Further Steps towards Driver Modeling according to the Bayesian Programming Approach

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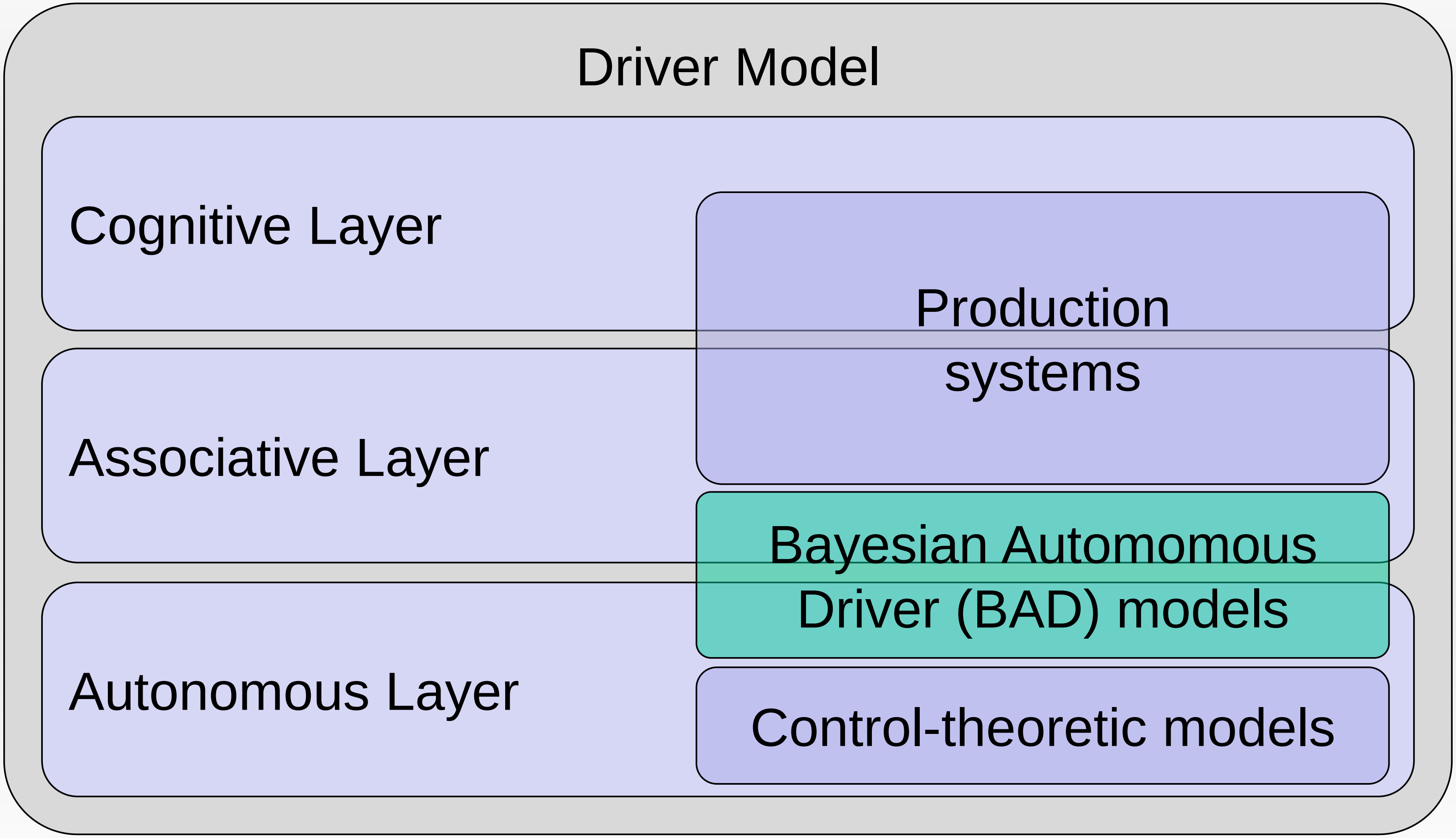
Human driver models



