Probabilistische Steuerung für logisch fundierte Szeneninterpretation

(Probabilistic Control of Logic-based Scene Interpretation)

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NAOS - Natural Language Description of Object Motions in Traffic Scenes

Neumann, B.; Novak, H.-J., **NAOS: Ein System zur natürlichsprachlichen Beschreibung zeitveränderlicher Szenen,** Informatik Forschung und Entwicklung 1, 83 - 92, 1986

Brauer: Was haben Sie damit erreicht?

Die Szene enthält vier bewegte Objekte: drei PKWs und einen Fußgänger.

Ein VW fährt von der alten Post vor den ... Informatik. Er hält an.

Ein anderer VW fä... n der Schlüterstraße ab. Er fährt in Richtung ...

Haralick: So what?

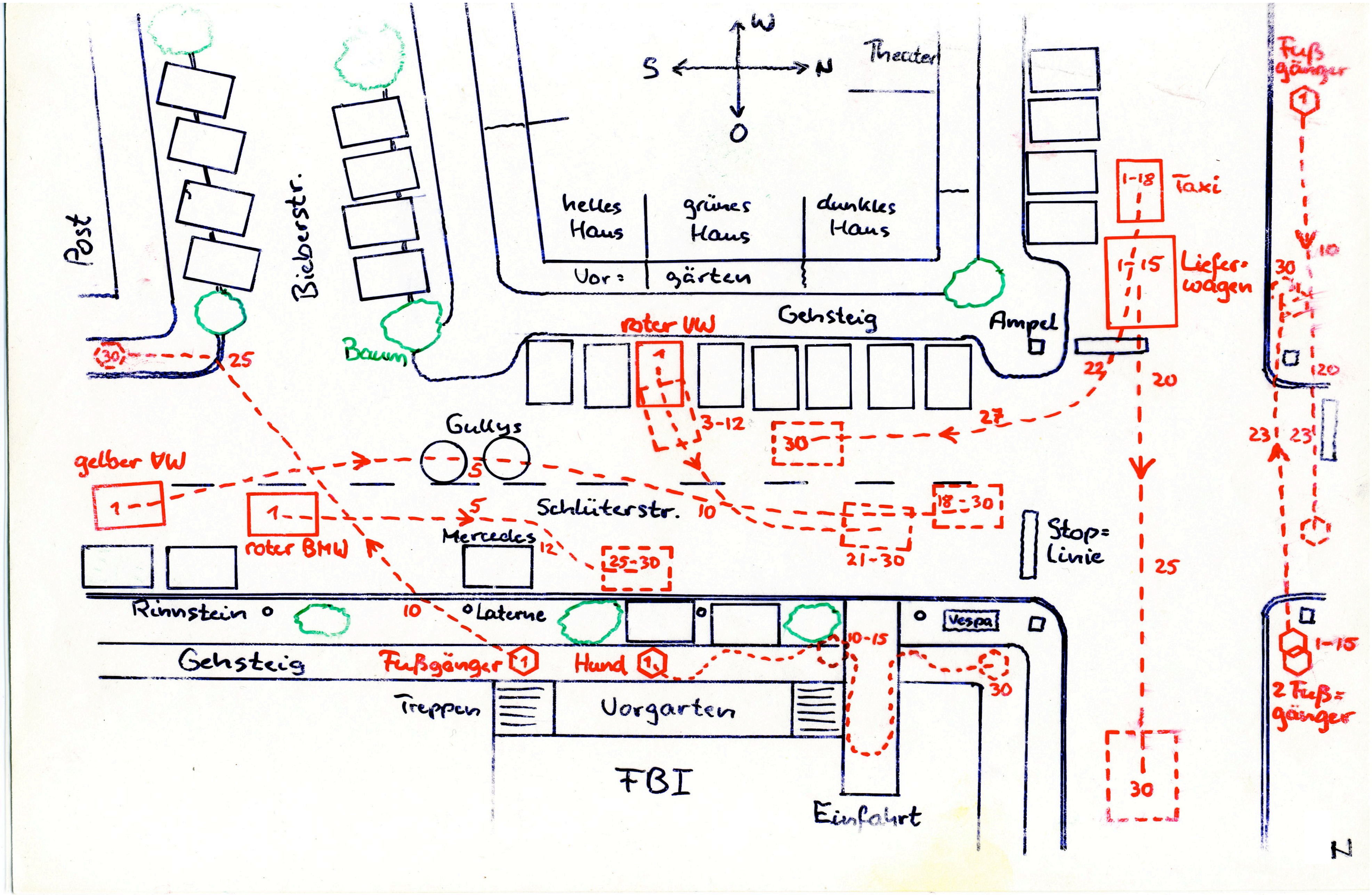
Ein BMW fährt in ... er den VW, der angehalten hat, vor der Bieb... hält an der Ampel an.

Der Fußgänger geht in Richtung Dammtor. Dabei überquert er die Schlüterstraße vor dem Fachbereich Informatik.

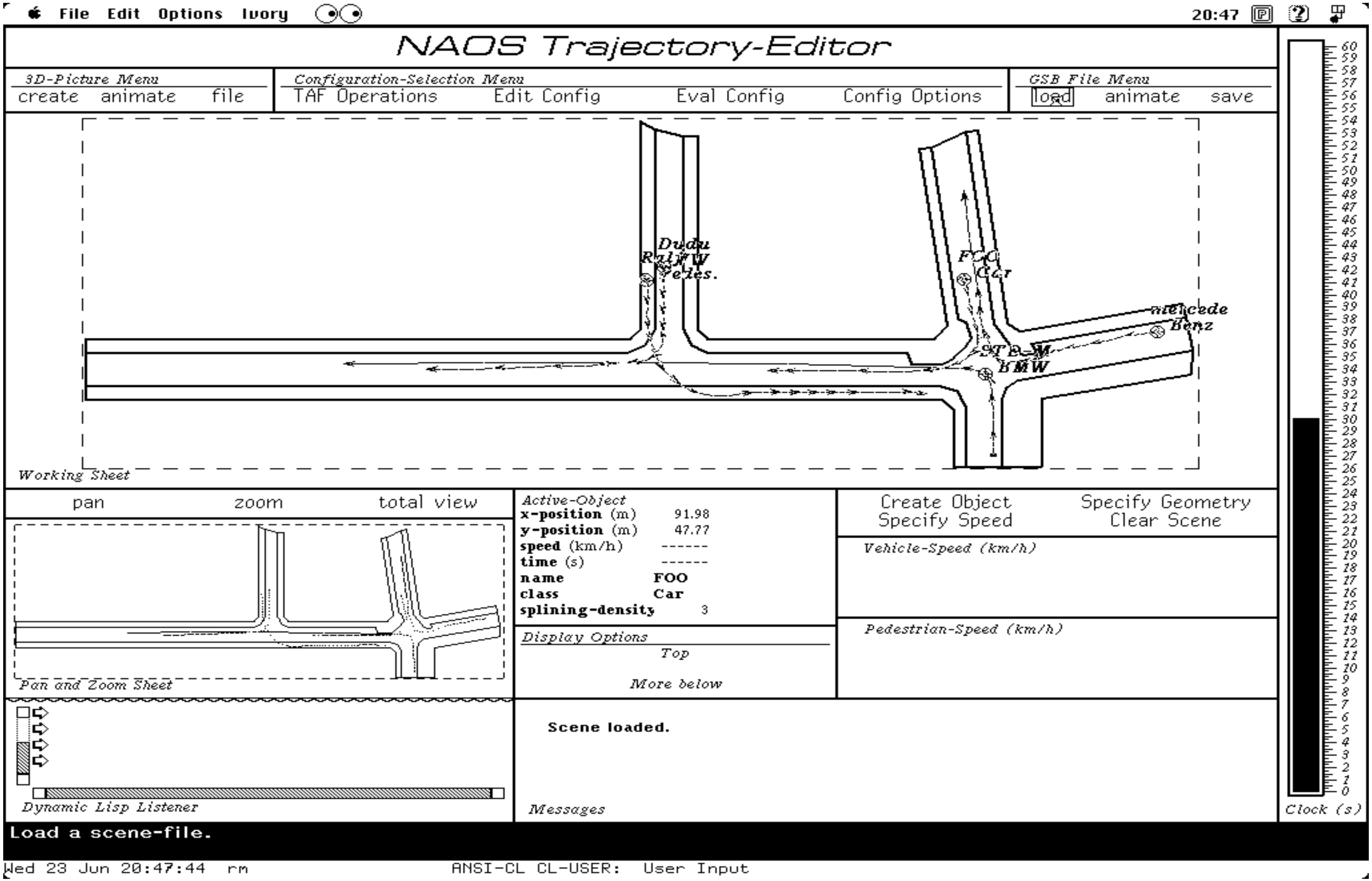
Agenda

- Looking back at NAOS
- What is a correct scene interpretation?
- Inferences for scene interpretation
- Bayesian Compositional Hierarchies
- Experiment with Gaussian distributions

Input Data of NAOS (1)



Input Data of NAOS (2)



Geometrical Scene Description (GSD) in NAOS

Quantitative description of all objects in a time-varying scene:

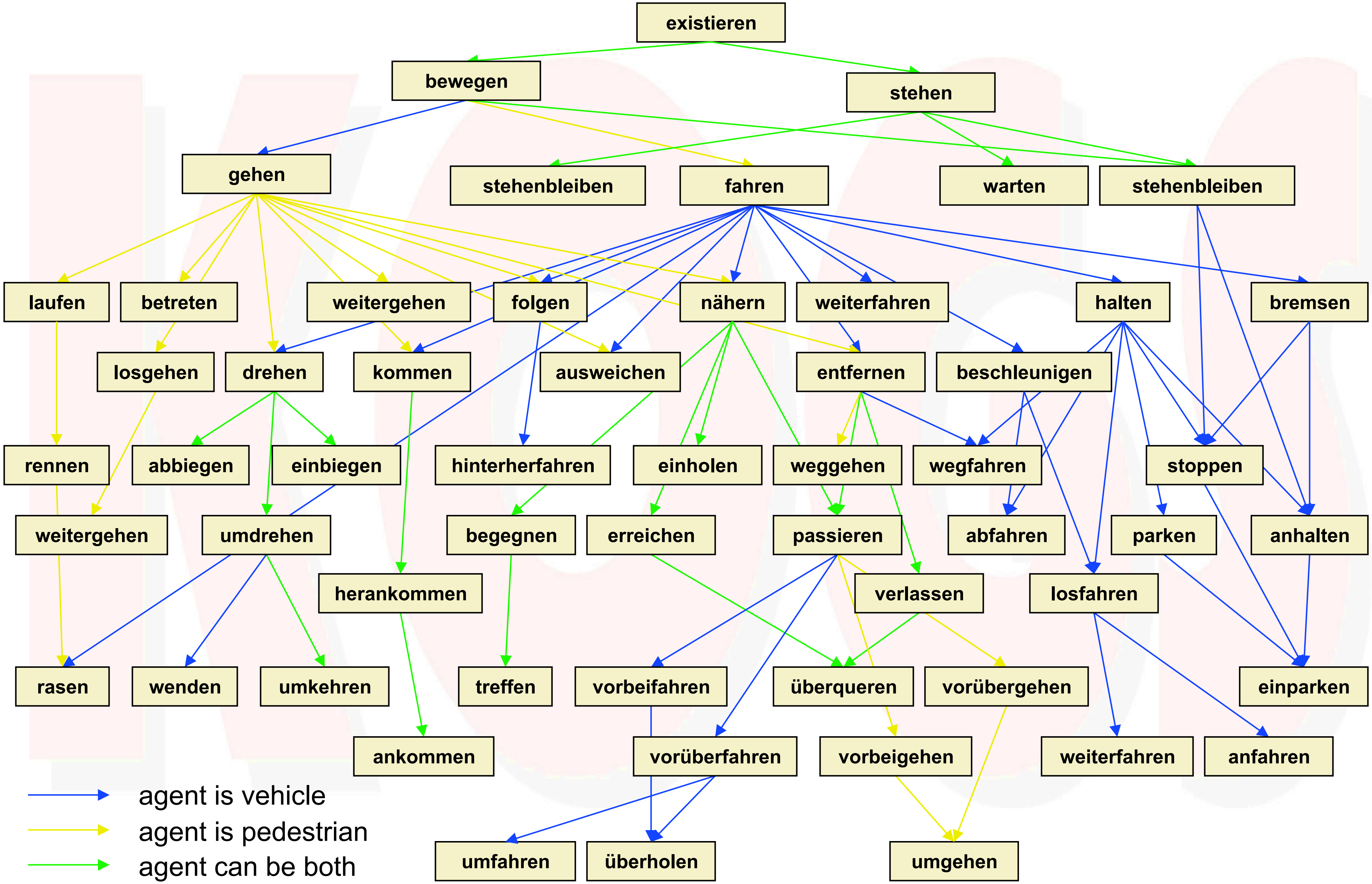
- **name of all objects (class or identity)**
- **position of all objects at all times (location and orientation)**
- **illumination (if required for high-level description)**

