Surrounding-aware, Early and Accurate Recognition of Maneuvers in Real Highway Traffic by Use of Bayesian networks

Applications in cognitive vehicles driving on real roads

Cognitive and object-oriented modeling under uncertainties as aspects of artificial intelligence in practical applications

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Based on talk at Cognitive Vehicles, 12 -13 June 2018, Berlin

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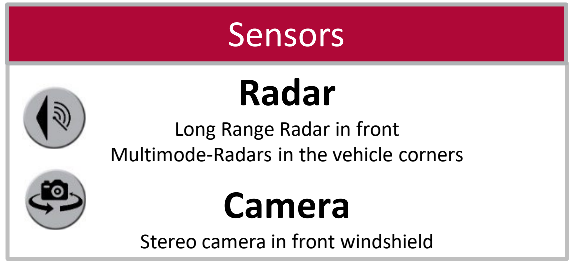
university of applied sciences

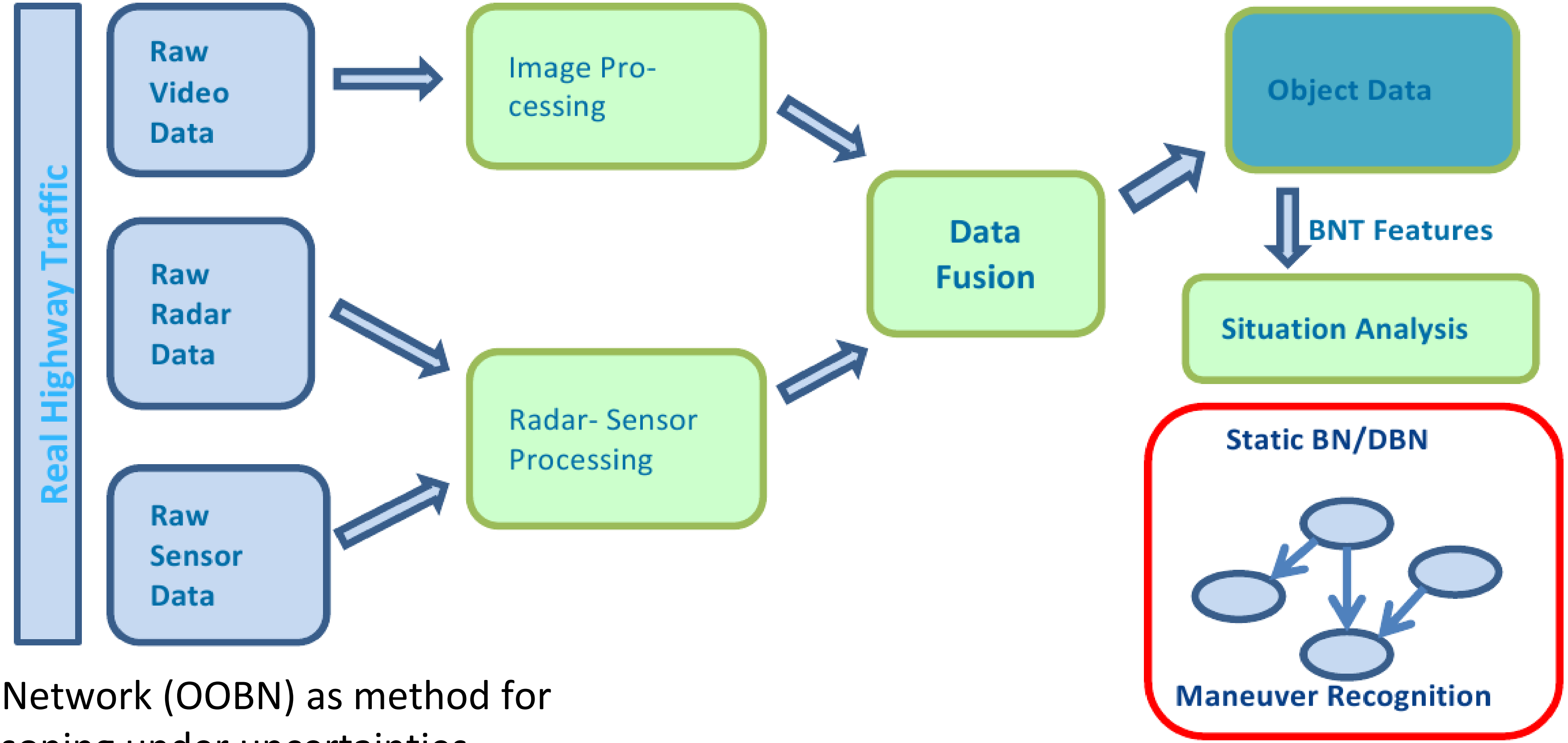
Cognitive Vehicles and Automated Driving Systems (ADS)

- What automated driving tasks can be supported by artificial cognitive systems?
  - Surrounding-aware understanding of driving scene
  - Early recognition of highway maneuvers and situation criticality → Suitable reaction of ADS
- How? Apply Bayesian networks
  - For development: represent the knowledge on the domain & learn from real data
  - For maneuver recognition during on-road driving: using data streams of high volume and high frequency
- Why to use Bayesian networks (BNs)? Allow to
  - model human reasoning & mimic the human decision process on situation analysis
  - deal with the inherited uncertainties in the automotive domain
  - explain conclusions

Experimental Cognitive Vehicle and Data for Maneuver Recognition

From data to maneuver recognition





- Use Object Oriented Bayesian Network (OOBN) as method for maneuver recognition and reasoning under uncertainties
  - Static (SBN) and Dynamic Bayesian Networks (DBN)

Surrounding-aware Maneuver Recognition

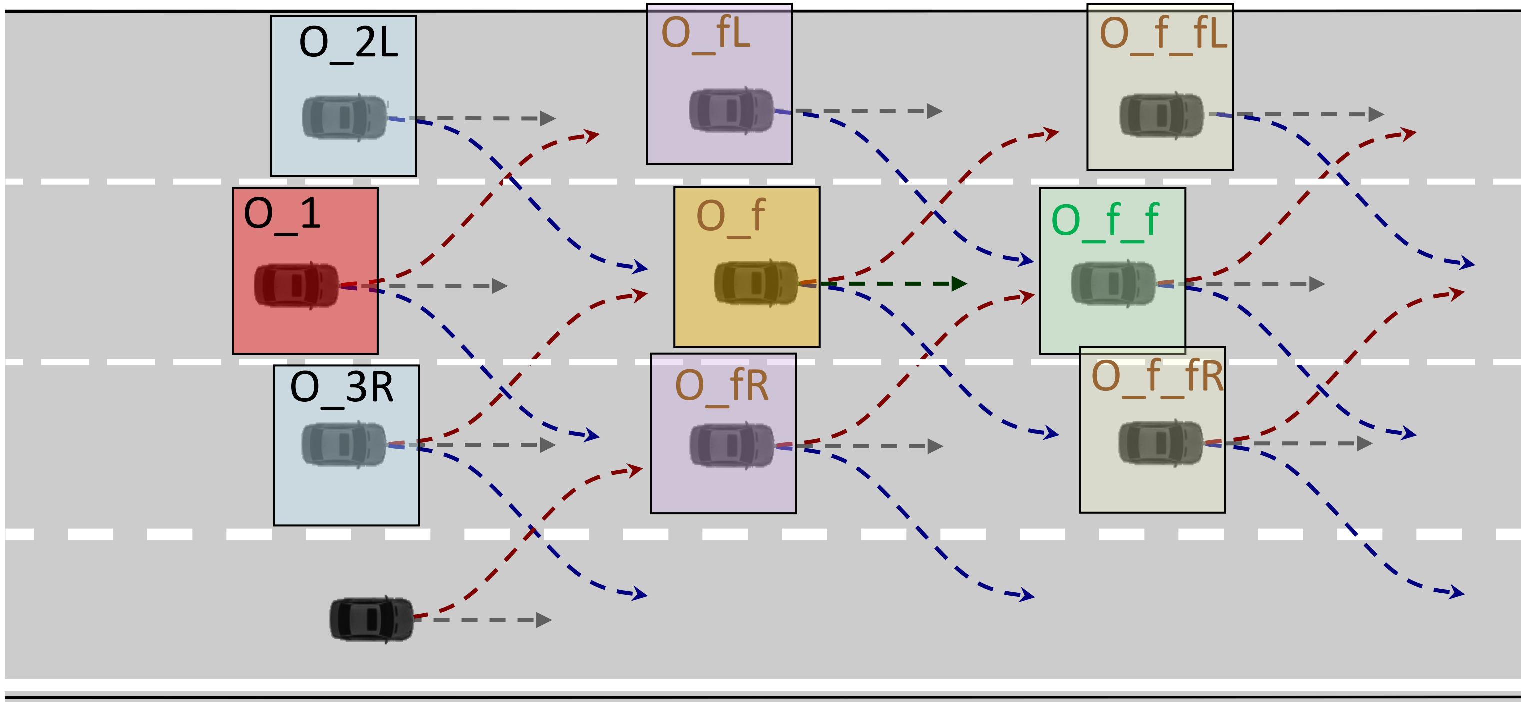
- **Goal**:
  - Recognition of follow and lane change

    by use of differentiating features & context
  - Prediction of driving intentions,

  based on the relative motion of a vehicles' pair
  - Prediction of beginning maneuvers:

    CutIn, CutOut,

    Drifting towards the lane marking



- **Analyze the context of the entire situation → Combinatorial and interpretation issues**
  - involving several vehicles on the surrounding lanes
  - all possible maneuvers of EGO and its surrounding vehicles (intersecting paths)
- **Provide computationally scalable solution** by analyzing pair of vehicles

Traffic Maneuvers of Interest

CutIn

CutOut

CutIn_Obj_f due to forced CutIn_Obj_f_r

Cognitive Approach (Knowledge-based modeling) by Bayesian Networks with Machine-learning

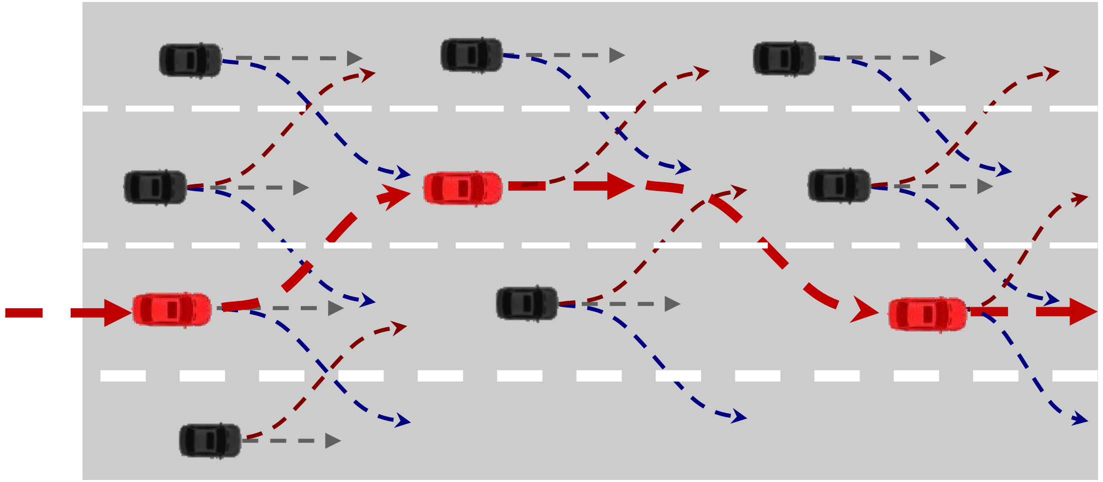
What? Situations characteristics on highway:

- **Massive data streams due to many surrounding vehicles and changing environment**
  - Situations develop quickly and requires information in the order of milliseconds for analysis
- **Inherited Uncertainties**
  - Heterogenic input: sensor measurements, fused, computed data (numeric, labeled);
  - Modelling of traffic environment: Digital map, localization, perception algorithms, maneuver recognition

How?

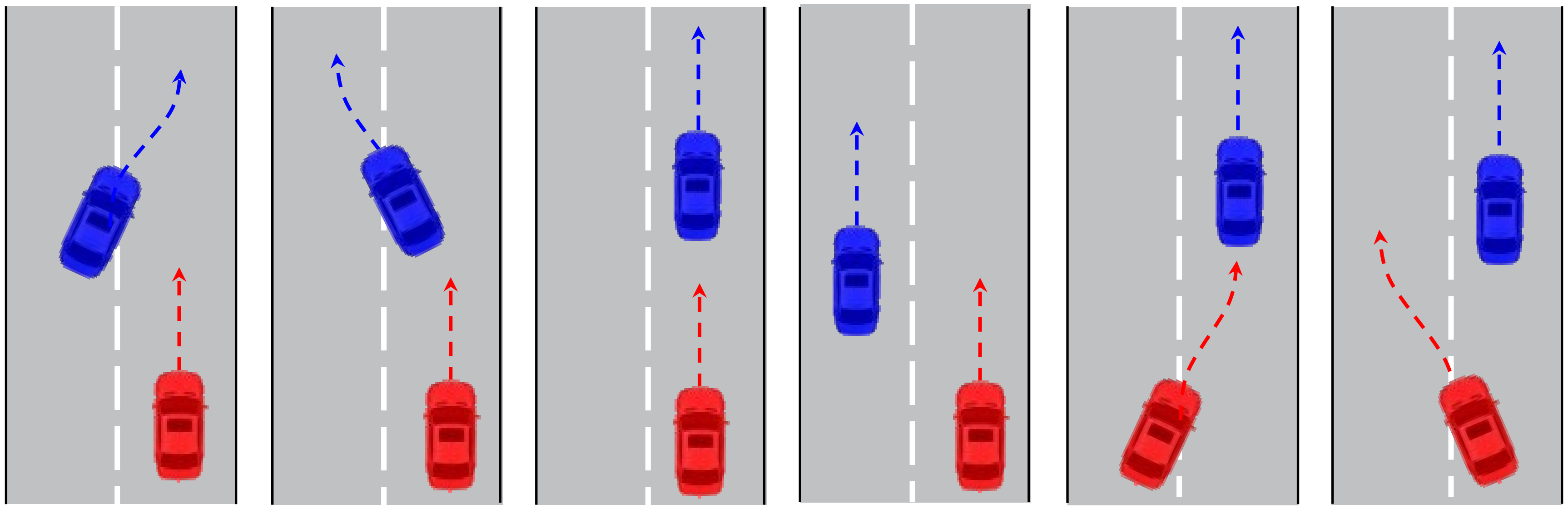
- **Cognitive Knowledge Representation** by Bayesian Networks
  - Mimic human reasoning and decision. Use a-priori knowledge in the modeling of Driving Behavior
  - Structured, easily extendable and probabilistic approach
  - more compact than rule-based systems. BNs represent all maneuvers/intentions in one model.
- Combination with **Machine-learning** (adapting the network parameters to real data)
  - models and predicts the real driving behavior of involved vehicles

Elementary maneuvers to recognize



Overtake maneuver =
Follow → Lane Change left →Follow → Lane Chane right → Follow

Situation 1 | Situation 2 | Situation 3 | Situation 4 | Situation 5 | Situation 6



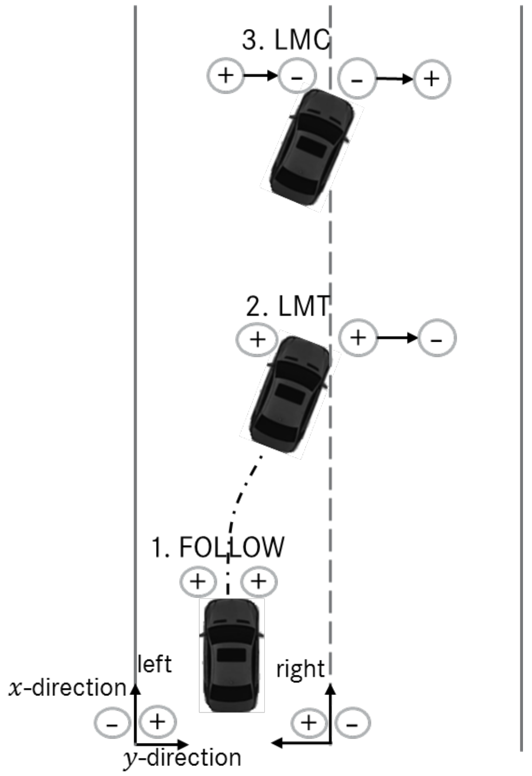
OBJCUTIN | OBJCUTOUT | OBJFOLLOW | LANEFOLLOW | EGOCUTIN | EGOCUTOUT

Surrounding-aware
Maneuver is defined by
Vehicle-Vehicle relations.

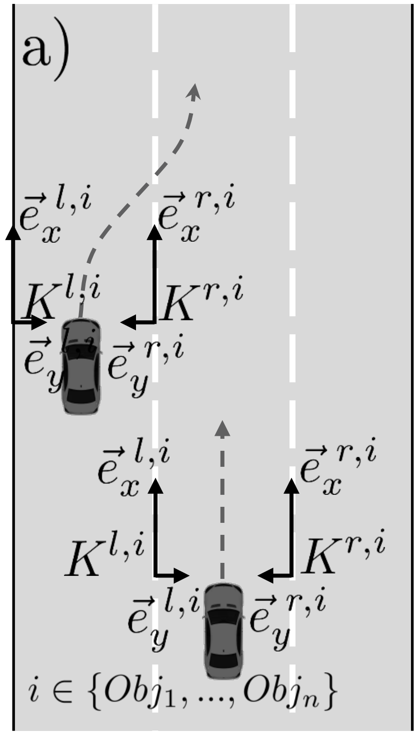
red = own (EGO) vehicle ;
blue = other vehicle (OBJ)
in the scene

Cognitive Hypotheses for Maneuver Recognition

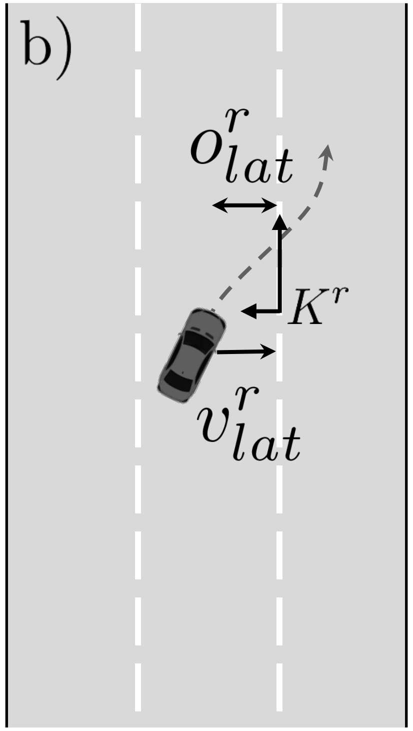
Features combined into cognitive hypotheses to mimic human reasoning



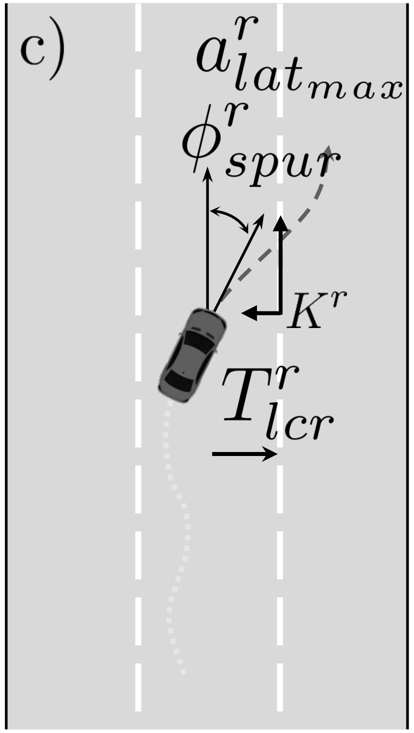
Lane Change Maneuver is defined
by Vehicle-Lane-Marking relation



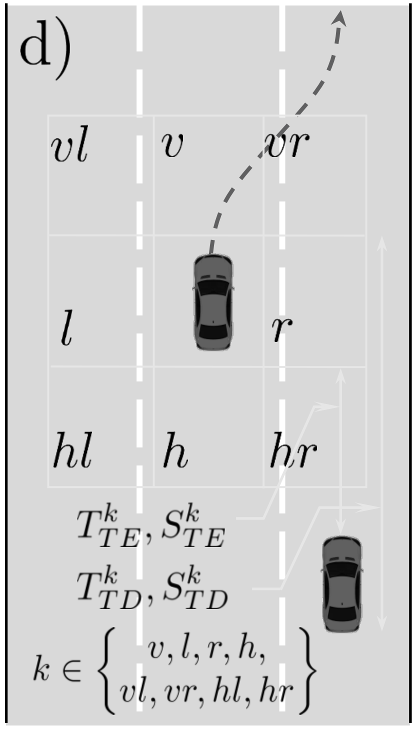
Symmetric Coordinate System



Lateral Movement Lateral Evidence (LE)



Trajectory



Free Space

Bayes Network

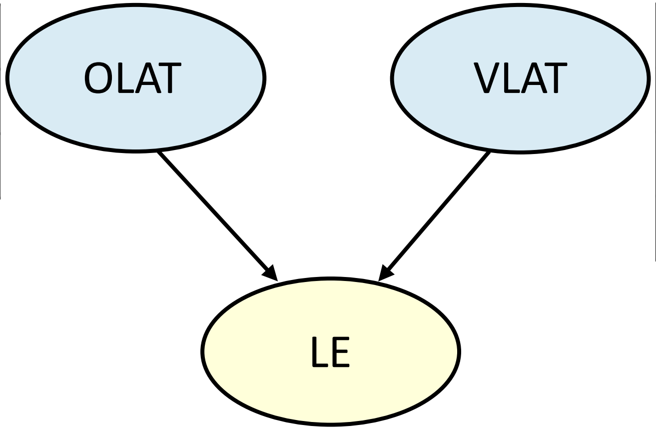
Bayes Network

$BN = (Graph, Parameters)$

Qualitative part: $Graph = (Variables, Links)$

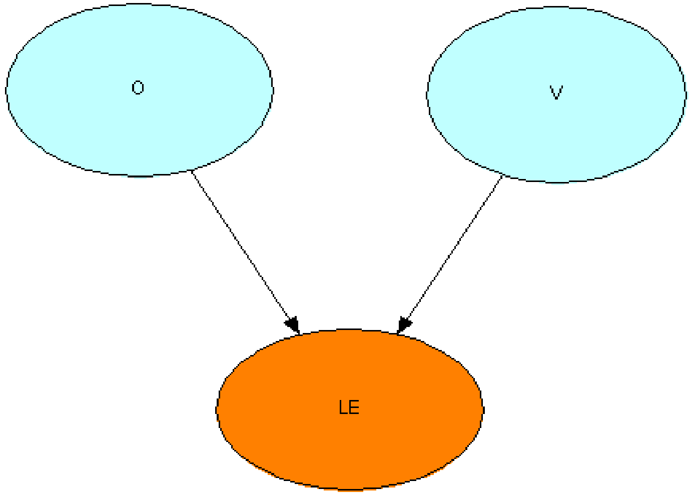
Quantitative part: $Parameters$ for discrete nodes given as (Conditional) Probability Table CPT
e.g. $P(OLAT), P(VLAT), P(LE|OLAT, VLAT)$

P(OLAT)	
near	0.5
far	0.5



P(VLAT)	
to	0.3
straight	0.4
from	0.3

P(LE/OLAT,VLAT)						
OLAT	near			far		
VLAT	to	straight	from	to	straight	from
false	0	0.4	0.8	0.7	0.9	1
true	1	0.6	0.2	0.3	0.1	0



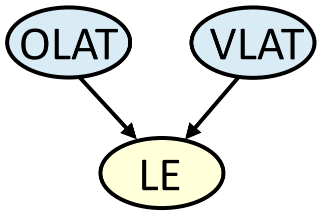
Joint Probability (Verbundwahrscheinlichkeit)

Chain Rule: $P(U) = \prod_{i=1}^{n} (A_i | pa(A_i))$

$\mathcal{U} = (A_1, \ldots, A_n)$

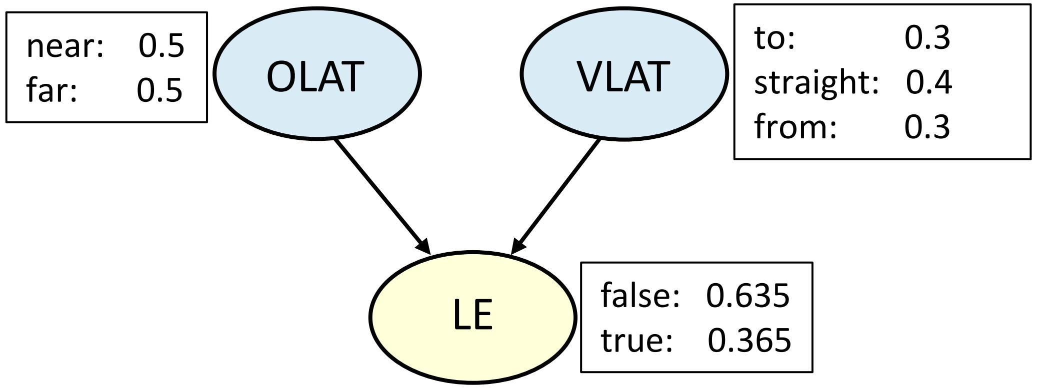
In the example:

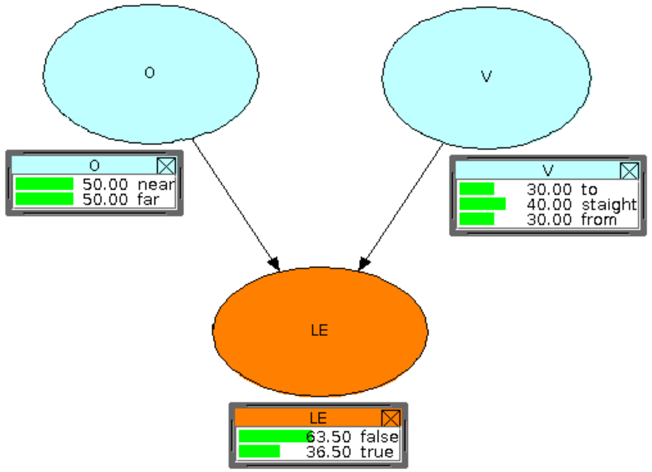
$$P(OLAT, VLAT, LE) = P(OLAT) \cdot P(VLAT) \cdot P(LE | OLAT, VLAT)$$



OLAT	**near = 0.5**			**far = 0.5**		
VLAT	**to = 0.3**	**straight = 0.4**	**from = 0.3**	**to = 0.3**	**straight = 0.4**	**from = 0.3**
false	$0.5 \cdot 0.3 \cdot 0$	$0.5 \cdot 0.4 \cdot 0.4$	$0.5 \cdot 0.3 \cdot 0.8$	$0.5 \cdot 0.3 \cdot 0.7$	$0.5 \cdot 0.4 \cdot 0.9$	$0.5 \cdot 0.3 \cdot 1$
true	$0.5 \cdot 0.3 \cdot 1$	$0.5 \cdot 0.3 \cdot 0.6$	$0.5 \cdot 0.3 \cdot 0.2$	$0.5 \cdot 0.3 \cdot 0.3$	$0.5 \cdot 0.4 \cdot 0.1$	$0.5 \cdot 0.3 \cdot 0$

Initial Distribution:

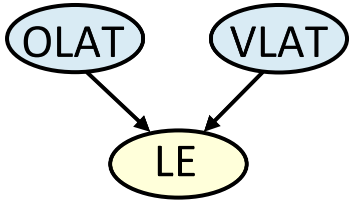




Bayesian Inference

$$P(U,e) = P(U)\cdot e = \prod_{i=1}^{n}(A_i|pa(A_i))\prod_{j=1}^{m}e_j$$

$$P(A_i|e) = \frac{\prod_{U/A_i}P(U,e)}{\sum_U P(U,e)}$$



Example: Evidence e=(1,0,0) in the variable $VLAT$

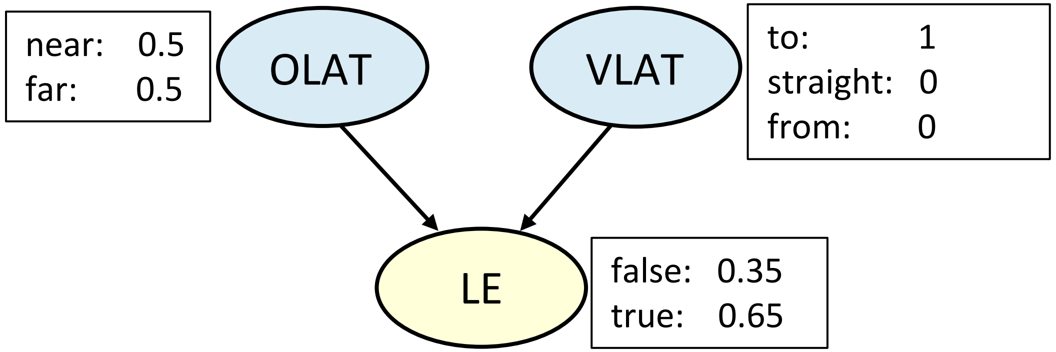
In the example:

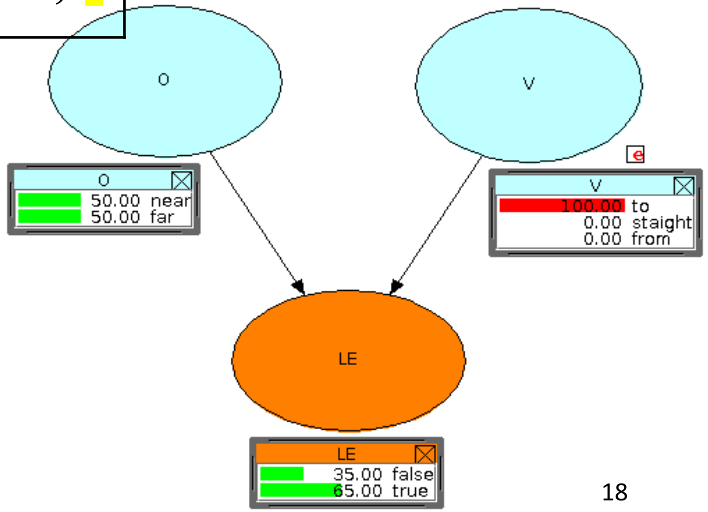
$$P(LE = false|e) = \sum_{LE=false} P(\mathcal{U},e) = \frac{0+0+0+0.105+0+0+0}{0.3} = 0.35$$

$$P(LE = true|e) = \sum_{LE=true} P(\mathcal{U},e) = \frac{0.15+0+0+0.045+0+0}{0.3} = 0.65$$

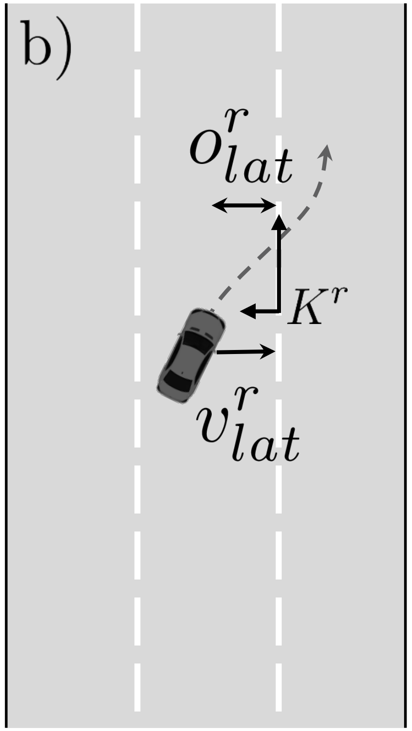
OLAT	**near = 0.5**			**far = 0.5**		
VLAT	**to = 0.3, e=1**	**straight = 0.4, e=0**	**from = 0.3, e=0**	**to = 0.3, e=1**	**straight = 0.4, e=0**	**from = 0.3, e=0**
false	$(0.5\cdot 0.3\cdot 0)\cdot 1$	$(0.5\cdot 0.4\cdot 0.4)\cdot 0$	$(0.5\cdot 0.3\cdot 0.8)\cdot 0$	$(0.5\cdot 0.3\cdot 0.7)\cdot 1$	$(0.5\cdot 0.4\cdot 0.9)\cdot 0$	$(0.5\cdot 0.3\cdot 1)\cdot 0$
true	$(0.5\cdot 0.3\cdot 1)\cdot 1$	$(0.5\cdot 0.3\cdot 0.6)\cdot 0$	$(0.5\cdot 0.3\cdot 0.2)\cdot 0$	$(0.5\cdot 0.3\cdot 0.3)\cdot 1$	$(0.5\cdot 0.4\cdot 0.1)\cdot 0$	$(0.5\cdot 0.3\cdot 0)\cdot 0$

Initial Distribution:



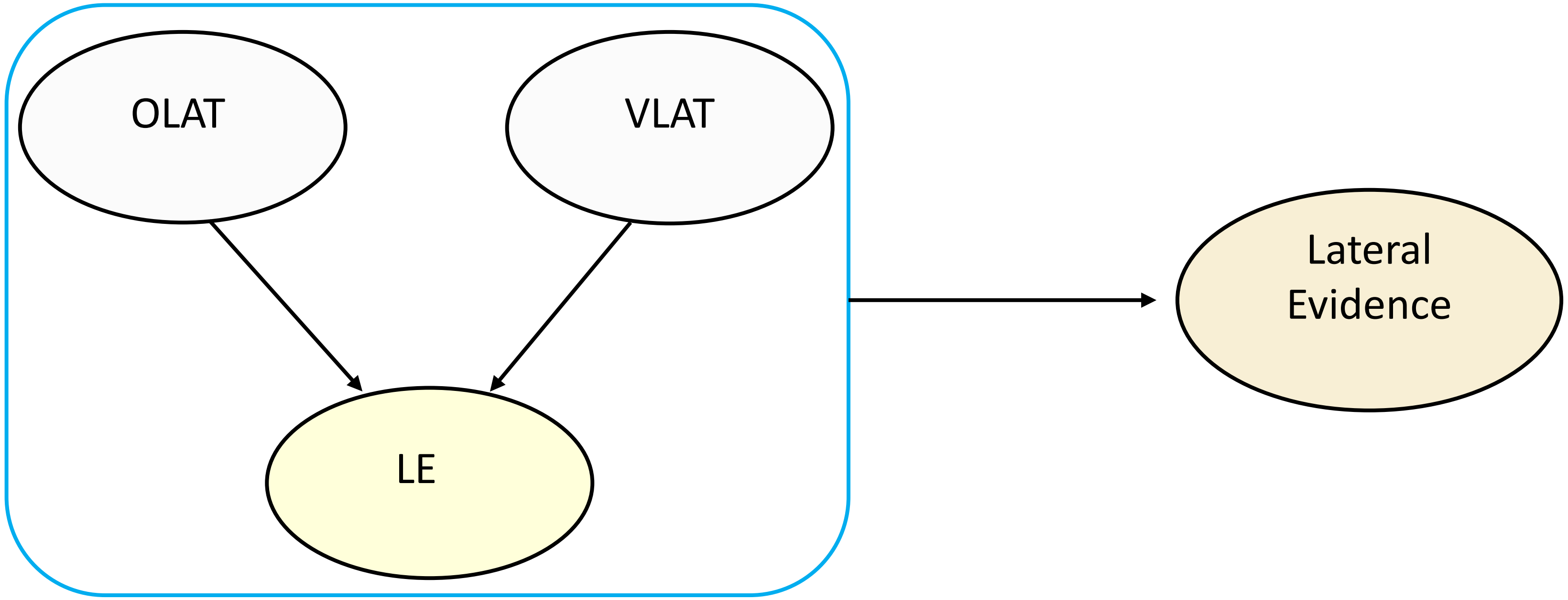


Object Orientierted Bayes Network (OOBN)



Lateral Movement Lateral Evidence (LE)

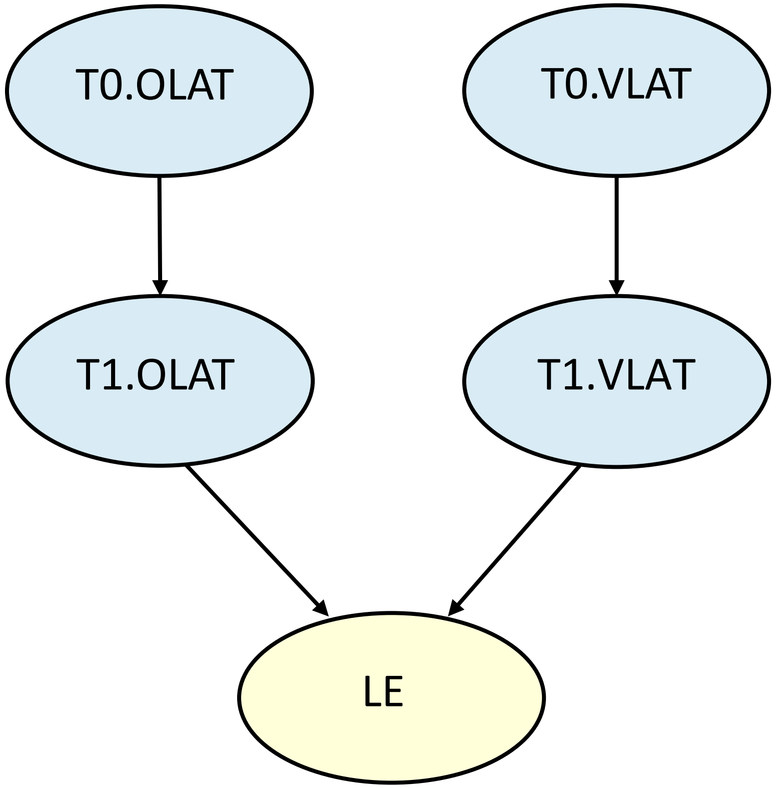
Encapsulate a set of variables and their causal relationship into a single Objected Oriented Fragment



Dynamic Bayes Network

- Modeling of temporal relation of the variables
- Inserting of temporal clones and links
- Causal relation between time slices is given by Transitional Conditional Probability Table (TCPT)

TCPT (T0.OLAT->T1.OLAT)		
T0.OLAT	**near**	**near**
near	?	?
far	?	?



TCPT (T0.VLAT->T1.VLAT)			
T0.VLAT	**to**	**straight**	**from**
to	?	?	?
straight	?	?	?
from	?	?	?

Example: Modeling of sensor uncertainties

– If the measurement instrument is not functioning properly (senor noise or fault),

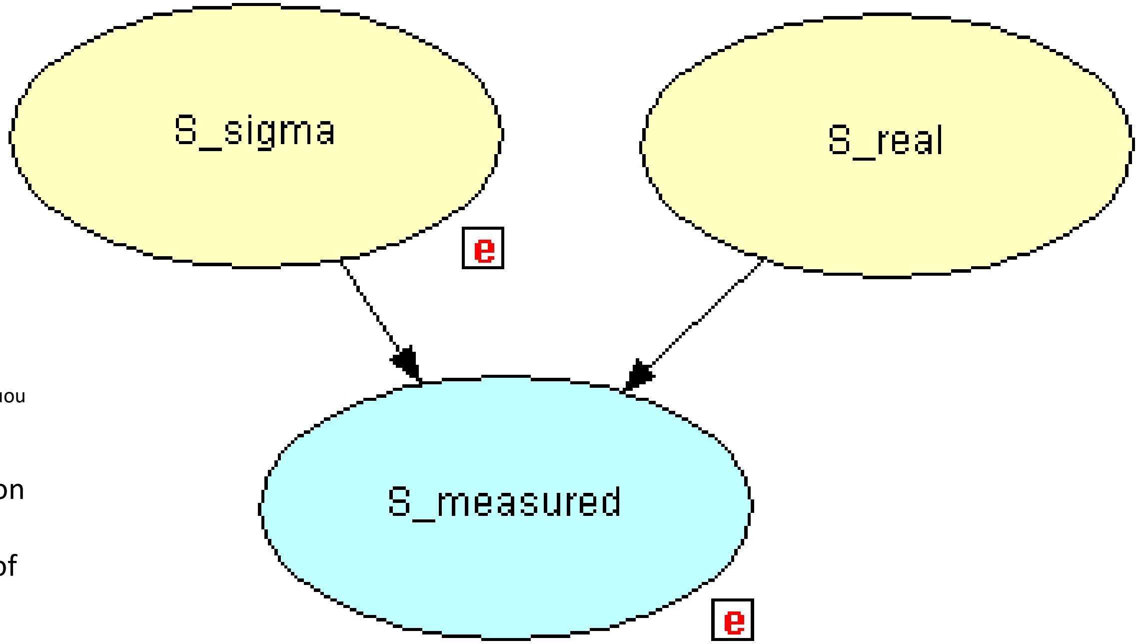
then the sensor_reading (S_measured) and the real variable (S_real) under measurement need not to be the same!

➔ Causal model structure:

The sensor_reading of any measured variable is conditionally dependent on random changes in two variables:

real value under measurement (S_real)

and sensor fault (S_sigma)

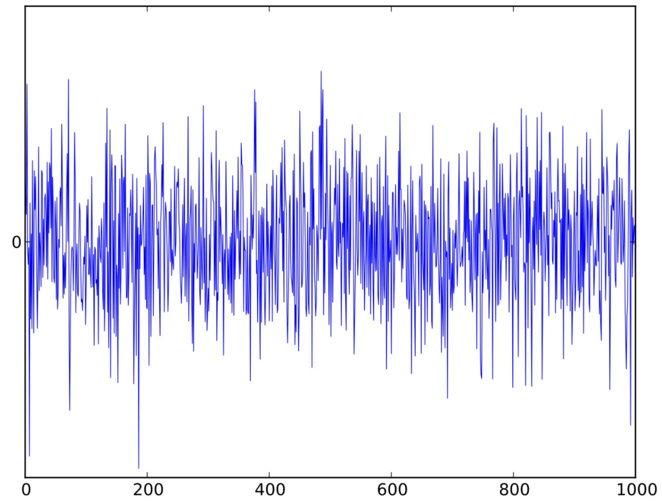


https://www.researchgate.net/profile/Galia-Weidl/publication/223839034_Applications_of_object-oriented_Bayesian_networks_for_condition_monitoring_root_cause_analysis_and_decision_support_on_operation_of_complex_continuous_processes/links/0deec529f09b6da3c7000000/Applications-of-object-oriented-Bayesian-networks-for-condition-monitoring-root-cause-analysis-and-decision-support-on-operation-of-complex-continuous-processes.pdf

Weidl G., Madsen, A.L., Israelsson S. (2005), Object-Oriented Bayesian Networks for Condition Monitoring, Root Cause Analysis and Decision Support on Operation of Complex Continuous Processes: Methodology & Applications, Technical Report 2005-1, 36 pages, IST- University of Stuttgart

9.12

BN: Modeling Uncertainties in Measurements



The waveform of a Gaussian white noise signal plotted on a graph

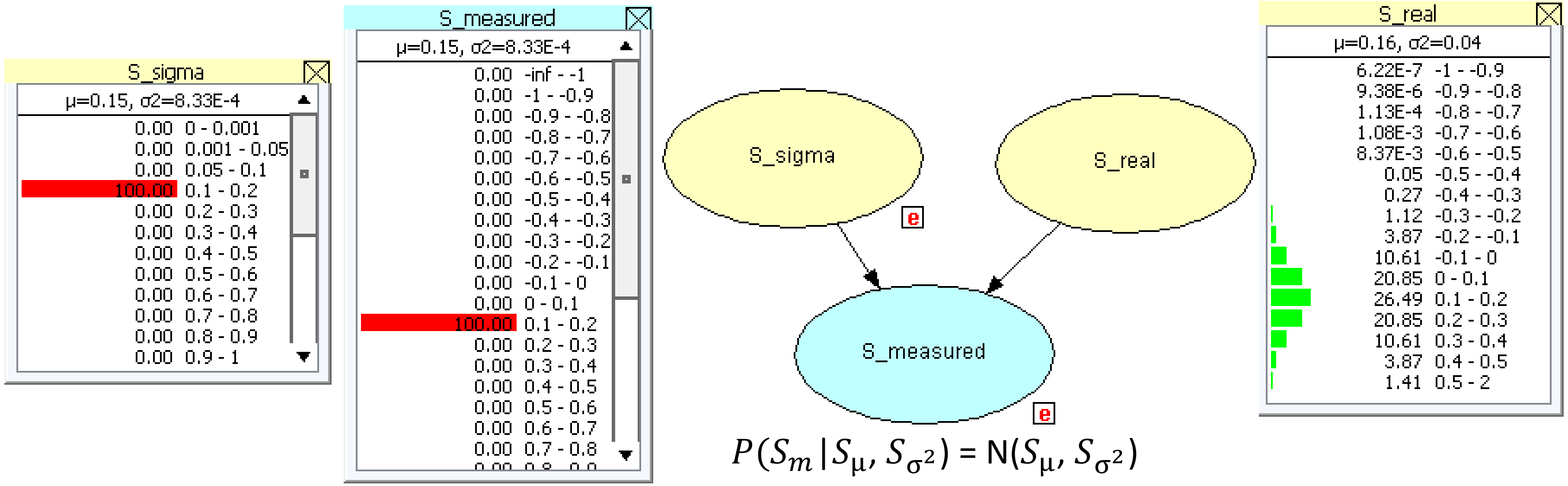
Proper Modeling of Noise in Measured Variables

- Probability of sensor measurement: as Normal (Gaussian) distribution

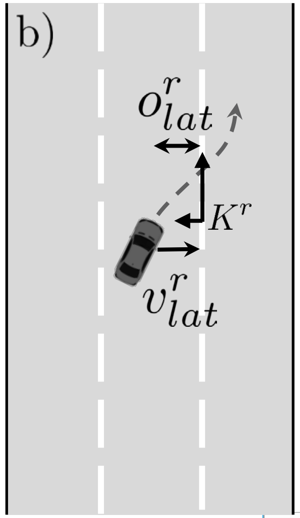
  $P(S_m \,|\, S_\mu, S_{\sigma^2})$ = N(S_μ, S_{σ^2})

- Supply evidence ≡ observation = {measured, communicated, computed value}:
  - measured situation features $S_m \equiv S_{measured}$ and their variance $S_{\sigma^2} \equiv S_{sigma}$
- Bayes Rule to infer (compute) the probability of the real value $S_\mu \equiv S_{real} = ?$
- Chain rule of probability:

$$P\left(S_m, S_\mu, S_{\sigma^2}\right) = P\left(S_m \middle| S_\mu, S_{\sigma^2}\right) * P\left(S_\mu\right) * P\left(S_{\sigma^2}\right)$$



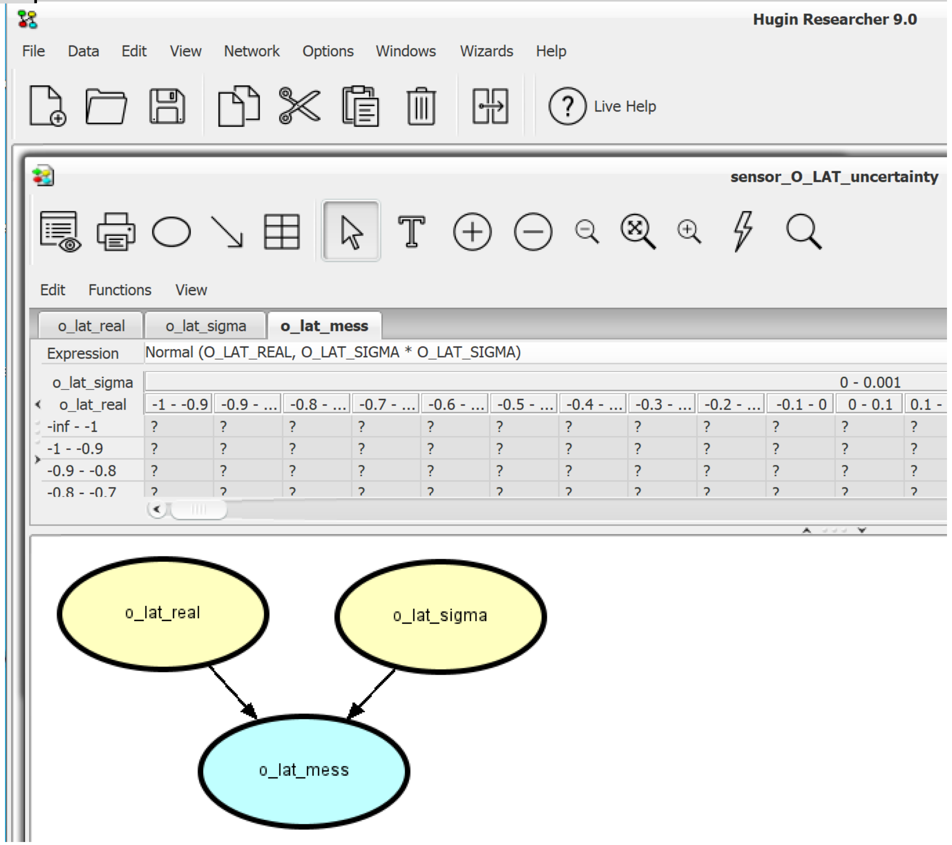
$P(S_m \,|\, S_\mu, S_{\sigma^2})$ = N(S_μ, S_{σ^2})

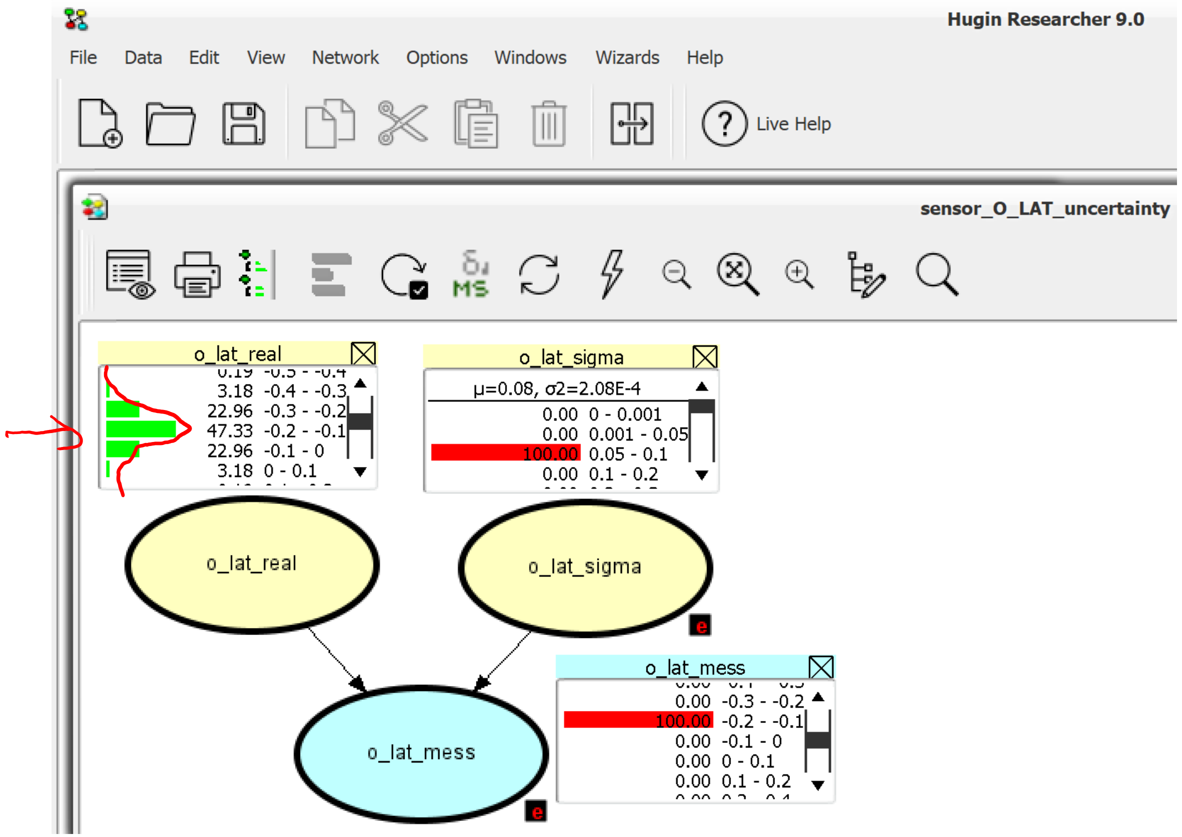


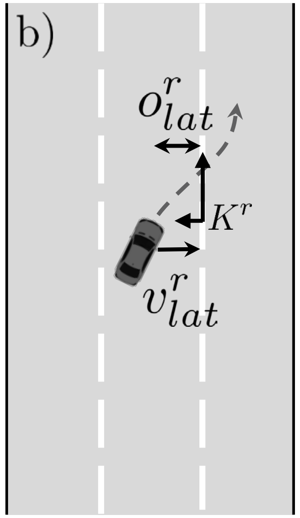
BN: Modeling Uncertainties in Distance Measurements

Proper Modeling of Noise in Measured Variables (O_LAT = lateral offset to lane marking)

- Probability of sensor measurement: as Normal (Gaussian) distribution
  $P(S_m | S_\mu, S_{\sigma^2})$ = N(S_μ, S_{σ^2}), where S_m = measured sensor value,
  S_μ = mean of expected real value under measurement
  S_{σ^2} = variance of the measurement (sensor noise)
- P(O_LAT_MESS) = Normal (O_LAT_REAL, O_LAT_SIGMA * O_LAT_SIGMA)



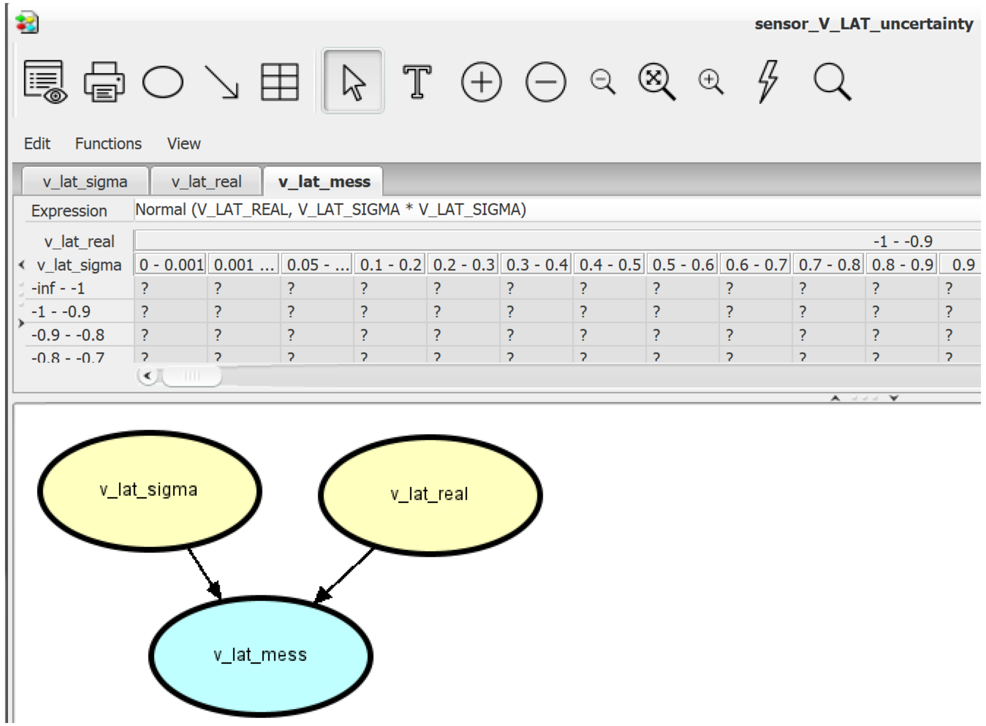


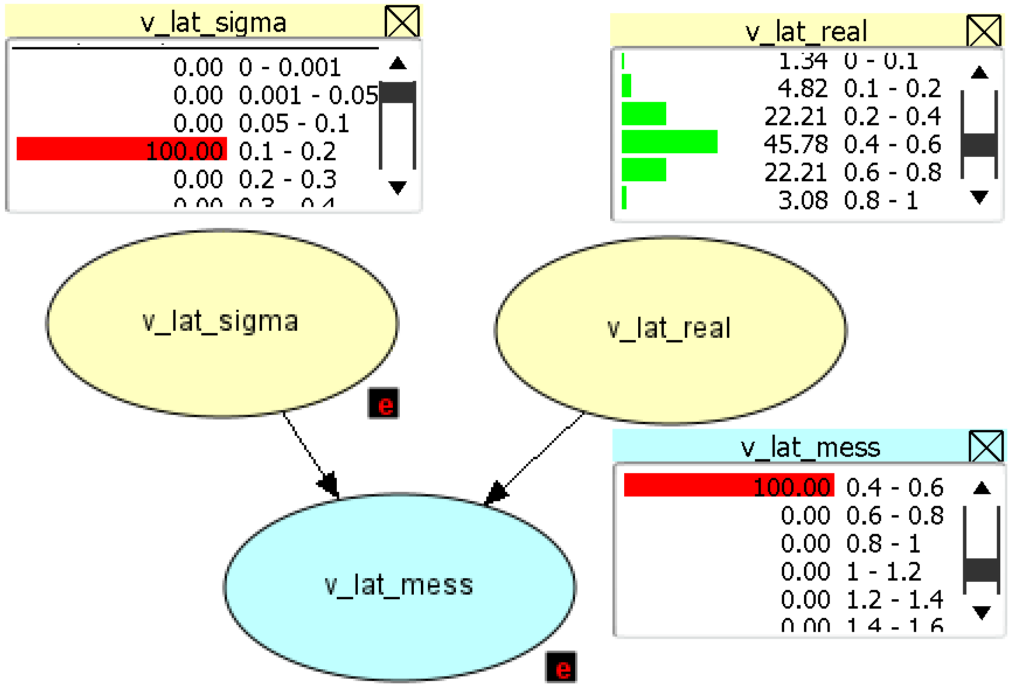


BN: Modeling Uncertainties in Velocity Measurements

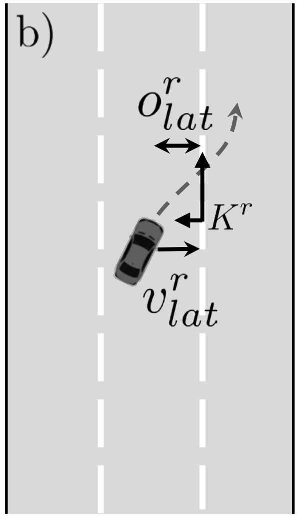
Proper Modeling of Noise in Measured Variables (V_LAT = lateral velocity towards lane marking)

