideas for Speeding up Inference

SIEMENS
TUHH
Technische Universität Hamburg-Harburg

Determining factors

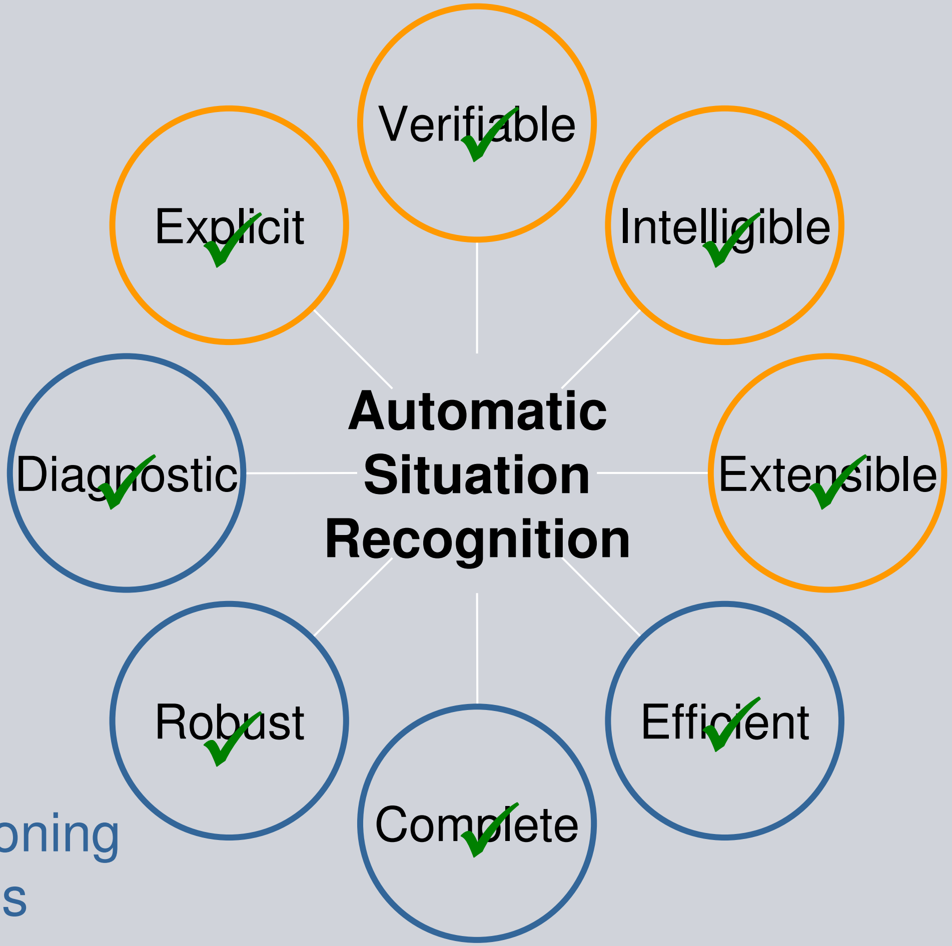
- Shallow ontological model
- Main criterion for the time required for inference is thus the number of possible hypotheses that have to be tested
- Reducing the number of plausible situations is crucial for reducing the number of hypotheses

→ The non-standard inference task LCS (least common subsumer) or its probabilistic variant *P*LCS (Kaplunova, 2007) might be adapted to reduce the universal set of situations (disjunction of all situation descriptions) to a smaller one

→ If time is more important than completeness, a heuristic approach to situation elimination or some anytime-capable algorithm might be used, testing more promising situations first.

Requirements Revisited

Logic-based
formal pattern



Abductive reasoning
with preferences

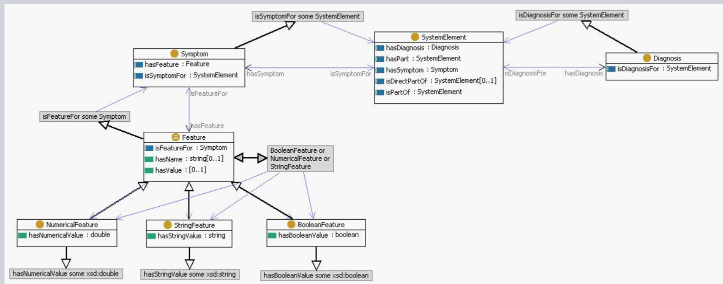
Talk Outline

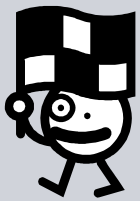
Principles

- Qualities of Information Imperfection
- Abductive Reasoning and Imperfect Information

Application to Situation Recognition

- Requirements
- Proposed Solution
  - An Ontology Pattern for Abduction-Based Situation Recognition
  - Efficient Abductive Model Evaluation