Behavior of human drivers

- The behavior of human drivers is stochastic
- The environment is stochastic

➢ **Model human drivers with probabilistic models**

Bayesian Autonomous Driver (BAD) models

- Valid and robust mapping from human percepts to human actions

- BAD models:
  - Instances of Bayesian networks
  - Consists of a set of variables we assume to be pertinent
  - Descripes relations between variables as conditional probability distributions (CPDs)
  - Infer actions under the evidence of percepts for real-time control

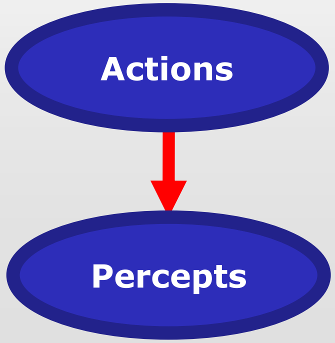
- Advantages:
  - Can be constructed with machine-learning procedures from raw sample data
  - Most assumptions testable by standard statistical methods (e.g. conditional mutual information index)

Structure of Bayesian Programs

- **Bayesian Program**
  - **Description**
    - **Preliminary Knowledge π**
      - **Variables of Interest**
        Actions, Percepts
      - **Joint probability distribution**
        P(Actions, Percepts | **π, δ***)*
      - **Decomposition**
        P(Actions, Percepts | **π, δ***)*
        = *P(Actions* | **π, δ***)*
        * *P(Percepts* | *Actions,* **π, δ***)*
      - **Forms**
        - **Parametric Forms**
          P(Actions) | **π, δ***)* = *G(μ,σ)*
        - **Bayesian Programs**
    - **Sample Data δ**
  - **Question**
    Best / Draw (P(Actions | Percepts = percepts, **π, δ**))

BAD models evolving

- **First steps: Static inverse BN**



BAD models evolving

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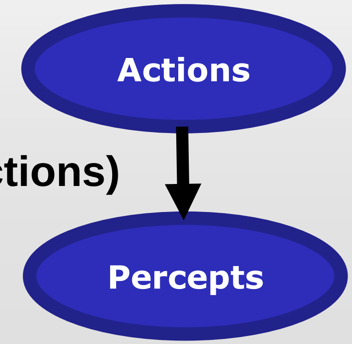
P(Percepts | Actions)



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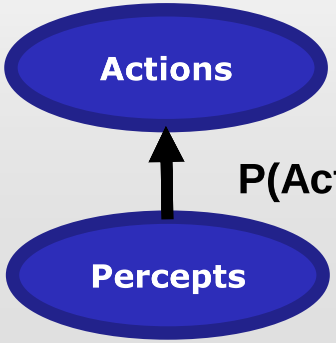
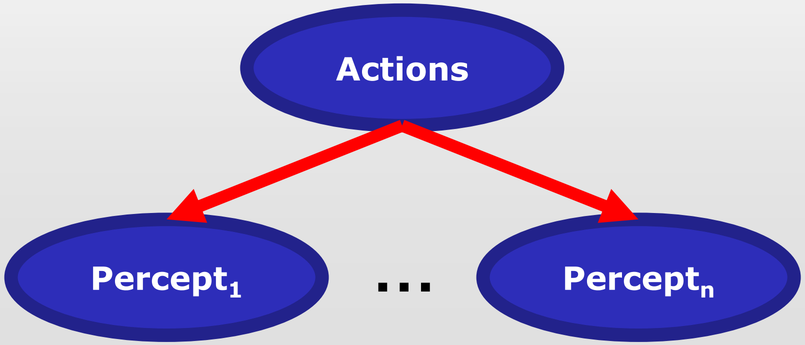


P(Actions | Percepts = percepts)