- Probability of sensor measurement: as Normal (Gaussian) distribution:
  $P(S_m | S_\mu, S_{\sigma^2})$ = N(S_μ, S_{σ^2}), where S_m = measured sensor value,
  S_μ = mean of expected real value under measurement
  S_{σ^2}= variance of the measurement (sensor noise)
- P(V_LAT_MESS) = Normal (V_LAT_REAL, V_LAT_SIGMA * V_LAT_SIGMA)





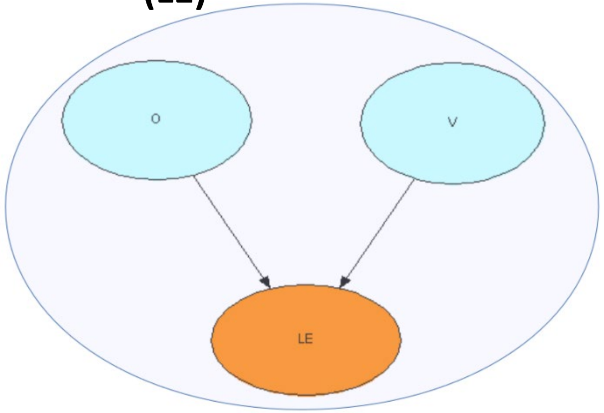
Build the hypothesis by combining the two BN models of sensor uncertainties for lateral velocity and lateral offset to lane marking

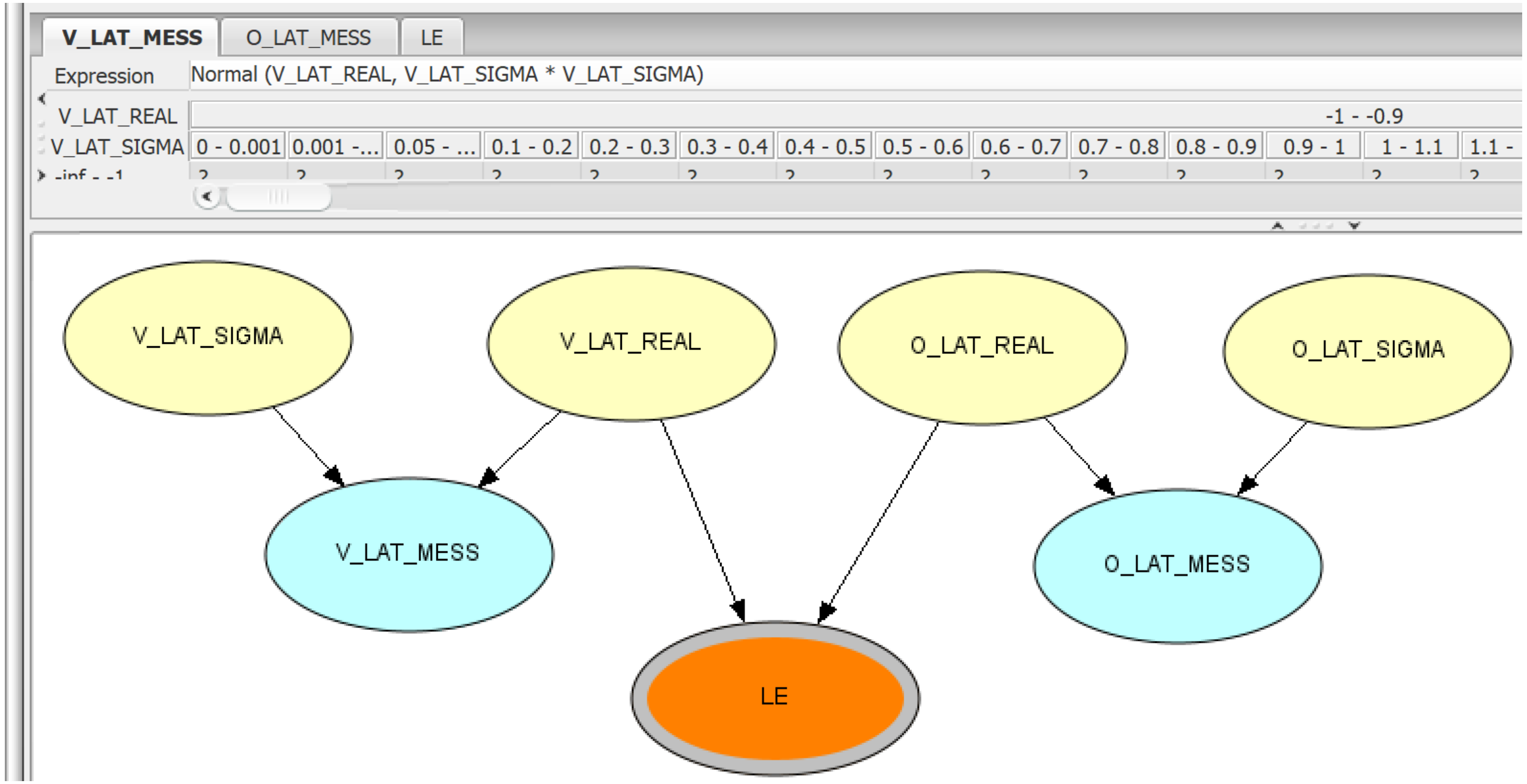


Try to model it in 3 different ways:

1) qualitatively: based on experience as in the previos pages 12-14
2) Learn the BN model from data, as explained in pages 22-25 (see next pages)
3) Change in the learned BN model the conditional probability tables (CPT) to the expressions as described in p.18-19

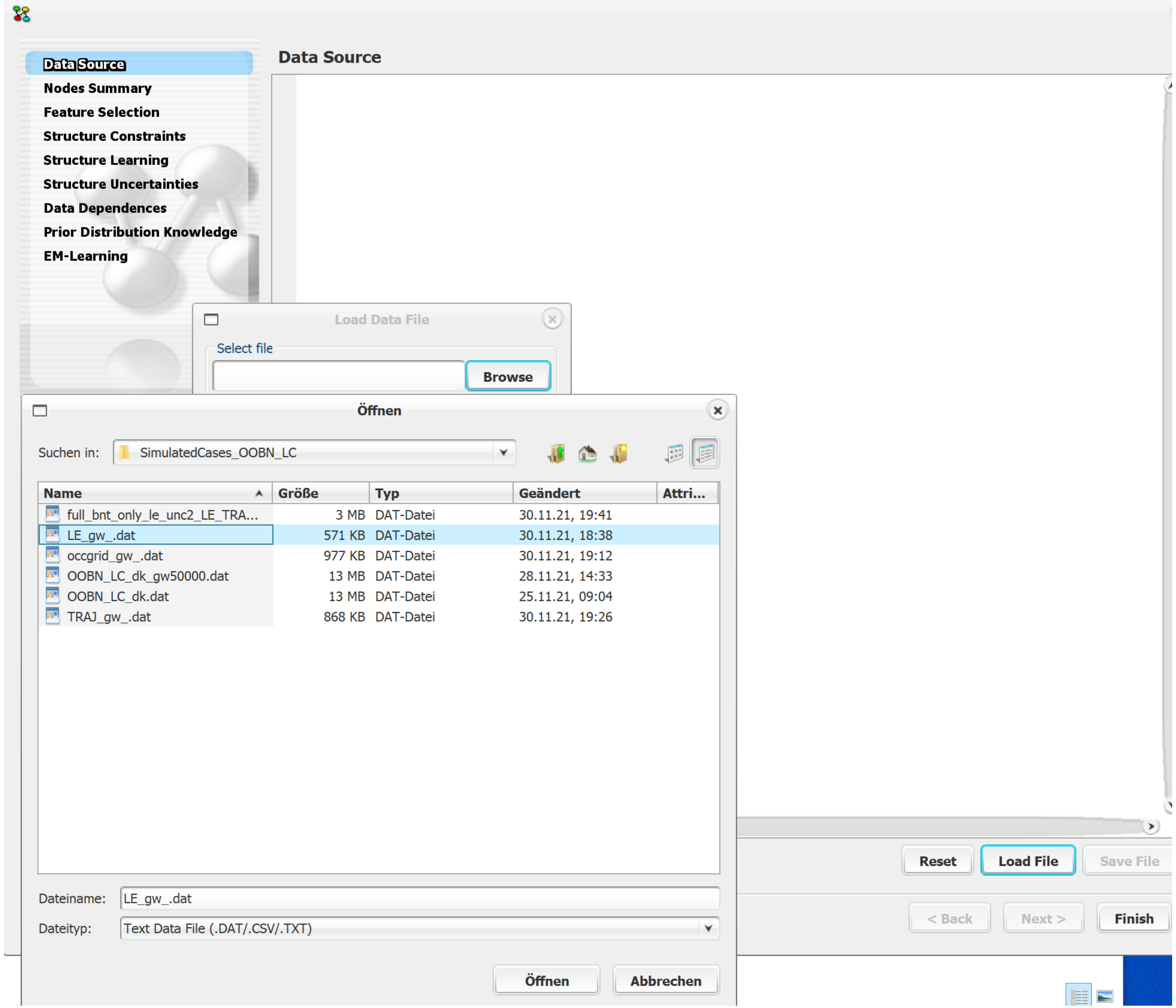
Lateral Movement
Lateral Evidence (LE)



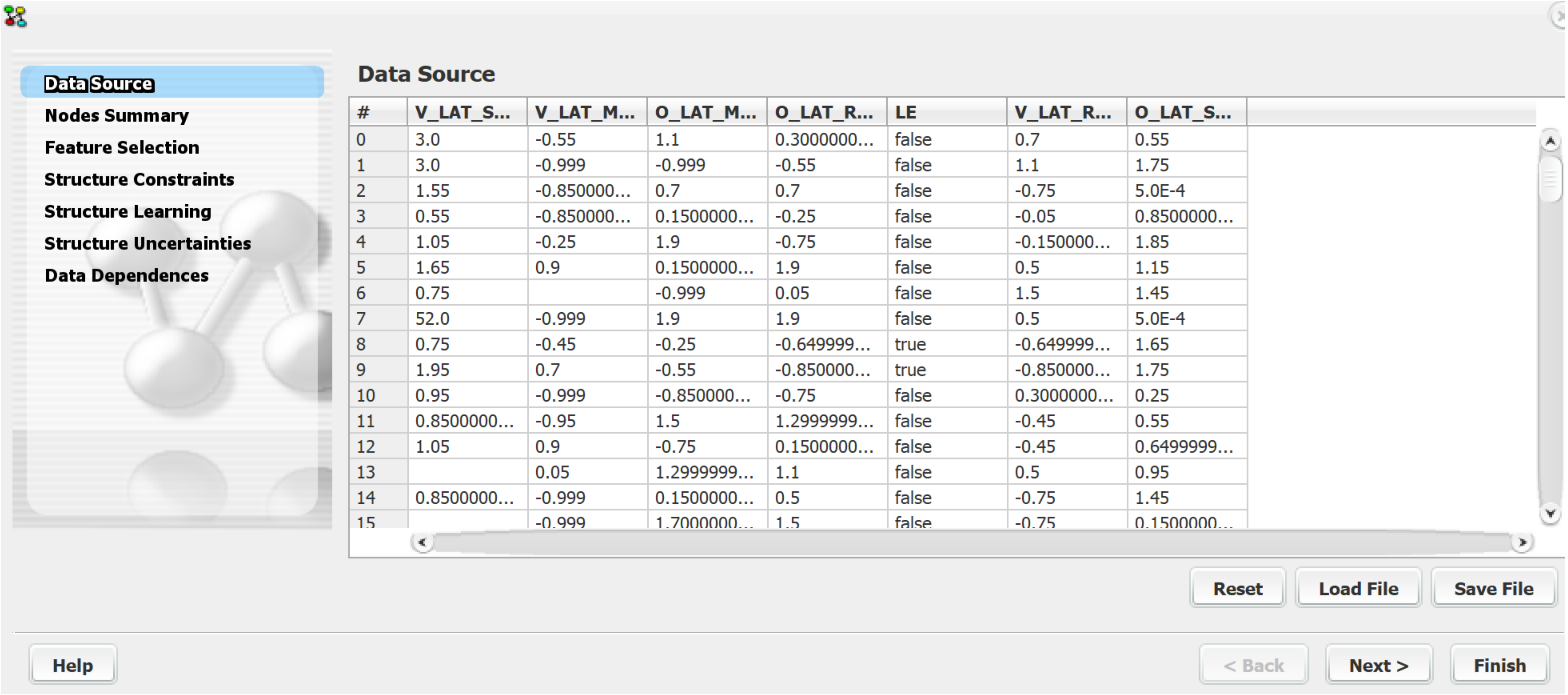


Use the learning Wizard to learn BN model structure and parameters from data

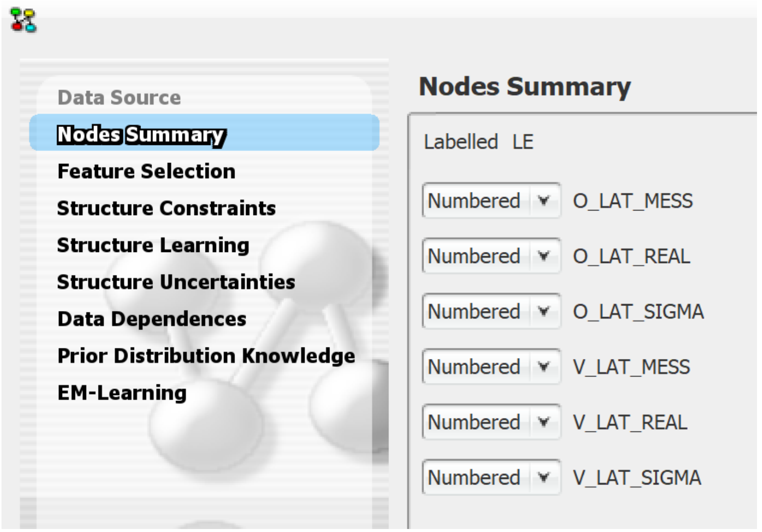
- öffnen data file
- load data

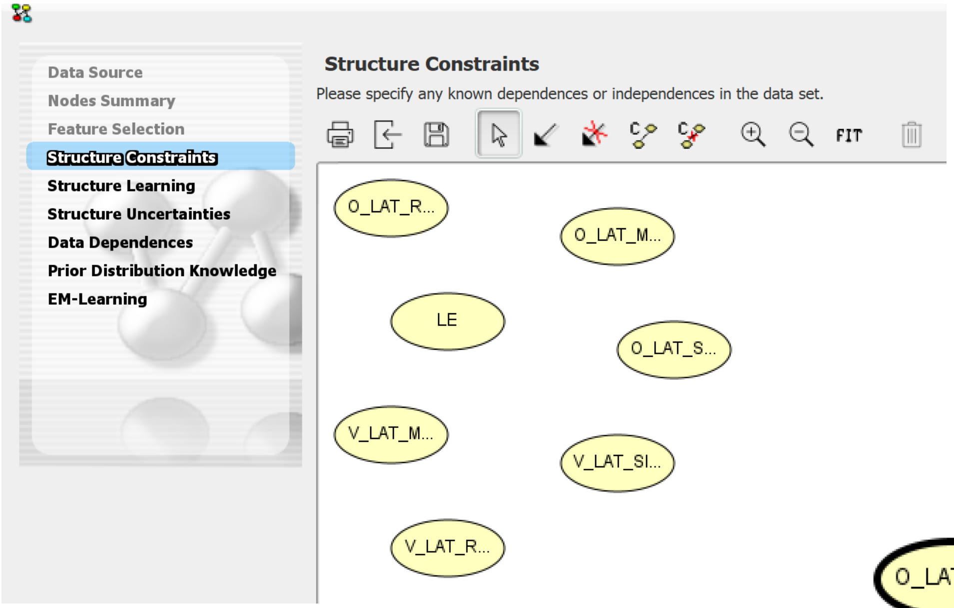


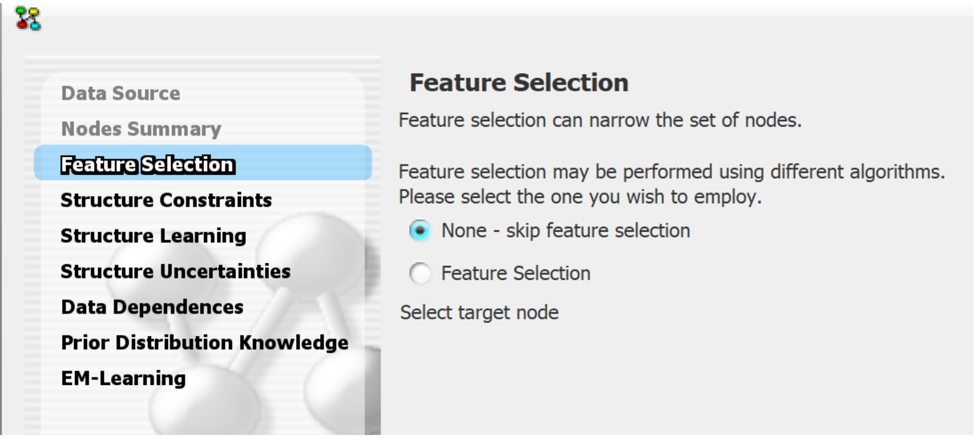
Use the learning Wizard and learn BN model structure and parameters from data



Use the learning Wizard and learn BN model structure and parameters from data





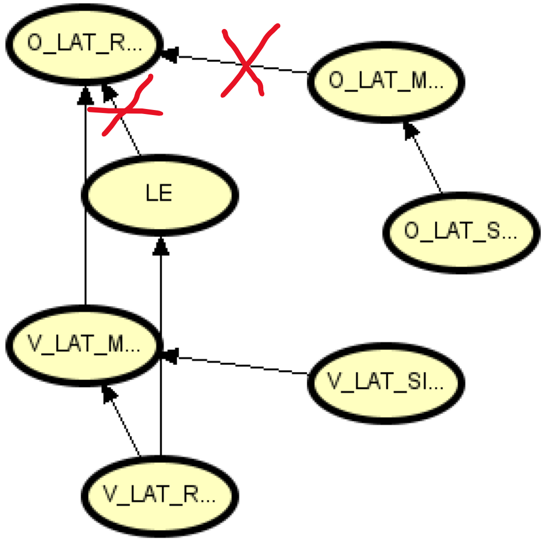


Analyse what is obviously wrong, e.g.
Classification (labeled) variable
is the result after inference

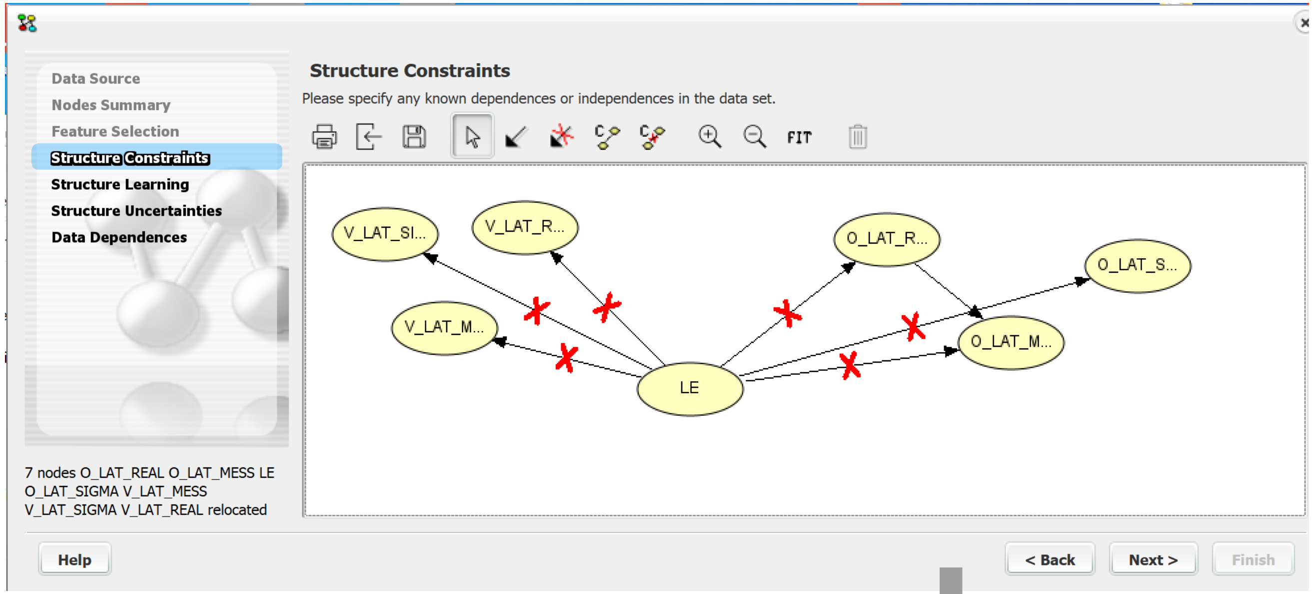
➔ wrong causality need constraint forbiding it

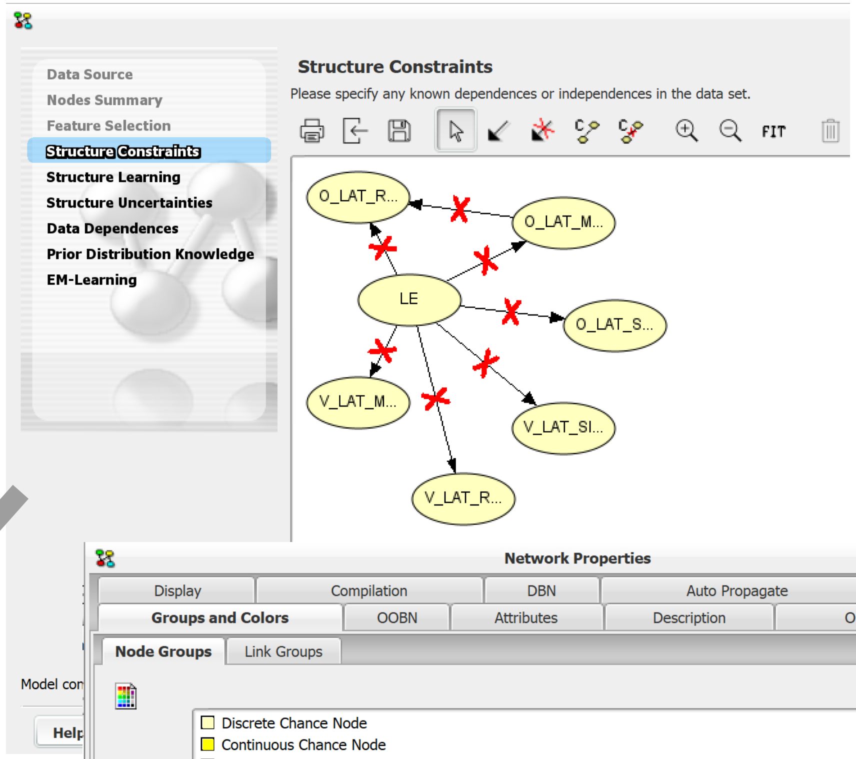
➔ Set constraint on measurement:

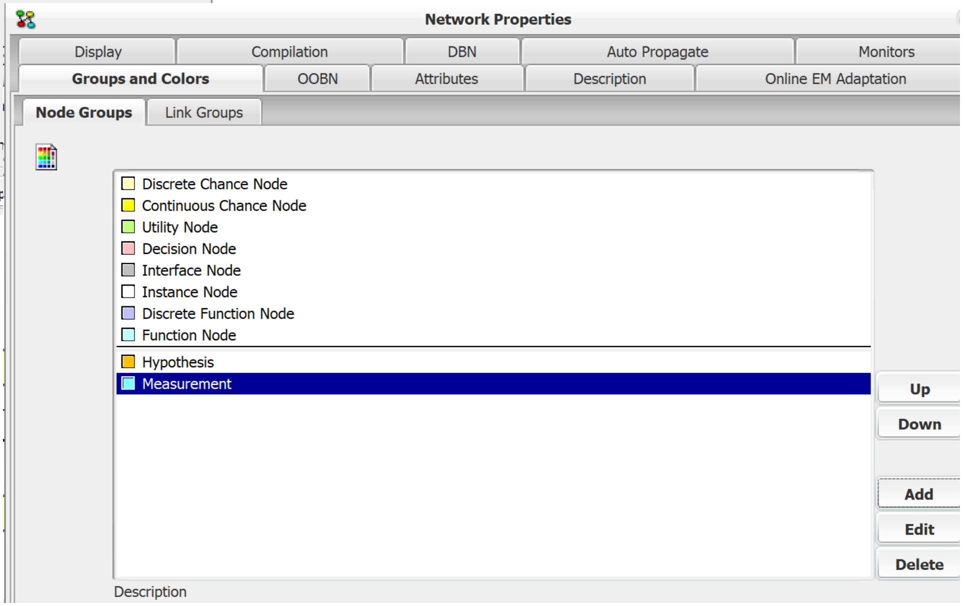
The measurement cannot influence the real value

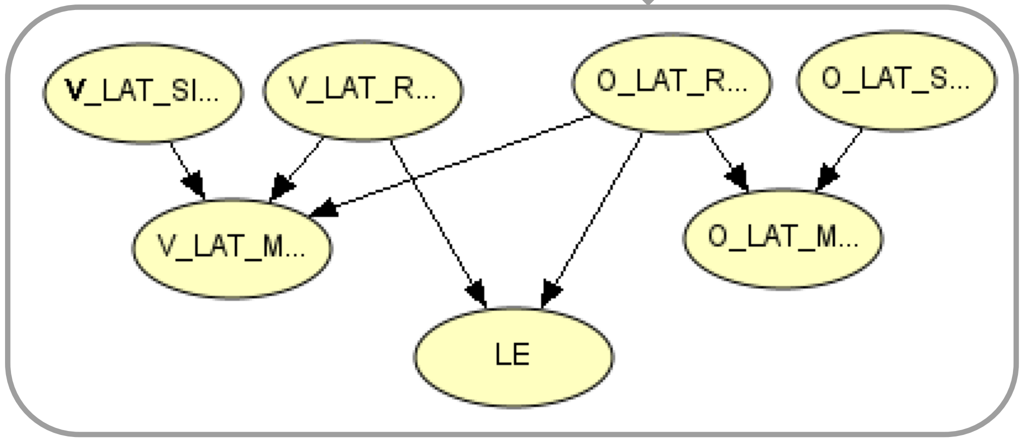


BN: Model learning with Uncertainties in Measurements









Hypotheses for Maneuver Recognition under Uncertainties

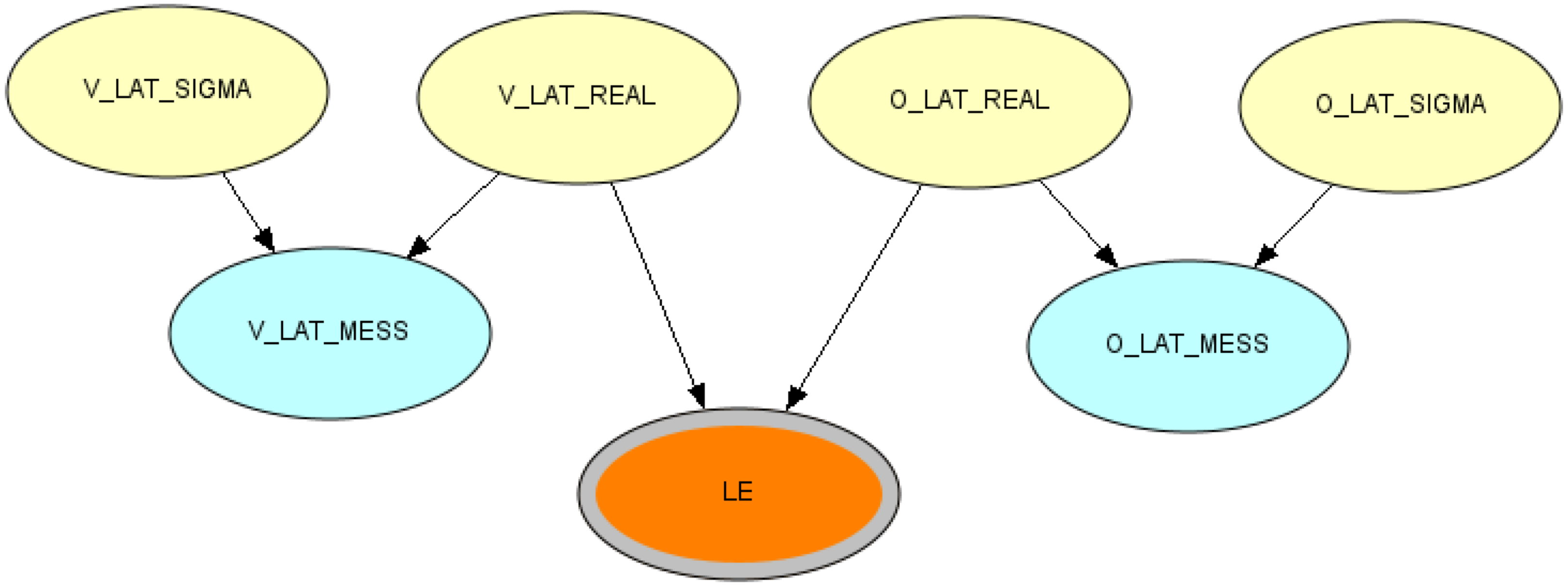
bis 9.12.21 – LE gelernt mit Learning Wizard HUGIN

