Towards Generic Models for Scene Interpretation

- Need for model-based approach
  - spatially and temporally coherent configurations
  - organising relevant knowledge
- Logic-based and probabilistic knowledge*
  - deduction, rules, uncertainty, consistency
- Interface to low-level vision
  - signal-symbol interface
  - quantitative-qualitative mapping
- Interpretation strategies
  - bottom-up vs. top-down
  - varying context
  - prediction

*) Probabilistic issues will be treated later

1

Conceptual Units for Scene Interpretation

What kind of concepts must be represented for scene interpretation?

Concepts for

- **object constellations**
  e.g. laid-table, kitchen, parking ground, town
- **activities, events, episodes**
  e.g. operating a CD-player, one car overtaking another, playing soccer

Typical scene interpretation concepts describe entities composed of sub-entities related to each other in space and time. We call such entities "aggregates".

Note: The term "aggregate" will at times be used for an aggregate model (a conceptual description of a kind of aggregates) and at other times for an aggregate instance (a concrete occurrence of an aggregate). Hopefully, the context clarifies the intended meaning.

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Aggregate Structure

Basic structure of a frame-based representation of an aggregate concept:

aggregate name
parent concepts
external properties
parts
constraints between parts

- *aggregate name* contains a symbolic ID
- *parent concepts* contains IDs of taxonomical parents
- *external properties* provide a description of the aggregate as a whole
- *parts* describe the subunits out of which an aggregate is composed
- *constraints* specify which relations must hold between the parts

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Occurrence Model for Overtaking

name:	overtake
	:local-name ov
parents:	:is-a occurrence-model
arguments:	(?veh1 :is-a vehicle)
	(?veh2 :is-a vehicle)
properties:	(ue.B ue.E)
parts :	(mv1 :is-a (move ?veh1 mv1.B mv1.E))
	(mv2 :is-a (move ?veh2 mv2.B mv2.E))
	(bh :is-a (behind ?veh1 ?veh2 bh.B bh.E))
	(bs :is-a (beside ?veh1 ?veh2 bs.B bs.E))
	(bf :is-a (before ?veh1 ?veh2 bf.B bf.E))
	(ap :is-a (approach ?veh1 ?veh2 ap.B ap.E))
	(rc :is-a (recede ?veh1 ?veh2 rc.B rc.E))
constraints:	(ov.B = bh.B)
	(ov.E = bf.E)
	(ap :during mv1)
	(ap :during mv2)
	(rc :during mv1)
	(rc :during mv2)
	(bh :overlaps bs)
	(bs :overlaps bf)
	(bh :during ap)
	(bf :during rc)

Note:
Aggregate format may vary according to expressiveness of knowledge representation language and syntactic conventions

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Table-laying Scenario

Important high-level characteristics:

- correlated multiple object motion
- intended actions
- influence of context (temporal, spatial, task context)
- qualitative spatial and temporal relations
- uncertainty
- smart room learning context (supervised, unsupervised)
- interface with common sense

Table-laying scenario of project CogVis:

Stationary cameras observe living room scene and recognize meaningful occurrences, e.g. placing a cover onto the table.

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Occurrence Model for Placing a Cover

```
name:         place-cover
parents:      :is-a agent-activity
parts:        pc-tp1 :is-a (transport with (tp-obj :is plate))     %transport of a plate
              pc-tp2:is-a (transport with (tp-obj :is saucer))     %transport of a saucer
              pc-tp3 :is-a (transport with (tp-obj :is cup))       %transport of a cup
              pc-cv :is-a cover                                    %cover configuration
properties:   tb, te :is-a timepoint        %begin and end timepoint of place-cover
constraints:  pc-tp1.tp-ob = pc-cv.cv-pl    %transport-plate object same as cover-plate
              pc-tp2.tp-ob = pc-cv.cv-sc    %transport-saucer object same as cover-saucer
              pc-tp3.tp-ob = pc-cv.cv-cp    %transport-cup object same as cover-cup
              pc-cv.tb ≥ pc-tp1.te          %cover begins after plate transport
              pc-cv.tb ≥ pc-tp2.te          %cover begins after saucer transport
              pc-cv.tb ≥ pc-tp3.te          %cover begins after cup transport
              pc-tp3.tp-te ≥ pc-tp2.tp-te   %cup transport ends after saucer transport
              tb = pc-tp1.tb min pc-tp2.tb min pc-tp3.tb           %begin of place-cover
              te = pc-tp1.te max pc-tp2.te max pc-tp3.te           %end of place-cover
              te ≤ tb + 80Dt                %place-cover may not last more than 80 time units
```