BAD models evolving

- First steps: Static inverse BN
  - Sensor Fusion



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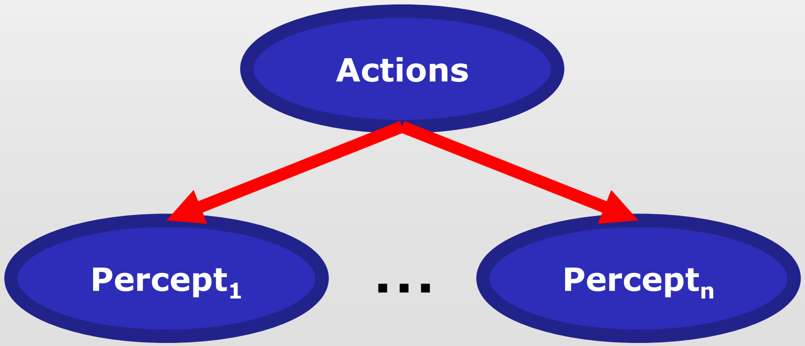
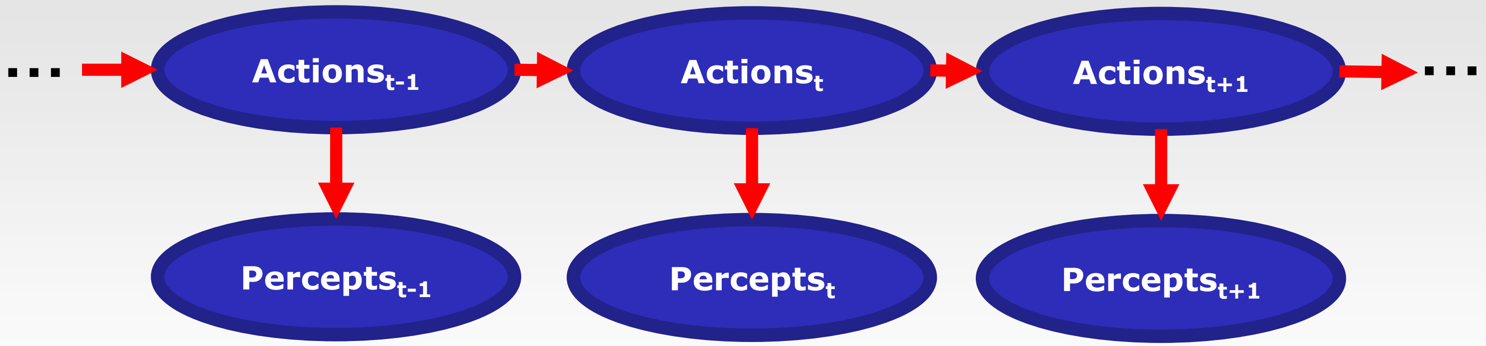


- Further steps: Partial inverse Dynamic BN (DBN)
  - Markov process



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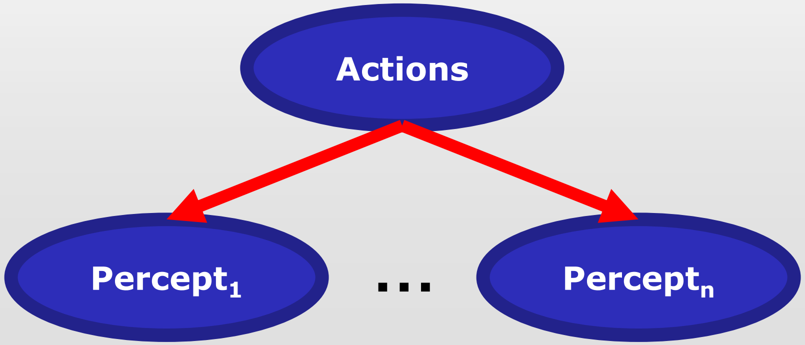