LE, TRAJ, OCCGRID

Data LE:

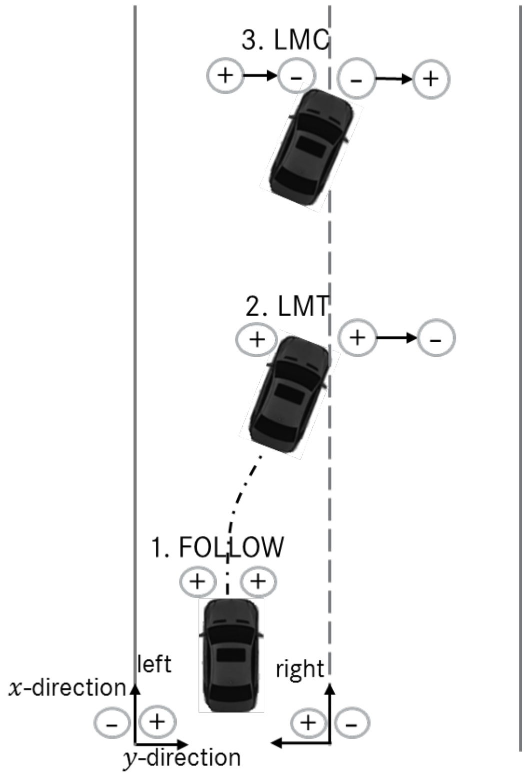
V_LAT_REAL, V_LAT_MESS, V_LAT_SIGMA

O_LAT_REAL, O_LAT_MESS, O_LAT_SIGMA

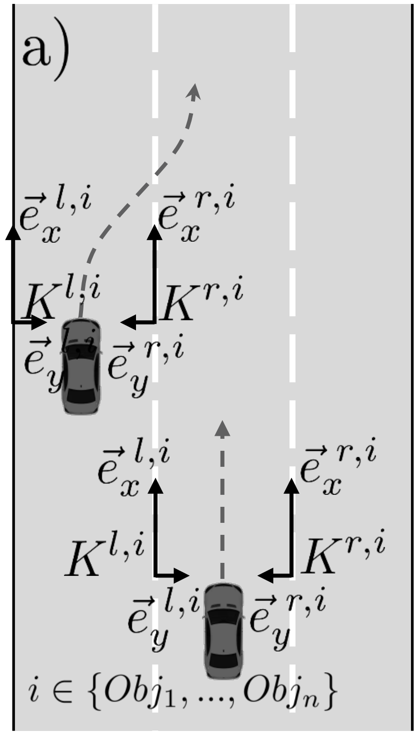


Cognitive Hypotheses for Maneuver Recognition

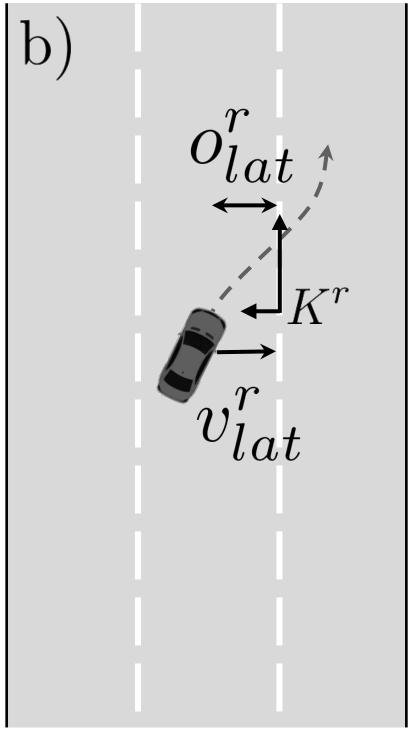
Features combined into cognitive hypotheses to mimic human reasoning



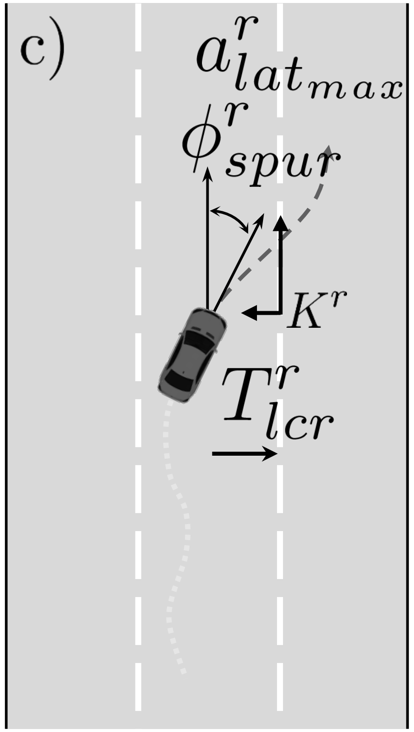
Lane Change Maneuver is defined
by Vehicle-Lane-Marking relation



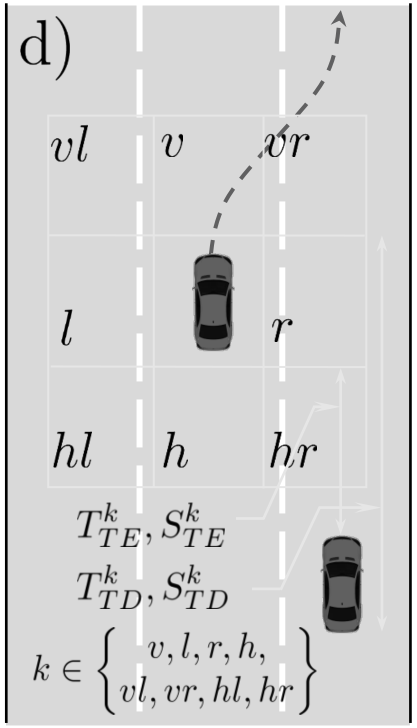
Symmetric Coordinate System



Lateral Movement Lateral Evidence (LE)



Trajectory

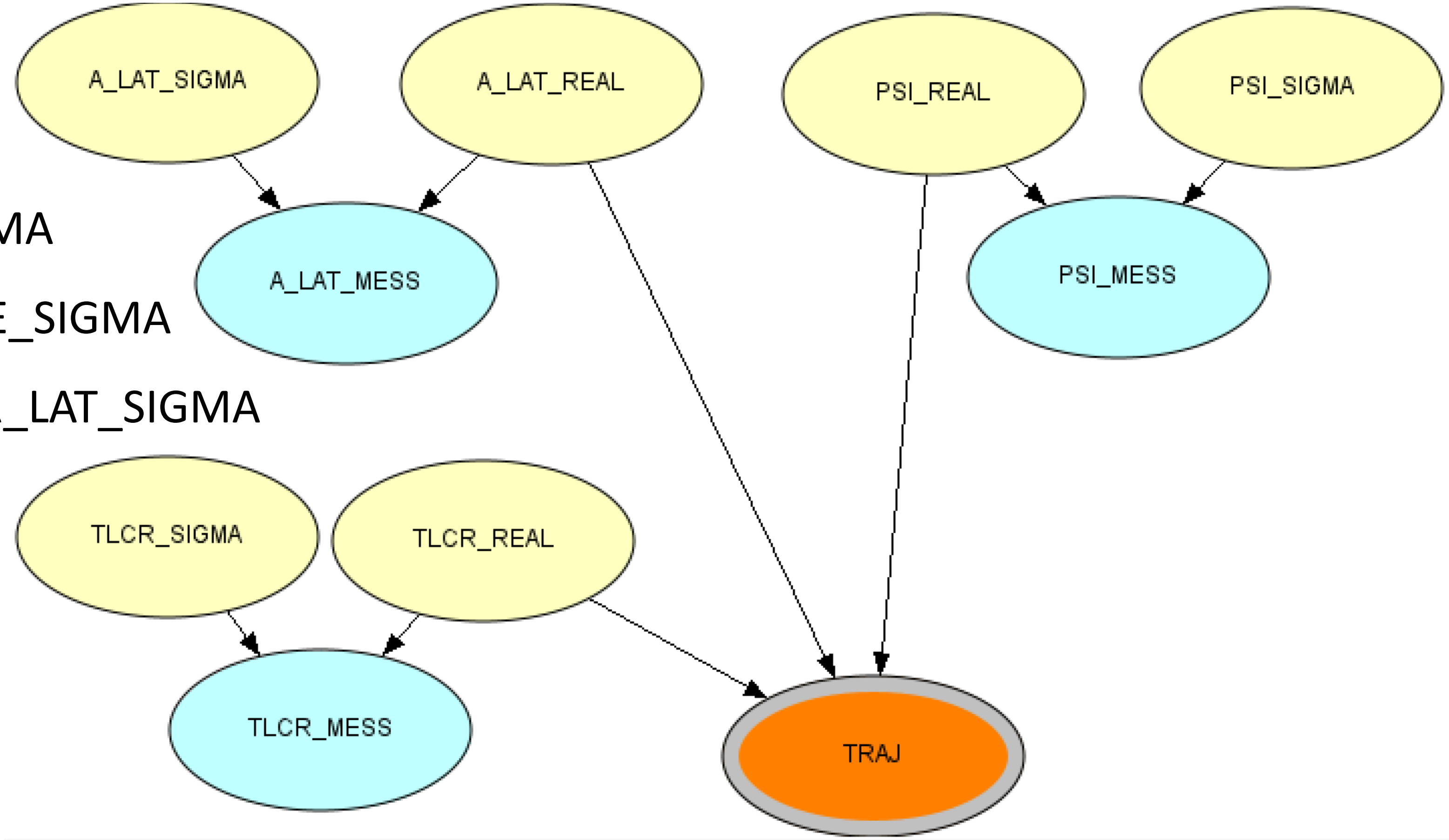


Free Space

Hypotheses for Maneuver Recognition under Uncertainties

TRAJ

- A_LAT_REAL, A_LAT_MESS, A_LAT_SIGMA
- PSI_ TTE_REAL, PSI_TTE_MESS, PSI_TTE_SIGMA
- TLCR_LAT_REAL, TLCR_LAT_MESS, TLCR_LAT_SIGMA

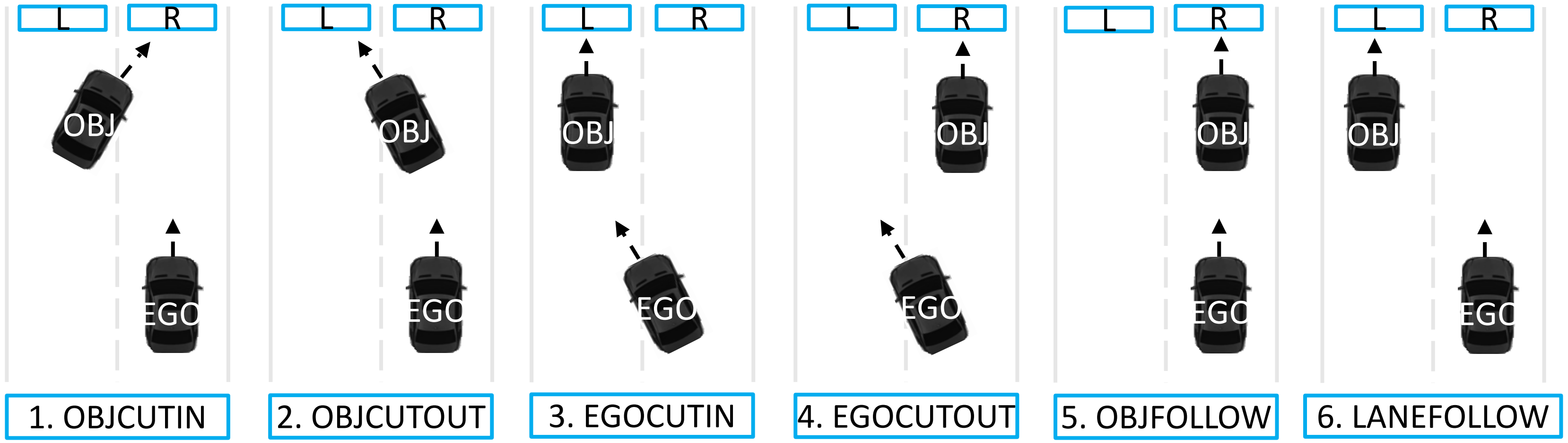


- Set the model structure to represent the qualitative relations in the model
- Introduce constraints where necessary
- Learn this Hypothesis from data

Cognitive (Knowledge-based)
Static Bayes model

Cognitive (Knowledge-based) modeling

- The modeling of network structure is based on physical Models und logical relation between the modeled variables
- Parametrization:
  - For logical cognitive variables: knowledge based hypotheses
  - For basic hypothesis in the input layer: learned from data
- Problem domain (output)



- Recognition logic is based on:
  - relative position
  - relative movement

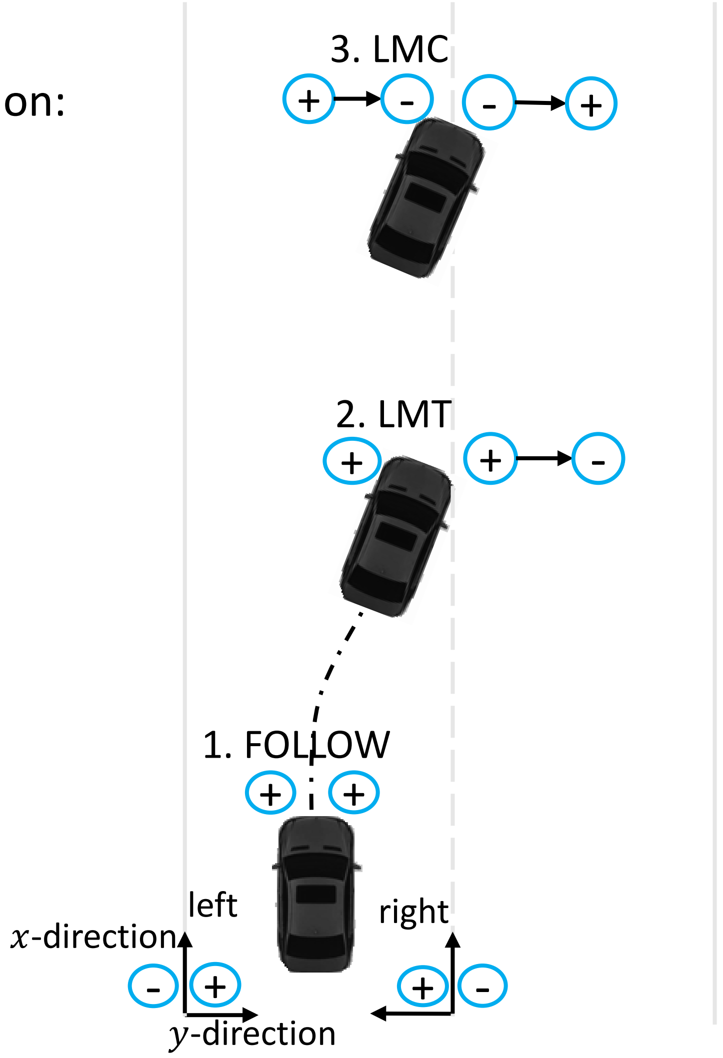
Definition of a Lane Change Maneuver

- A Lane Change Maneuver is defined based on: Vehicle-Lane-Marking relation

- Symmetric coordinates

- Three states:

1. FOLLOW: Vehicle follows the lane without touching the Lane Marking
2. Lane-Marking-Touch (LMT): Vehicle side touches the Lane Marking
3. Lane-Marking-Cross (LMC): Vehicle mid bumper crosses the Lane Marking



4.7.1 Network Logic Layers

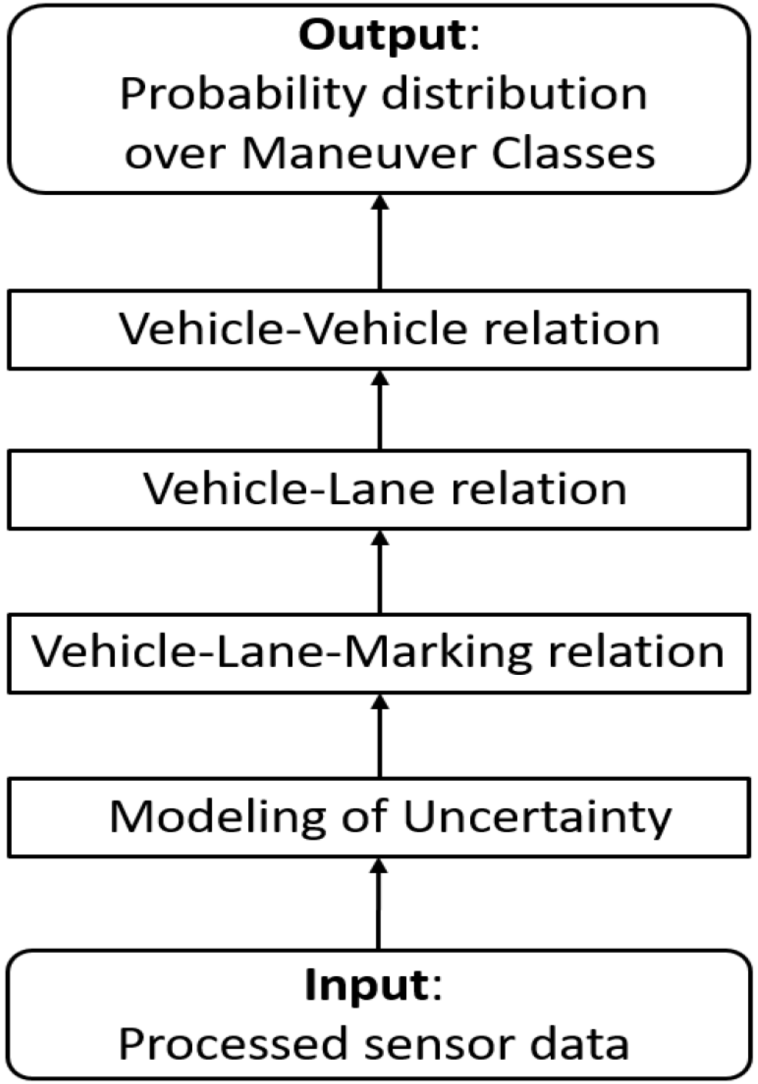
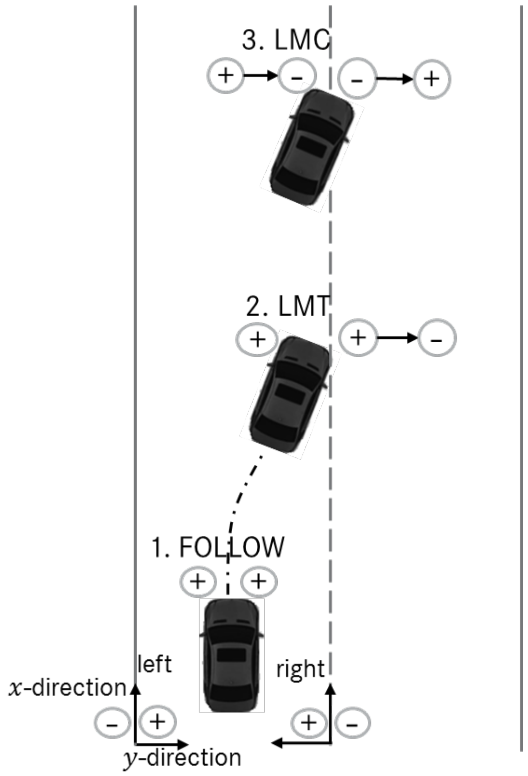


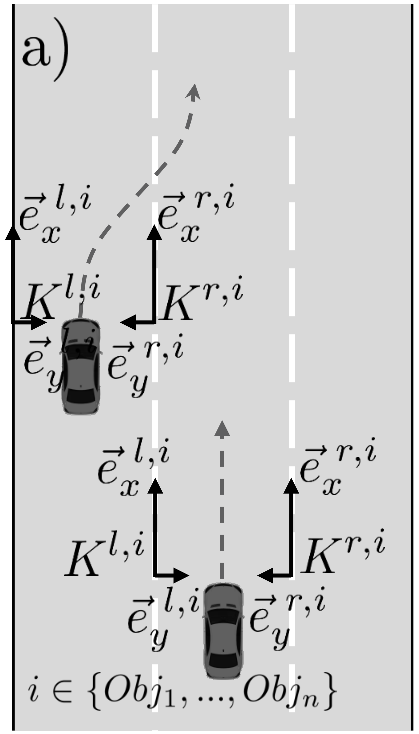
Figure 4.5: Description of the logic layers (according to [14])

Cognitive Hypotheses for Maneuver Recognition

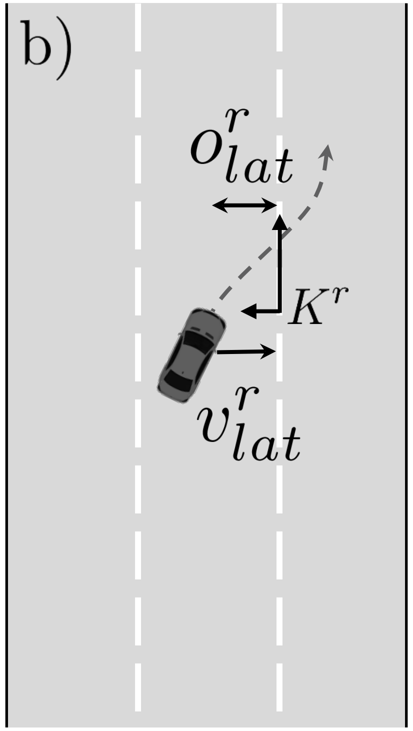
Features combined into cognitive hypotheses to mimic human reasoning



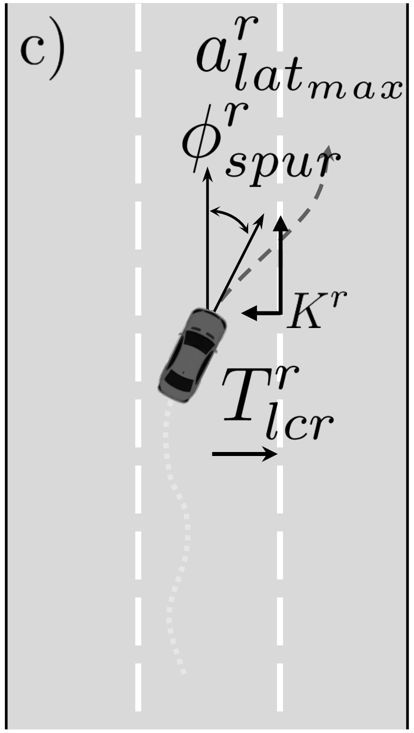
Lane Change Maneuver is defined
by Vehicle-Lane-Marking relation



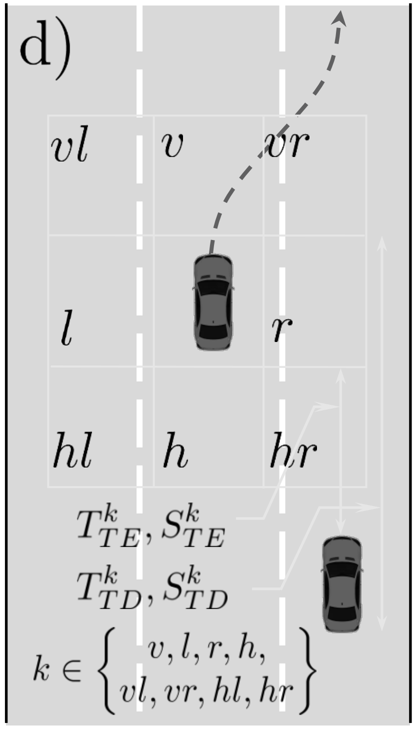
Symmetric Coordinate System



Lateral Movement Lateral Evidence (LE)



Trajectory



Free Space

Hypotheses for Maneuver Recognition under Uncertainties

TRAJ, OCCGRID (free space = safety), REL_DYN

OCCGRID (TTE = Time to Enter; TTD = = Time to Disapear)

- TTE_REAL, TTE_MESS, TTE_SIGMA,
  - same for TTD
- S_ TTE_REAL, S_TTE_MESS, S_TTE_SIGMA;
  - same for S_TTD

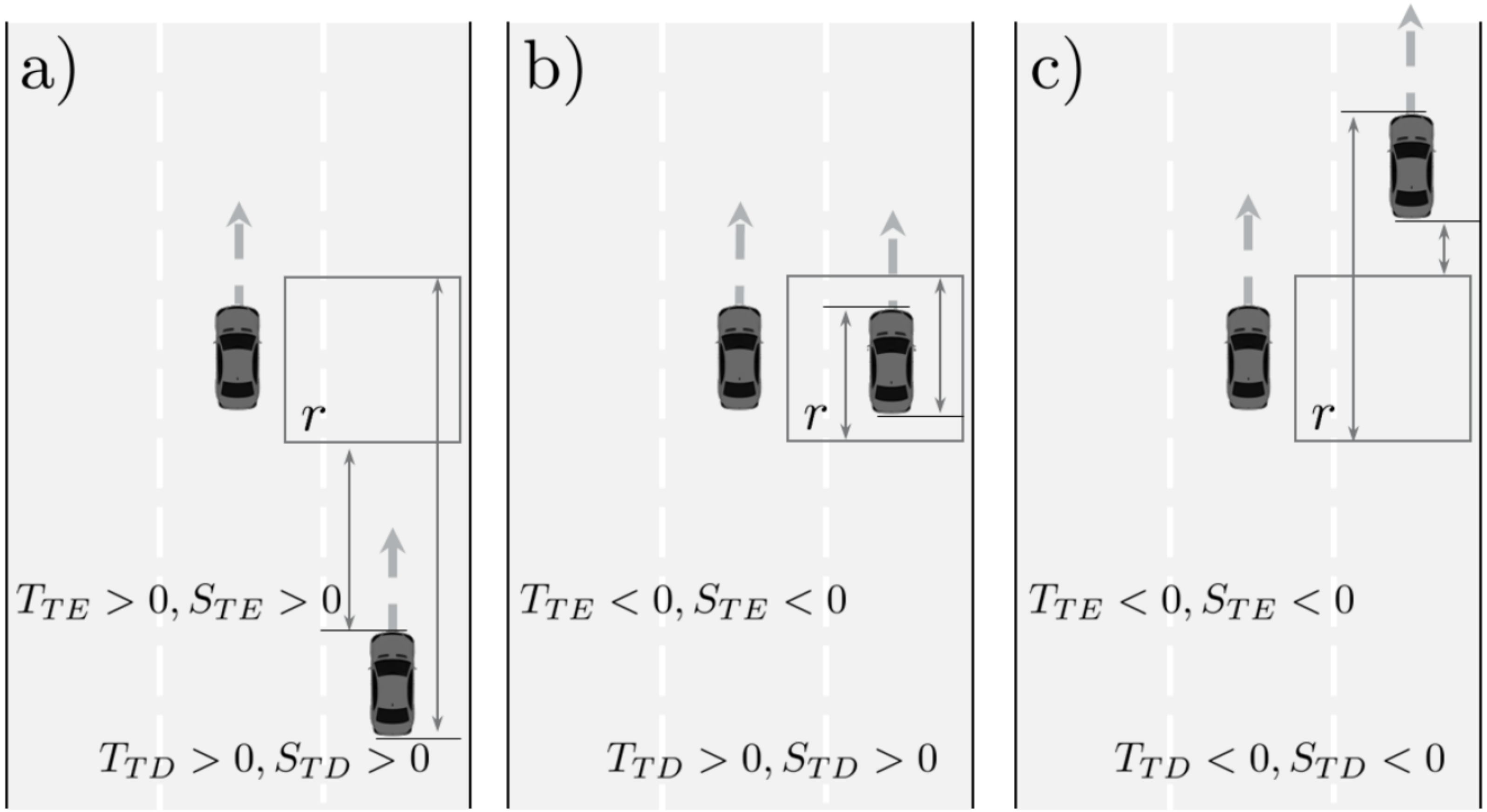


Abbildung 4.9: Modellierung einer Freiraum-Hypothese. a) Fahrzeug nähert sich der Zelle an. b) Fahrzeug befindet sich in der Zelle. c) Fahrzeug entfernt sich von der Zelle.