Example of a synthesized GSD in NAOS:

```
(LAGE VW2 (779. 170. 0.) (-1.0 0.0 0.0) 0)
(LAGE VW2 (753. 170. 0.) (-1.0 0.0 0.0) 1)
(LAGE VW2 (727. 170. 0.) (-1.0 0.0 0.0) 2)
(LAGE VW2 (701. 170. 0.) (-1.0 0.0 0.0) 3)
(LAGE VW2 (675. 170. 0.) (-1.0 0.0 0.0) 4)
(LAGE VW2 (649. 170. 0.) (-1.0 0.0 0.0) 5)
(LAGE VW2 (623. 170. 0.) (-0.999 0.037 0.0) 6)
(LAGE VW2 (596. 171. 0.) (-1.0 0.0 0.0) 7)
(LAGE VW2 (570. 171. 0.) (-1.0 0.0 0.0) 8)
(LAGE VW2 (544. 171. 0.) (-1.0 0.0 0.0) 9)
.
.
.
```

location — orientation — time

Object Motion Hierarchy in NAOS



Occurrence Model for "OVERTAKE" in NAOS

```
(OVERTAKE OBJ1 OBJ2 T1 T2)  <=>
        (MOVE OBJ1 T1 T2)
        (MOVE OBJ2 T1 T2)
        (BEHIND OBJ1 OBJ2 T1 T3)
        (BESIDE OBJ1 OBJ2 T3 T4)
        (BEFORE OBJ1 OBJ2 T4 T2)
        (APPROACH OBJ1 OBJ2 T1 T3)
        (DIS-APPROACH OBJ1 OBJ2 T4 T2)
```

- **Parts of "overtake" are taken to be necessary and sufficient**
- **Limited expressivity of temporal relations**
- **Event recognition by search and temporal constraint solver**

Generate-and-Test Event Recognition (1)

```
SUCHE:

      (UEBERHOLEN X1? X2? (1 40) (1 40))
      (INNERHALB2 1 40 5 16)
      (VOR X1? X3? 1 40)

  G:  (UEBERHOLEN X1? X2? (1 40) (1 40))
     G:  (BEWEGEN OBJ1? 1 40)
     T:  (BEWEGEN PKW2 32 39)
        G:  (BEWEGEN OBJ2? 32 39)
        T:  (BEWEGEN PKW2 32 39)
           G:  (NAEHERN PKW2 PKW2 32 40)
           T:  (BEWEGEN PKW1 1 32)
           T:  (BEWEGEN LKW1 29 34)
           G:  (NAEHERN PKW2 LKW1 32 40)
              G:  (BEWEGEN PKW2 1 40)
              T:  (BEWEGEN PKW2 32 39)
                 G:  (SYM-NAEHERN PKW2 LKW1 32 39)
                 >> (SYM-NAEHERN PKW2 LKW1 32 39)
                 T:  (SYM-NAEHERN PKW2 LKW1 32 39)
                    >> (NAEHERN PKW2 LKW1 32 39)
                    T:  (NAEHERN PKW2 LKW1 32 39)
              G:  (ENTFERNEN PKW2 LKW1 1 34)
              T:  (BEWEGEN LKW1 1 23)
              T:  (BEWEGEN PKW1 1 32)
        G:  (BEWEGEN OBJ2? 1 32)
        T:  (BEWEGEN PKW2 32 39)
        T:  (BEWEGEN PKW1 1 32)
           G:  (NAEHERN PKW1 PKW1 1 40)
           T:  (BEWEGEN LKW1 29 34)
           G:  (NAEHERN PKW1 LKW1 29 40)
              G:  (BEWEGEN PKW1 1 40)
              T:  (BEWEGEN PKW1 1 32)
                 G:  (SYM-NAEHERN PKW1 LKW1 1 32)
                 >> (SYM-NAEHERN PKW1 LKW1 1 12)
                 T:  (SYM-NAEHERN PKW1 LKW1 1 12)
                    >> (NAEHERN PKW1 LKW1 1 12)
                    T:  (NAEHERN PKW1 LKW1 1 12)
                    T:  (BEWEGEN LKW1 1 23)
                 G:  (NAEHERN PKW1 LKW1 1 40)
                 T:  (NAEHERN PKW1 LKW1 1 12)
                    G:  (ENTFERNEN PKW1 LKW1 1 23)
                       G:  (BEWEGEN PKW1 1 40)
                       T:  (BEWEGEN PKW1 1 32)
                          G:  (SYM-ENTFERNEN PKW1 LKW1 1 32)
                          >> (SYM-ENTFERNEN PKW1 LKW1 12 34)
                          T:  (SYM-ENTFERNEN PKW1 LKW1 12 34)
                             >> (ENTFERNEN PKW1 LKW1 12 32)
                             T:  (ENTFERNEN PKW1 LKW1 12 32)
                       G:  (HINTER PKW1 LKW1 1 12)
                       >> (HINTER PKW1 LKW1 1 11)
                       T:  (HINTER PKW1 LKW1 1 11)
                          G:  (HINTER LKW1 PKW1 12 23)
                          >> (HINTER LKW1 PKW1 13 40)
                          T:  (HINTER LKW1 PKW1 13 40)
                             G:  (NEBEN PKW1 LKW1 2 22)
                             >> (NEBEN PKW1 LKW1 10 14)
                             >> (NEBEN LKW1 PKW1 10 14)
                             T:  (NEBEN PKW1 LKW1 10 14)
                                >> (UEBERHOLEN PKW1 LKW1 (1 10) (14 23))
                                T:  (BEWEGEN LKW1 29 34)
              G:  (BEWEGEN OBJ2? 29 34)
              T:  (BEWEGEN PKW2 32 39)
                 G:  (NAEHERN LKW1 PKW2 32 40)
                 T:  (BEWEGEN PKW1 1 32)
                 G:  (NAEHERN LKW1 PKW1 29 40)
                 T:  (BEWEGEN LKW1 29 34)
                 G:  (NAEHERN LKW1 LKW1 29 40)
                 T:  (BEWEGEN LKW1 1 23)
                 T:  (BEWEGEN LKW1 1 23)
              G:  (BEWEGEN OBJ2? 1 23)
              T:  (BEWEGEN PKW2 32 39)
```

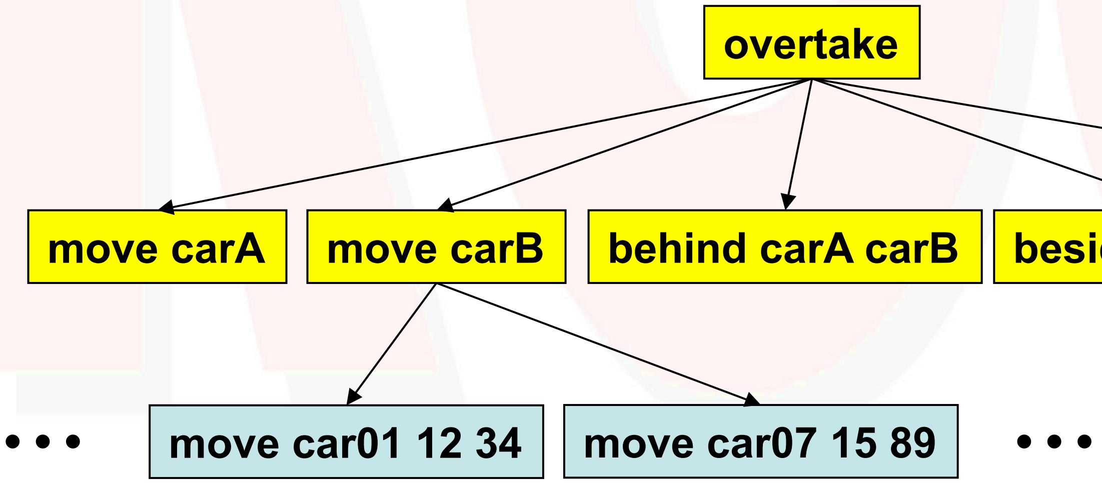
Generate-and-Test Event Recognition (2)

```
        T:   (BEWEGEN PKW1 1 32)
            G:   (NAEHERN LKW1 PKW1 1 40)
            T:   (BEWEGEN LKW1 29 34)
            T:   (BEWEGEN LKW1 1 23)
            G:   (NAEHERN LKW1 LKW1 1 40)
            T:   (UEBERHOLEN PKW1 LKW1 (1 10) (14 23))
    G:  (VOR PKW1 X3? 1 23)
    >> (VOR PKW1 HAUS1 1 17)
    T:  (VOR PKW1 HAUS1 1 17)
         G:  (INNERHALB2 1 17 5 16)


GEFUNDEN:

        (UEBERHOLEN PKW1 LKW1 (5 10) (14 16))
        (INNERHALB2 5 16 5 16)
        (VOR PKW1 HAUS1 5 16)
```

Control Issues in NAOS

- Strictly top-down processing according to compositional hierarchy
- Don´t-care-nondeterminism ("select") for order of parts

  Prefer predicates with
  (i) smallest chances of success
  (ii) largest cost
- Don´t-know-nondeterminism ("choose") for choice of instantiations



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What is a correct scene interpretation?

Intermediate Insights (1)

1990: Reiter & Mackworth
A logical framework for depiction and image interpretation

Scene interpretation can be viewed as logical model construction over a finite domain.

1996: Schröder & Neumann
On the Logics of Image Interpretation: Model-Construction in a Formal Knowledge-Representation Framework

Scene interpretation can be viewed as partial model construction over a potentially infinite domain.

Intermediate Insights (2)

2005: Hotz & Neumann
Scene Interpretation as a Configuration Task

Scene interpretation can be modelled as a configuration task

- ***Stepwise interpretation using 5 kinds of configuration steps***
- ***Expressive knowledge representation of configuration systems can be used***

2005: Shanahan
Perception as abduction: Turning sensor data into meaningful representation

Scene interpretation can be modelled as abduction: Finding an explanation for evidence

2006: Neumann & Möller
On Scene Interpretation with Description Logics

Scene interpretation can take advantage of standard inference procedures of Description Logics, but:

- ***Stepwise model construction is not supported***
- ***Limitations of expressivity are arkward***

So what is a correct scene interpretation?

All logical models indicate:

There may be many correct interpretations for a single scene.

➡ **A preference measure is needed for choosing between alternative interpretations.**

"Lonely Dinner" or "Cluttered Table"?

Analysis of interpretation steps indicates:

Interpretation steps are partly logical inferences, partly preference decisions.