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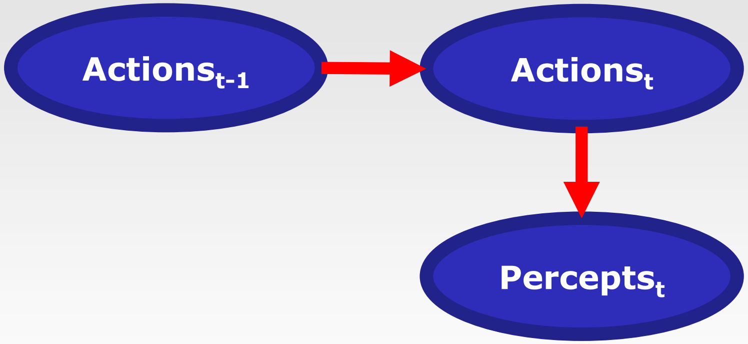
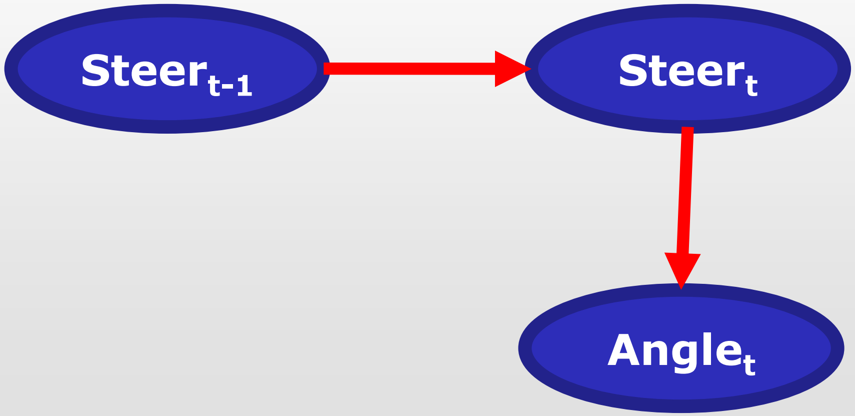
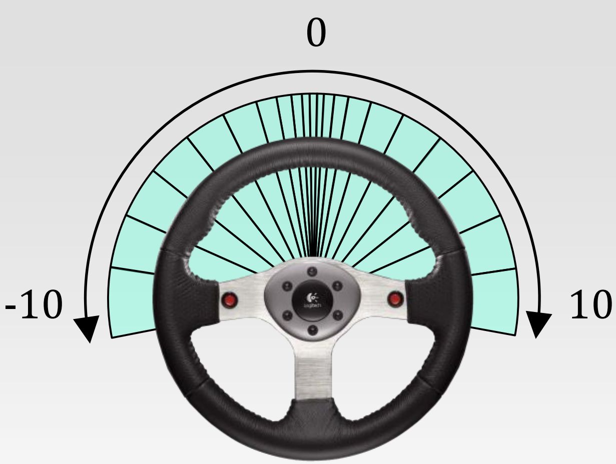


Partial inverse DBN of lateral control

- **Variables of interest:**
  - $Steer_t$, $Steer_{t-1} \in \{-10, -9, \ldots, 10\}$
  - $Angle_t \in \{-10, -9, \ldots, 10\}$
  - JPD: $P(Steer_{t-1}, Steer_t, Angle_t)$
- **Decomposition of JPD:**
  - $P(Steer_{t-1}, Steer_t, Angle_t)$
    $= P(Steer_{t-1}) * P(Steer_t \mid Steer_{t-1})$
    $* P(Angle_t \mid Steer_t)$
- **Parameters will be derived from time series of variables**
- **Question:**
  - $Draw(P(Steer_t \mid steer_{t-1}, angle_t))$





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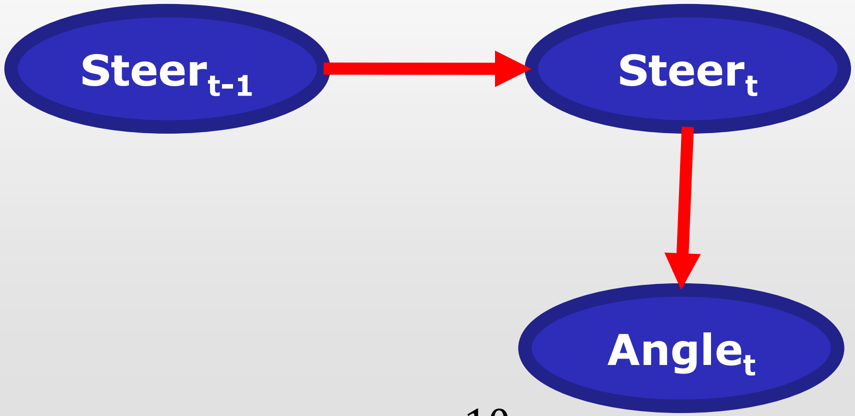

