Integration of Probabilistic Models

eTRIMS Meeting 4.-5. October 2007 in London

Bernd Neumann
CSL, Hamburg University

Reviewer Remarks

- What are your challenges? Specify problems for the next 2 years.
- Document progress by benchmarking.
- How do you control low-level by high-level processing?
- Stop working with preclassified images to let high-level interpretation show its effect on low-level image analysis.
- Bridge gap between low-level and high-level work.
- Provide seamless integration of logic-based and probabilistic approaches.

Purpose of Presentation

- Provide conceptual view of probabilistic scene interpretation from the Hamburg perspective
- Show possible ways for integrating probabilistic information into SCENIC
- Discuss concrete integration steps

Uncertainty in Scene Interpretation

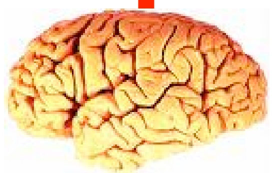
Human-assigned meaning

Computer-assigned meaning

interpretation probabilities

Human-constructed physical world

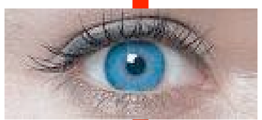
Computer-constructed physical world



reconstruction probabilities

Retinal images

Sensory information / images

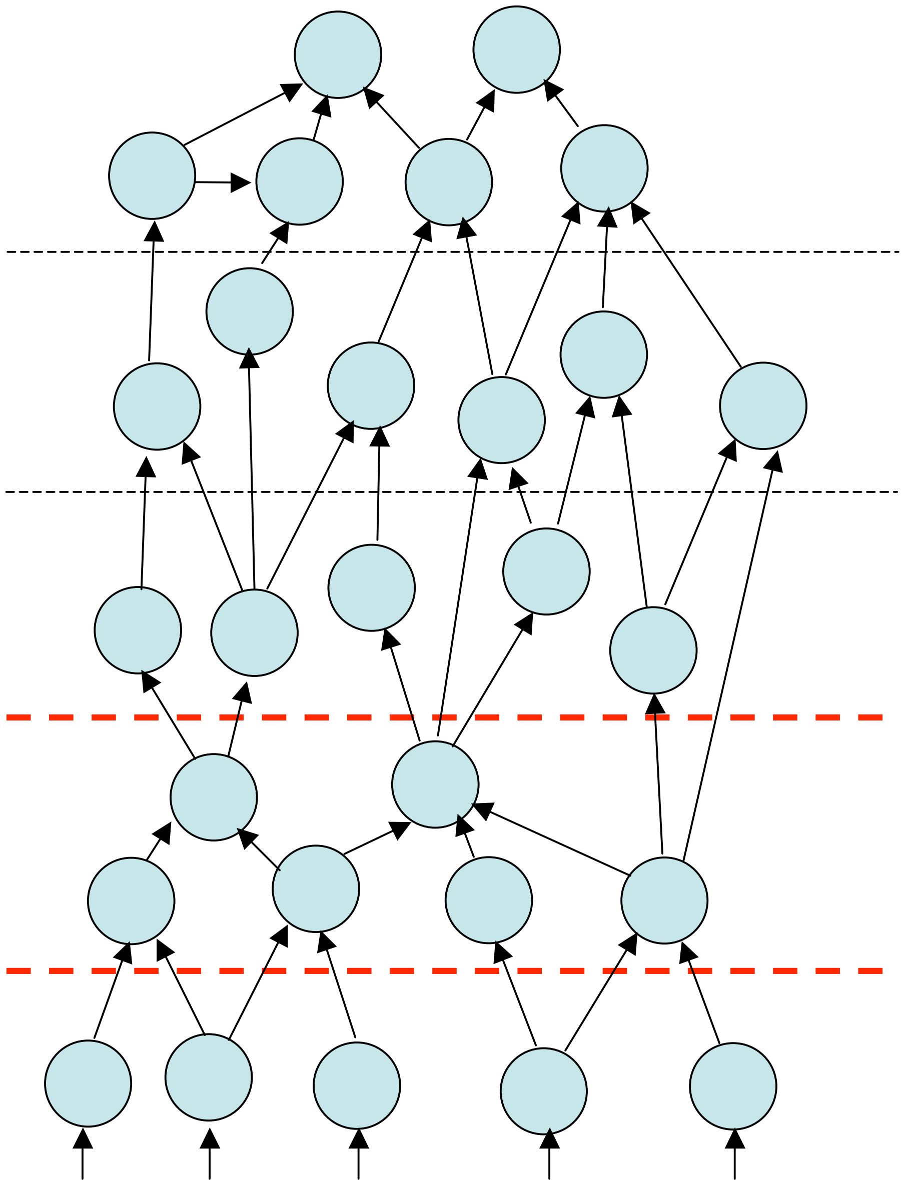


sensor probabilities

real-world probabilities

Real world

Bottom-to-top Probabilistic Model



labelled
aggregates

labelled
scene elements

scene elements

hierarchy of
image elements

real world

How far can we get with flat models (e.g. for labelling pixels)?

Probabilistic Inference Services for Scene Interpretation

TRIMS

- **Stepwise evidence classification**
  - Choose class for evidence to maximise interpretation probability (or utility)