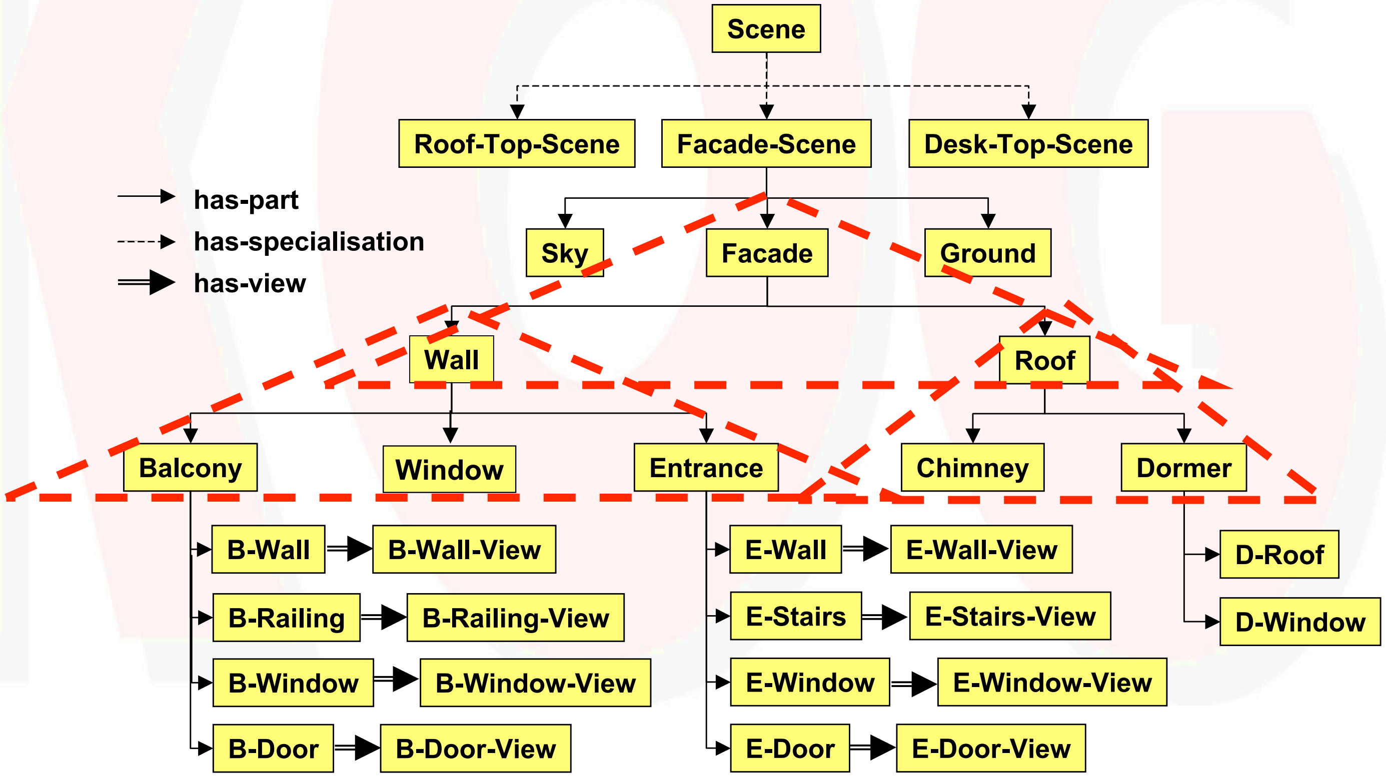
➡ **Logical standard inferences are useful but do not suffice.**

Inferences for scene interpretation

Structuring High-level Knowledge (1)

To interface with human concepts and common knowledge, a generic approach requires:

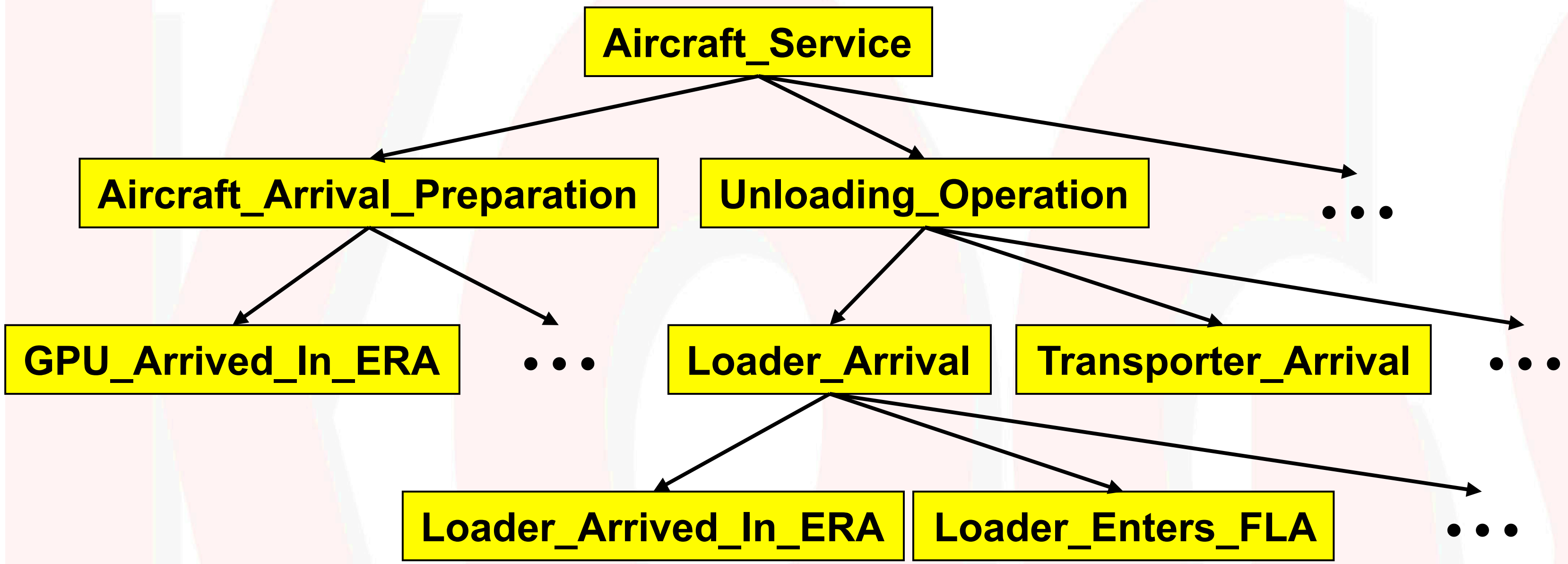
- **Object-centered representations**
- **Compositional hierarchies with abstraction => aggregates**
- **Taxonomical hierarchies**



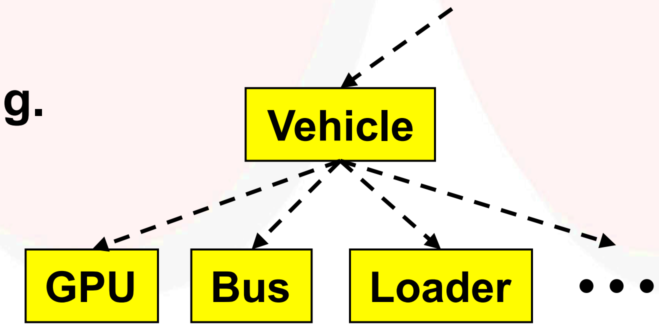
Animated Slide!

Structuring High-level Knowledge (2)

Compositional Structure of Aircraft Servicing Operations in Co-Friend



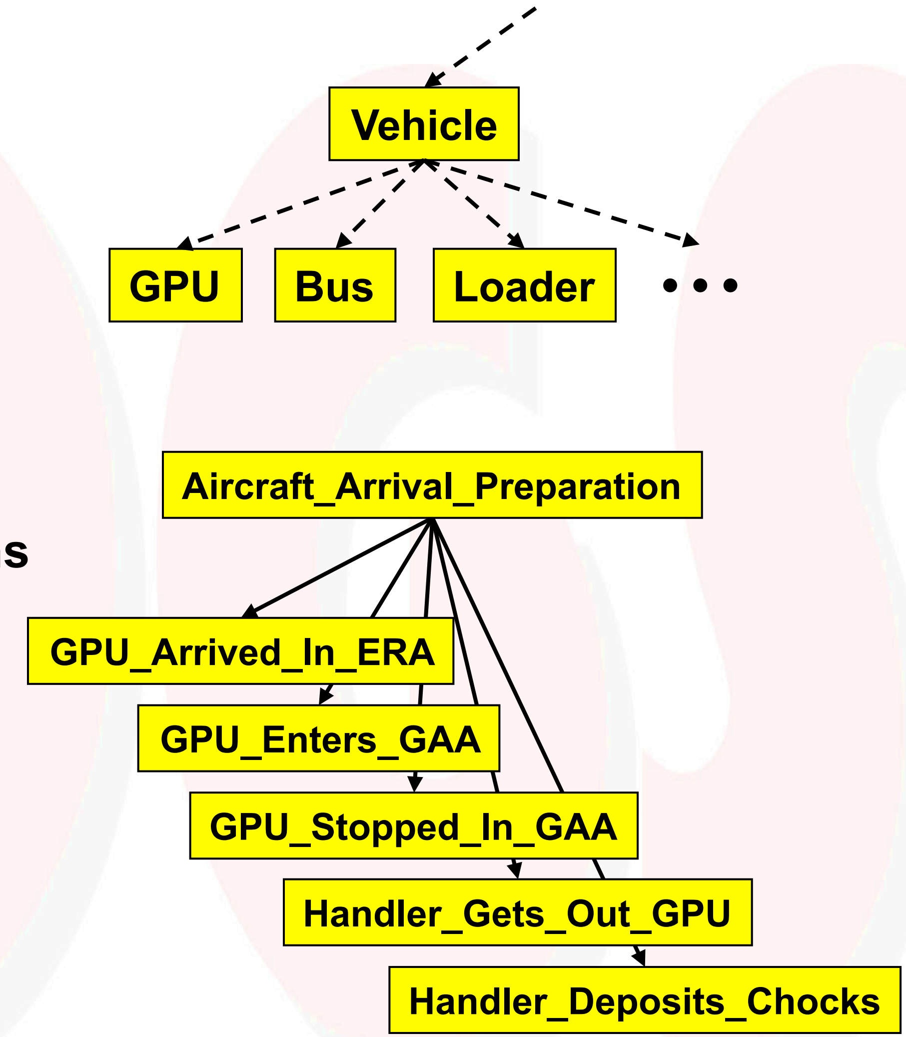
Taxonomical structure, e.g.



Logical Inferences

Ontological inferences

- inheritance
- disjunctiveness
- exhaustiveness
- mandatory parts
- mandatory properties
- equivalent concept definitions



Descriptions Logics serves as a reference!

Physical and Common Sense Inferences

"An object can only be at one location at a given time"

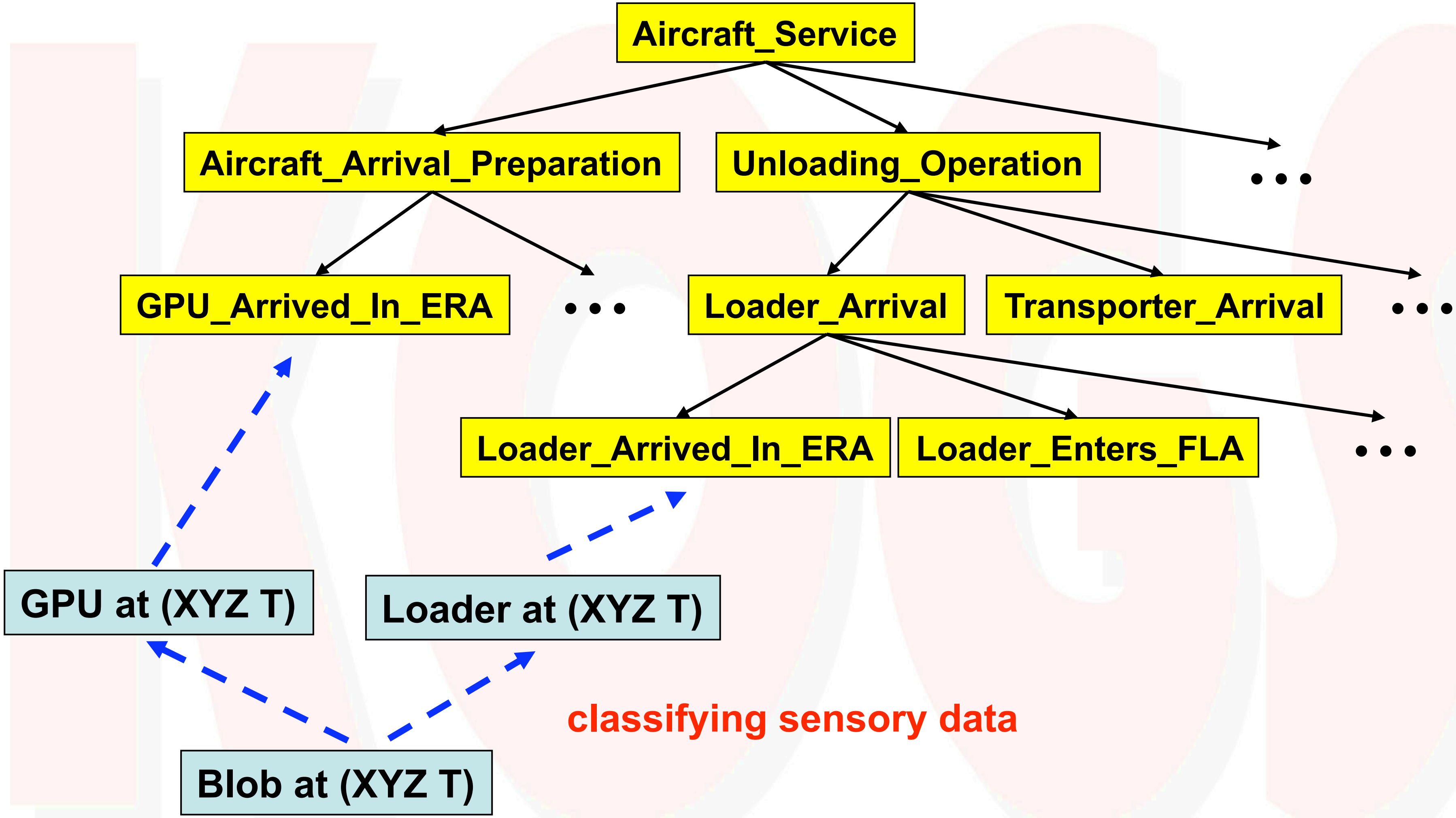
"Solid objects are persistent"
(but ...)