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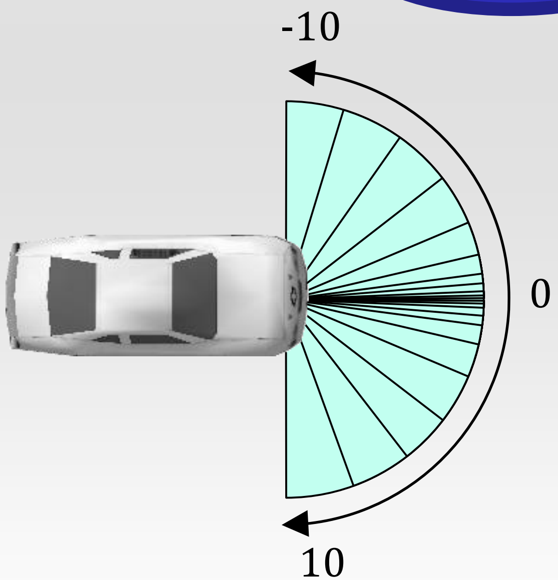

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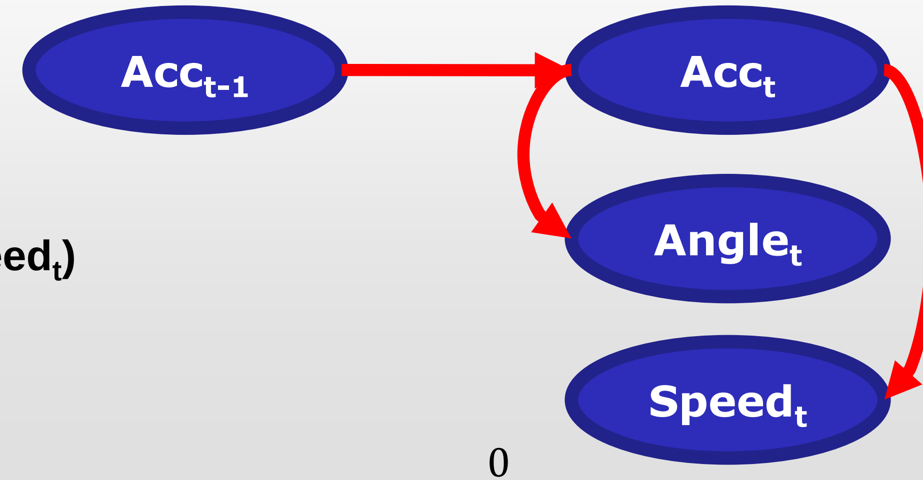
Partial inverse DBN of longitudinal control

- **Variables of interest:**
  - Acc_{t-1}, $Acc_t \in$ {-10, -9, …, 10}
  - $Angle_t \in$ {-10, -9, …, 10}
  - $Speed_t \in$ {0, 1, …, 9}
  - JPD: $P(Acc_{t-1}, Acc_t, Angle_t, Speed_t)$



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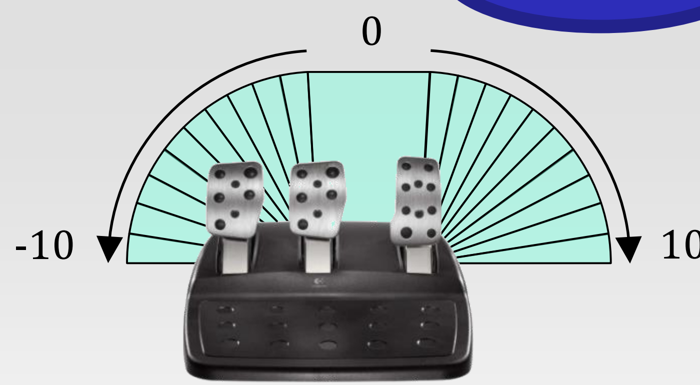