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Model for a Cover Configuration

name:	cover	
parents:	:is-a configuration	
parts:	cv-pl :is-a plate	
	cv-sc :is-a saucer	
	cv-cp :is-a cup	
	cv-tt :is-a table-top	
properties:	w, h, tb, te	%width and height of cover
constraints:	cv-sc.pos NE cv-pl.pos	%saucer position northeast of plate position
	cv-sc.rim CLOSE cv-pl.rim	%saucer rim close to plate rim
	cv-cp.pos = cv-sc.pos	
	cv-tt.rim SO cv-pl.rim	%table-top rim south of plate rim

Spatial relations NO (north), NE (northeast), ... , SO (south), ... ,
CLOSE must be defined and computable based on parts properties.

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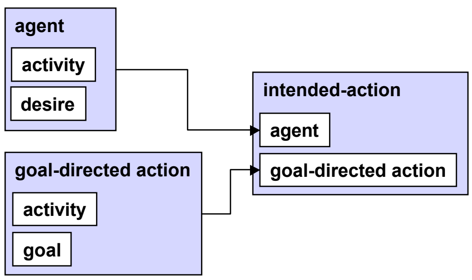
Models for Intention Recognition

Intended actions may be described by aggregates which connect observable actions with (unobservable) intentions of an actor.

name:	intended-place-cover
parents:	:is-a intended-action
parts:	ipc-pc :is-a place-cover
	ipc-ag :is-a agent with (ipc-ag.desire = ipc-pc.goal)
properties:	tb, te :is-a timepoint
constraints:	(temporal, spatial and other constraints on parts)



If an action is known to be goal-directed and an agent performs such an action, the agent is ascribed the intention to attain the goal.

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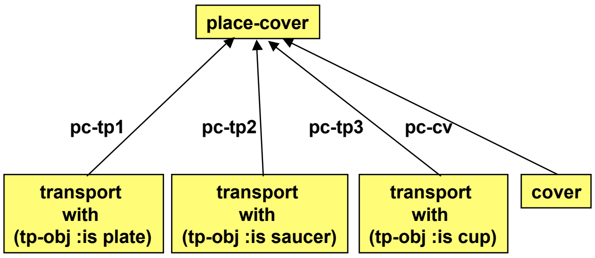
Parts Structure

Associational structure between aggregates and their parts



"In a place-cover occurrence one will see transport occurrences with plate, saucer and cup, and a cover configuration."

Note that redundant parts could be added, e.g. plate, saucer, cup, table-top and linked to other parts by equality constraints. Redundant parts may be useful for triggering part-whole reasoning ("*If you see a plate and the transport of a saucer, hypothesise a place-cover*").

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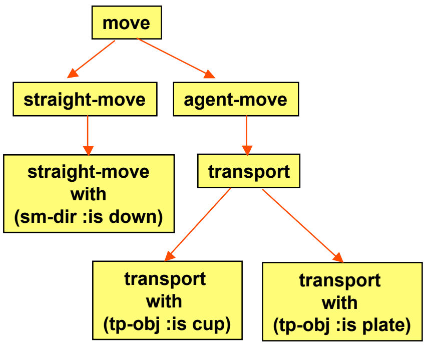
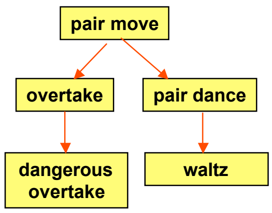
Forming a Taxonomical Hierarchy

Remember:
- **A concept denotes a set of "objects".**
- **"Objects" may be physical objects, occurrences, configurations, ...**
- **A specialisation denotes a subset of a parent concept.**
- **Different kinds of "objects" require different hierarchies.**

motion of a physical object



motion of a pair of physical objects



Note that *pair move* could also be represented as a specialisation of *move* (a moving object specialised by a relation to an accompanying object).