Conclusion

Conclusion

- Abductive Reasoning to handle incomplete information
- Hypothesis ranking and information-gathering guidance
- Exploitation of taxonomy in preference measures

References

- (Dubois, 2006) Dubois, D., Prade, H.: Représentations Formelles de l‘Incertain et de l‘Imprécis. In Bouyssou, D., Dubois, D., Pirlot, M., Prade, H., eds.: Concepts et Méthodes pour l'Aide a la Décision, pp. 111-171. Lavoisier, Cachan Cedex (2006)
- (Elsenbroich, 2006) Elsenbroich, C., Kutz, O., Sattler, U.: A Case for Abductive Reasoning over Ontologies. In Proceedings of OWL: Experiences and Directions Workshop (2006)
- (Kaplunova, 2007) Kaplunova, A., Möller, R.: Probabilistic LCS in a P-Classic Implementation (Technical Report). Hamburg University of Technology (2007)
- (Möller, 2008) Möller R., Neumann B.: Ontology-based Reasoning Techniques for Multimedia Interpretation and Retrieval. In Semantic Multimedia and Ontologies : Theory and Applications. Springer (2008)

Thank You!

Questions? Comments? Ideas?

Backup-Slides

Mathematical Models of Imperfection

Formalism	Imprecision	Uncertainty	Gradual information	Granularity	Distinguishes focusing and revision	Supports all fusion types
Probabilities	○	+	−	−	−	○
Imprecise probabilities	+	+	−	−	+	+
Belief functions	+	+	+	+	+	+
Transferable belief model	+	+	+	+	+	○
Possibilities	○	○	+	+	+	+
Certainty factors	○	○	○	−	−	−
Fuzzy logic	−	−	+	○	+	○

Formalisms for Reasoning with Imperfection

SIEMENS TUHH Technische Universität Hamburg-Harburg

Name	Math. Model	Type of Semantics
Propositional Representations		
Bayesian Network	P	model
Credal Network	$[P_*, P^*]$	model
(Hidden) Markov Model	P	proof (model[1])
SCFG[2]	P	proof
First-Order Representations		
KBMC[3]	P	model
Probabilistic Logic Program	P	model
Bayesian Logic Program	P	model
Logical Bayesian Network	P	model
Object-Oriented Bay. Netw.	P	model
Hierarchical Bay. Netw.	P	model
Markov Logic Network	*log-odds*[4]	model
Stochastic Logic Program	P	proof
PRISM[5]	P	proof
Logical Hidden MM	P	proof (model)
CLP($\mathcal{BN}$)	$[P_*, P^*]$	model

Name	Math. Model	Type of Semantics
Relational Representations		
Relational Bay. Netw.	P	model
Relational Dynamic Bay. Netw.	P	model
Probabilistic Relational Model	P	model[6]
Stochastic Relational Model	P	model[6]
Relational Markov Model	P	proof (model)
Description Logic Representations		
Fuzzy $\mathcal{ALC}$	$\mathcal{F}$	model
$\mathcal{PALC}$	$[P_*, P^*]$	model
P-Classic	P	model
pDatalog	P	model
P-$\mathcal{SHOIN}$(D)	$[P_*, P^*]$	model
SPDL-programs	$[P_*, P^*]$	model
Decision-Theoretic Representations		
Independent Choice Logic	P	model

Classical Methods of Reasoning

SIEMENS
TUHH
Technische Universität Hamburg-Harburg

	Deduction	Induction	Abduction	By Analogy
Principle	▪ Application of formal rules to facts ▪ Implicit factual information is made explicit ▪ Formal Logic	▪ Similar observations are generalized ▪ The assumed underlying law is expressed as a rule	▪ Derives hypothetical explanations for observations ▪ Missing data may be hypothesized	▪ Partial similarity is generalized to all properties ▪ Basis for CBR
Direction of argument	F & C → F	F → C	F & C → F	F → F C → C
Result validity guaranteed	✓	✗	✗	✗
Generates new knowledge	✗	✓	✓	✓

Outlook
Diagnosis Workflow Support Tool

SIEMENS
TUHH
Technische Universität Hamburg-Harburg

Support technicians in diagnosing machines based on their symptoms:

- By extending and instantiating the generic pattern, the manufacturer can define machines, components and possibly symptoms

- GUI-supported on-site workflow
  - The technician selects a machine
  - The tool presents a list of components
  - The technician enters the observed features for the respective components
  - Using the explanations generated, the tool returns a diagnosis (with attached repair solutions) or guides the technician through a list of additional tests until a single diagnosis is found

- A future extension might integrate learning (either completely new diagnoses or simply adapting probabilities)