"Solid objects may not penetrate each other"
(but ...)

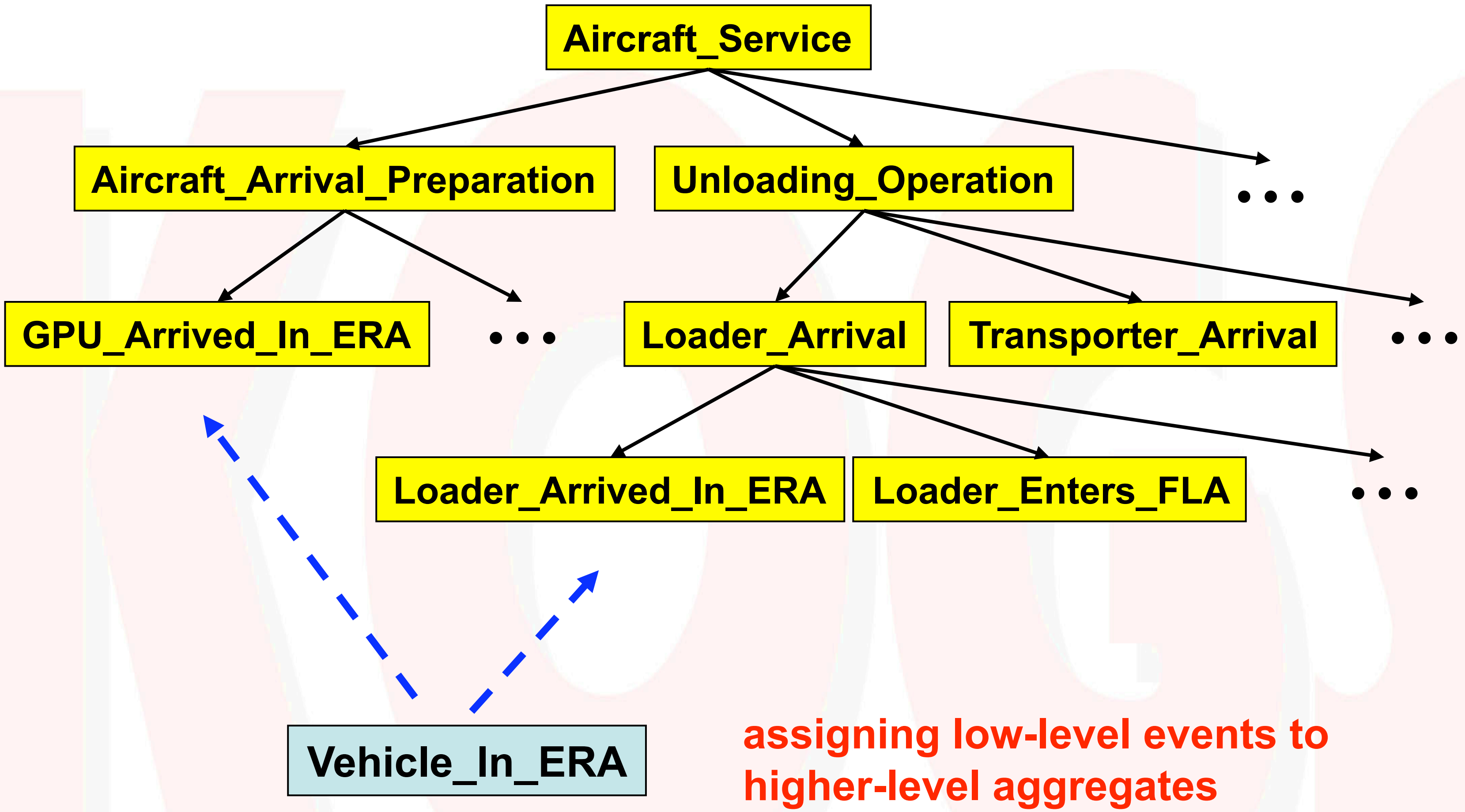
"Persons do not move faster than 30km/h"
(but ...)

"Airport ground vehicles do not move faster than 50km/h"
(but ...)

Probabilistic Inferences (1)

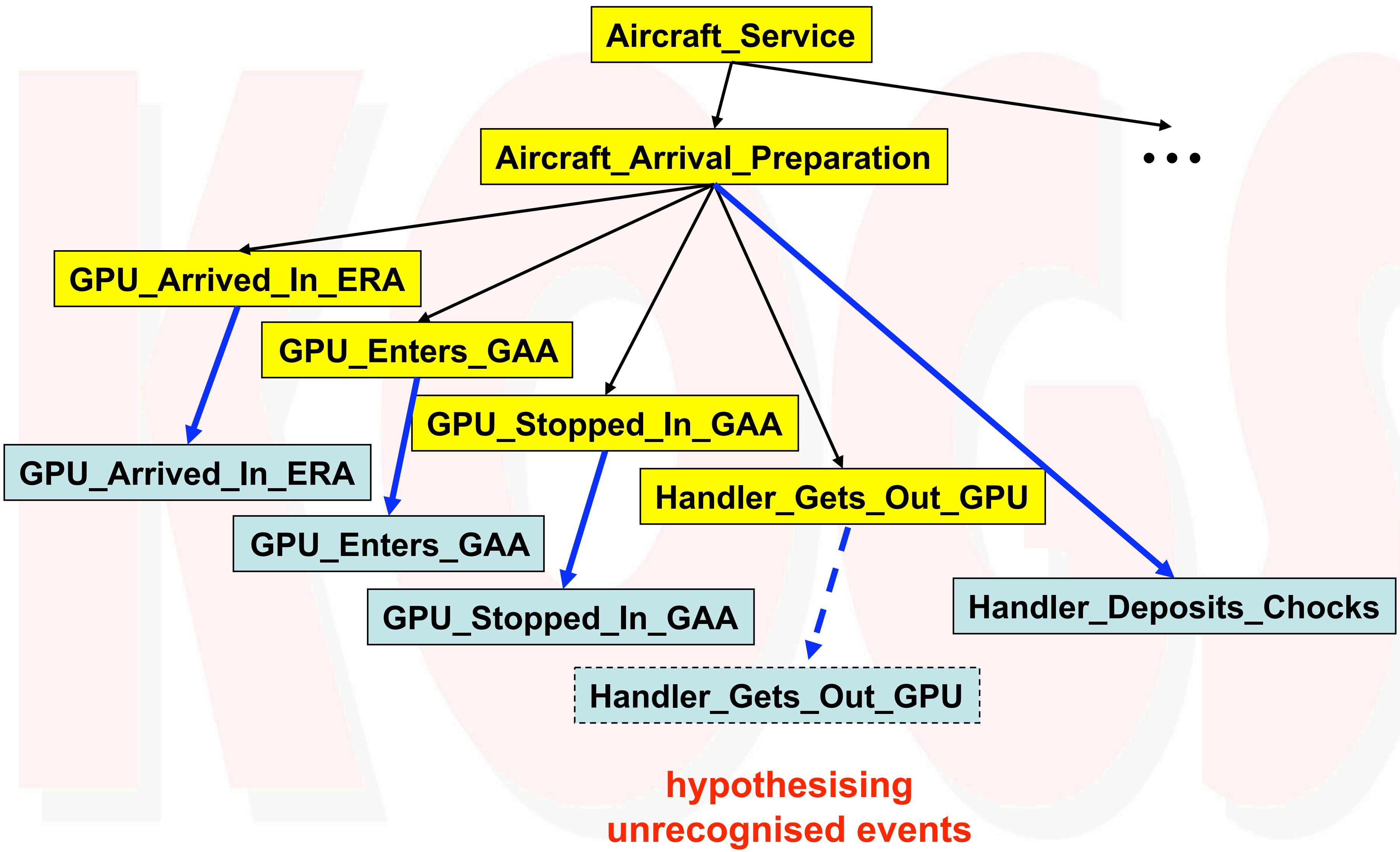


Probabilistic Inferences (2)

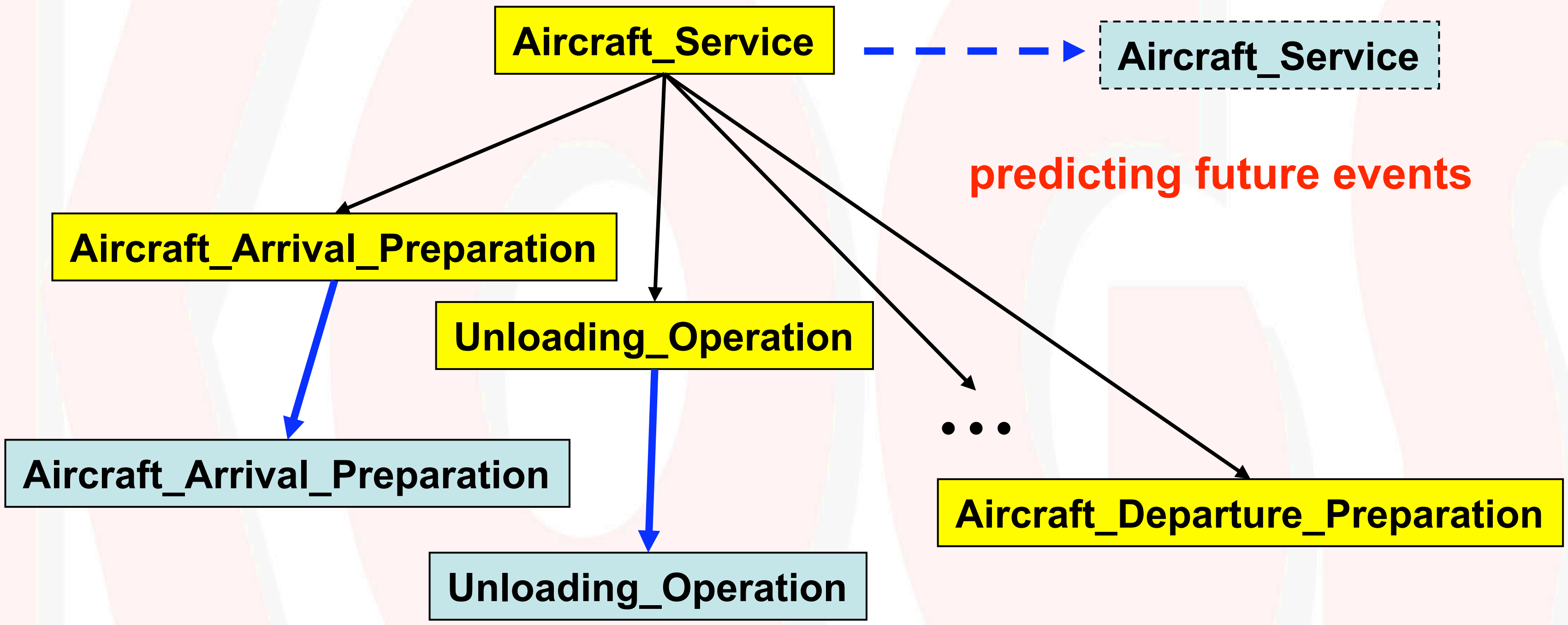


assigning low-level events to higher-level aggregates

Probabilistic Inferences (3)



Probabilistic Inferences (4)



Probabilistic Inferences (5)

Hypothesizing internal properties of an aggregate:

- **Optional parts**
- **Parameters**

Handler_Gets_Out_GPU
Parts:
GPU [1 1]
Handler [1 2]
Blocks [1 2]
Begin: [00:00:00 24:00:00]
End: [00:00:00 24:00:00]
Duration: [2 30 sec]

→

Handler_Gets_Out_GPU
Parts:
GPU [1 1]
Handler [1 1]
Blocks [1 1]
Begin: [12:10:30 24:00:00]
End: [12:10:32 24:00:00]
Duration: [2 30 sec]

Probability Propagation

Relevant probabilities for all probabilistic inferences depend on assertions about concrete scene:

- Prior information

  => static context for interpretation steps

- Instantiated objects, parameters

  => dynamic context for interpretation steps

➡ We need propability propagation when context changes

"dynamic priors"