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Physical Objects and Views

Representations of physical (3D) objects must be distinguished from representations of evidence obtained by sensors, e.g. 2D views.

Suggested conceptual representation:

physical object x $\xrightarrow{\text{has-view}}$ views of physical object x

In a conceptual knowledge base ...

- **a physical object model describes properties of 3D objects irrespective of sensors,**
- **a view model describes the responses of a specific sensor for a 3D object.**

Views may alternatively be represented as "properties" of physical objects, but the explicit representation above emphasises the dependency on sensors and alleviates multi-sensor modelling.

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Signal-symbol Interface

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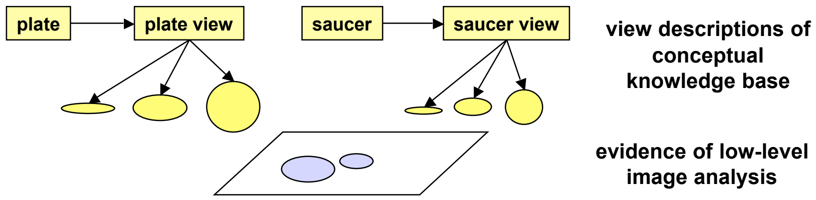
Results of Low-level Image Analysis

Assumptions

- Low-level image analysis provides evidence which can be matched with object views of the conceptual knowledge base.



- Evidence is represented in metric space.
- Evidence may be
  - regions corresponding to objects
  - blobs corresponding to object parts
  - descriptive features around interest points

  ...

depending on sophistication of object recognition and categorisation

Tasks of Signal-Symbol Interface

- **Matching evidence with views**
  - bottom-up: classification
  - top-down: hypothesis verfication
- **Depth management**
  - maintaining a qualitative depth map
  - maintaining consistency of occlusion hypotheses
- **Computing predicates on perceptual primitives**
  - providing useful primitives for inter-object relations
  - enabling temporal segmentation

All of these tasks are still research topics.
Some ideas and possible approaches will be shown in the following slides.

Matching Evidence with Views

Bottom-up classification

Assign evidence to one of several view classes.

Model-based recognition problem with view classes as models.

In a probabilistic setting same as Bayesian classification, except that a priori class probabilities depend on interpretation context.

Top-down hypothesis verfication

Check compatibility of top-down view hypothesis with available evidence and other top-down hypotheses.

Checking with evidence is similar to bottom-up classification, except that model is given and evidence is selected.

Checking with other top-down hypotheses is a harder task, as all hypotheses may have uncertainty ranges. How can several hypotheses with uncertain views and locations fit into an image, observing factual evidence and occlusion rules?

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Predicates on Perceptual Primitives

Useful for describing relations between objects (e.g. "close-to", "beside", "parallel") and inducing primitive occurrences (e.g. "approach", "turn")

1. **Measurements of perceptual primitives**
    - **Evidence objects provide reference features:**
        - locations (center of gravity, corners, surface markings, etc.)
        - lines (edges, surface markings, axes of minimal inertia, etc.)
        - orientations (inate, motion-dependent, viewer-dependent)
        - size, shape, photometric properties
    - **Measurements between geometric reference features:**
        - distance, relative orientation, orientation of location difference vector
        - temporal derivatives thereof
2. **Qualitative predicates**
    - **Qualitatively constant values** e.g. constant orientation, constant distance
    - **Values within a certain range** e.g. topological relations, degrees of nearness, typical speeds, slowing down, inceasing distance

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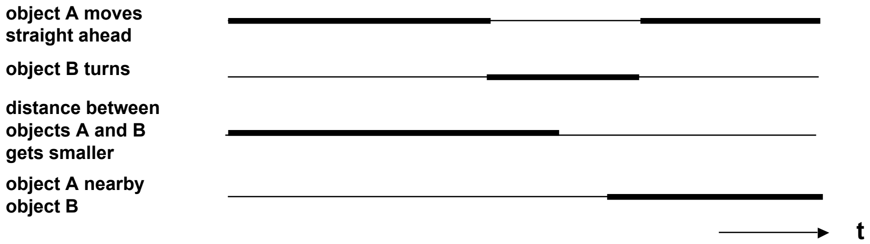
Primitive Occurrences

A primitive occurrence is a symbolic entity involving one or more evidence objects for which a qualitative predicate is true over a time interval.