  - Choose evidence for hypothesis to maximise interpretation probability

  Service: max $P(\underline{i} \mid \underline{e})$

- **Generate high-level hypotheses which maximise interpretation probability**
  - existence and number of parts
  - part membership in aggregates
  - temporal expectations

  Service: max $P(\underline{i}\ i^h \mid \underline{e})$

- **Generate low-level hypotheses**
  - most probable evidence (e.g. behind occlusion)
  - control parameters for low-level image analysis

  Service: max $P(\underline{i}\ e^h \mid \underline{e})$

Structuring High-level Knowledge

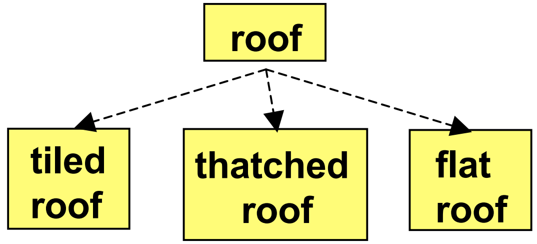
Yes, we need probabilistic representations and inferences

<u>But</u>:

- **Distinction of fuzzy definitions and probabilistic events**
- **Natural compositional hierarchy**
- **Taxonomies useful for logical reasoning**
- **Need for logical reasoning:**
  - **Common-sense knowledge**
  - **Spatial and temporal reasoning**
  - **Classification**
- **Ontological embedding and machine readability**

Our Approach

- **Maintain logic-based framework**
- **Introduce probabilities for nondeterministic choices within logic-based framework**



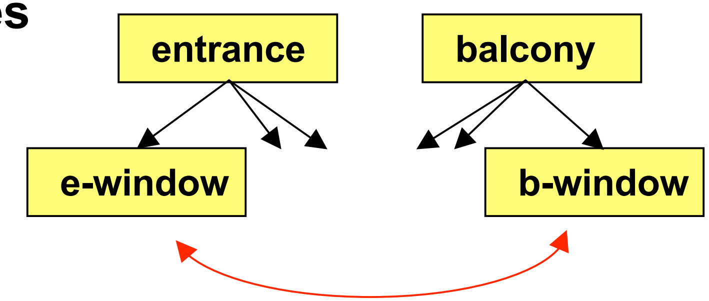
  - **specialisations**
  - **optional parts**
  - **range-valued attributes**
  - **set-valued attributes**

window-array has-parts [3 to inf] window

window size-X [30 to 200], size-Y [50 to 300]

window colour {whie, grey, black, brown}

- **Allow correlations between parts of aggregates within aggregates but not across aggregates**