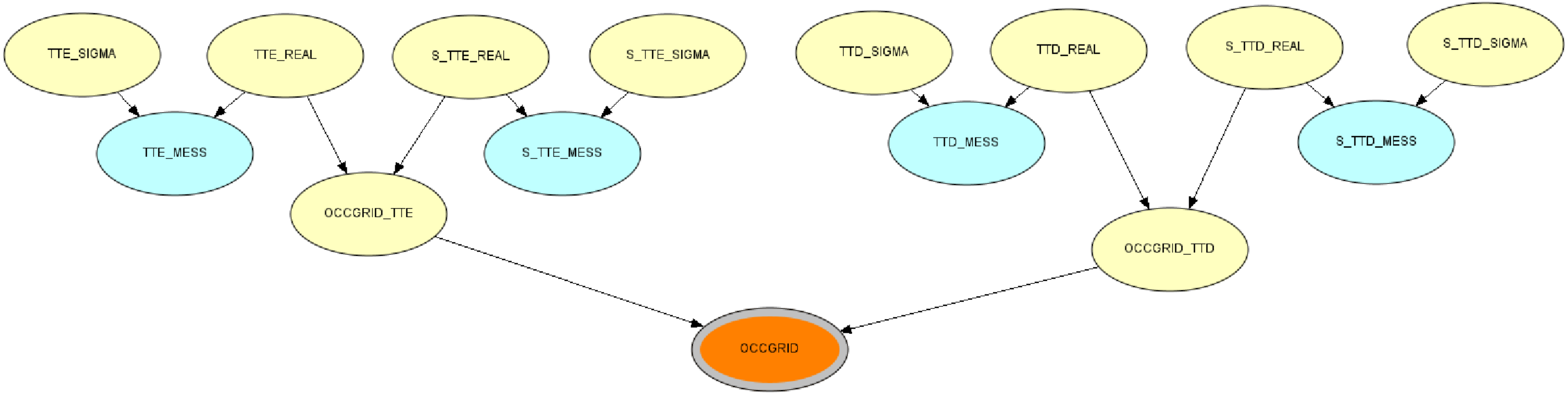
Hypotheses for Maneuver Recognition under Uncertainties

TRAJ, OCCGRID (free space = safety), REL_DYN

OCCGRID (TTE = Time to Enter; TTD = = Time to Disapear)

- TTE_REAL, TTE_MESS, TTE_SIGMA, same for TTD
- S_ TTE_REAL, S_TTE_MESS, S_TTE_SIGMA; same for S_TTD

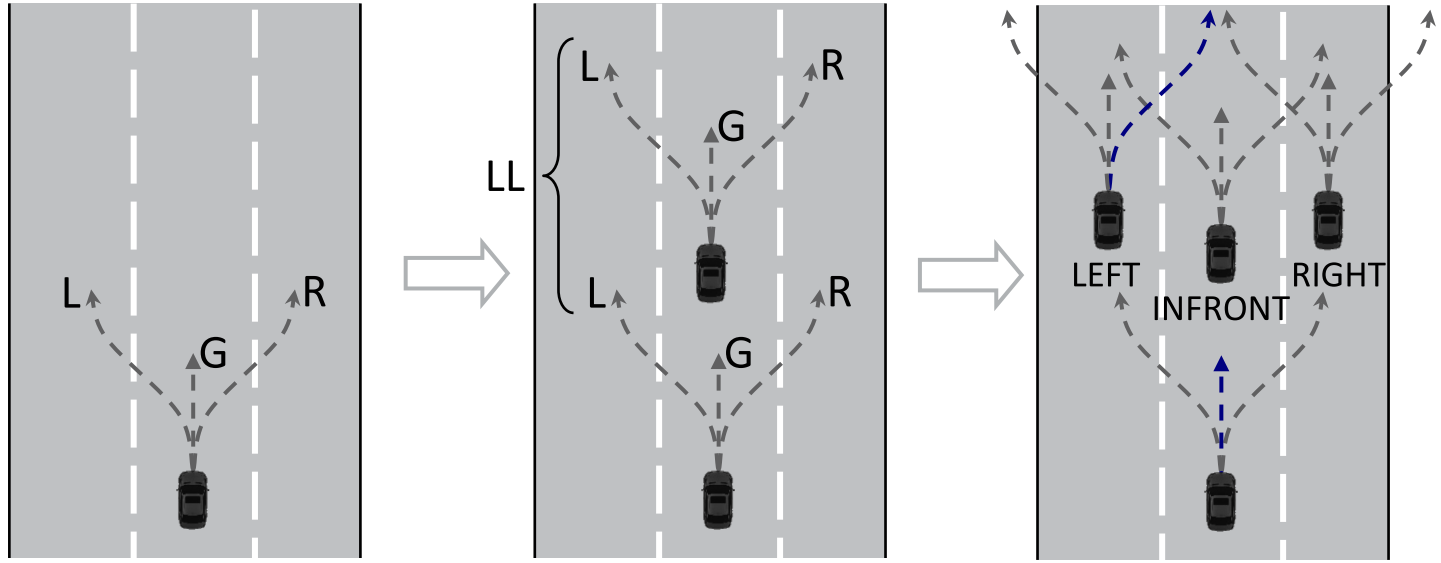
- Set the model structure to represent the qualitative relations in the model
- Introduce constraints where necessary
- Learn this Hypothesis from data



Modelling of Lane Change Maneuvers with OOBNs

Idea

- An Object is described in 3 Motion Classes (L, R ,G). G=Gerade=Straight
- This gives for an Object-Object relation: 9 Relation Classes (LL, LR, LG, RL, RR, RG, GL, GR, GG)
- Positioning of the reference vehicle (LEFT, RIGHT, INFRONT) results in 27 possible Driving Maneuvers

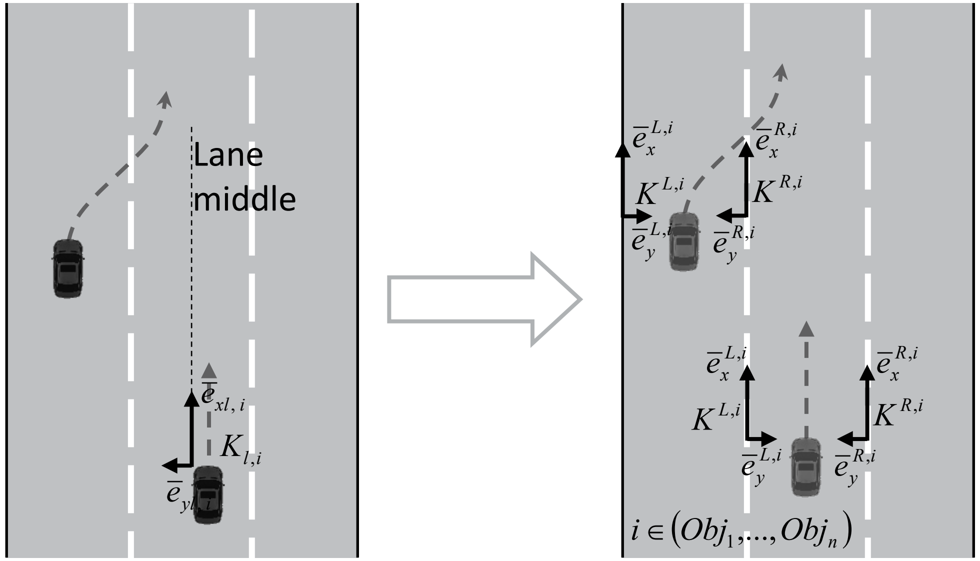


CUT-IN Maneuver is one of all possible 27 Driving Maneuvers

Modelling of Lane Change Maneuvers with OOBN's

Modeling process

- Definition of symmetric lane coordinate systems (left, right) for each Object



Use of Symmetry!

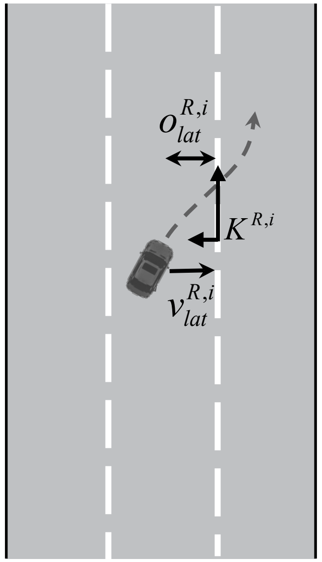
L R G

L
R
G

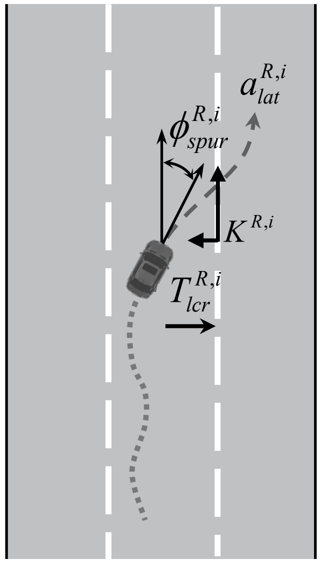
- Design of OOBNs:
  - Modelling of a Lane Change from the point of view of a lane coordinate systems
  - Classification of the Motion Class per Object: Motion towards the lane: left, right, straight
  - Classification by O-O Relation Class: Relative Position of Objects to each other
    - All Pairs as Relative Positions LRG – LRG
      - (k=2-Permutation from n=3 Elements with returning back → n^k = 3^2)
    - Recognition of Driving Maneuver Situation in an Object-Object relation (EGO-OBJ) or (OBJ-OBJ)

Modelling of Lane Change Maneuvers with OOBN’s

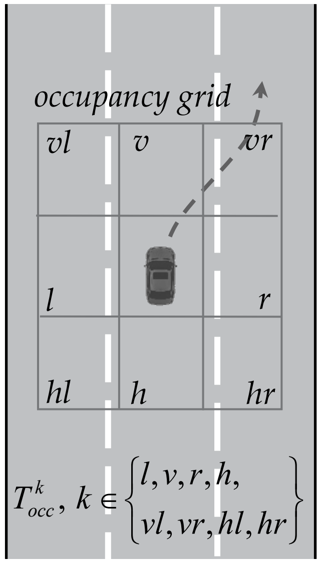
Situation features to Modell Lane Change Maneuvers



- distance to lane marking
- lateral speed



- time to cross the lane marking
- max usable acceleration
- lane orrientation error



- occupancy time of a cell

Laterale Evidence (LE)

Trajectory (TR)

occupancy grid (OCCG)

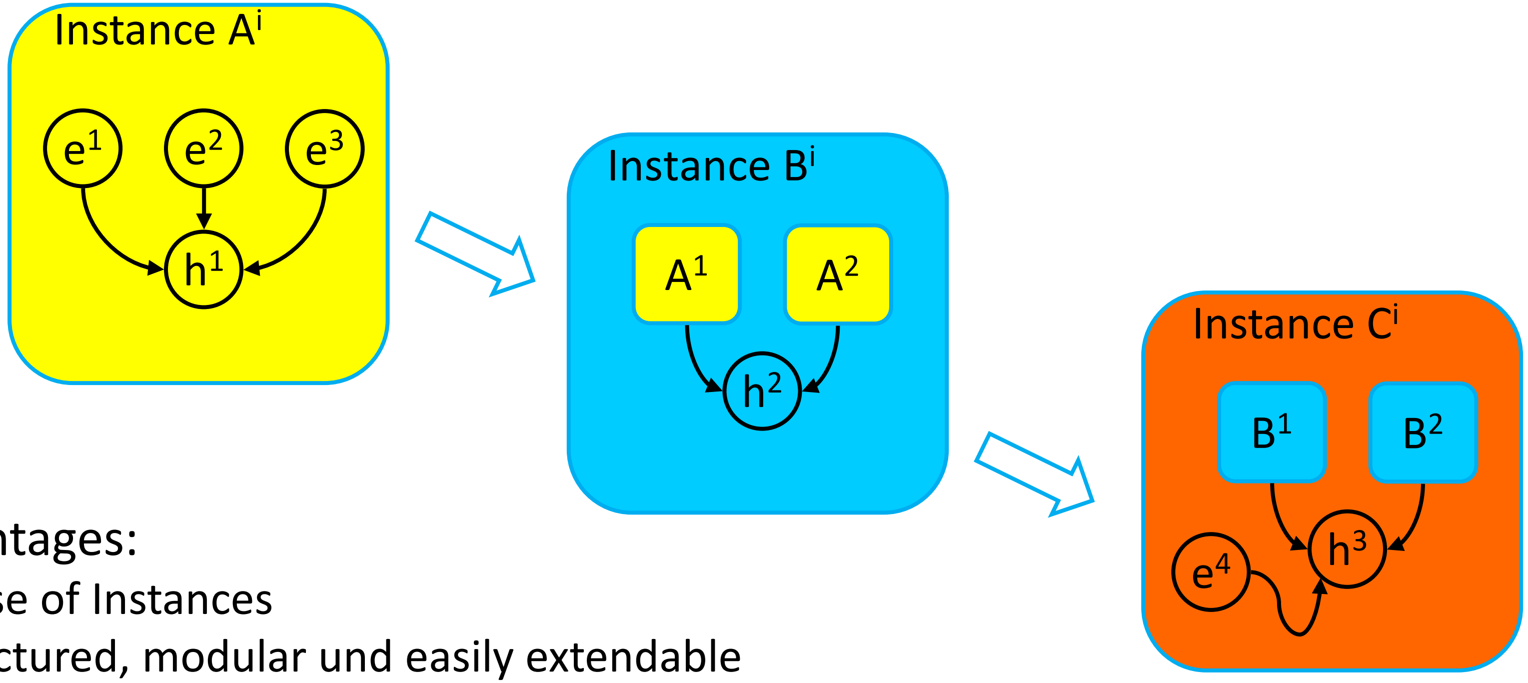
Object-orriented

Bayes Nets

Object orriented Bayesian-Networks

OOBN:

- A Bayes-Net is designed hiercicaly in layers
- Each Layer involves Incapsulations of BN-Fragments to Instance nodes
- Definition of IN- and OUT-puts per Instance
- Transfer of Information from one Instance to another



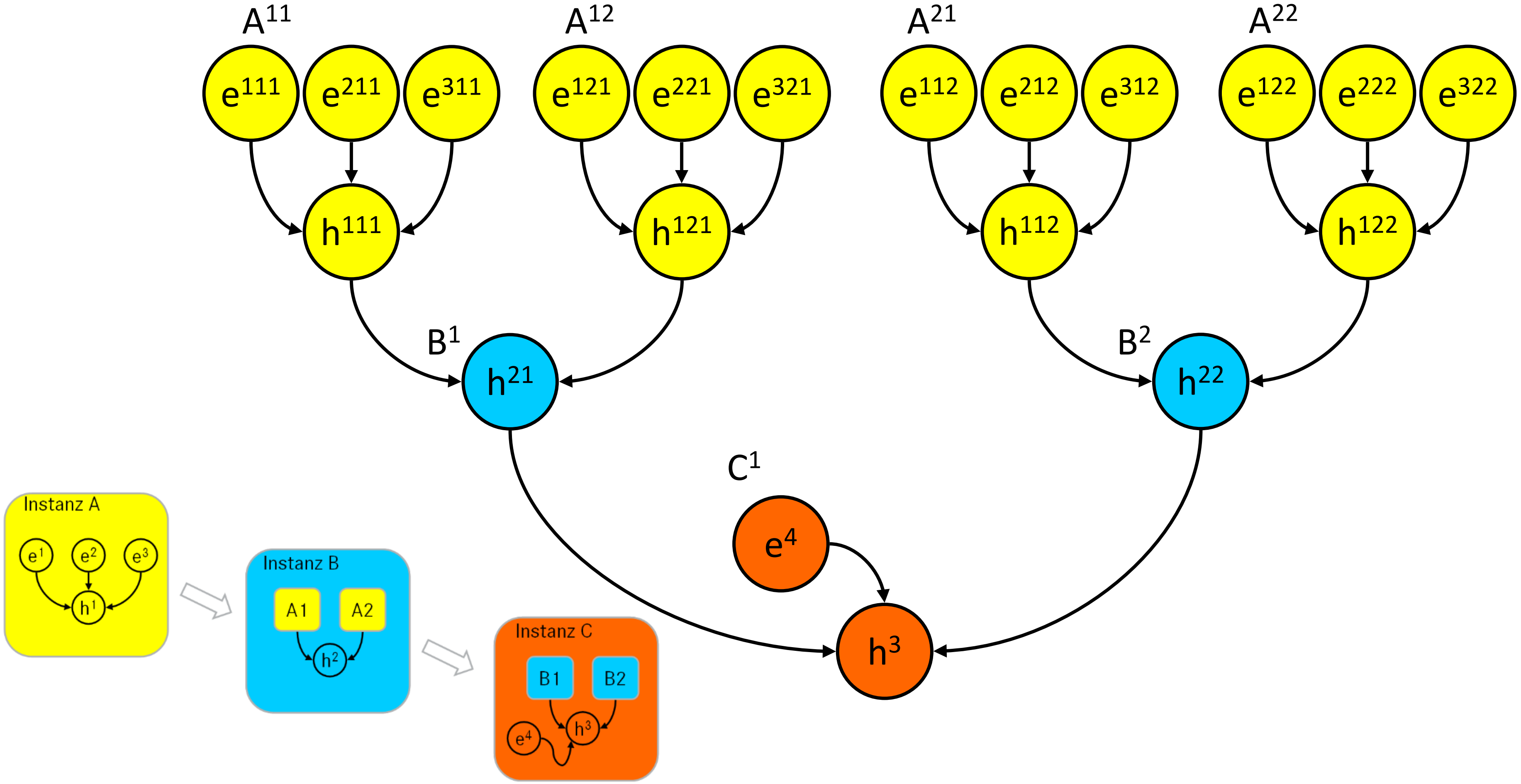
Advantages:

- Reuse of Instances
- Structured, modular und easily extendable

Object orientierte Bayes-Netze

Bayes Nets vs. OOBN

- Lack of overview
- Hard for changes in multiple objects and for extentions



Hypotheses for Maneuver Recognition under Uncertainties

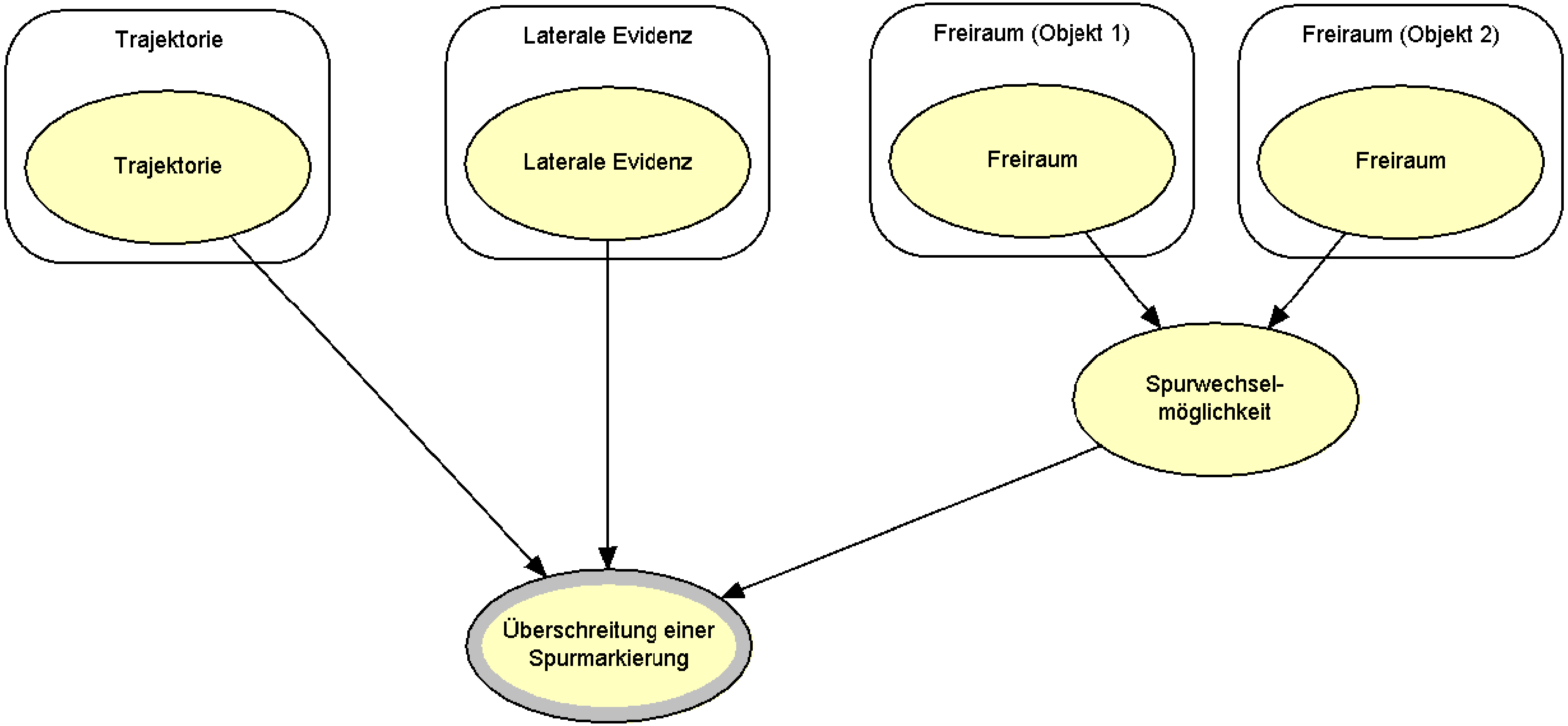
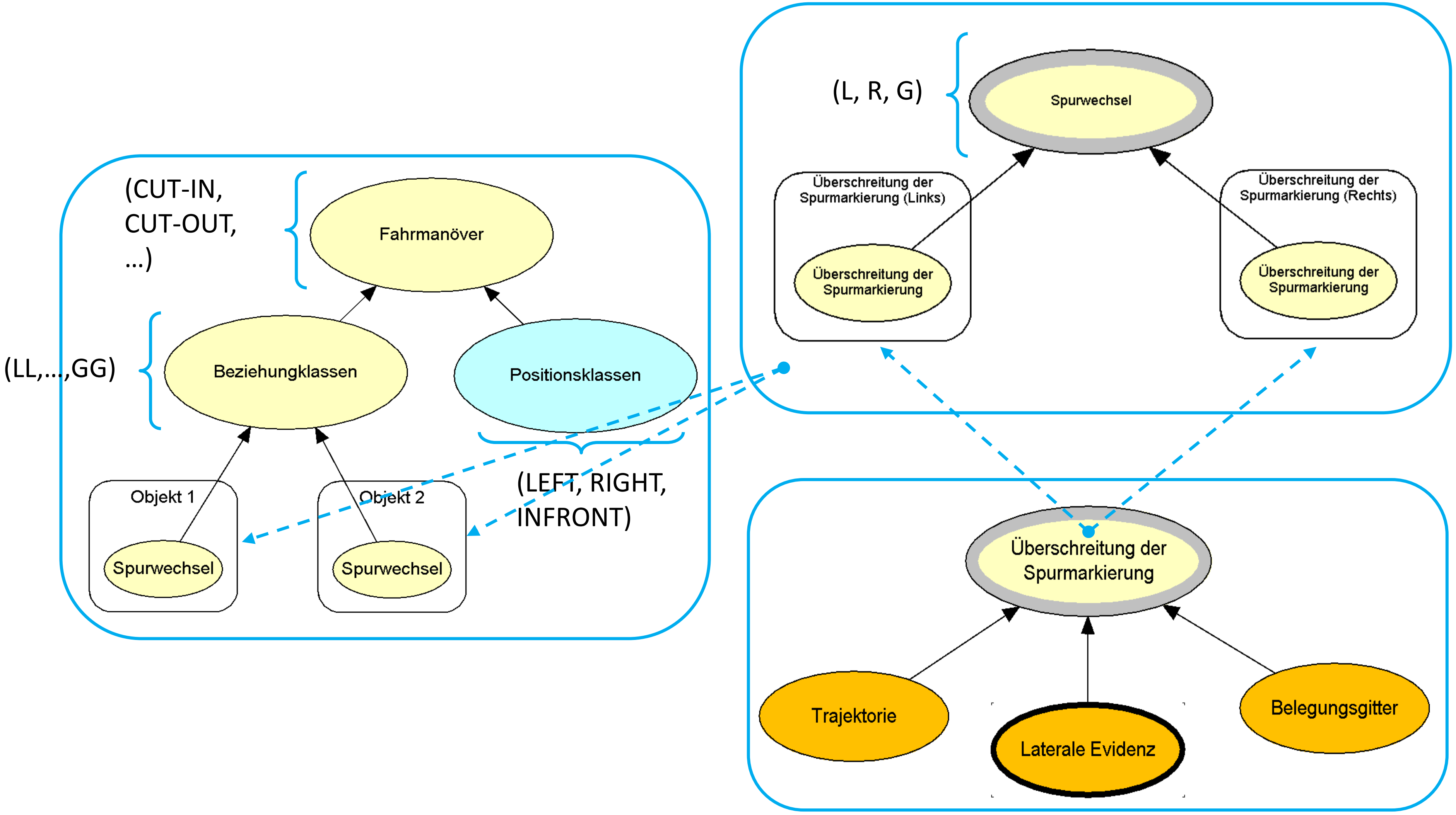


Abbildung 4.15: Hypothese *Übeschreitung einer Spurmarkierung*

Modelling von
Lane Changen
with OOBN's

Modelling of Lane Change Maneuvers with OOBNs

Overview of OOBNs for Recognition of a Lane Change :



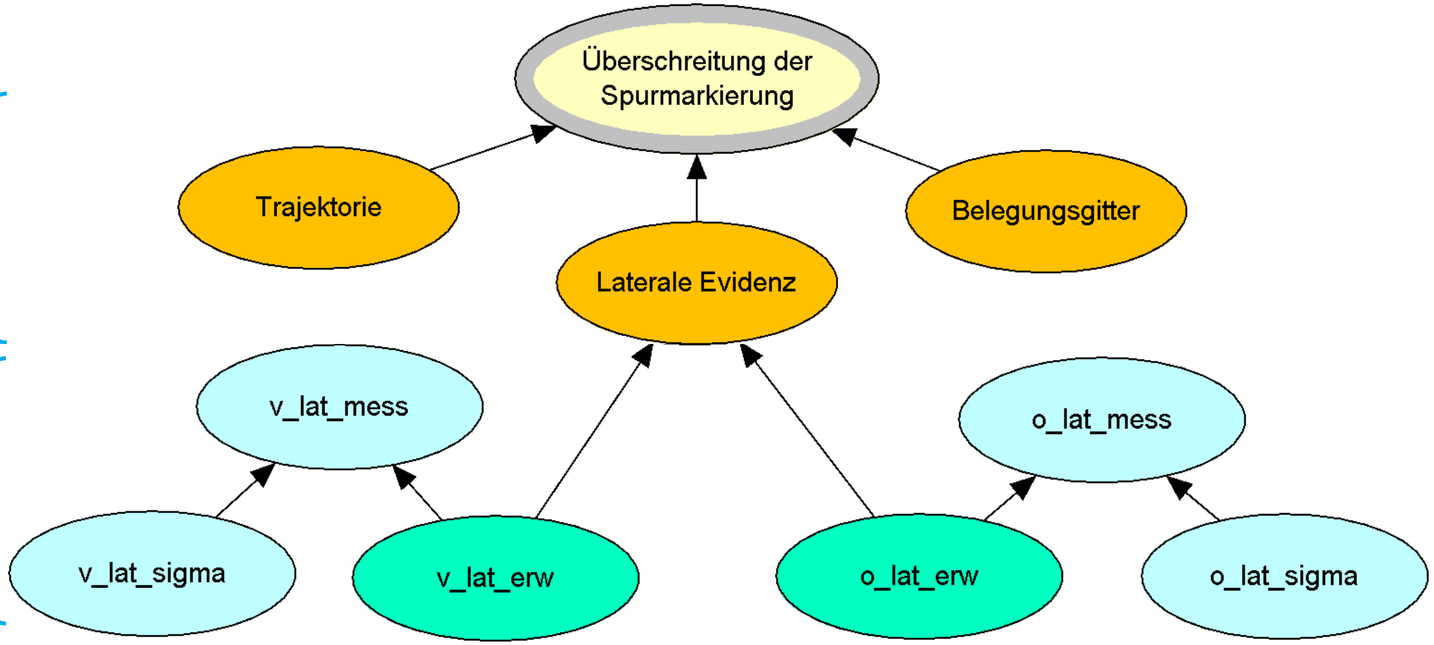
Modelling of Lane Change Maneuvers with OOBNs

Crossing of a lane marking

- Generation of Lane Change Hypotheses and Free Space hypothesis
- Aggregation into one Main hypothesis
- Treatment of Uncertainties in Measurements

Lane Change Hypotheses and Free Space hypothesis

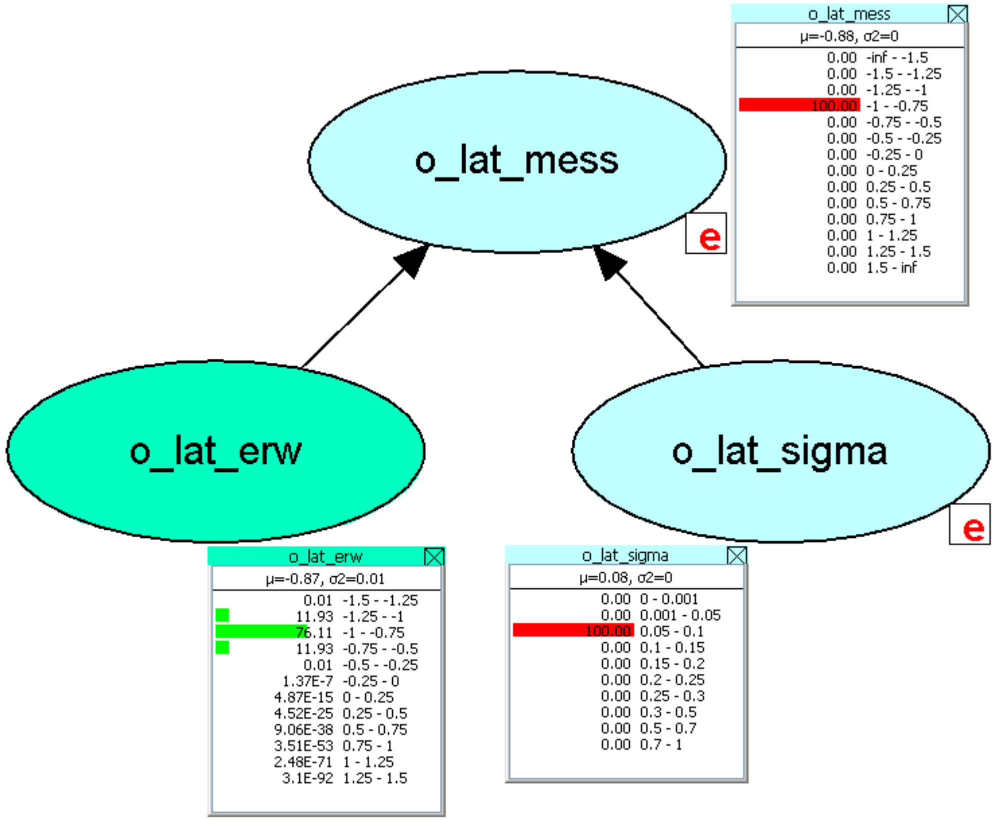
Treatment of Uncertainties in Measurements