Primitive occurrences provide the raw material for the interpretation of time-varying scenes.



In a natural scene, one may observe many time-dependent perceptual primitives and determine many primitive occurrences. Hence it may be useful to compute primitive occurrences on demand (attention driven).

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Primitive Occurrences in Traffic Scenes

B. Neumann: Natural Language Description of Time-Varying Scenes. In: Semantic Structures, D. Waltz (Hrsg.), Lawrence Erlbaum, 167-206, 1989

exist
move
decelerate, accelerate
turn_left, turn_right
increasing_distance, reducing_distance
along, across
in_front_of, behind, beside
on, above, under, below
at, near_to
between
(and others)

Note that qualitative predicates are often (but must not be) part of natural language.

For technical applications one may use technical (artificial) qualitative predicates, e.g.

v50 (= $45 \le v \le 55$ km/h)

shape_x (= shape_index ≤ 4.174)

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Temporal vs. Spatial Decomposition of Scenes

Temporal decomposition

- **by temporal segmentation:**
  constancies of time-dependent properties of an image sequence
- **by model matching:**
  occurrences which obey a model

Compare with spatial decomposition

- **by spatial segmentation:**
  image regions with spatially constant (uniform) properties
- **by model matching:**
  image regions which obey a model

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Scene Interpretation Process

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Stepwise Construction of Scene Interpretations

Given taxonomical and compositional concept hierarchies, there are five kinds of interpretation steps for constructing interpretations consistent with evidence:

Evidence matching
Assignment of evidence to object view classes or verification of view hypotheses.

Aggregate instantiation
Inferring an aggregate from (not necessarily all) parts

Instance specialization
Refinements along specialization hierarchy or in terms of aggregate parts

Instance expansion
Instantiating parts of an instantiated aggregate

Instance merging
Merging identical instances constructed by different interpretation steps

Repertoire of interpretation steps allows flexible interpretation strategies
e.g. mixed bottom-up and top-down, context-dependent, task-oriented

Basic Interpretation Algorithm

Enter context information
Repeat
- **Check for goal completion**
- **Check for new evidence**
- **Determine possible interpretation steps and update agenda**
- **Select from agenda one of**
  - **{ evidence matching,**
  - **aggregate instantiation,**
  - **aggregate expansion,**
  - **instance specialization,**
  - **parameterization,**
  - **constraint propagation }**
- **Check for conflict**