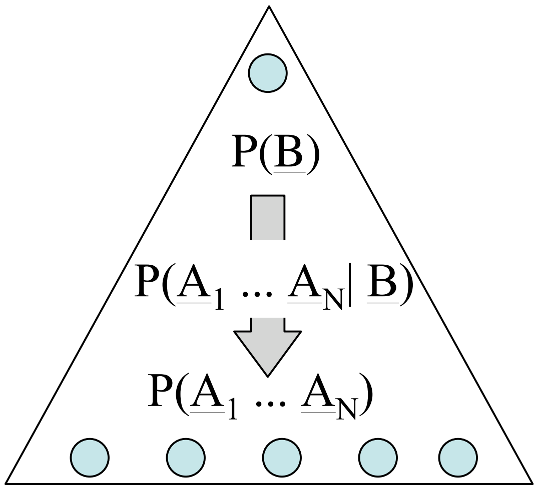


correlation may not be directly represented

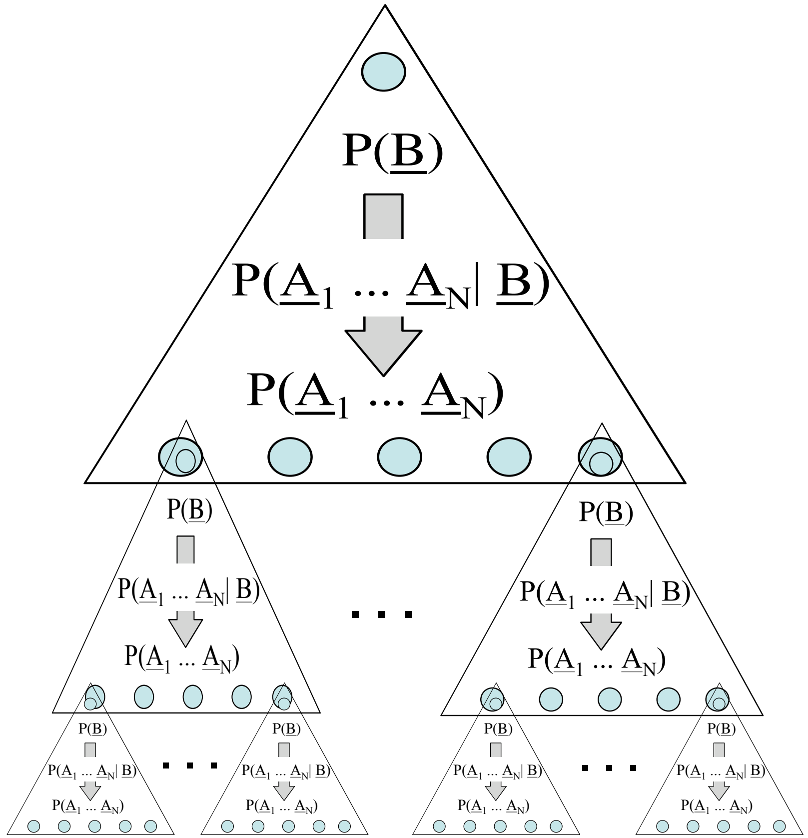
Probabilistic Aggregate Hierarchy

Plausible independence assumptions give rise to probabilistic aggregation hierarchy with useful abstraction properties

external representation in terms of aggregate properties



internal representation in terms of component properties



Structuring the Middle Layer (1)

<u>**Select view hypothesis for evidence**</u>

Using Hamburg aggregation hierarchy:

- View description type must match low-level evidence type
- Construct abstraction hierarchy by hand or by many interpretation examples
- Classify evidence to achieve maximally probable interpretation
- Exact probabilistic inference by propagation

Using London MRF model:

- Consider region classification
- Learn probabilistic influence of spatial context
- Exploit spatial context model for region classification

Structuring the Middle Layer (2)

TRIMS

Select evidence for view hypothesis

Using Hamburg aggregation hierarchy:

- Select evidence to achieve maximally probable interpretation
- Trial and error

Using London MRF model:

- Exploit spatial context model to determine most probable location of region with given class (?)