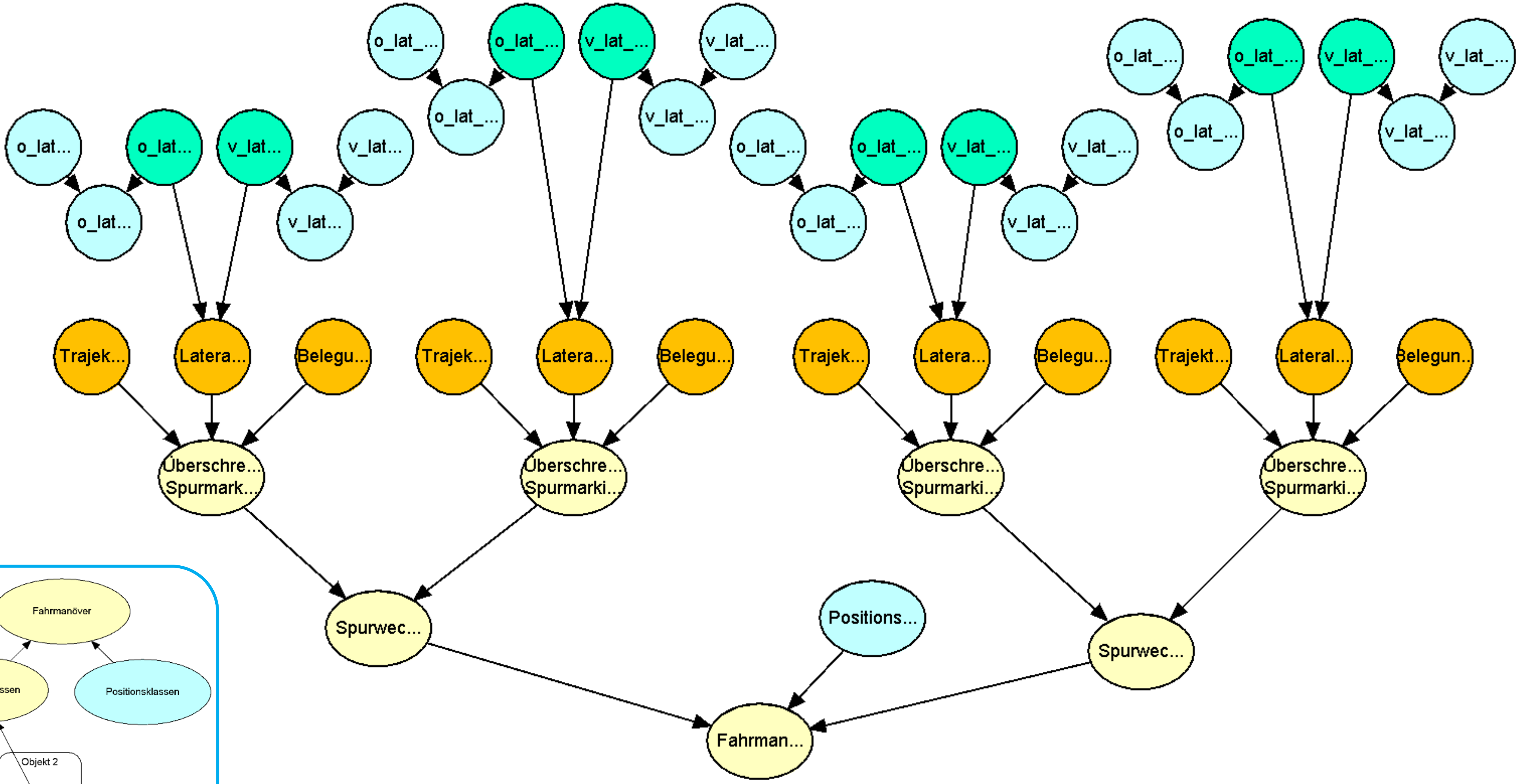
Modelling of Lane Change Maneuvers with OOBNs

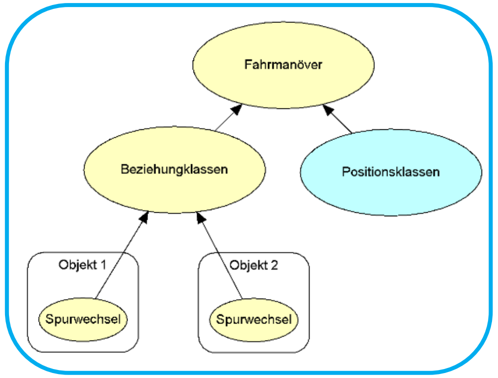
- Treatment of Uncertainties in Measurements
- Modelling of noisy measurements as Normal distribution
- $S_{mess} = S_{erw} + S_{rauschen}, \qquad S_{rauschen} \sim N(0, S_{\sigma^2})$

- Hard Evidence – as input of the computed Situation features s_{mess} and their Variances s_{σ^2}
  Computation of their expected values (Probability of real values) s_{erw}

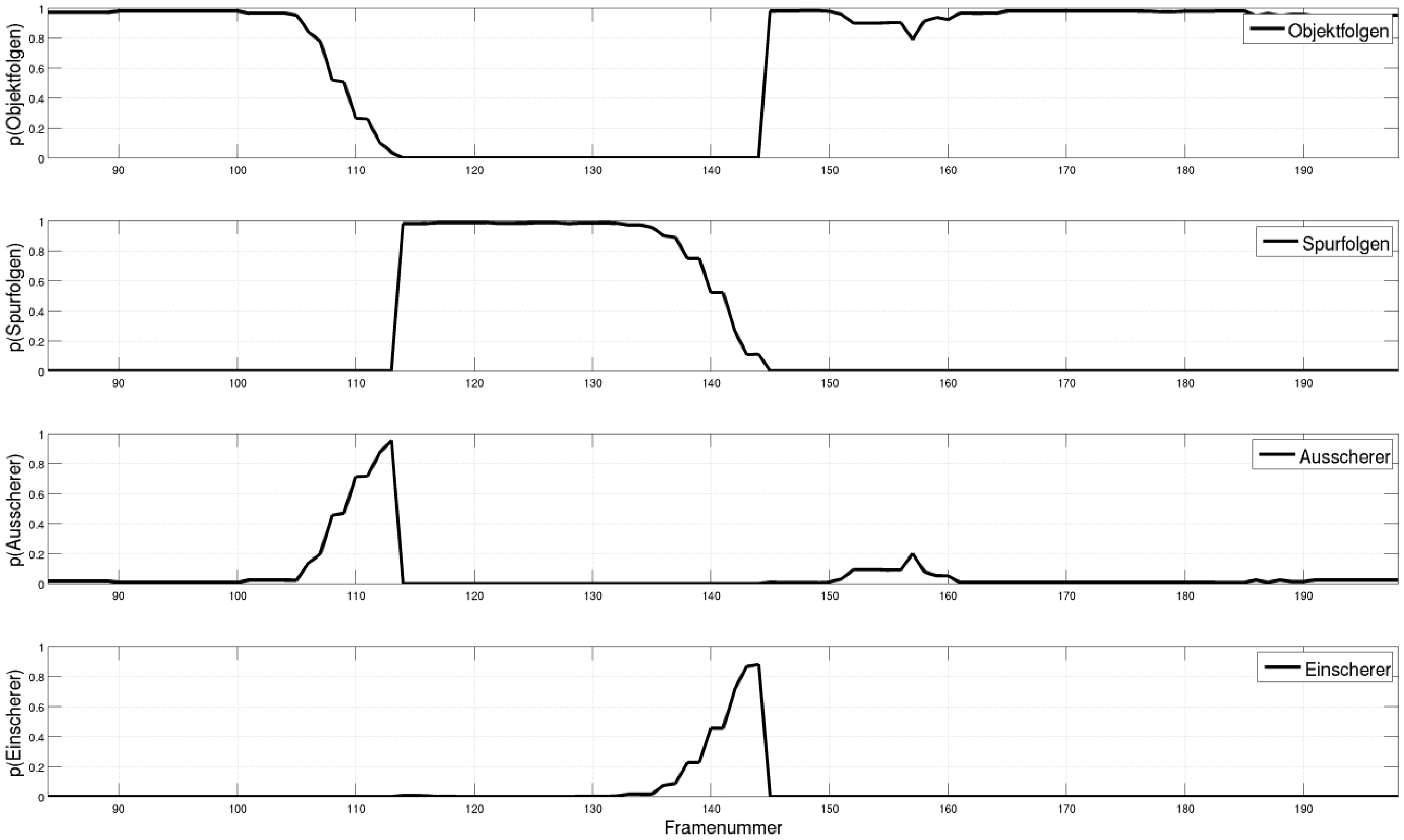


Modelling of Lane Change Maneuvers with OOBNs





Results


p(Objektfolgen)
Objektfolgen
p(Spurfolgen)
Spurfolgen
p(Ausscherer)
Ausscherer
p(Einscherer)
Einscherer
0
0.2
0.4
0.6
0.8
1
90
100
110
120
130
140
150
160
170
180
190
Framenummer

Results

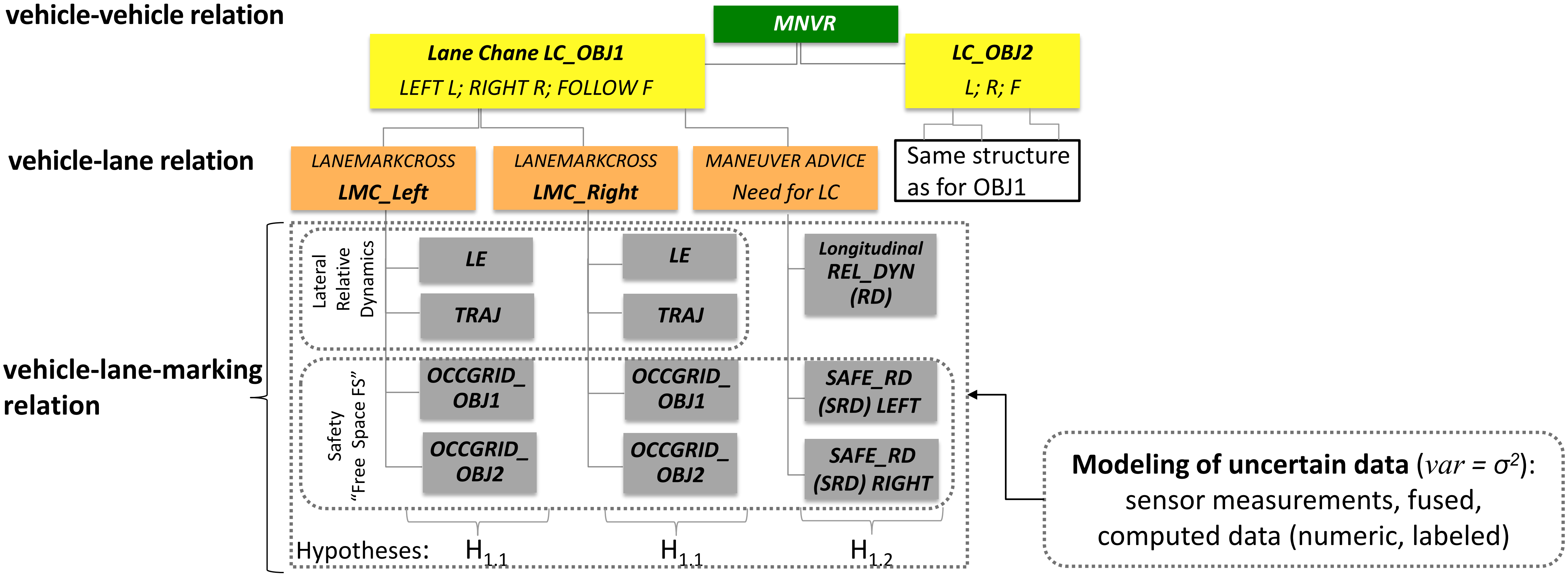
- Unified Representation of a Scene by the worled modell

- Recognition of Lane Changes with OOBN
  – simple Design
  – modular, easy extendable

- Integration of the Driving Maneuver Recognitionmoduls on theImage Processing-PC of the vehicle
  – Cycle time ~ 2 ms per Object relation

- Use of Learn methods to Parameterize the Bayes Nets

Cognitive Model Structure and Layers for Situation-aware Maneuver Recognition

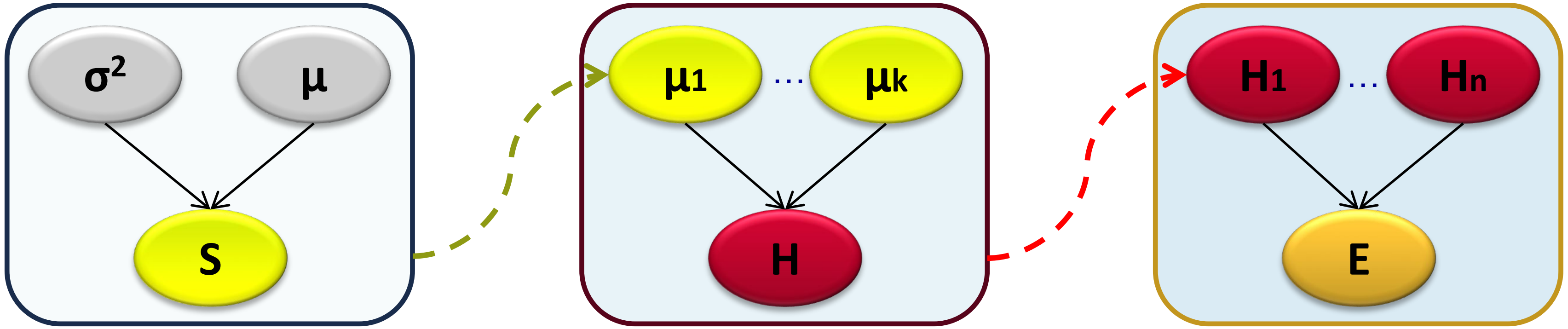


Object Oriented Bayesian Network (OOBN)

Bayesian Network in terms of classes and objects

- Reduces modeling complexity of BN in large complex domains

  by model library of fragments (for repetitive modelling elements)
- Allows BN fragments to be reused in similar situation context
- Enables easy modification in network design without disturbing the whole network
- Easily extendable



Modeling of uncertain data
Class: level_S

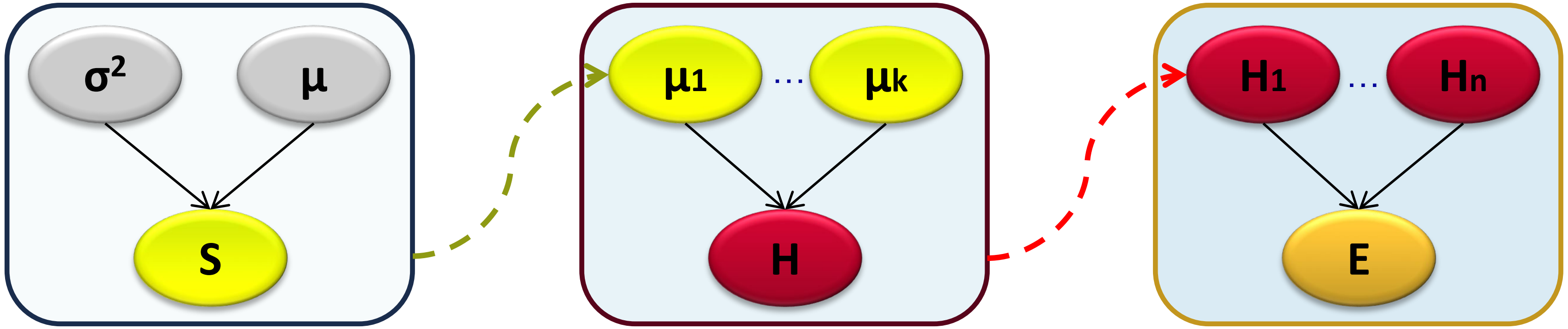
Evaluation of hypotheses
Class: level_H
(with *k* instances of ***level_S***)

Modeling of Events
Class: level_E
(with *n* instances of class ***level_H***)

Object Oriented Bayesian Network

Bayesian Network in terms of classes and objects

- Reduces modeling complexity of BN in large complex domains
  - by model library of fragments
- Allows BN fragments to be reused in similar situation context
- Enables easy modification in network design without disturbing the whole network
- Easily extendable



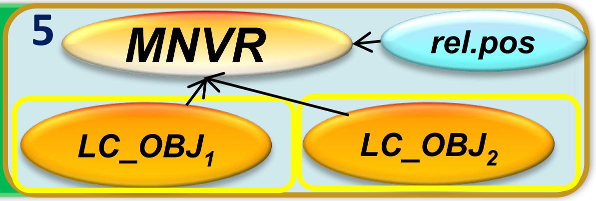
Modeling of noisy data
Class: level_S

Evaluation of hypotheses
Class: level_H
(with *k* instances of ***level_S***)

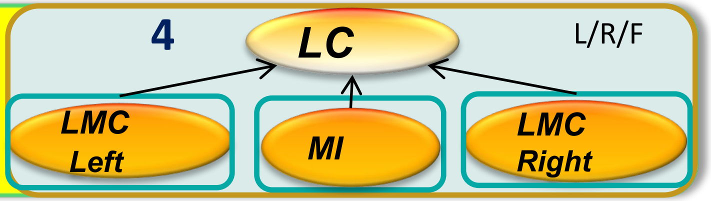
Modeling of Events
Class: level_E
(with *n* instances of class ***level_H***)

Maneuver Recognition: OOBN Hierarchical Abstraction Levels

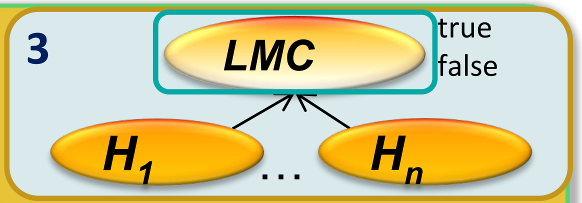
Modeling of Driving Maneuvers
Decision on Event: *Class MNVR*
(Vehicle-Vehicle-Relation) *MNVR*



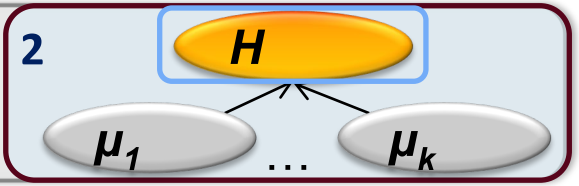
Modeling of Lane Change Maneuver
Decision on Event: *Class LC*
(Vehicle-Lane-Relation) LC



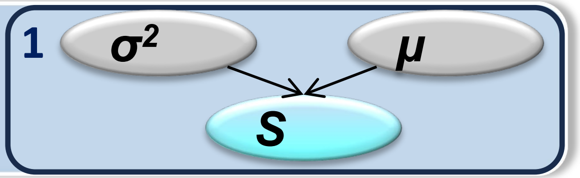
Modeling of Lane Change Behavior
Decision on Event: *Class LMC* or *MI*
*Lateral relative dynamics: *LMC*
*Longitudinal relative dynamics: Maneuver Intention(MI)



Evaluation of hypotheses: *Class* $H_{1.i}$
$H_{1.1} \equiv$ *{LE, TRAJ, FS (OCCGRID1, OCCGRID2)}*
$H_{1.2} \equiv$ *{RD, SAFE_RD}*



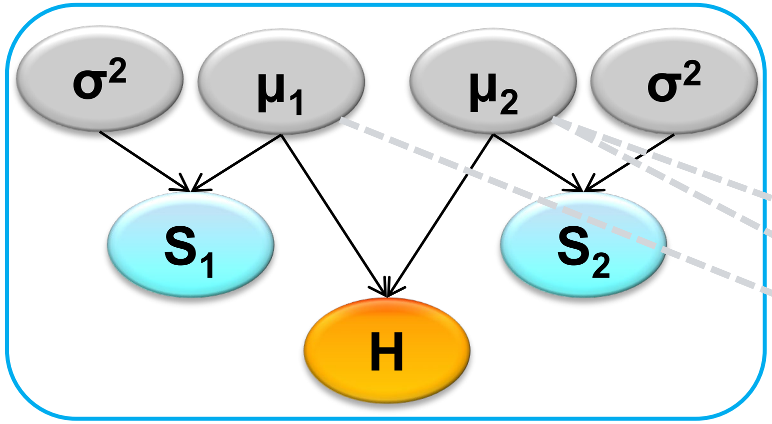
Modeling of noisy data ($var = \sigma^2$)
Measurements: *Class S*
Inference on *real value* μ



Dynamic Bayesian Networks for Early Maneuver Prediction

Model the observed Trends by Causal Relations between the time steps & Transitional Conditional Probability

Time t



$O(t+1)=O(t)+v(t)\cdot dt + N$,
N = white noise $N(0,\sigma^2)$ due to possible acceleration term $(a\cdot dt^2)/2$

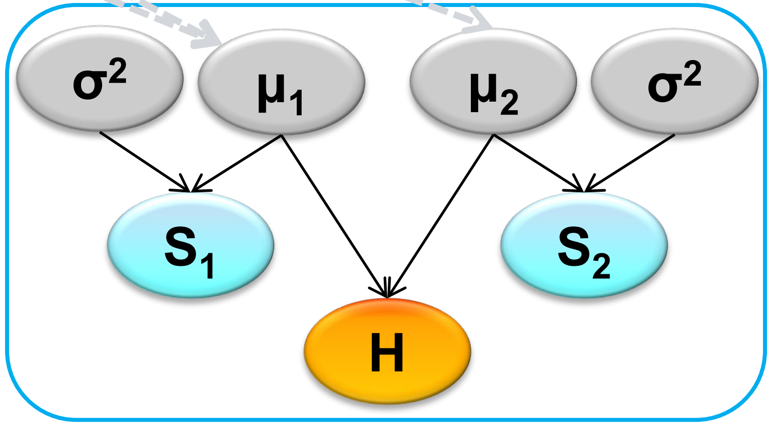
DBN = Dynamic Bayesian Network

Time t+1

DBN → New Challenges:

- Memory
- Computation time
- Prediction horizon

→ Need for efficient inference algorithms for DBN



Cognitive Systems by Bayesian Networks

- The network structure reflects relations from physical models and logical relations between the variables
- Knowledge-based Structure with recognition logic based on:
  - relative position
  - relative movement

  to lane marking; to lane; to surrounding vehicles
- Vehicle-Vehicle relation → One Model for all maneuver states as 6 classes (= elementary maneuvers):
  - ObjCutIn; ObjCutOut; EgoCutIn; EgoCutOut; ObjFollow; LaneFollow
- Parametrization based on knowledge and adapted by data:
  - For each logical variable: knowledge based growth function (sigmoid/logistic functions)
  - For basic hypothesis in the input layer: learned/adapted from data

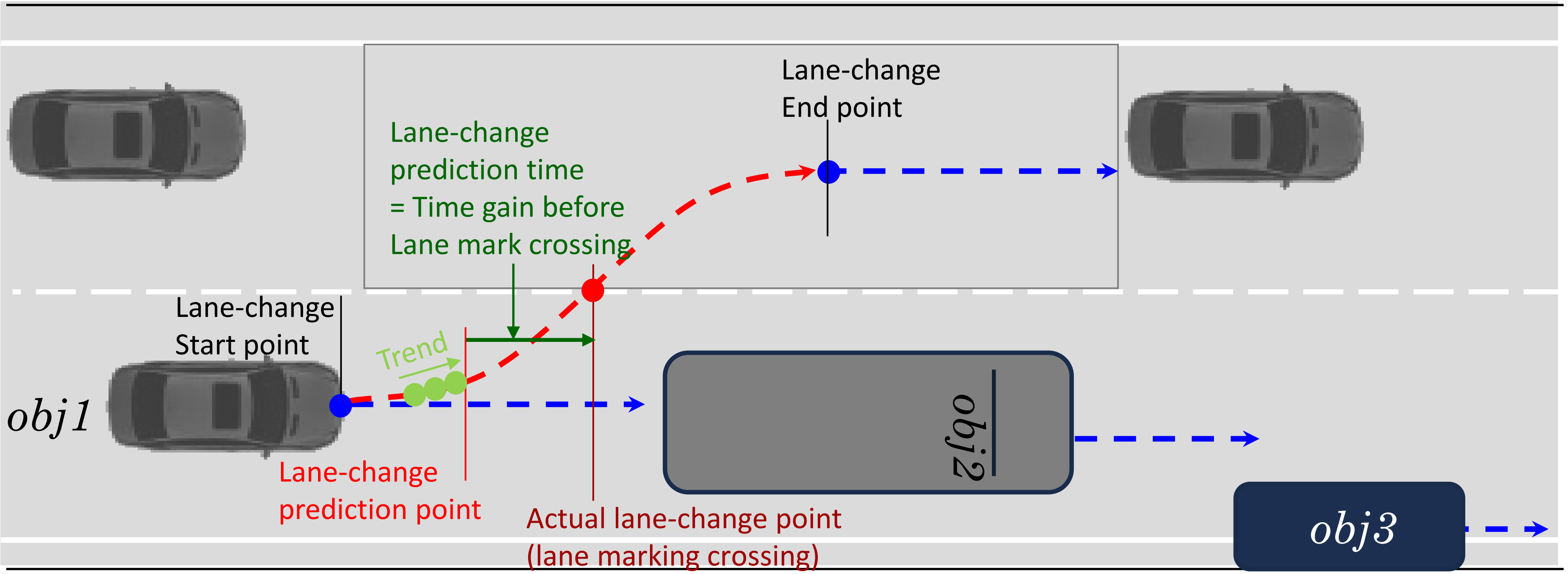
Structure

1. Bayes Network
2. Development Environment
3. Knowledge-based static Model
4. Trend Analysis
5. Dynamic Bayes Model
6. Naive Bayes Model
7. Evaluation Results
8. Summary
9. Future development

Early Recognition/Prediction of Needed Lane Change Maneuver

Scenario 1: Observed behavior during lateral relative dynamics towards the lane marking. It allows early recognition of **beginning** lane change (**LC**) before crossing the Lane Marking.