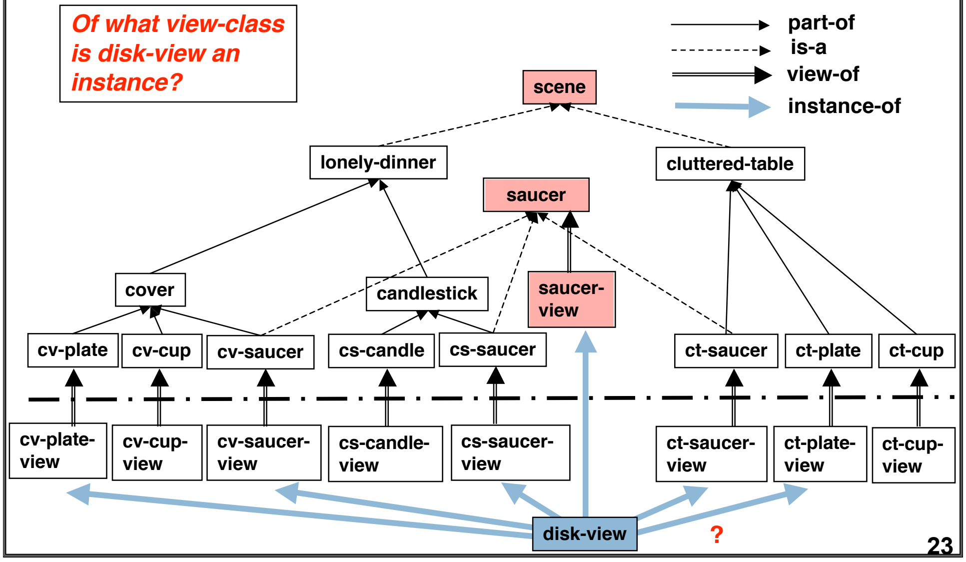
end

Conflict = unsatifiable constraint net

=> need for backtracking

Example for Interpretation Steps (1)

Of what view-class is disk-view an instance?



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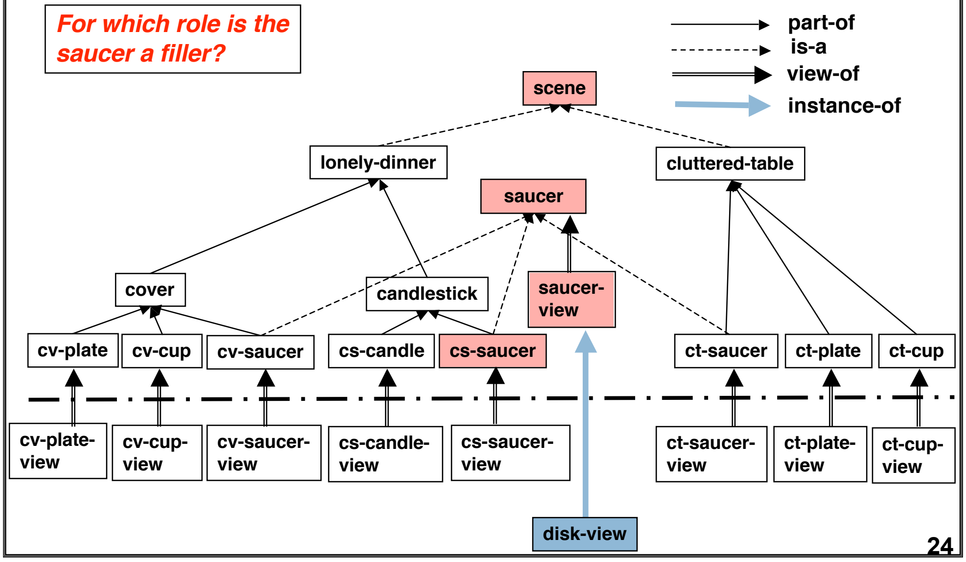
Example for Interpretation Steps (2)

For which role is the saucer a filler?



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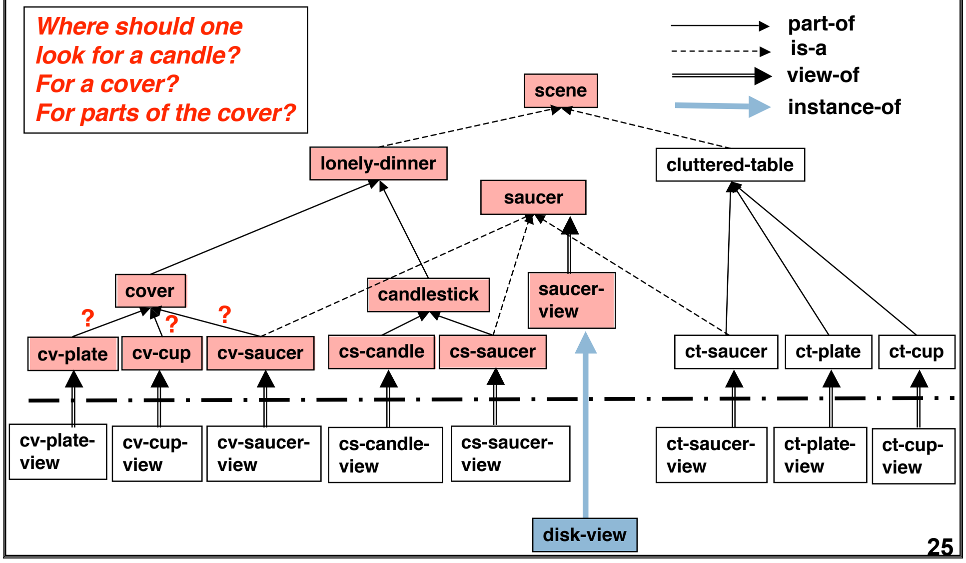
Example for Interpretation Steps (3)