In general:

- Provide prediction of evidence based on relevant interpretation context (e.g. for tracking)

Structuring Low-level Image Analysis

Kinds of bottom-up processing:

- **Non-probabilistic image analysis**
  - evidence classified as views of specific object classes
  - unclassified evidence

  => instances for probabilistic view descriptions

- **Probabilistic image analysis**
  - top-down expectations
  - sensor uncertainties

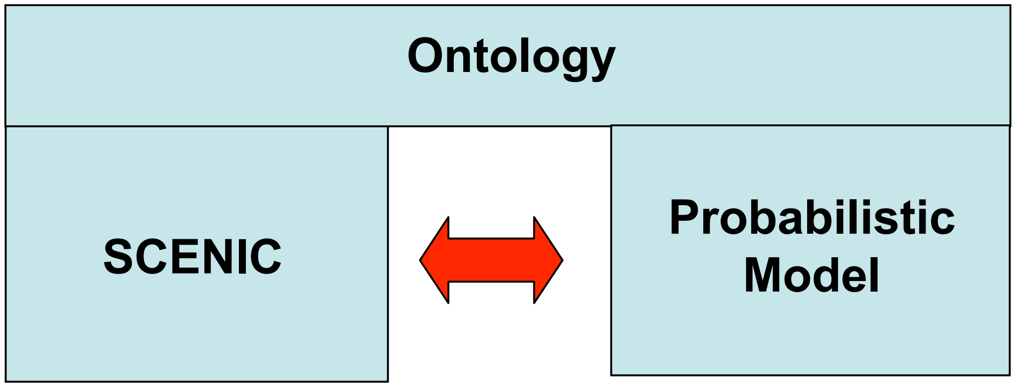
  => instances or distributions for probabilistic view descriptions

In eTRIMS currently:

- **IPMs deliver view <u>instances</u>**
- **Top-down control via IPM selection and location constraints**