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Partial inverse DBN of longitudinal control

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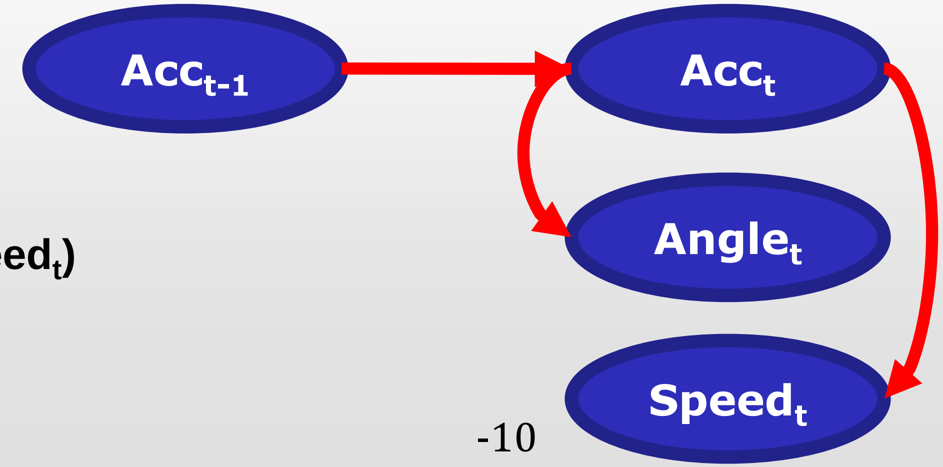

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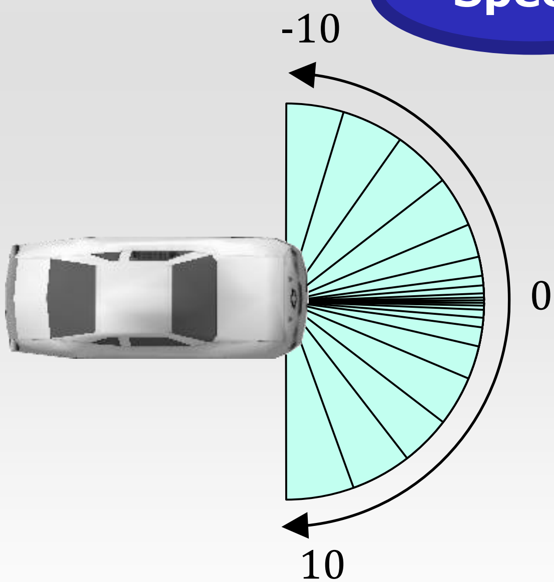

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Partial inverse DBN of longitudinal control

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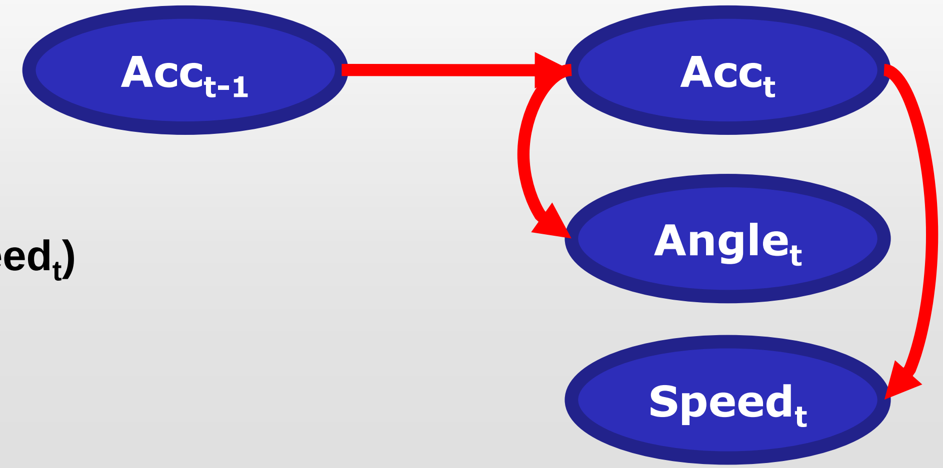