Scenario 2: Intended behavior due to longitudinal relative dynamics between following and front vehicles on the same lane**:** car drives on a highway at constant speed. It allows to predict early a **needed LC**



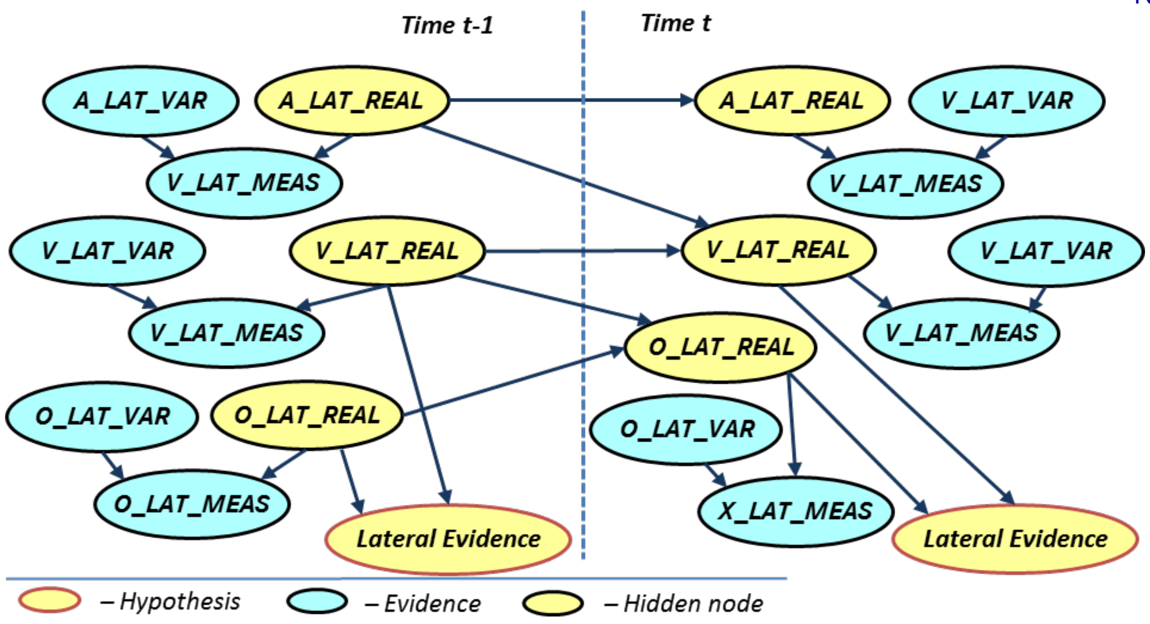
Dynamic Bayesian Networks
for Lateral and Longitudinal Relative Dynamics

LE_DBN →By analogy: REL_DYN_DBN

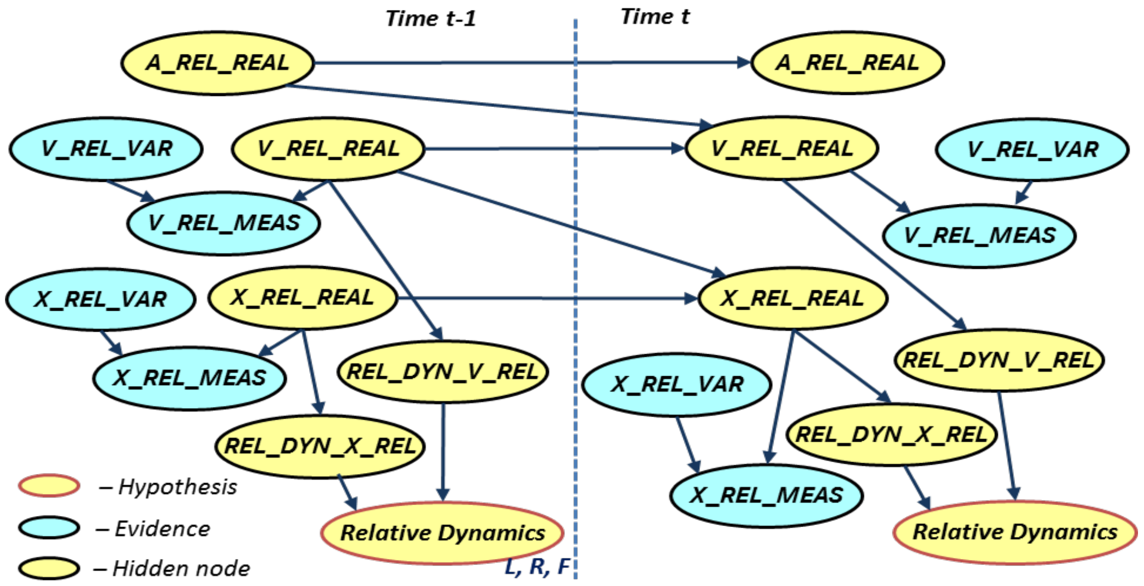
$$X_{REL\_REAL}(t) \sim N(X_{REL\_REAL}(t\text{-}1) + V_{REL\_REAL}(t\text{-}1)\cdot\Delta t,\ \sigma_{X(t)}^{2})$$

$$V_{REL\_REAL}(t) \sim N(V_{REL\_REAL}(t\text{-}1) + A_{REL\_REAL}(t\text{-}1)\cdot\Delta t,\ \sigma_{V(t)}^{2})$$

$$A_{REL\_REAL}(t) \sim N(A_{REL\_REAL}(t\text{-}1),\ \sigma_{A(t)}^{2})$$

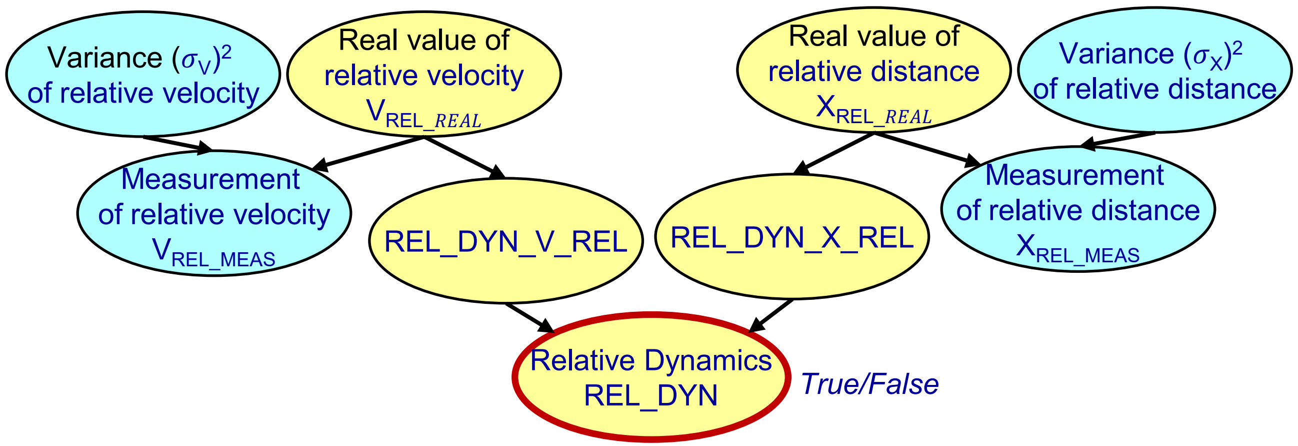


Lateral features:
LE_DBN: 2T-DBN structure
for the hypothesis *LE* (Lateral Evidence)
for Lateral Relative Dynamics towards the lane marking



Longitudinal features:
REL_DYN_DBN: The 2T-DBN structure
for the hypothesis *REL_DYN* (RD)
(Longitudinal Relative Dynamics)
with *A_REL_REAL* as hidden node

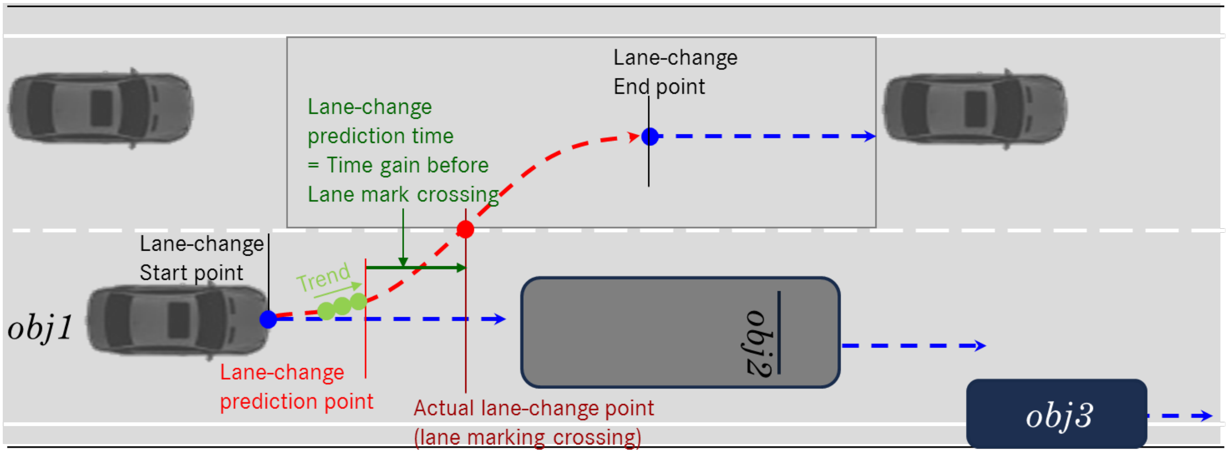
Relative Dynamics & Safety

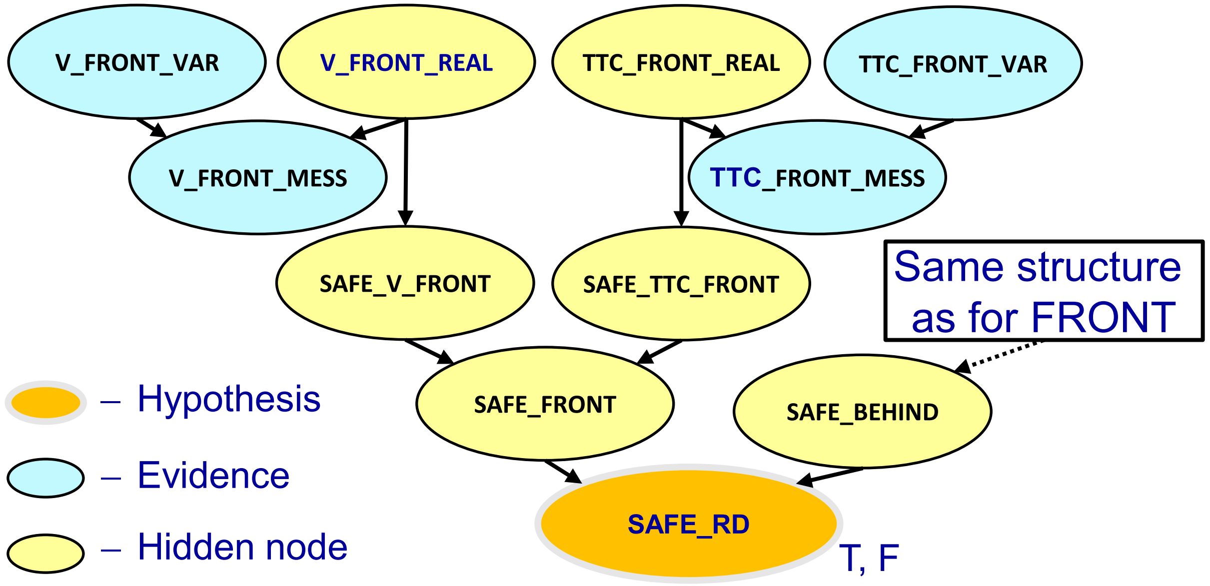


Data: REL_DYN + SAFE_REL_DYN
V_REL_OBJ_MESS, V_REL_OBJ_VAR
X_REL_OBJ_MESS, X_REL_OBJ_VAR
V_REL_EGO_MESS,X_REL_EGO_MESS

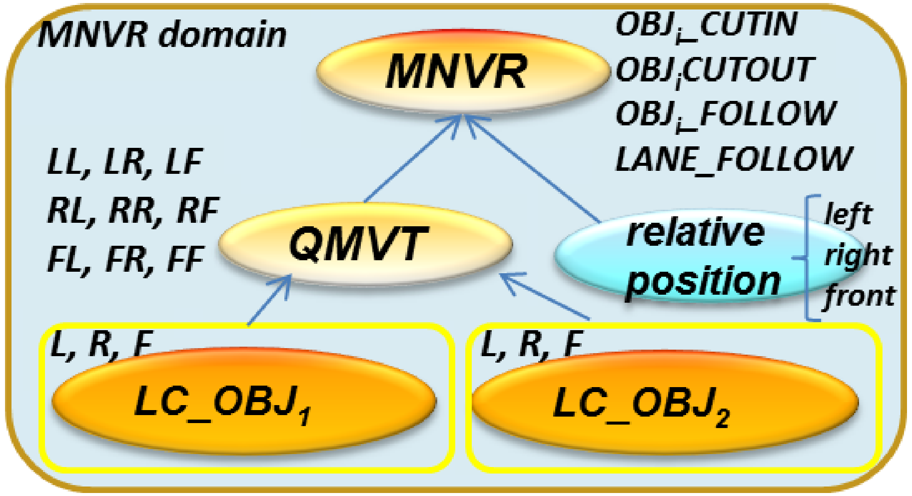
X_REL_FRONT, V_REL_FRONT,
T_REL_FRONT

X_REL_BACK, V_REL_BACK,
T_REL_BACK

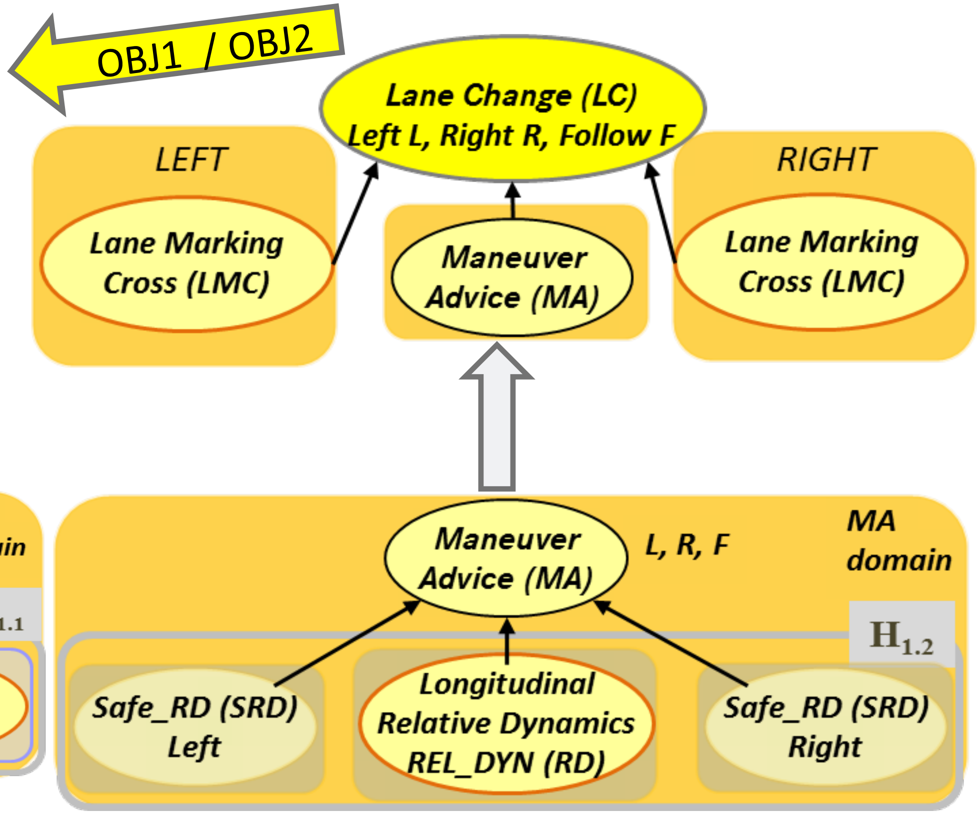




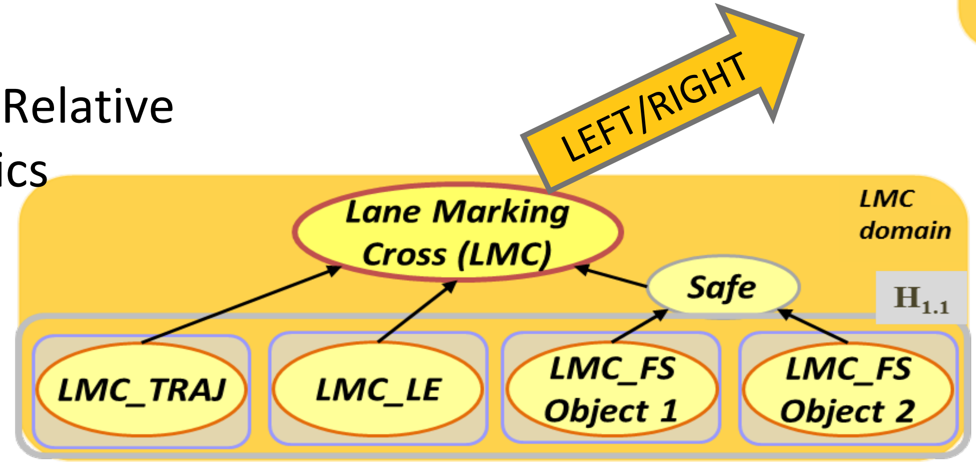
Cognitive OOBN with lateral and longitudinal dynamics



Computationally tractable solution uses **Divide&Conquer** to split the original OOBN model into BN-fragments → performs inference in each BN-fragment and uses the inference results as likelihood at the next level



Lateral Relative Dynamics



Longitudinal Relative Dynamics

Testing of Bayesian Network Performance for Maneuver Recognition

- The developed scalable software system for maneuver recognition has been implemented/transferred on the Linux target platform, emulating the automotive platform of the experimental car.
- The car is used to collect streaming data and to test the developed algorithms.
- The best performing classifiers - selected as trade-off between high accuracy and prediction time, based on
  - optimal initial guess,
  - learning and adaptation of parameters in the models,
  - linear and logistic regression.
- The framework has been deployed on the prototype car and tested both statistically and during driving on real highways in Germany and Luxembourg. Proven feasibility of approach to required accuracy and prediction time for DBNs with adaptation and using save-to-memory, instantiation junction tree techniques and the divide-&-conquer approach.
- Recognition performance - visualized in the user display - observed during the drive on the highway.

Testing & Evalutation Results

How to test the system performance? Use statistical evaluation.

- Clean the test data set of 350 sequences (balance: 50% Lane Change + 50% Follow)

- Evaluation is based on the time point of lane cross, which is marked in the data (annotation)

Classifier\Performance	**Lane Change**	**Follow**	**Time gain [sec]**	**Trend Analysis: Performance with Logistic Regression**		
				Lane Change	Follow	Time gain [sec]
ORIG OOBN	96.1%	98.3%	0.77			
ORIG OOBN (opt param)	98%	100%	1.05			
DBN_4fragm with ***LogReg***	**98.9%**	**100%**	**1.13**	99.4%	98.4%	**1.29**
STAT with ***LinReg* & *LogReg***	99.4%	96.2%	**1.40**	**99.4%**	**88.6%**	**1.54**
(Dynamic) **NaiveBN**	99.4%	55.2%	2.13			

- Network parameters of the knowledge based structures are learned from a (big) data set, collected in real highway driving
- Only learning (DNaiveBN without knowledge) is not accurate enough for Follow; Good (time gain) recognition of Lane Change
- Trend analysis - uses logistic regression approaches for early recognition
- Extension to DBN improves both accuracy and recognition time gain

- Demonstrate feasibility: System deployment on experimental vehicle and test in real highway drives

When to use Bayesian Networks to the nature of the problem to ensure, that probabilistic networks are an appropriate choice of method?

Highly structured domain with cause-effect relations

- Detailed knowledge about structure and probabilities (can be also learned from data)
  - (causal) relations among the variables, the conditional probabilities quantifying the relations.
- Static structure (qualitative relations remain), but drifting probabilities
- The variables and events (i.e., possible values of the variables) of the problem domain must be well-defined.

Possibly different sources of uncertainty with known relations among the variables

- Incomplete knowledge,
- Noisy observations/measurements,
- Abstractions of information

Efficient solution of queries given evidence and (conditional) dependence and independence relations

When to use Bayesian Networks over other machine learning approaches?

Assume you have a set of inputs, X, and outputs Y.

Bayesian Networks (BN's) are generative models, i.e. allow to learn the joint probability distribution of data P(X,Y),
which is more difficult than learning the conditional probability distribution P(Y|X)P(Y|X) for (discriminative models), e.g. logistic regression or Support Vector Machine,

Generative models are more versatile, where you can run queries such as P(X1|Y) or P(X1|X2=A,X3=B), etc. With the discriminative model, your sole aim is to learn P(Y|X)P(Y|X).

Advantages:

1.When you have a lot of missing data, e.g. in medicine, BN's can be very effective since modeling the joint distribution (i.e. your assertion on how the data was generated) reduces your dependency in having a fully observed dataset.

2.When you want to model a domain in a way that is visually transparent, and also aims to capture cause→effect relationships, BN's can be very powerful. Note that the causality assumption in BN's is open to debate though.

3.Learning the joint distribution is a difficult task, modeling it for discrete variables (through the calculation of conditional probability tables, i.e. CPT's) is substantially easier than trying to do the same for continuous variables though. So BN's are practically more common with discrete variables.

4.BN's not only allow observational inference (as all machine learning models allow) but also causal interventions. This is a commonly neglected and underappreciated advantage of BN's and is related to counterfactual reasoning.

* In the advantage 1 where you say BNs are effective for modelling data with lots of missing values, don't these missing values affect the correct identification of independencies in the data?

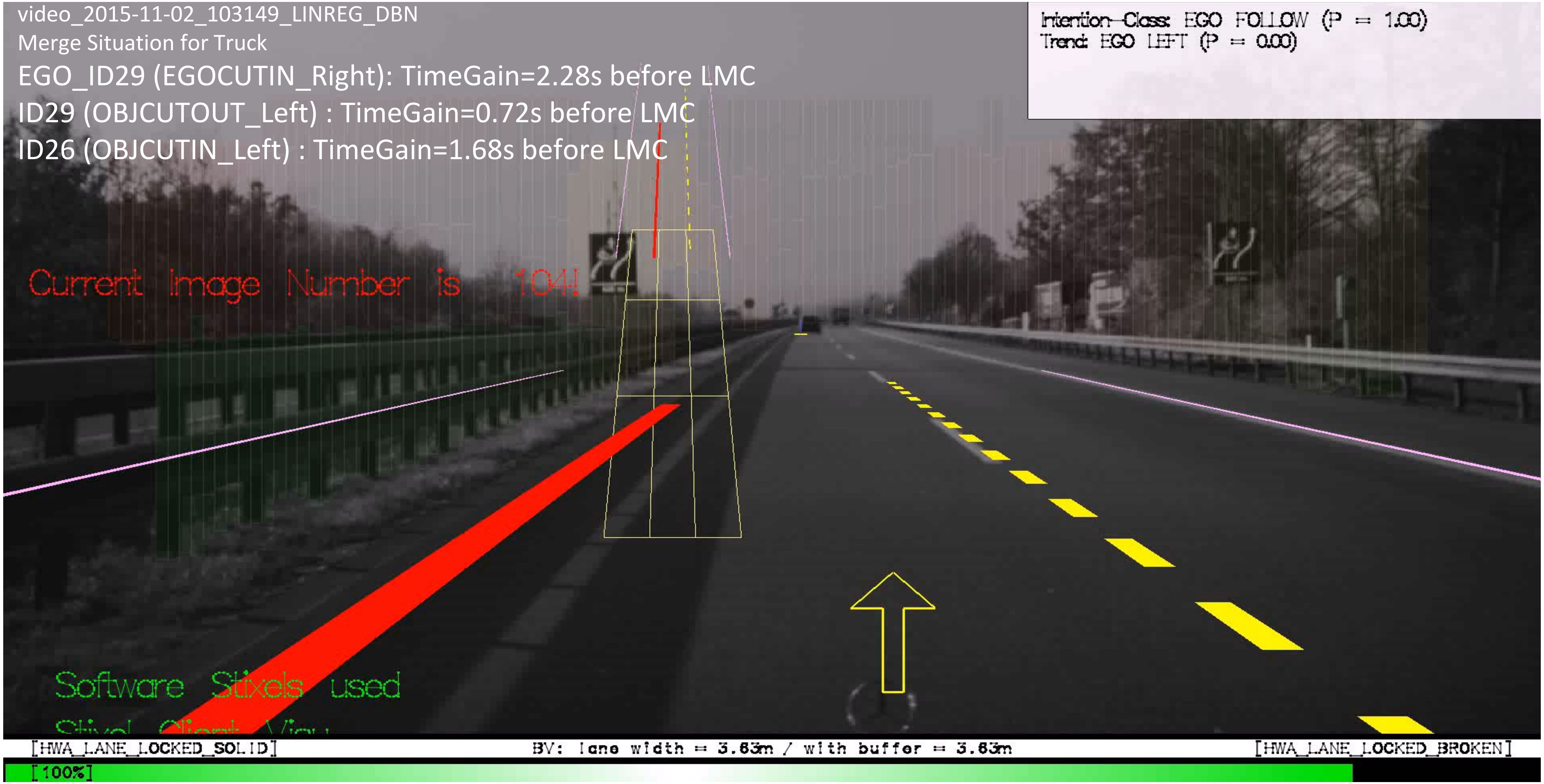
*Yes, while fitting the model you would still need to impute with some assumptions, but once you have a structure for, e.g. P(Y,X1,X2)P(Y,X1,X2), depending on the factorization of your DAG (that encapsulates your independence assumptions), you may not need X1 if X2 is already available, or vice versa.

*In my experience, Bayesian Networks work very well when there is **high dimensional categorical data**. They give interpret-able models, which (sometimes) aid in making sense of how the different variables interact.

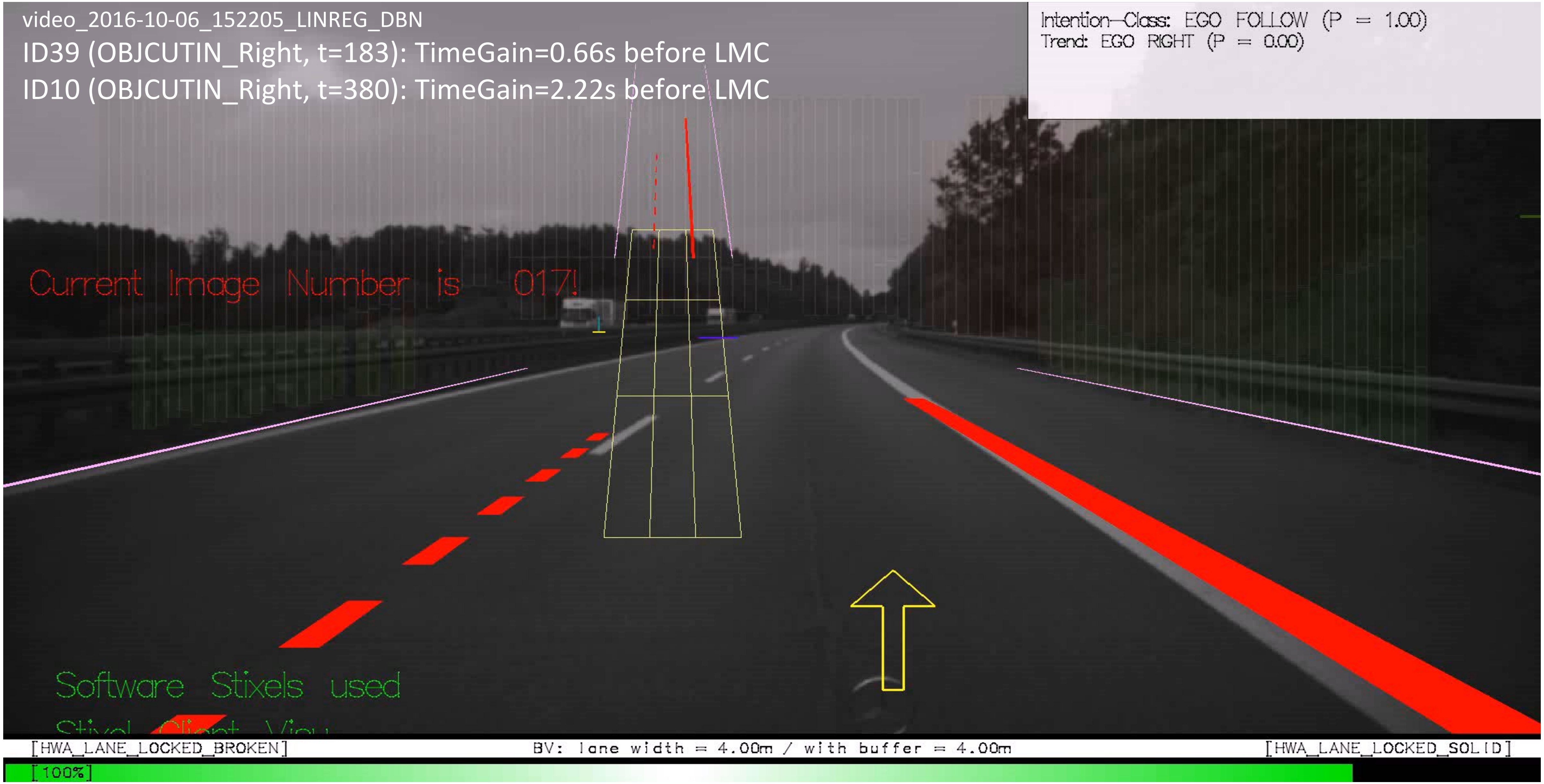
Testing in the experimental cognitive car on highway drive