Where should one look for a candle?
For a cover?
For parts of the cover?



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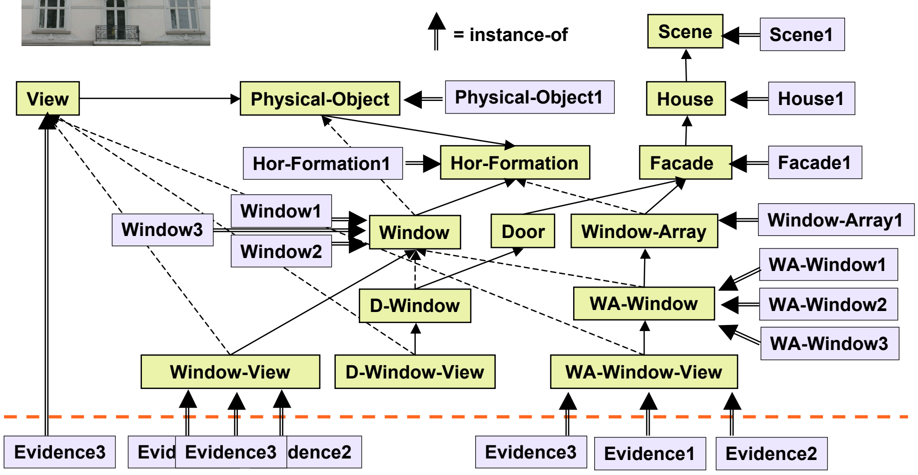
Facade Interpretation



Animated Slide!

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Hallucination Space

Interpretation steps allow to liberally hypothesise ("hallucinate") parts of aggregates and to come up with multiple alternative interpretations.

The validity of an interpretation depends on the available evidence and the readiness to believe in an interpretation based on scarce or no evidence.

Hallucination is desirable
- to predict future occurrences,
- to cope with occluded or unobserved evidence.

Hallucination is problematic because
- many alternative interpretations are permitted,
- a single interpretation may include many unsupported hypotheses.

Practical use of hallucination for scene interpretation requires that interpretation steps are guided by a preference measure (later in this course).

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Alternative Scene Representations

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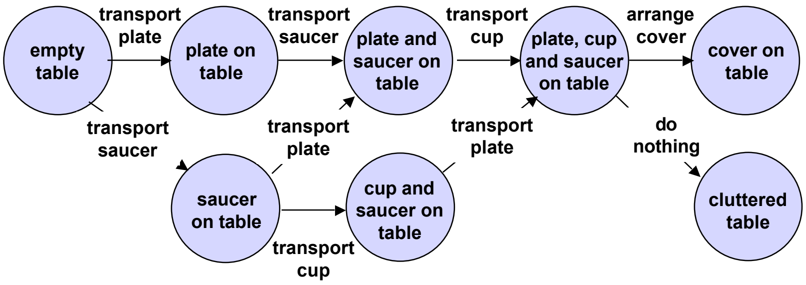
State Transition Models (1)

Sometimes occurrences can be descibed as transitions between states.

Placing a cover:



State transition models provide an explicit representation of

- states = intervals with specific constant properties
- state transitions = events leading from one state to another
- partial temporal ordering of states based on temporal succession

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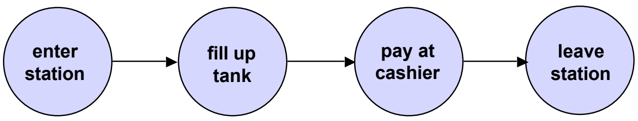
State Transition Models (2)

States need not be stationary, e.g. filling up at a gas station:



Here the transitions denote "temporal succession" without specifying events or activities associated with the transitions.