➡ Early decisions will always have weaker context support than later decisions

Criteria for Interpretation Strategy

- Perform all logically entailed interpretation steps immediately (within scope of interest)
- Perform probabilistic decisions in the order of certainty
- Use all evidence relevant for a decision
- Postpone uncertain decisions when more evidence can be expected
- If several alternatives are promising, entertain alternative interpretation threads (e.g. Beam Search)

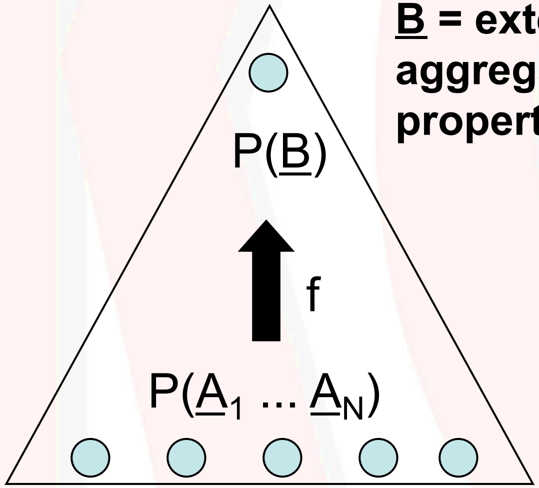
Bayesian Compositional Hierarchies

Frequentist Probabilistic Model

Basic view:

An aggregate

- **is a set of correlated parts which together constitute a meaningful entity**
- **specifies an abstraction from the descriptions of its parts**



B = external aggregate properties

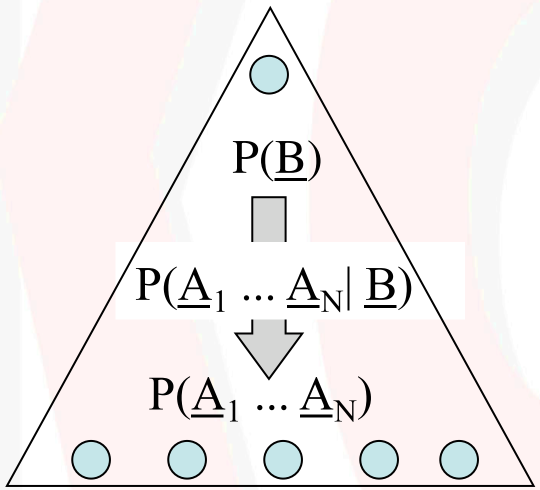
Example: Bounding-box abstraction

$\underline{A}_1$ ... $\underline{A}_N$ = internal parts properties

There exists a functional mapping f : $\underline{A}_1$ ... $\underline{A}_N$ => $\underline{B}$

Probabilistic Aggregate Structure

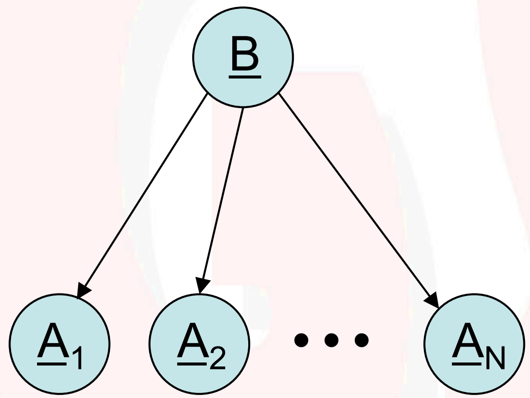
external representation in terms of aggregate properties



internal representation in terms of component properties

Rimey 93:

Tree-shaped part-of nets, is-a trees, expected-area nets, and task nets



→ unrealistic conditional independence:

$$P(\underline{A}_1 \ldots \underline{A}_N | \underline{B}) = P(\underline{A}_1|\underline{B})\, P(\underline{A}_2|\underline{B}) \ldots P(\underline{A}_N|\underline{B})$$

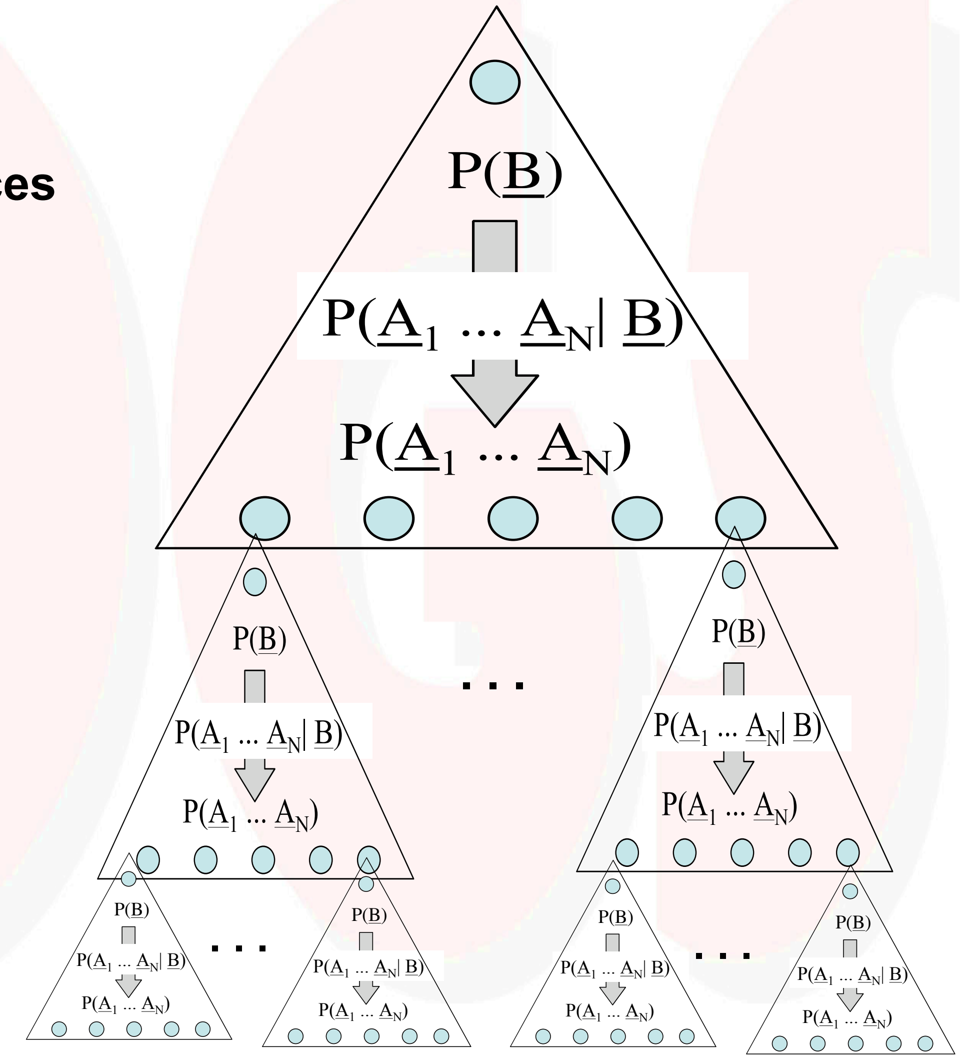
Probabilistic Aggregate Hierarchy

What are useful (and plausible) independence assumptions

- **for efficient probabilistic inferences**
- **for intuitive aggregate models?**

Simplifying assumptions (initially):

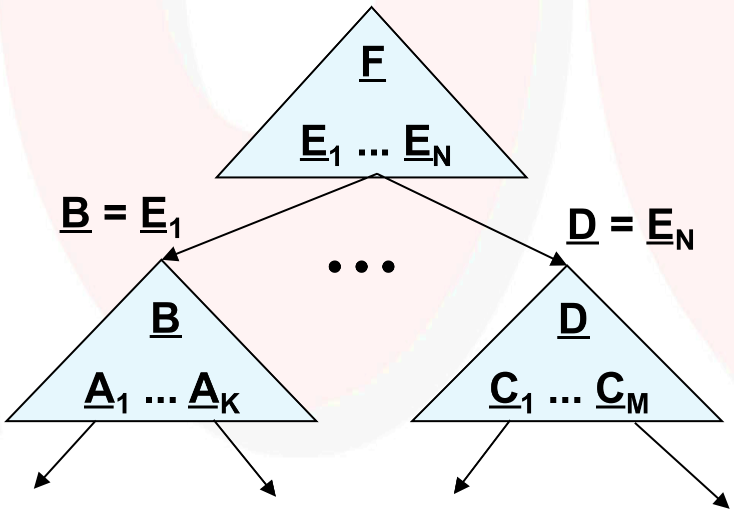
- **Distinct names for multiple parts of the same kind**
- **Fixed set of parts per aggregate**
- **No specialization branchings**



Bayesian Compositional Hierarchy (1)

Conditional-independence requirements for a compositional hierarchy to be an "Bayesian compositional hierarchy":

- ***Aggregate properties do not depend on details below the part properties.***
- ***Part properties depend only on the properties of the corresponding parent aggregate.***
- ***Parts of different aggregates are statistically independent given their parent aggregates***



Bayesian Compositional Hierarchy (2)

$$P(\underline{Z}_0 \,..\, \underline{Z}_M) = P(\underline{Z}_0) \prod_{i=0 \ldots M} P(\text{parts}(\underline{Z}_i) \mid \underline{Z}_i)$$

Z_0 is a node and Z_i, $i = 1 \,..\, M$ are its successors.

The complete JPD of an abstraction hierarchy can be computed from the conditional aggregate JPDs.

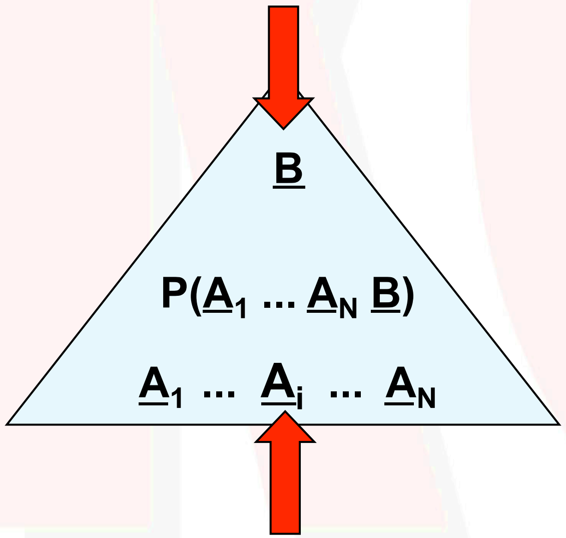
Probability changes may be propagated along tree-shaped hierarchy.

Change Propagation

After initialization, the state of each aggregate is represented by $P(\underline{A}_1 \ldots \underline{A}_N)$ with marginalizations $P(\underline{A}_i)$, $i = 1 \ldots N$, and $P(\underline{B})$.

A change has to be propagated if $P(\underline{B}) \Rightarrow P'(\underline{B})$ or $P(\underline{A}_i) \Rightarrow P'(\underline{A}_i)$, some i.

Crisp evidence $\underline{e}$ for $\underline{A}_i$ is modelled as $P(\underline{A}_i = \underline{e}) = 1$ and $P(\underline{A}_i \neq \underline{e}) = 0$.