Practical Steps for Integration of Probabilistic Knowledge into SCENIC

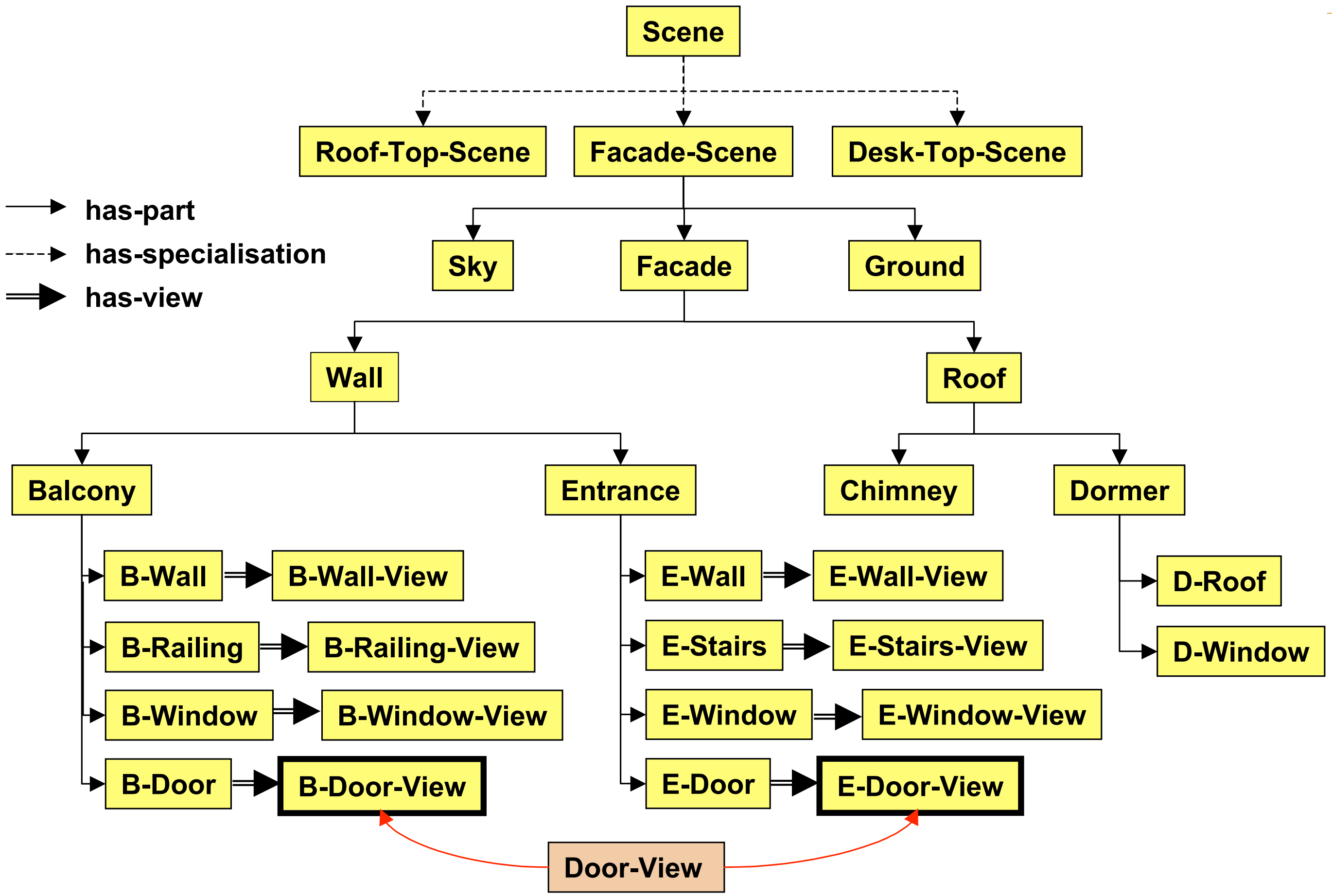
SCENIC calls external probabilistic services at choice points



What models have we got in eTRIMS?