Testing in the experimental cognitive car on highway drive

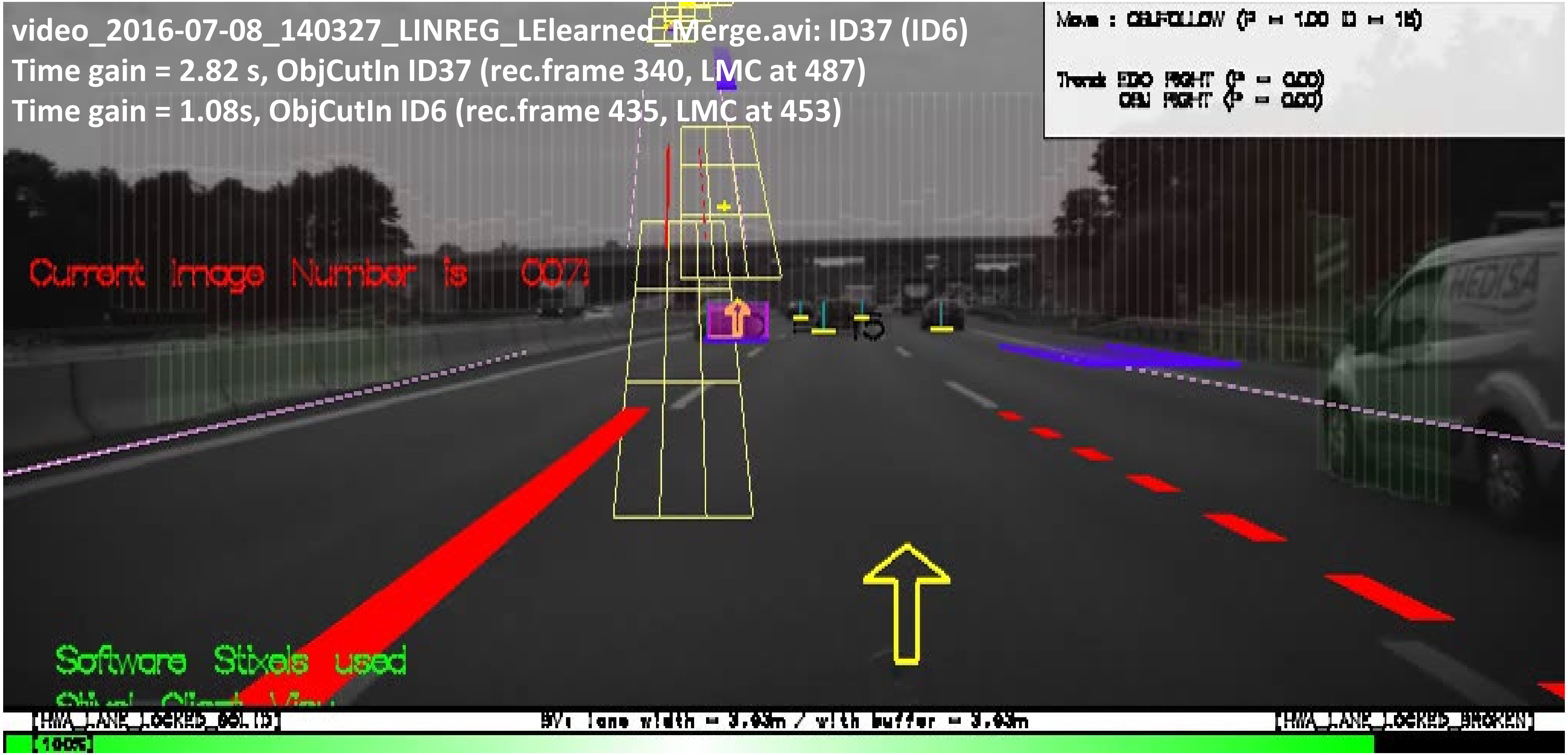
DBN: adapted TCPT + 4 learned LE fragm



DBN: adapted TCPT + 4 learned LE fragm

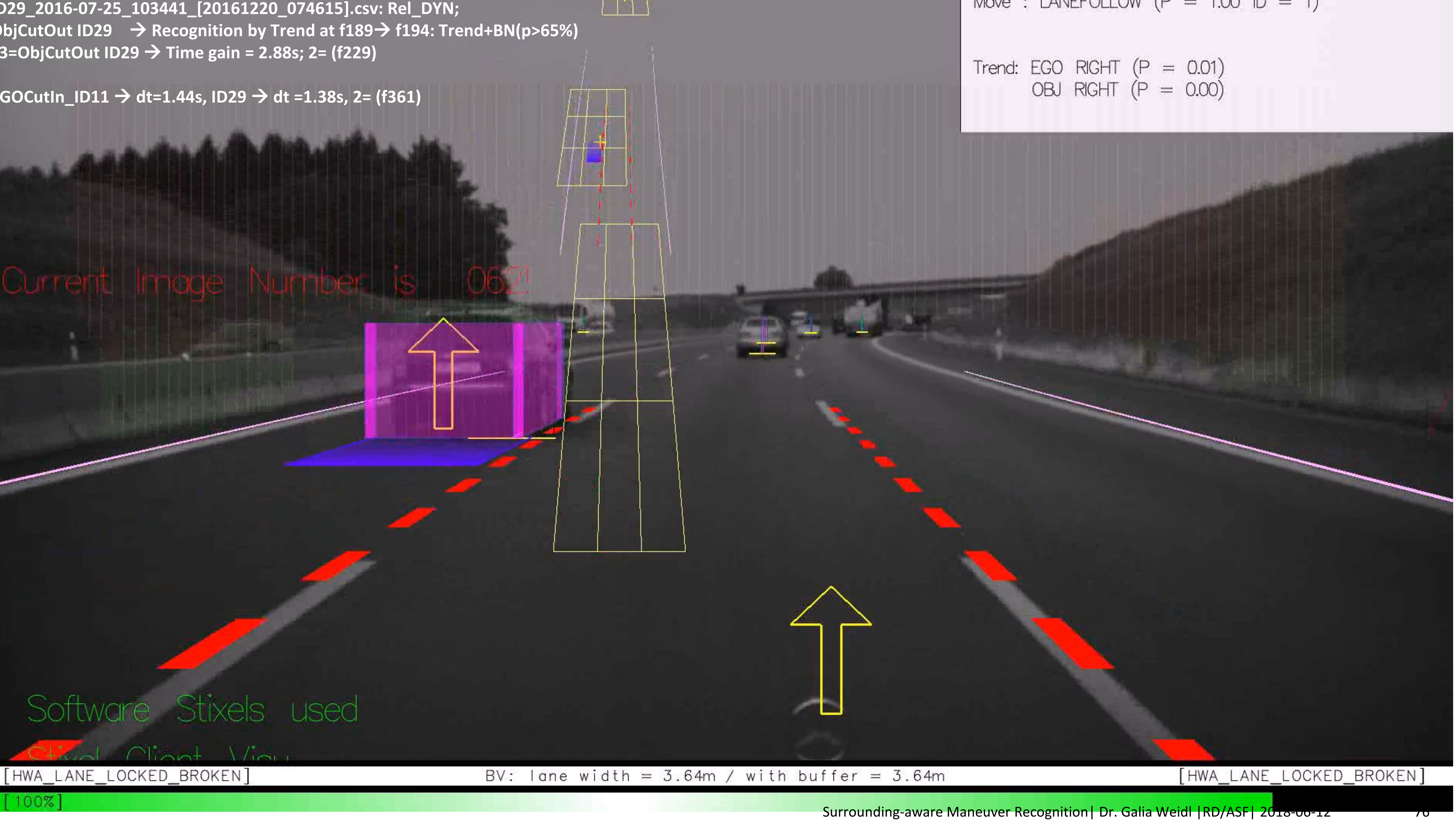


video_2016-07-08_140327_LINREG_LElearned_Merge.avi

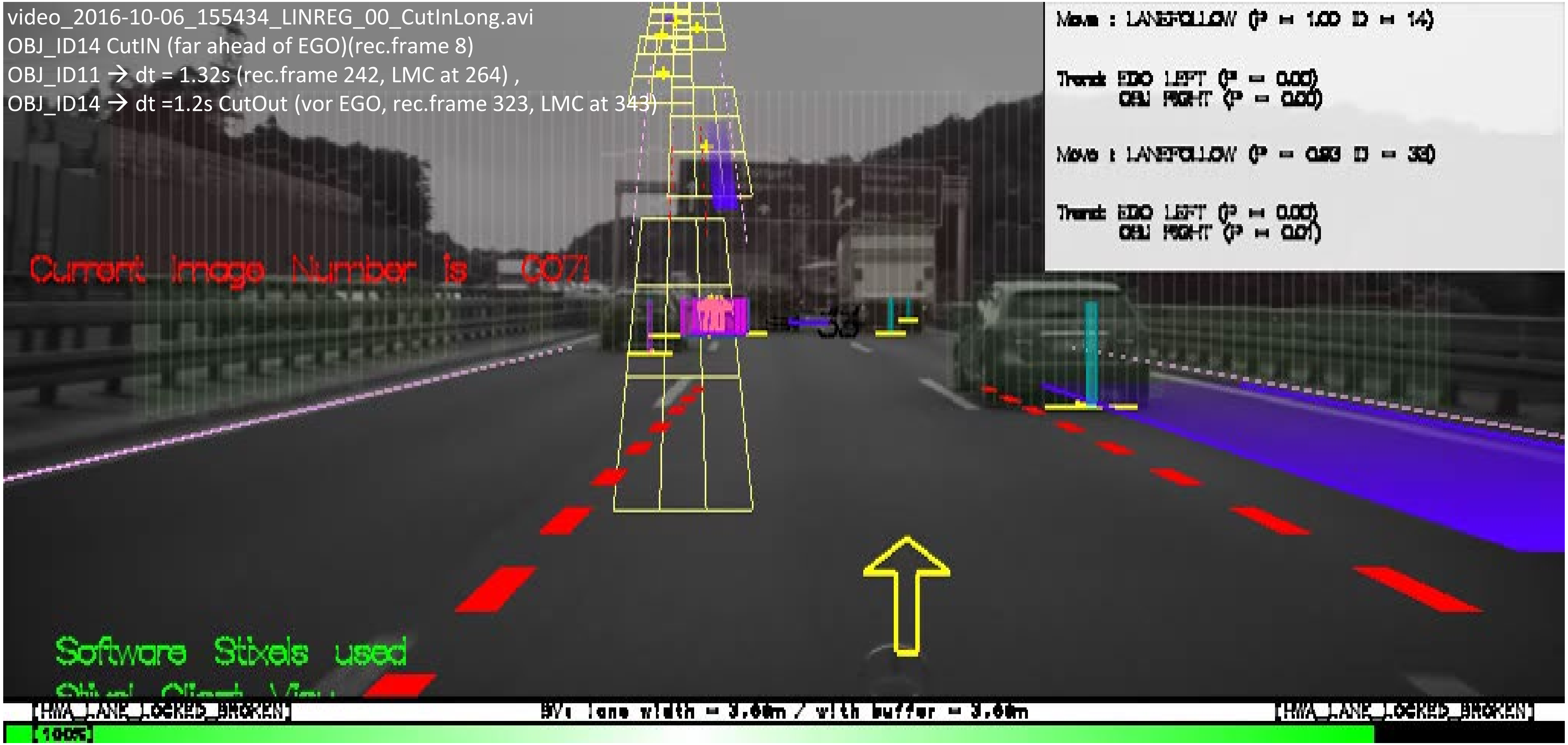


D29_2016-07-25_103441_[20161220_074615].csv: Rel_DYN;
bjCutOut ID29 → Recognition by Trend at f189→ f194: Trend+BN(p>65%)
3=ObjCutOut ID29 → Time gain = 2.88s; 2= (f229)

GOCutIn_ID11 → dt=1.44s, ID29 → dt =1.38s, 2= (f361)



video_2016-10-06_155434_LINREG_00_CutInLong.avi

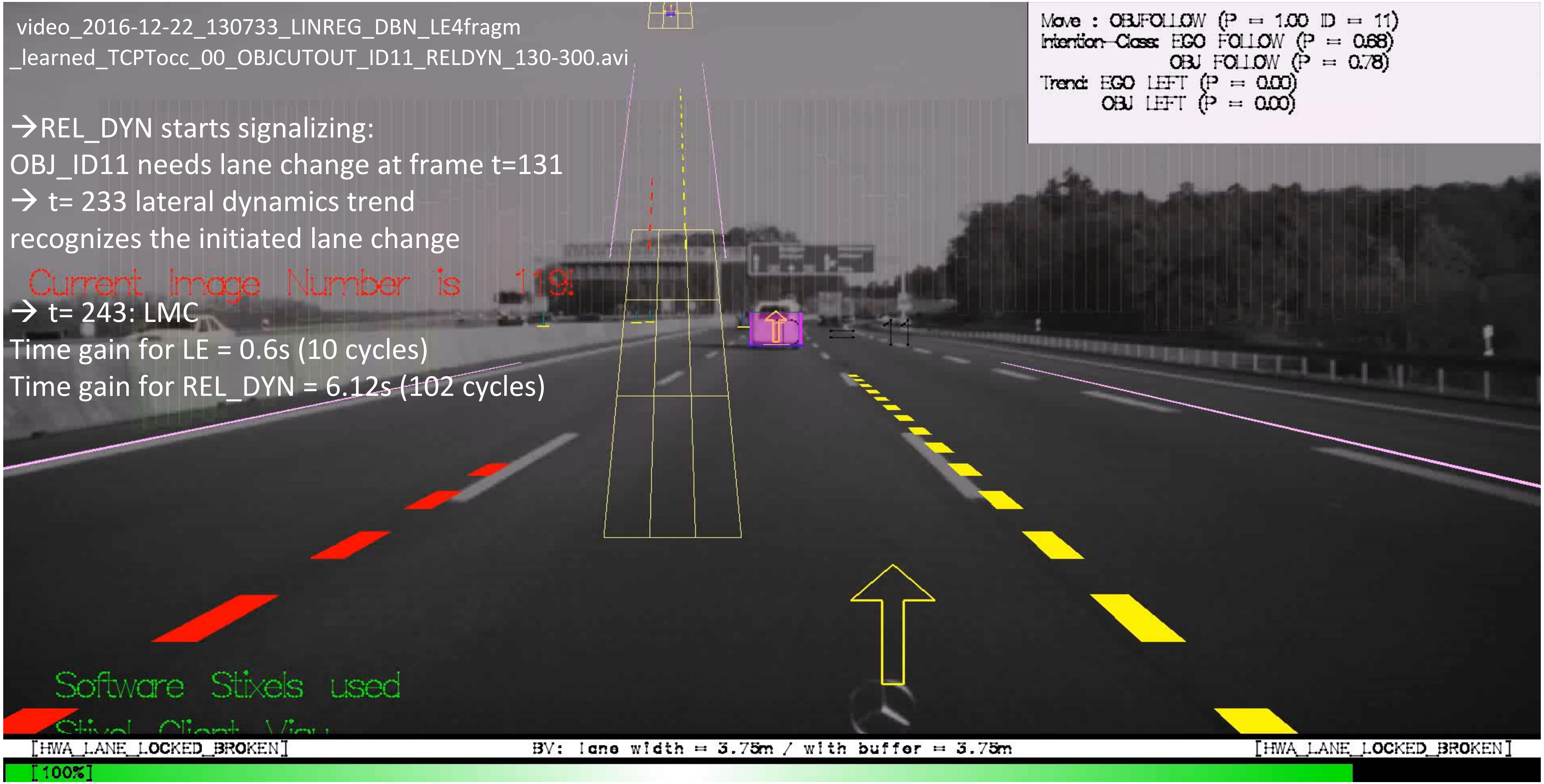


DBN: adapted TCPT + 4 learned LE fragm

video_2016-12-22_130733_LINREG_DBN_LE4fragm
_learned_TCPTocc_00_OBJCUTOUT_ID11_RELDYN_130-300.avi

→REL_DYN starts signalizing:
OBJ_ID11 needs lane change at frame t=131
→ t= 233 lateral dynamics trend
recognizes the initiated lane change

→ t= 243: LMC
Time gain for LE = 0.6s (10 cycles)
Time gain for REL_DYN = 6.12s (102 cycles)



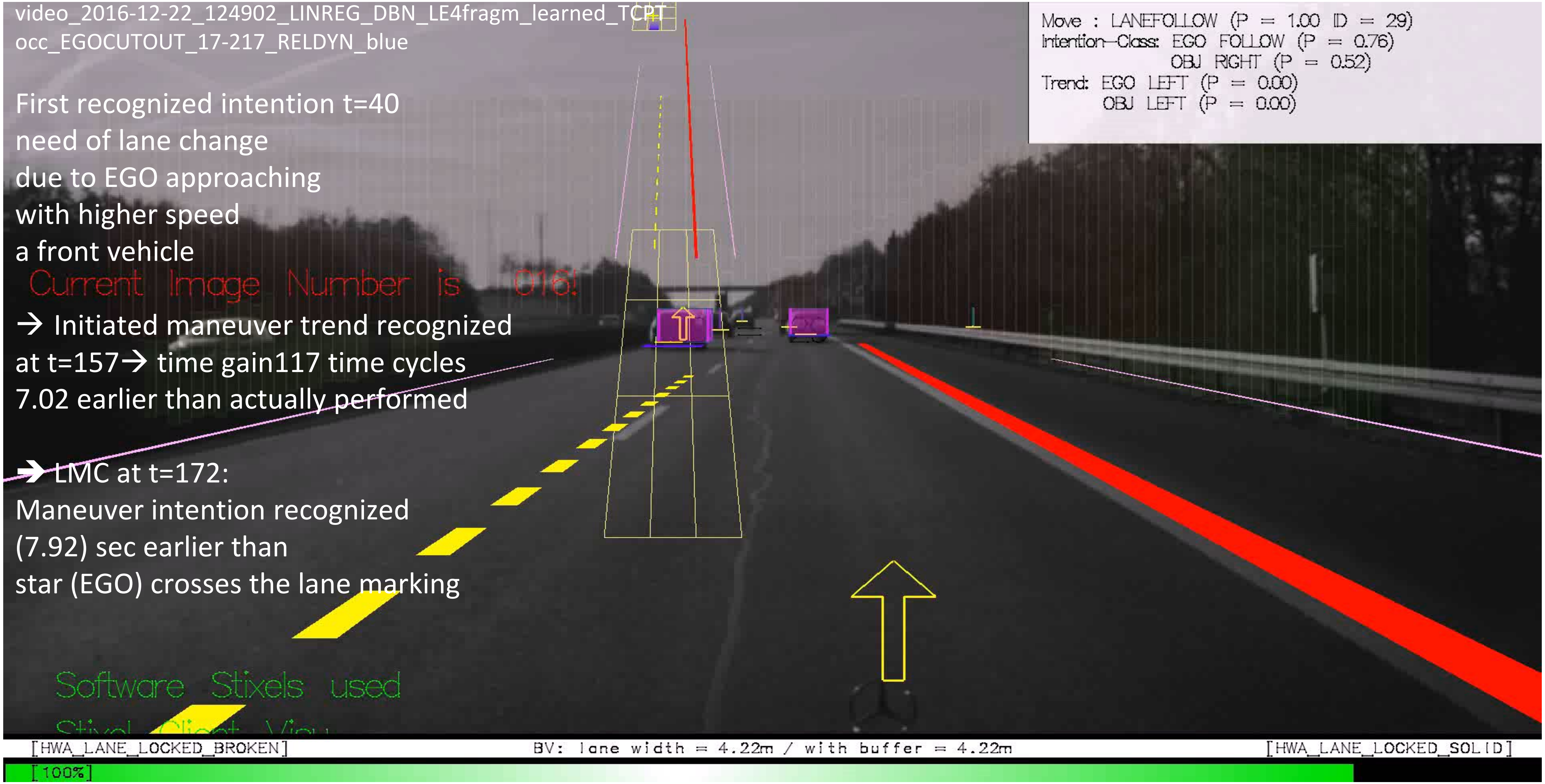
DBN: adapted TCPT + 4 learned LE fragm

video_2016-12-22_124902_LINREG_DBN_LE4fragm_learned_TCPT
occ_EGOCUTOUT_17-217_RELDYN_blue

First recognized intention t=40
need of lane change
due to EGO approaching
with higher speed
a front vehicle

→ Initiated maneuver trend recognized
at t=157→ time gain117 time cycles
7.02 earlier than actually performed

→ LMC at t=172:
Maneuver intention recognized
(7.92) sec earlier than
star (EGO) crosses the lane marking



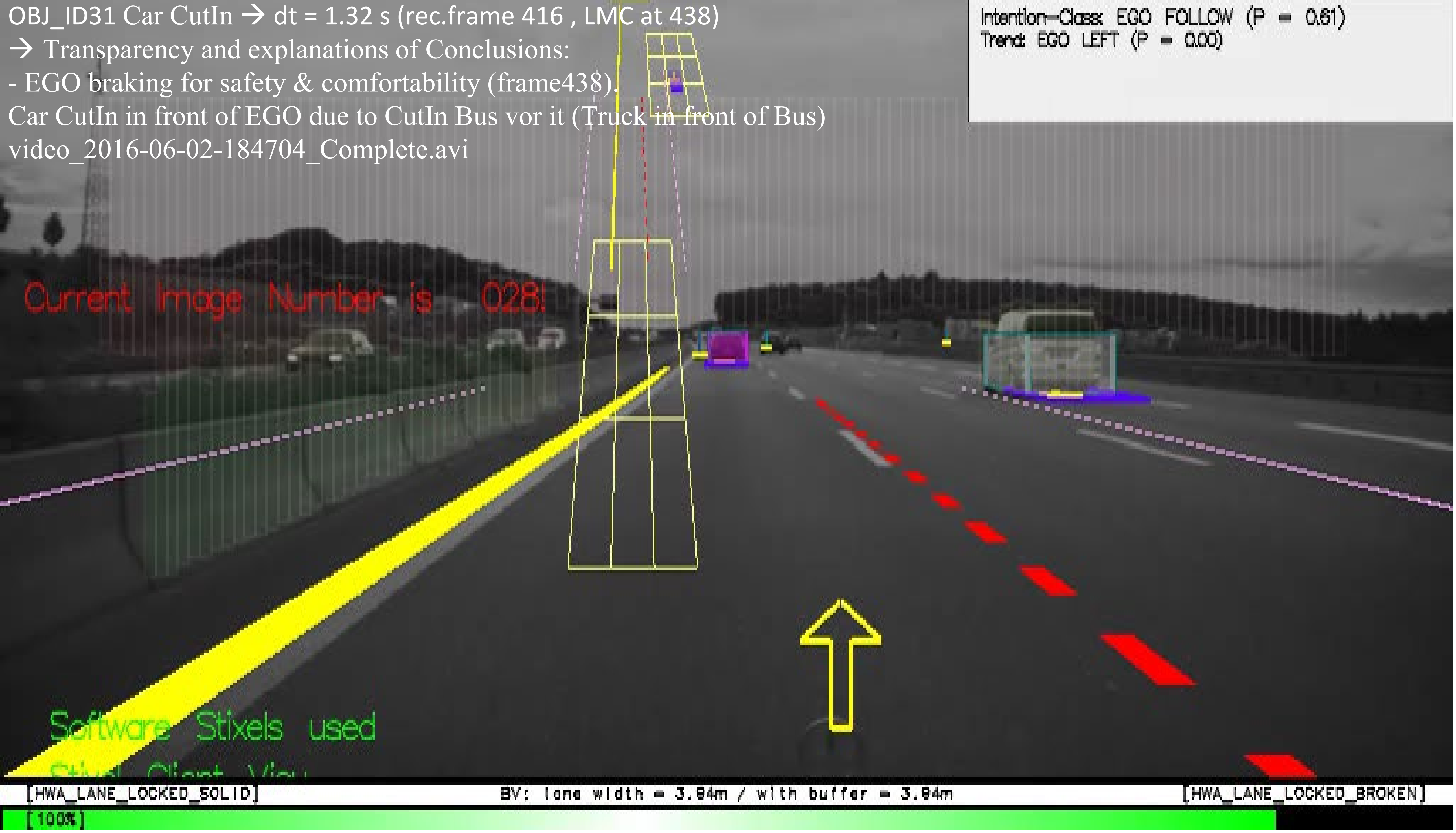
OBJ_ID31 Car CutIn → dt = 1.32 s (rec.frame 416 , LMC at 438)

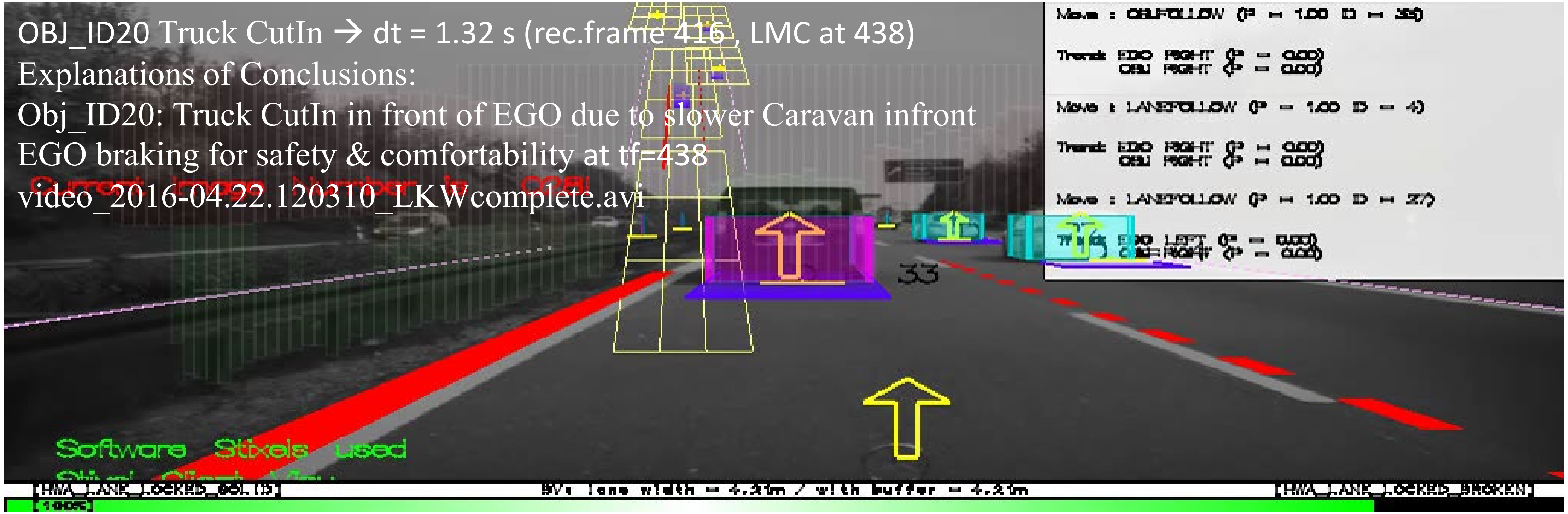
→ Transparency and explanations of Conclusions:

- EGO braking for safety & comfortability (frame438).

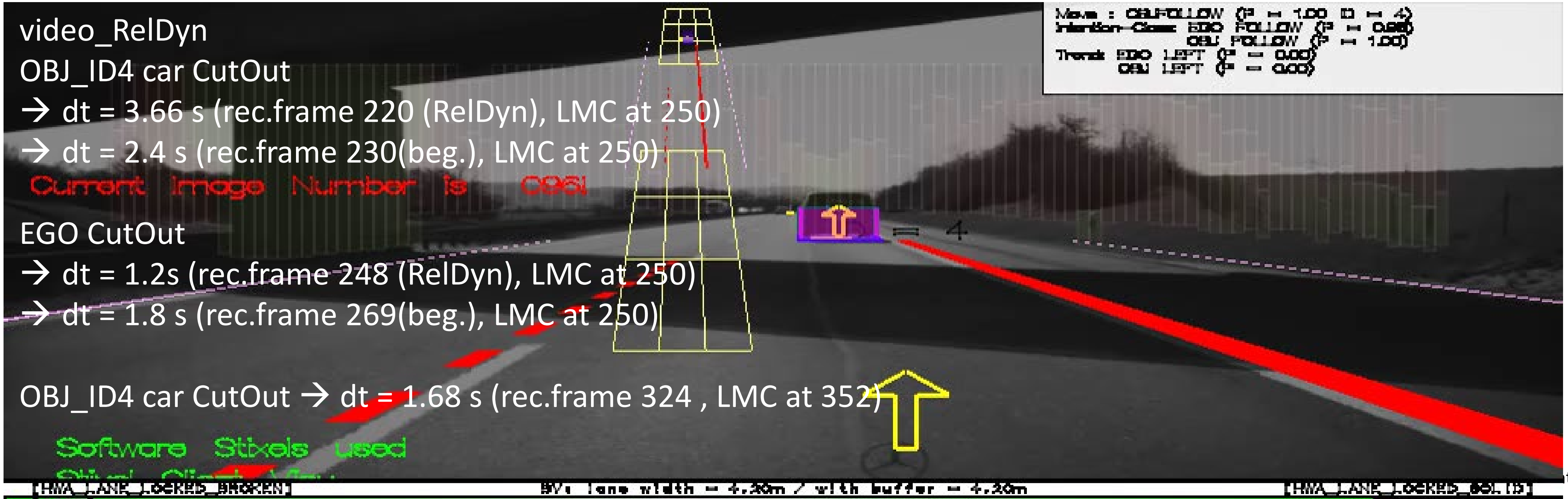
Car CutIn in front of EGO due to CutIn Bus vor it (Truck in front of Bus)

video_2016-06-02-184704_Complete.avi





OBJ_ID20 Truck CutIn → dt = 1.32 s (rec.frame 416 , LMC at 438)
Explanations of Conclusions:
Obj_ID20: Truck CutIn in front of EGO due to slower Caravan infront
EGO braking for safety & comfortability at tf=438
video_2016-04.22.120310_LKWcomplete.avi



video_RelDyn
OBJ_ID4 car CutOut
→ dt = 3.66 s (rec.frame 220 (RelDyn), LMC at 250)
→ dt = 2.4 s (rec.frame 230(beg.), LMC at 250)

EGO CutOut
→ dt = 1.2s (rec.frame 248 (RelDyn), LMC at 250)
→ dt = 1.8 s (rec.frame 269(beg.), LMC at 250)

OBJ_ID4 car CutOut → dt = 1.68 s (rec.frame 324 , LMC at 352)

Summary: Situation Interpretation in Cognitive Cars

We developed a scalable system approach for **surrounding-aware maneuver recognition**, realized as **combination** of

- **Knowledge Representation** by hierarchical dynamic object-oriented Bayesian Networks
- **Machine Learning** (from real highway data) for improvement of recognition performance of the dynamic model by use of EM learning or sequential adaptation

It demonstrates **Stable Trend Analysis**

- achieved by integrating **knowledge and data** in the models & logistic **regression** on the trend
- meeting the automotive requirements on **accuracy** and **prediction**
- system transparency by explanation of conclusions.,

System is successfully deployed and tested in the experimental cognitive vehicles in real traffic.

Acknowledgments

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Questions?

Thank you!