Propagating down:

$P(\underline{B}) \Rightarrow P'(\underline{B})$

$P'(\underline{A}_1 \ldots \underline{A}_N \underline{B}) = P(\underline{A}_1 \ldots \underline{A}_N \underline{B})\, P'(\underline{B}) / P(\underline{B})$

followed by marginalizations

Propagating up:

$P(\underline{A}_i) \Rightarrow P'(\underline{A}_i)$

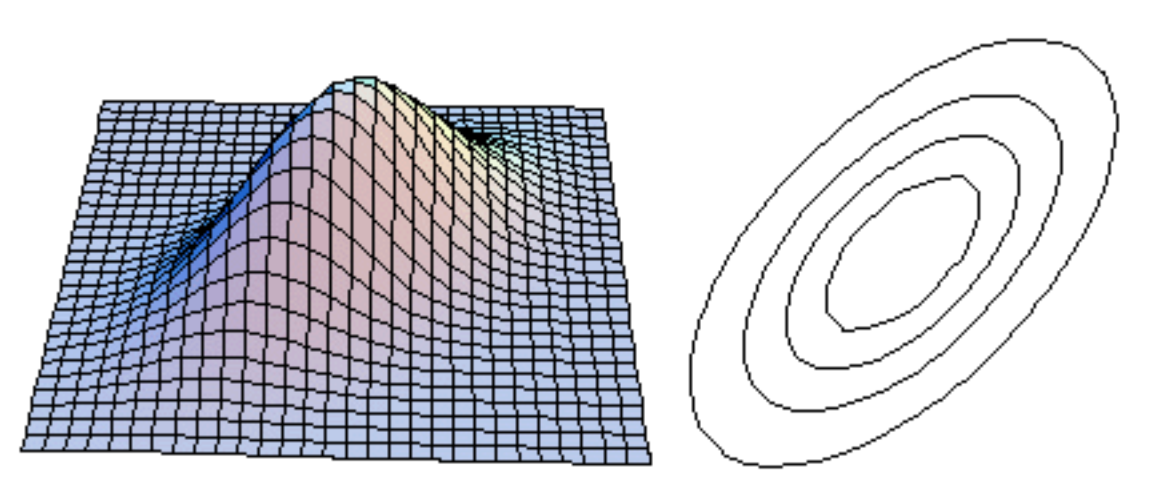
$P'(\underline{A}_1 \ldots \underline{A}_N \underline{B}) = P(\underline{A}_1 \ldots \underline{A}_N \underline{B})\, P'(\underline{A}_i) / P(\underline{A}_i)$

followed by marginalizations

Experiment with Gaussian Distributions

Multivariate Gaussian Distributions

$$f_X(x_1, \ldots, x_N) = \frac{1}{(2\pi)^{N/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)\right)$$



- **Unimodal**
- **Fully specified by mean vector and covariance matrix**
  => for K random variables K + K^2 numbers
- **Nice mathematical properties**

Example of Multivariate Gaussian Distribution

	c1	d1	c2	d2	c3	d3	c4
mean	2	1,5	1	2	1	5	2
standard deviation	0,5	0,4	0,3	0,5	0,3	1	0,5

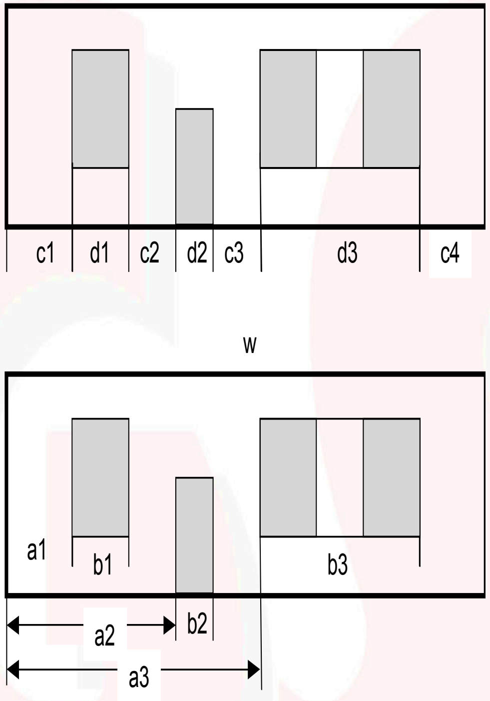
covariance special

	c1	d1	c2	d2	c3	d3	c4
c1	0,25	0,00	0,05	0,00	0,05	0,00	0,20
d1	0,00	0,16	0,00	0,06	0,00	0,32	0,00
c2	0,30	0,00	0,09	0,00	0,07	0,00	0,05
d2	0,00	0,30	0,00	0,25	0,00	0,15	0,00
c3	0,30	0,00	0,80	0,00	0,09	0,00	0,05
d3	0,00	0,80	0,00	0,30	0,00	1,00	0,00
c4	0,80	0,00	0,30	0,00	0,30	0,00	0,25

covariance

det 0,00015

	c1	d1	c2	d2	c3	d3	c4
c1	0,250	0,000	0,045	0,000	0,045	0,000	0,200
d1	0,000	0,160	0,000	0,060	0,000	0,320	0,000
c2	0,045	0,000	0,090	0,000	0,072	0,000	0,045
d2	0,000	0,060	0,000	0,250	0,000	0,150	0,000
c3	0,045	0,000	0,072	0,000	0,090	0,000	0,045
d3	0,000	0,320	0,000	0,150	0,000	1,000	0,000
c4	0,200	0,000	0,045	0,000	0,045	0,000	0,250



Properties of Multivariate Gaussian Distributions (1)

- **Distributions of subsets of variables are immediately available**

  => marginalisations at no cost

mean

	c1	d1	c2	d2	c3	d3	c4
	2	1,5	1	2	1	5	2

covariance

	c1	d1	c2	d2	c3	d3	c4
c1	0,25	0	0,045	0	0,045	0	0,2
d1	0	0,16	0	0,06	0	0,32	0
c2	0,045	0	0,09	0	0,072	0	0,045
d2	0	0,06	0	0,25	0	0,15	0
c3	0,045	0	0,072	0	0,09	0	0,045
d3	0	0,32	0	0,15	0	1	0
c4	0,2	0	0,045	0	0,045	0	0,25

Properties of Multivariate Gaussian Distributions (2)

- **Linear combinations are also multivariate Gaussians**

Example:

$s = d1 + c2 + d2$

$m_s = m_{d1} + m_{c2} + m_{d2}$

$s_s^2 = s_{d1}^2 + s_{c2}^2 + s_{d2}^2 + 2*(s_{d1\ c2} + s_{d1\ d2} + s_{c2\ d2})$

	c1	d1	c2	d2	c3	d3	c4
mean	2	1,5	1	2	1	5	2

covariance

	c1	d1	c2	d2	c3	d3	c4
c1	0,25	0	0,045	0	0,045	0	0,2
d1	0	0,16	0	0,06	0	0,32	0
c2	0,045	0	0,09	0	0,072	0	0,045
d2	0	0,06	0	0,25	0	0,15	0
c3	0,045	0	0,072	0	0,09	0	0,045
d3	0	0,32	0	0,15	0	1	0
c4	0,2	0	0,045	0	0,045	0	0,25

Properties of Multivariate Gaussian Distributions (3)

- **Closed-form expressions for conditionals** [edit]

ı and Σ are partitioned as follows

$$\mu = \begin{bmatrix}\mu_1\\ \mu_2\end{bmatrix} \text{with sizes} \begin{bmatrix} q \times 1 \\ (N-q) \times 1 \end{bmatrix}$$

$$\Sigma = \begin{bmatrix}\Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22}\end{bmatrix} \text{with sizes} \begin{bmatrix} q \times q & q \times (N-q) \\ (N-q) \times q & (N-q) \times (N-q) \end{bmatrix}$$

then the distribution of x_1 conditional on $x_2 = a$ is multivariate normal $(X_1 | X_2 = a) \sim N(\bar{\mu}, \overline{\Sigma})$ where

$$\bar{\mu} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(a - \mu_2)$$

and covariance matrix

$$\overline{\Sigma} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}.$$

This matrix is the Schur complement of Σ_{22} in Σ.

Note that knowing the value of x_2 to be a alters the variance; perhaps more surprisingly, the mean is shifted by $\Sigma_{12}\Sigma_{22}^{-1}(a - \mu_2)$; compare this with the situation of not knowing the value of a, in which case x_1 would have distribution $N_q(\mu_1, \Sigma_{11})$.

The matrix $\Sigma_{12}\Sigma_{22}^{-1}$ is known as the matrix of regression coefficients.

Properties of Multivariate Gaussian Distributions (4)

- **Closed-form expressions for partial updates**

$$\Sigma_G = \begin{vmatrix} \Sigma_C & \Sigma_{CD} \\ \Sigma_{CD}^T & \Sigma_D \end{vmatrix} \qquad \underline{\mu}_G = \begin{vmatrix} \underline{\mu}_C \\ \underline{\mu}_D \end{vmatrix}$$

For a probability update, we assume that the distribution of $\underline{D}$ is changed to

$$P(\underline{D}') = N(\underline{\mu}_D', \Sigma_D').$$

Then the new distribution $P'(\underline{G})$ is

$$P'(\underline{G}) = N(\underline{\mu}_G', \Sigma_G')$$

with $\Sigma_G' = \begin{vmatrix} \Sigma_C' & \Sigma_{CD}' \\ \Sigma_{CD}'^T \Sigma_D' \end{vmatrix} \qquad \underline{\mu}_G' = \begin{vmatrix} \underline{\mu}_C' \\ \underline{\mu}_D' \end{vmatrix}$

where $\Sigma_C' = \Sigma_C - \Sigma_{CD}\,\Sigma_D^{-1}\,\Sigma_{CD}^T + \Sigma_{CD}\,\Sigma_D^{-1}\,\Sigma_D'\,\Sigma_D^{-1}\,\Sigma_{CD}^T$

$$\Sigma_{CD}' = \Sigma_{CD}\,\Sigma_D^{-1}\,\Sigma_D'$$

$$\underline{\mu}_C' = \underline{\mu}_C + \Sigma_{CD}\,\Sigma_D^{-1}\,(\underline{\mu}_D' - \underline{\mu}_D)$$

Properties of Multivariate Gaussian Distributions (5)

- **Conditional independence**

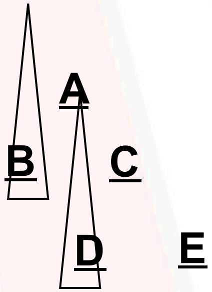
Given a multivariate Gaussian distribution with

$$S = \begin{vmatrix} \Sigma_X & \Sigma_{XY} & \Sigma_{XZ} \\ \Sigma_{XY} & \Sigma_Y & \Sigma_{YZ} \\ \Sigma_{XZ} & \Sigma_{YZ} & \Sigma_Z \end{vmatrix}$$

then $P(\underline{X}|\underline{Y}) = P(\underline{X}|\underline{YZ})$ holds iff

$$\Sigma_{XZ} = \Sigma_{XY}\,\Sigma_Y^{-1}\,\Sigma_{YZ}$$

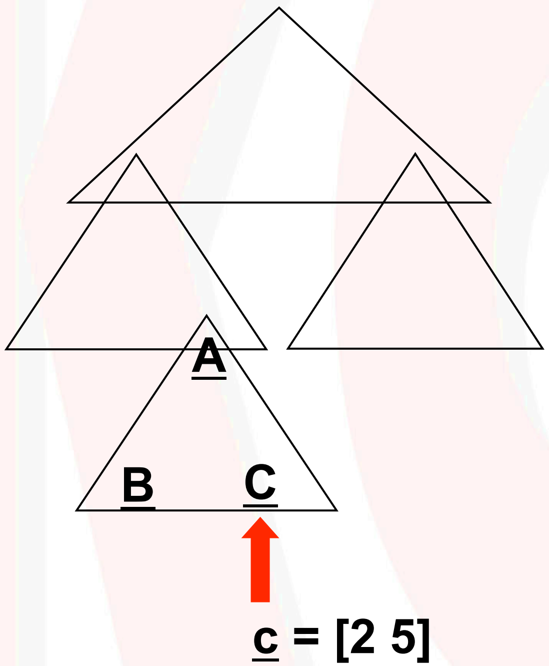
Easy chaining of aggregates with abstraction property:



$$\begin{vmatrix} \Sigma_A & \Sigma_{AB} & \Sigma_{AC} & \Sigma_{AD} & \Sigma_{AE} \\ \Sigma_{AB} & \Sigma_B & \Sigma_{BC} & \Sigma_{BD} & \Sigma_{BE} \\ \Sigma_{AC} & \Sigma_{BC} & \Sigma_C & \Sigma_{CD} & \Sigma_{CE} \\ \Sigma_{AD} & \Sigma_{BD} & \Sigma_{CD} & \Sigma_D & \Sigma_{DE} \\ \Sigma_{AE} & \Sigma_{BE} & \Sigma_{CE} & \Sigma_{DE} & \Sigma_E \end{vmatrix}$$

Propagation Procedures (1)