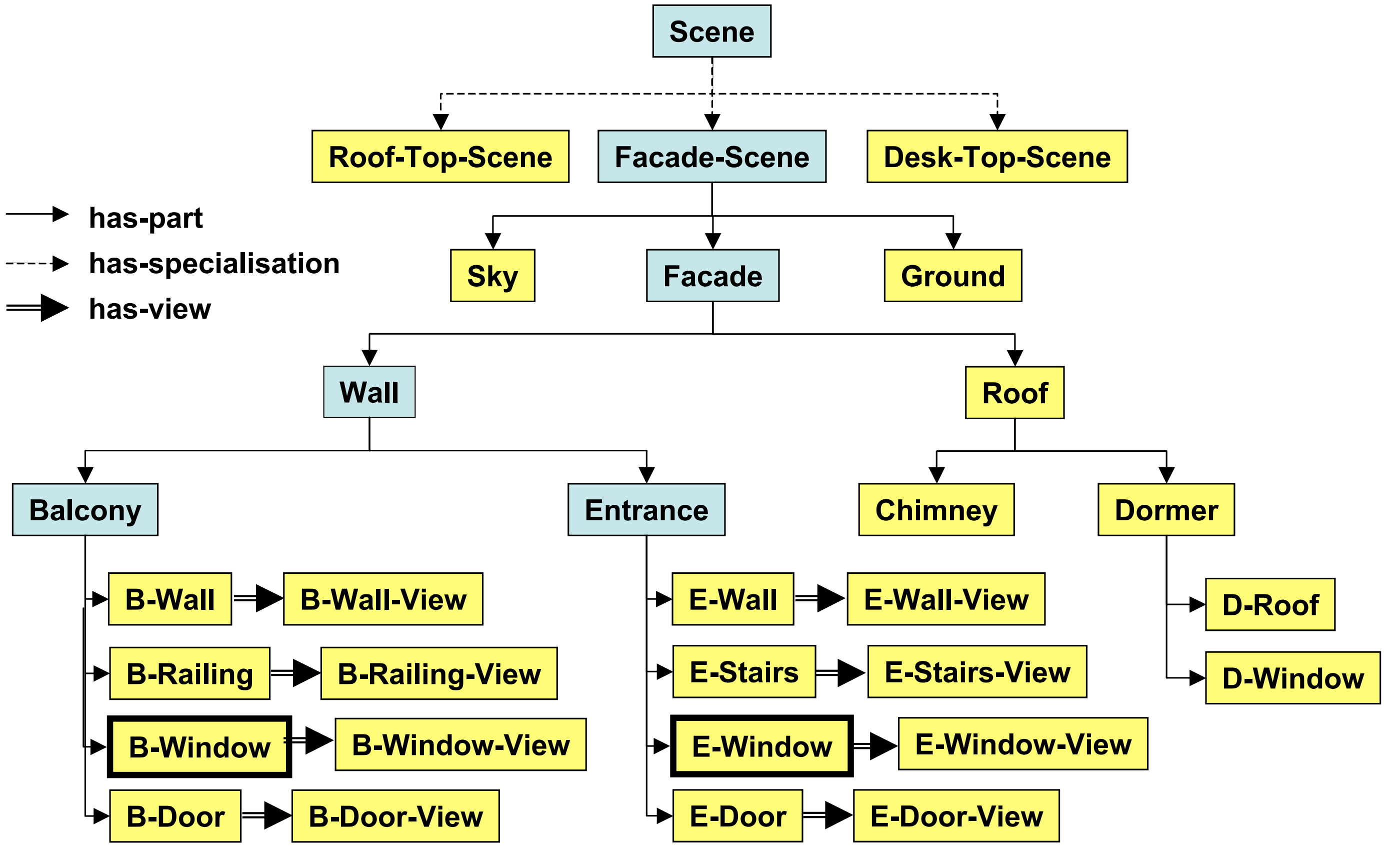
- Probabilistic model is initialised with prior probabilities
- SCENIC updates model with evidence and interpretation decisions
- Model computes updated probabilities
- SCENIC queries model for probabilities

Example: Evidence Classification



If Door-View **is made an instance of** B-Door-View **or** E-Door-view, **which decision allows the most probable scene interpretation?**

Example: Hypothesis Generation



If a hypothesis B-Window **or** E-Window **is created, which one allows the most probable scene interpretation?**

Deep Integration into the SCENIC High-level Interpretation System

- Describe specialisation choices, range-type and set-type attributes by marginal probability distributions
- Replace constraints by joint probability distributions
- Replace constraint propagation by probability propagation

Problems:

- Current SCENIC constraints do not necessarily respect encapsulation according to abstraction properties of the aggregation hierarchy
- Probabilistic model corresponding to current constraints may be difficult to obtain and to operate
- SCENIC activates costraints only for instantiated concepts
- SCENIC "instances" may be hypotheses which have remaining uncertainties, different from instances of random variables

Using Partial Probabilistic Models

Pragmatic approach:

- **Import probabilistic information whenever useful**
- **Evaluate interpretation performance with and without partial probabilistic guidance**

Conceptual problems:

- **Partial probabilistic model may not pertain to most probable interpretation**
- **Information in separate models may overlap and be inconsistent**

Goal and Context Information

We must be able to introduce

- **context information from other sources**
- **goal information for purposive vision**

Context:

Provide service for introducing external context information in terms of

- **specific instances for concepts (for sets of random variables)**
- **changed constraints (distributions) for concepts (for sets of random variables)**

Goal:

- **Provide service for specifying goals in similar terms as context**
- **Restrict interpretation (propagation) process to determine goal**

  E.g. "Is there an X in the image?"   "Give all examples of X with attribute Y"