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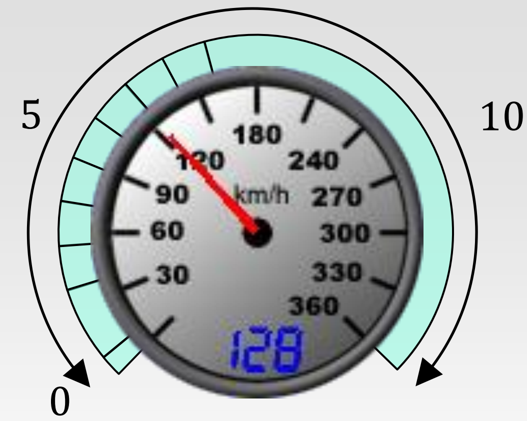

- **Parameters will be derived from time series of variables**

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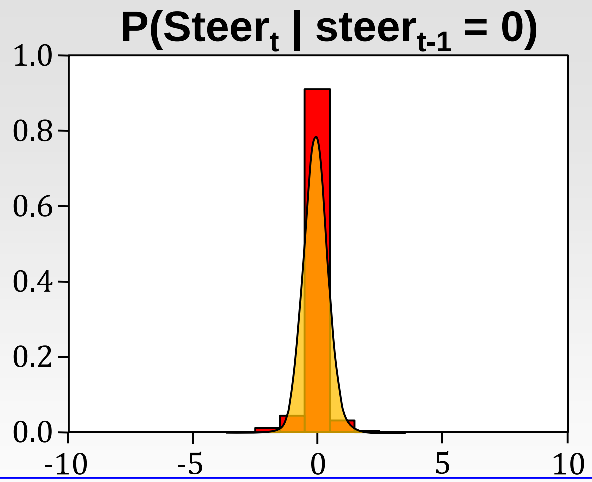
Exerimental setting

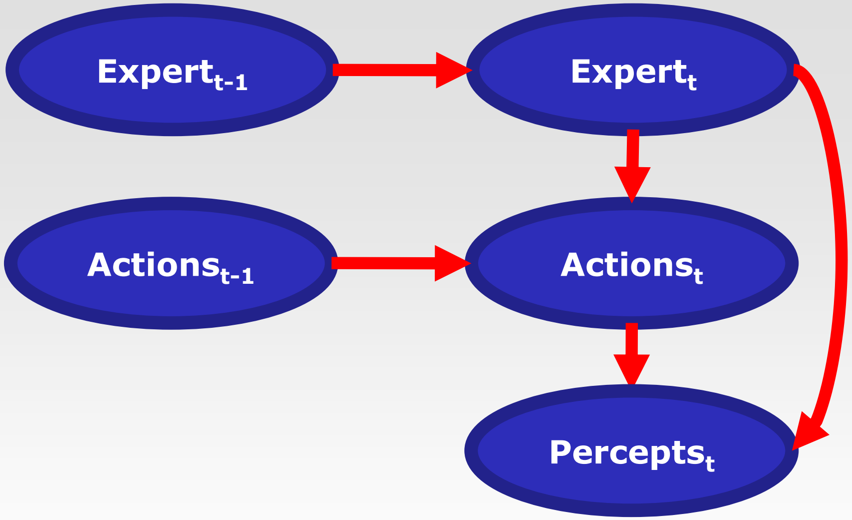
- TORCS racing simulation
  - Racing track „Aalborg“
- ProBT API and inference engine
- Recorded time series of variables during manually driving one single lap
  - Δt = 50 ms
- Deriving conditional histograms from time series for each conditional probability distribution
- Discretized histograms by mean and standard deviation when plausible



BAD model performance in TORCS

Steps beyond...

- Mixture of Experts BAD model
  - Experts make related actions and percepts more probable
  - Context dependent driver behavior by mixing pure behavior from different experts
  - Learn new skills without forgetting allready learnt ones
  - Avoid the stability-plasticity dilemma
- Combine models of lateral / longitudinal control
- Improve perception



Thank You for Your Attention