Integrating local evidence



evidence modelled as distribution with 0 variance

1. P(C) => P´(C) = N(m=[2 5], S=0)
3. P(ABC) => P´(ABC)

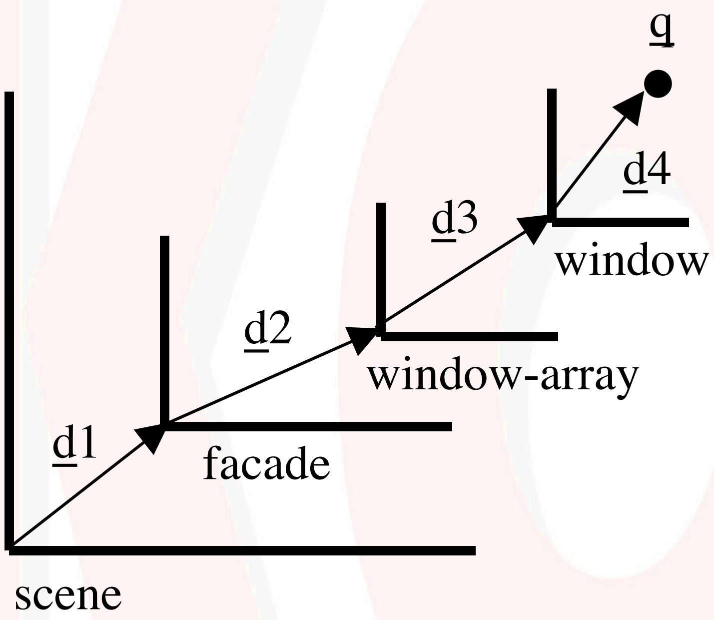
   using partial update formulas

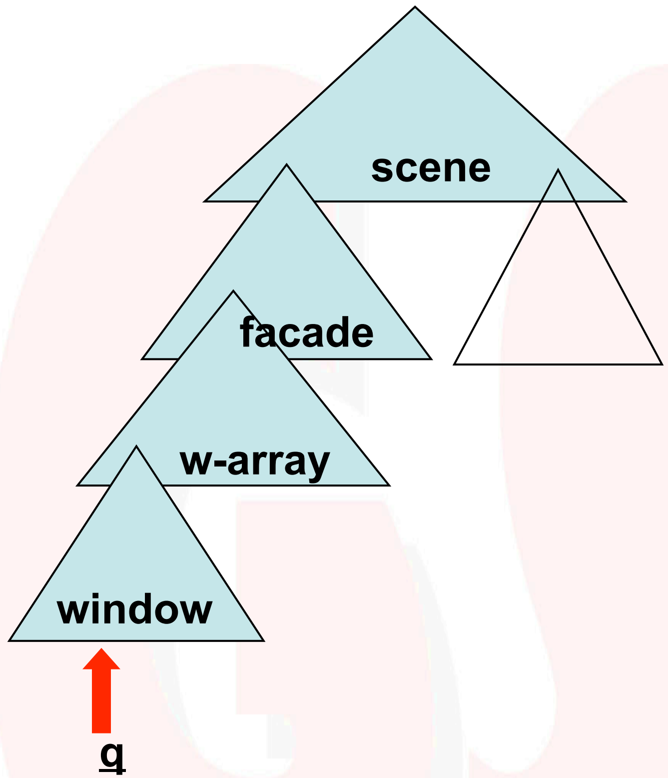
3. Propagate through tree

   using partial update formulas

Propagation Procedures (2)

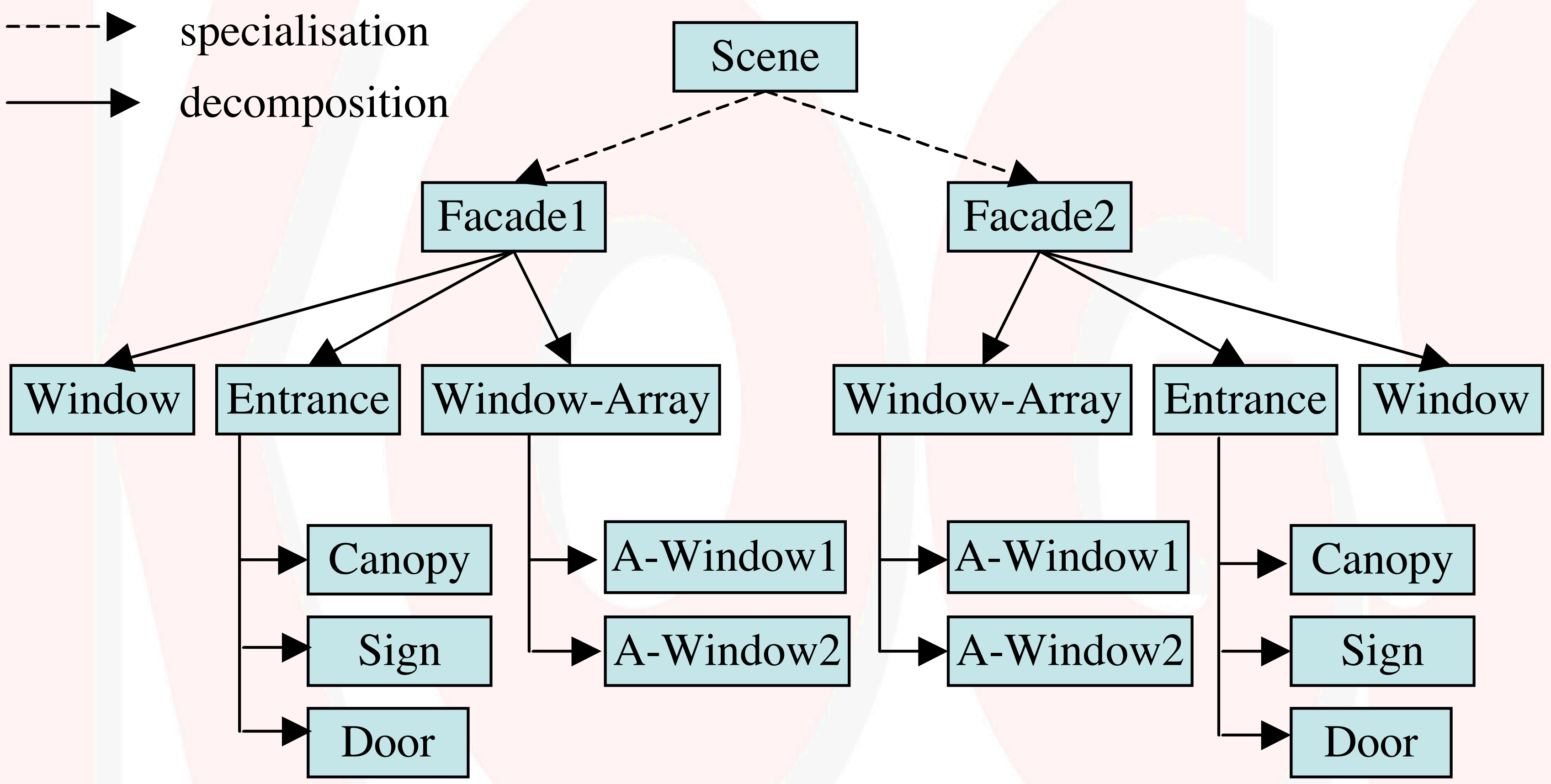
<u>Integrating absolute position evidence</u>





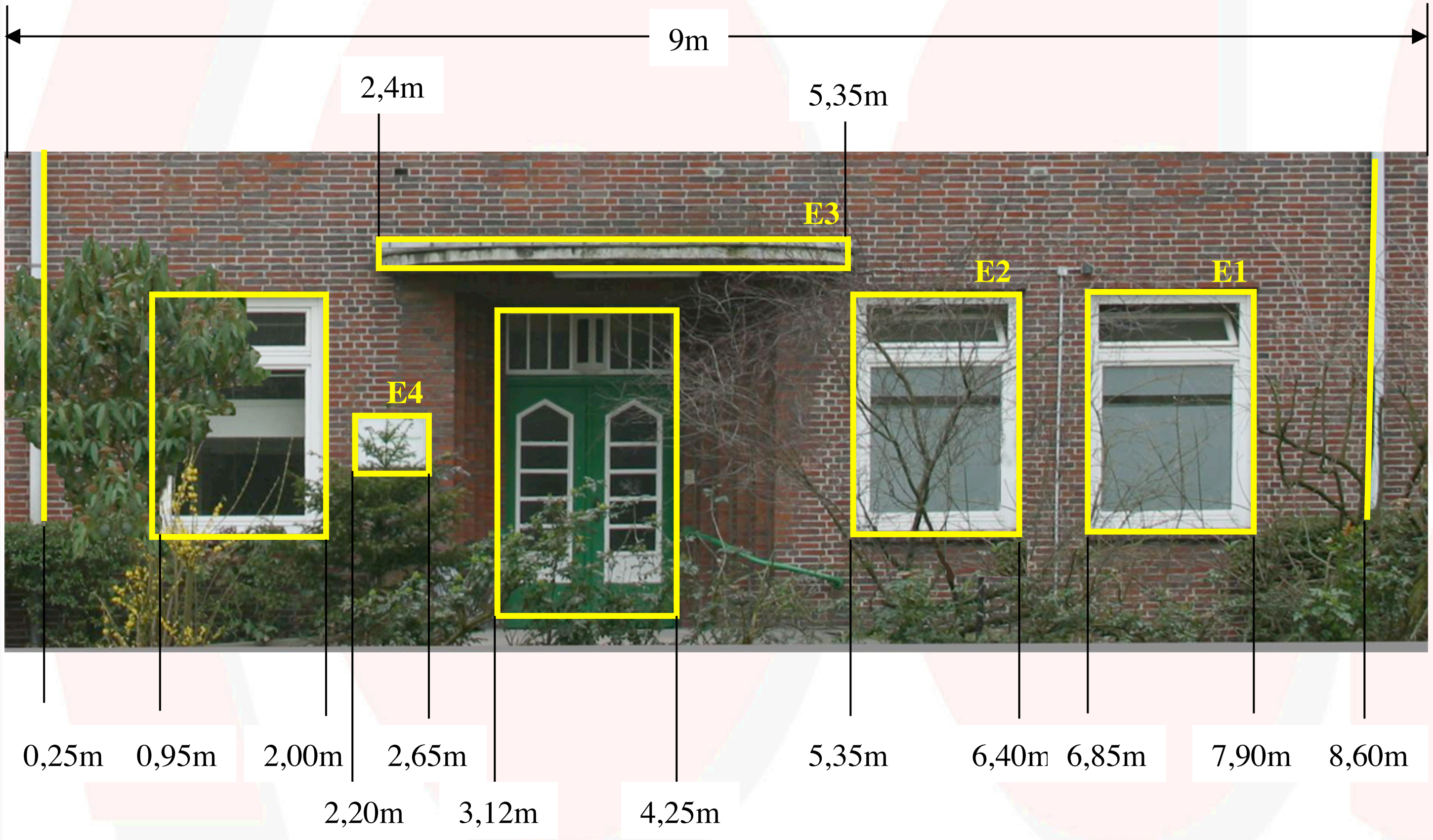
1. Determine JPD N_{chain} of aggregate chain from leaf to root using conditional independence requirements
2. q is sum of components of N_{chain}. Extend chain by q to N'_{chain}
3. Update N'_{chain} using evidence q
4. Propagate from N'_{chain} to connected aggregates (lazy)

Example Hierarchy



Example Image

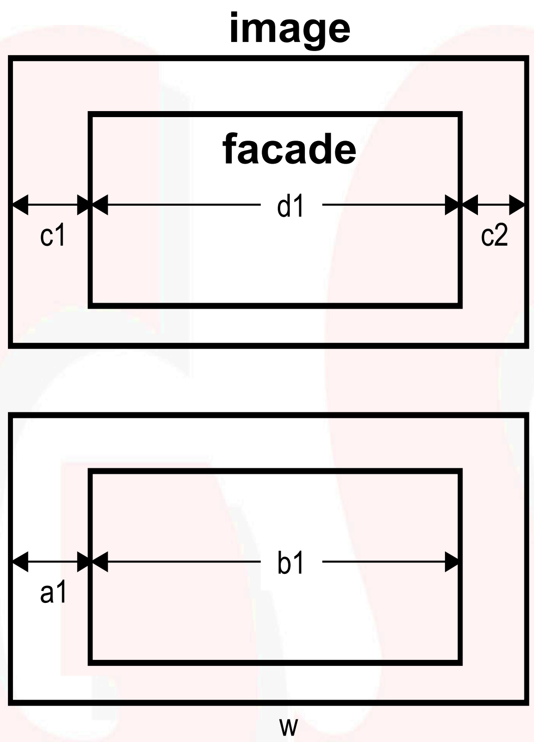
Initial evidence



Scene Model

mean		1	12	1
standard deviation		3	3	2
covariance special	c1	9	0	3
	d1	0	9	0
	c2	0,5	0	4
covariance	c1	9	0	3
	d1	0	9	0
	c2	3	0	4