State transition models are atractive because they allow to abstract from many details and also relate to probabilistic Markov Models.

But the operational semantics are not always clear, e.g.

Are there temporal constraints for state transitions?

If a state is defined by several predicates -
what is the temporal extent of a state?

What is a generalisation or a specialisation of a state transition model?

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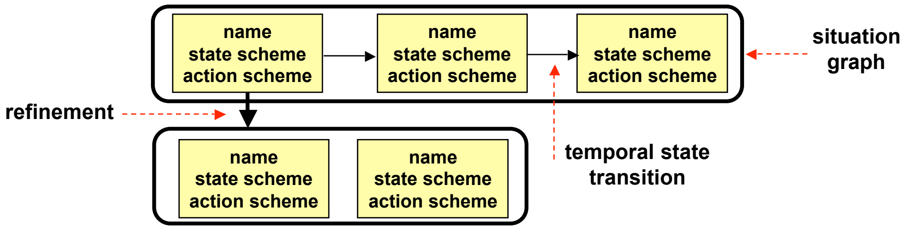
Situation Graph Trees (SGTs)

H.-H. Nagel, Natural Language Description of Image Sequences as a Form of Knowledge Representation, Proc. KI-99, Springer, 1999, pp. 45-60

- Knowledge about agent behavior is expressed in terms of situations an agent can be in.
- A situation scheme is a generic situation description. It consists of a state scheme and an action scheme.
- If the predicates of the state scheme are satisfied, an agent instantiates the situation and is expected to execute the actions of the action scheme.
- Transitions between situations describe a temporal change.
- Situation schemes are refined in a tree structure.



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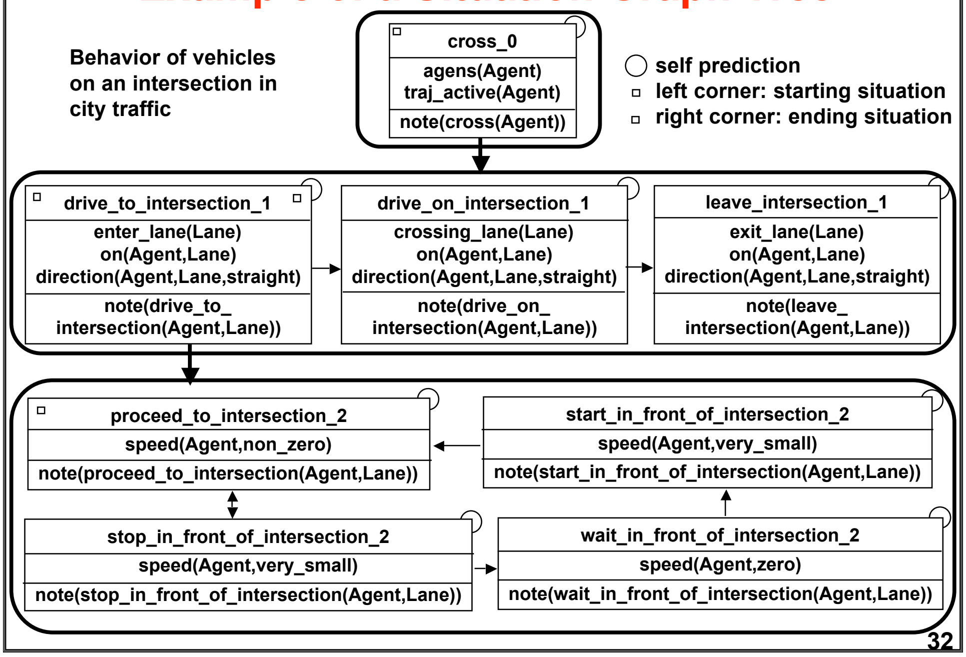
Example of a Situation Graph Tree

Behavior of vehicles on an intersection in city traffic



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Behavior Recognition with SGTs

(See details in Nagel 99)

Basic recognition algorithm is graph traversal:

Startnodes = {root node of SGT}.
VERIFY(startnodes)
Try to instantiate node of startnodes.
A Instantiated node is leaf node: Follow prediction arrows until situation graph is completely instantiated.
B: Instantiated node is not a leaf node: Obtain startnodes of refined situation graph and VERIFY(startnodes).
Return to next higher level of SGT.