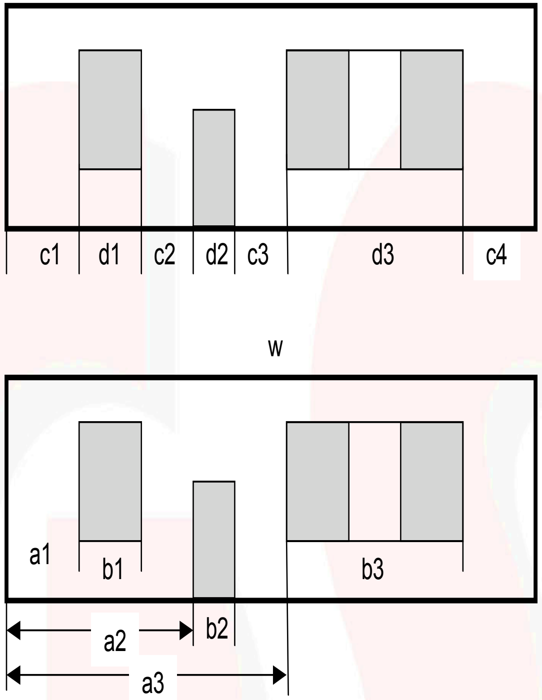
		S.a1	S.b1	S.w	
aggregate mean		1	12	14	
aggregate variance		9	9	28	
aggregate covariance	S.a1	9	0	12	a1=c1
	S.b1	0	9	9	b1=d1
	S.w	12	9	28	w=c1+d1+c2



- **Mean and standard deviation in meters**
- **S.w is determined by pixel-per-meter annotation**

Facade1 Model

		c1	d1	c2	d2	c3	d3	c4
mean		2	1,5	1	2	1	5	2
standard deviation		0,5	0,4	0,3	0,5	0,3	1	0,5
covariance special	c1	0,25	0,00	0,05	0,00	0,05	0,00	0,20
	d1	0,00	0,16	0,00	0,06	0,00	0,32	0,00
	c2	0,30	0,00	0,09	0,00	0,07	0,00	0,05
	d2	0,00	0,30	0,00	0,25	0,00	0,15	0,00
	c3	0,30	0,00	0,80	0,00	0,09	0,00	0,05
	d3	0,00	0,80	0,00	0,30	0,00	1,00	0,00
	c4	0,80	0,00	0,30	0,00	0,30	0,00	0,25



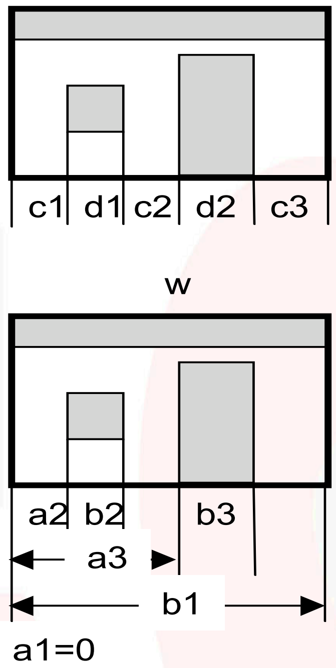
		F1.a1	F1.b1	F1.a2	F1.b2	F1.a3	F1.b3	F1.w	
aggregate mean		2	1,5	4,5	2	7,5	5	14,5	
aggregate variance		0,25	0,16	0,25	0,25	1,66	1	4,05	
aggregate covariance	F1.a1	0,25	0,00	0,30	0,00	0,34	0,00	0,54	a1=c1
	F1.b1	0,00	0,16	0,16	0,06	0,22	0,32	0,54	b1=d1
	F1.a2	0,30	0,16	0,59	0,06	0,77	0,32	1,33	a2=c1+d1+c2
	F1.b2	0,00	0,06	0,06	0,25	0,31	0,15	0,46	b2=d2
	F1.a3	0,34	0,22	0,77	0,31	1,28	0,47	2,04	a3=c1+d1+c2+d2+c3
	F1.b3	0,00	0,32	0,32	0,15	0,47	1,00	1,47	b3=d3
	F1.w	0,54	0,54	1,33	0,46	2,04	1,47	4,05	w=c1+d1+c2+d2+c3+d3+c4

Facade2 has parts in reverse order

Entrance Model

	c1	d1	c2	d2	c3
mean	0,3	0,3	0,3	1	0,5
standard deviation	0,3	0,1	0,15	0,2	0,25

covariance special		c1	d1	c2	d2	c3
	c1	0,09	0,00	0,01	0,00	0,02
	d1	0,10	0,01	0,00	0,01	0,00
	c2	0,30	0,00	0,02	0,00	0,02
	d2	0,00	0,30	0,00	0,04	0,00
	c3	0,30	0,00	0,80	0,00	0,06



	E.a1	E.b1	E.a2	E.b2	E.a3	E.b3	E.w
aggregate mean	0	2,4	0,3	0,3	0,9	1	2,4
aggregate variance	0	0,36	0,09	0,01	0,16	0,04	0,36

aggregate covariance		E.a1	E.b1	E.a2	E.b2	E.a3	E.b3	E.w	
	E.a1	0	0	0	0	0	0	0	a1=0
	E.b1	0	0,36	0,13	0,02	0,21	0,05	0,36	b1=c1+d1+c2+d2+c3
	E.a2	0	0,13	0,09	0,00	0,11	0,00	0,13	a2=c1
	E.b2	0	0,02	0,00	0,01	0,01	0,01	0,02	b2=d1
	E.a3	0	0,21	0,11	0,01	0,16	0,01	0,21	a3=c1+d1+c2
	E.b3	0	0,05	0,00	0,01	0,01	0,04	0,05	b3=d2
	E.w	0	0,36	0,13	0,02	0,21	0,05	0,36	w=b1

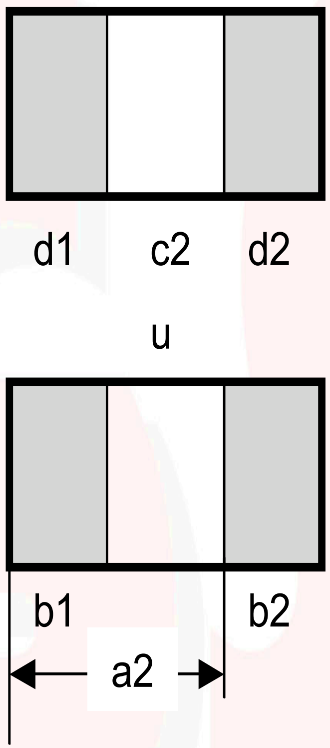
Window-Array Model

	d1	c2	d2
mean	1,5	2	1,5
standard deviation	0,5	1	0,5

covariance special		d1	c2	d2
	d1	0,25	0	0,225
	c2	0	1	0
	d2	0,9	0	0,25

	a1	b1	a2	b2	w
aggregate mean	0	1,5	3,5	1,5	5
aggregate variance	0	0,25	1,25	0,25	1,95

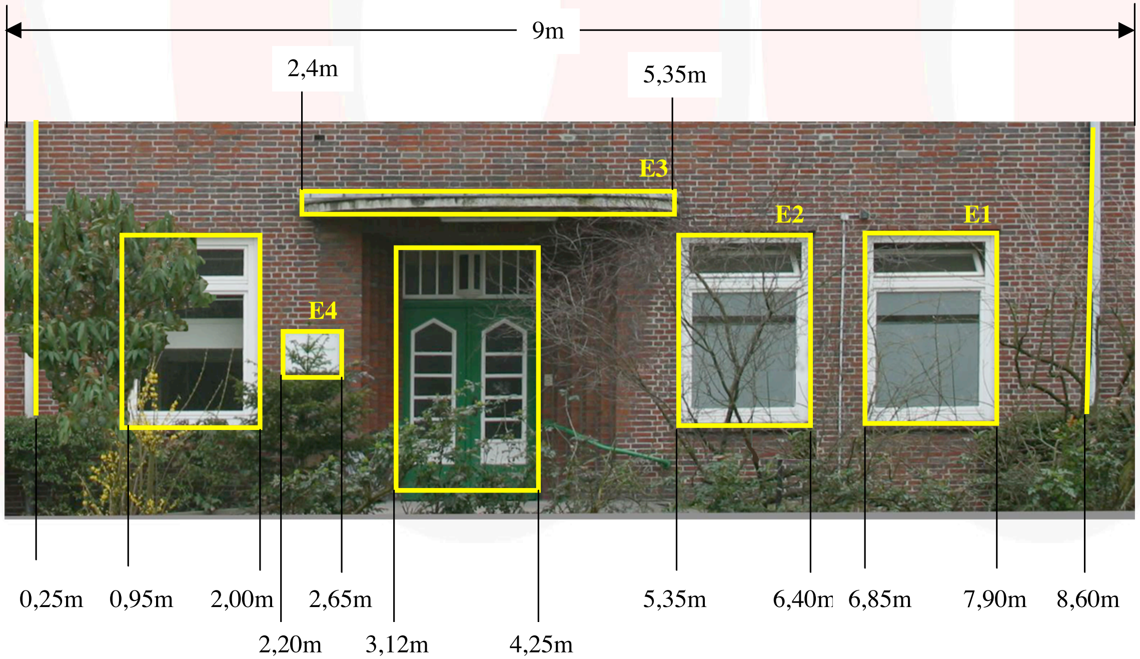
aggregate covariance		a1	b1	a2	b2	w	
	a1	0	0	0	0	0	a1=0
	b1	0	0,25	0,25	0,23	0,48	b1=d1
	a2	0	0,25	1,25	0,23	1,48	a2=d1+c2
	b2	0	0,23	0,23	0,25	0,48	b2=d2
	w	0	0,48	1,48	0,48	1,95	w=d1+c2+d2



Stepwise Interpretation (1)

Range values after initialisation (range = mean ± 2*standard deviation)

after initialisation	S.a1	S.b1	F1.a1	F1.b1	F1.a2	F1.b2	F1.a3	F1.b3	WA.b1	WA.a2	WA.b2	E.b1	E.a2	E.b2	E.a3	E.b3
range min [m]	-5,07	5,45	0,38	0,07	1,35	0,48	2,74	1,26	0,22	0,52	0,22	0,48	-0,57	0,06	-0,31	0,50
range max [m]	2,79	15,34	2,52	1,84	4,95	2,59	8,12	5,76	2,05	4,23	2,05	2,59	0,55	0,45	1,12	1,28
after initialisation			**F2.a1**	**F2.b1**	**F2.a2**	**F2.b2**	**F2.a3**	**F2.b3**	**WA.b1**	**WA.a2**	**WA.b2**	**E.b1**	**E.a2**	**E.b2**	**E.a3**	**E.b3**
range min [m]			0,39	1,29	2,85	0,49	4,33	0,08	0,23	0,54	0,23	0,49	-0,57	0,06	-0,30	0,50
range max [m]			2,53	5,77	8,57	2,59	11,67	1,84	2,06	4,24	2,06	2,59	0,56	0,45	1,12	1,28



Stepwise Interpretation (2)

Testing window models for evidence E2

after initialisation	Facade1 left window	Facade1 Window-Array	Facade1 Window-Array Window2	Facade2 Window-Array Window1	Facade2 Window-Array Window2	Facade2 right window
Absolute position range min [m]	-3,22	1,62	3,98	-3,22	-0,15	4,34
Absolute position range max [m]	3,84	6,95	9,34	3,86	5,56	9,38
Likelihood of evidence E2	0,0017	0,0981	0,0788	0,0012	0,0108	0,0670

Testing canopy models for evidence E3

after initialisation	Facade1 canopy	Facade2 canopy
Absolute position range min [m]	-0,91	2,03
Absolute position range max [m]	4,93	7,11
Likelihood of evidence E4	0,01036	0,00015

Stepwise Interpretation (3)

Updated priors after assigning evidence E3

after assigning canopy	S.a1	S.b1	F1.a1	F1.b1	F1.a2	F1.b2	F1.a3	F1.b3	WA.b1	WA.a2	WA.b2	E.b1	E.a2	E.b2	E.a3	E.b3
range min [m]	-1,12	12,77	1,51	1,24	3,52	2,4	7,22	4,09	0,41	1,21	0,41	2,4	0,50	0,329	1,22	1,07
range max [m]	0,69	3,705	0,28	0,15	0,69	0	1,07	0,89	2,14	4,41	2,14	0	0,04	0,009	0,04	0,03

Updated priors for evidence E2

after assigning canopy evidence	Facade1 left window	Facade1 Window-Array Window1	Facade1 Window-Array Window2
Absolute position range min [m]	-3,22	4,94	7,17
Absolute position range max [m]	3,84	7,26	10,66
Likelihood of evidence E2	4,5E-19	0,163	0,00008

=> likelihood quotient p(Window1) / p(Window2) > 2000

Stepwise Interpretation (4)

Updated priors after assigning evidences E1 - E4

after assigning evidence E1 - E4	Facade1		Left window		Door	
abolute position / width						
range min	-1,12	6,88	0,76	0,35	2,94	1,01
range max	1,30	10,95	1,96	1,31	3,33	1,67
actual values in the image	0,25	7,35	0,95	1,05	3,12	1,13

=> focussed expectations for fine-grained low-level image analysis

Vielen Dank für die Aufmerksamkeit!