Note correspondences:

- situation graph = aggregate
- situation scheme = part of aggregate
- SGT = specialisation hierarchy of aggregates

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Scenarios

B. Georis, M. Mazière, F. Brémond, M. Thonnat: Evaluation and Knowledge Representation Formalisms to Improve Video Understanding. Proc. ICVS-06, 2006.

- **Scenario = symbolic description of a long-term activity**
  e.g. "fighting", "vandalism"
  Scenarios may be structured into hierarchies (subscenarios, etc.)
- **Event = significant change of States**
  "enters", "stands up", "leaves"
- **State = a spatio-temporal property involving one or several actors in a time interval**
  e.g. "close", "walking", "seated"

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Types of States and Events

<u>Several types of States</u>:

- **posture** e.g. lying, crouching, standing
- **direction** e.g. towards the right, towards the left, leaving, arriving
- **speed** e.g. stopped, walking, running
- **distance/object** e.g. close, far
- **distance/person** e.g. close, far
- **posture/object** e.g. seated, any

<u>Several types of Events</u>:

- **person** e.g. falls down, crouches down, stands up, goes right, goes left, goes away, arrives, stops, starts running
- **person & zone** leaves, enters
- **person & equipment** moves close to, sits on, moves away from
- **2 persons** moves close to, moves away from

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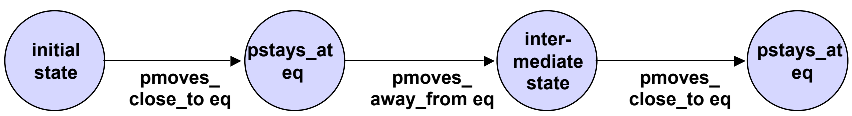
Example Scenario "Vandalism"

Vandalism scenario description:

```
Scenario(vandalism_against_ticket_machine,
        Physical_objects((p : Person),
                         (eq : Equipment, Name= "Ticket_Machine") )
        Components(      (event s1: pmoves_close_to eq)
                         (state s2: pstays_at eq)
                         (event s3: pmoves_away_from eq)
                         (event s4: pmoves_close_to eq)
                         (state s5: pstays_at eq) )
        Constraints(     (s1 != s4) (s2 != s5)
                         (s1 before s2) (s2 before s3)
                         (s3 before s4) (s4 before s5) ) ) )
```

Notation as state transition graph:



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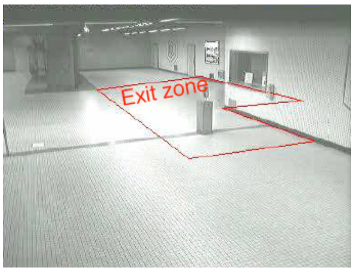
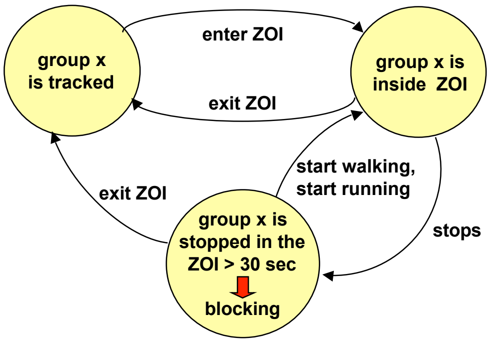
Scenario Recognition

- States and Events: Recognition by specific routines and classification
- Scenarios: Recognition based on finite state automata and propagation of temporal constraints

Example: Finite state automaton for scenario "A group of people blocks an exit" in a subway station monitoring task

Zone of interest (ZOI)





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