Bayesian Driver Agent Model For Autonomous Vehicle System Based on Knowledge-Aware and Real Time Data

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How do humans drive a vehicle?

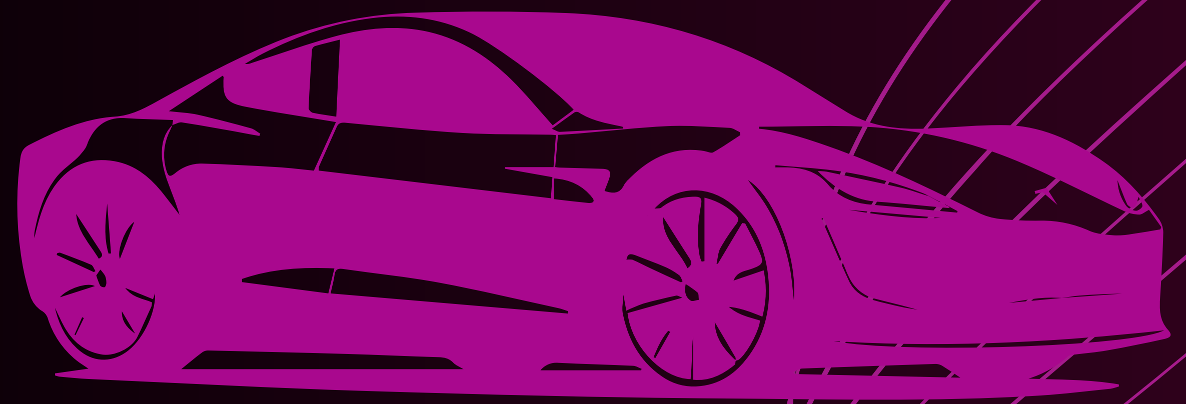
The driving response can be loosely divided into

Scene Cognition

Infer Decision

Execution

Introduction
Autonomous Driving



- Uncertain characteristics on urban roads
  - Pedestrian trajectories
  - Other vehicles
  - Road sides
  - Obstructions
- An autonomous agent must be able to drive **like humans**

The Driving Agent

Rule Based Formula Method

- Algorithms such as if-else rules

Learning Based End-to-End Methods

- CNNs and GPU computations
- Deep NNs with supervised learning
- ALVINN and DAVE systems

Probabilistic Reasoning Methods

- Decision AV systems on DBNs based on knowledge aware and real time data
- Data from real human drivers
- DBNs can transfer real human skills to autonomous systems

Dynamic Bayesian Network as a Driving Agent

- Modeling of driving behavior based on inference methods makes the decision model interpretable
- Overcomes the challenge of the black box characteristics of the end-to-end networks

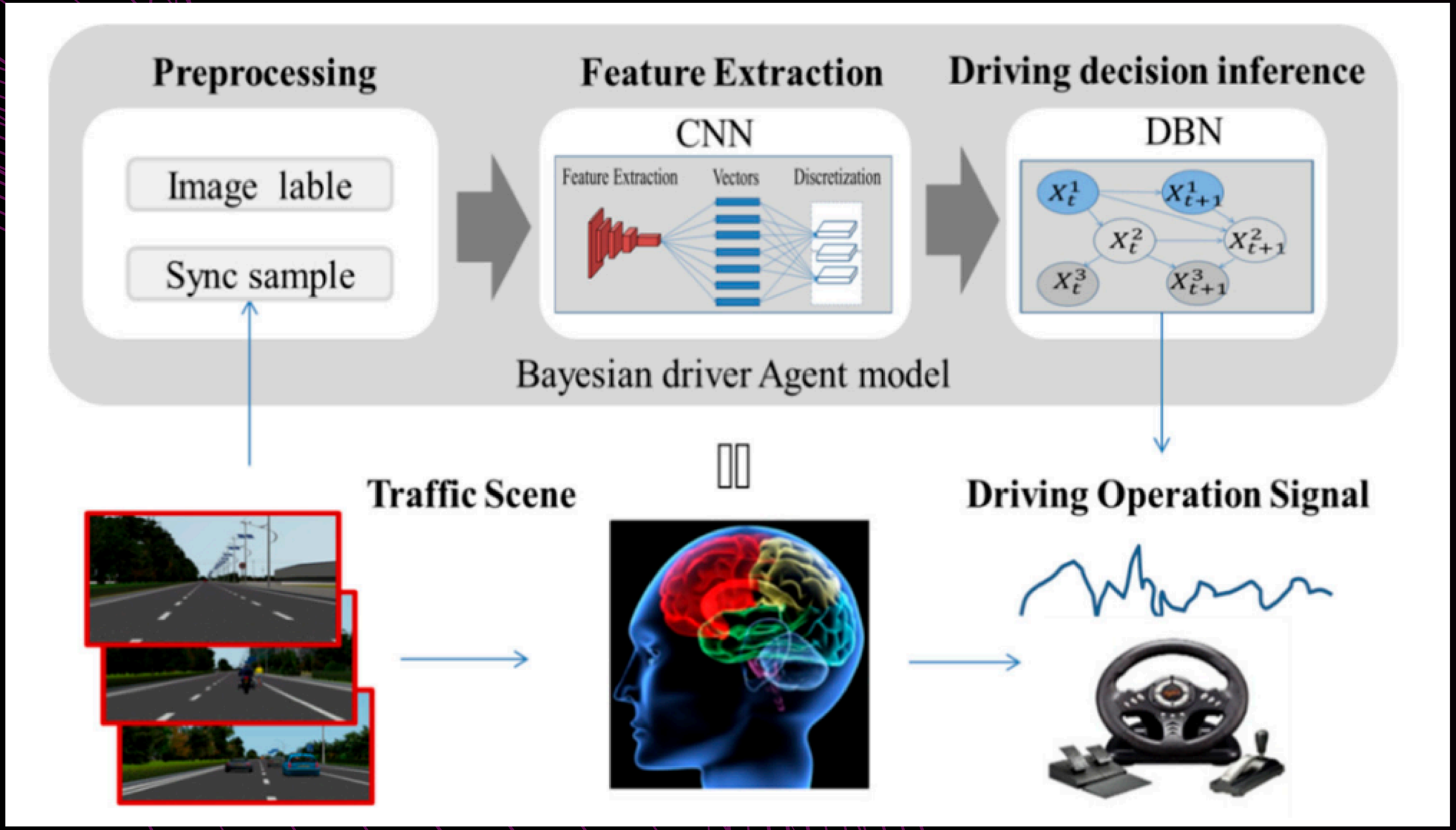
The Bayesian Driver Agent

Knowledge Aware and Real Time Data Based on Human Driver’s Cognitive Psychology

Integration of Convolutional Neural Networks (CNNs) with DBNs

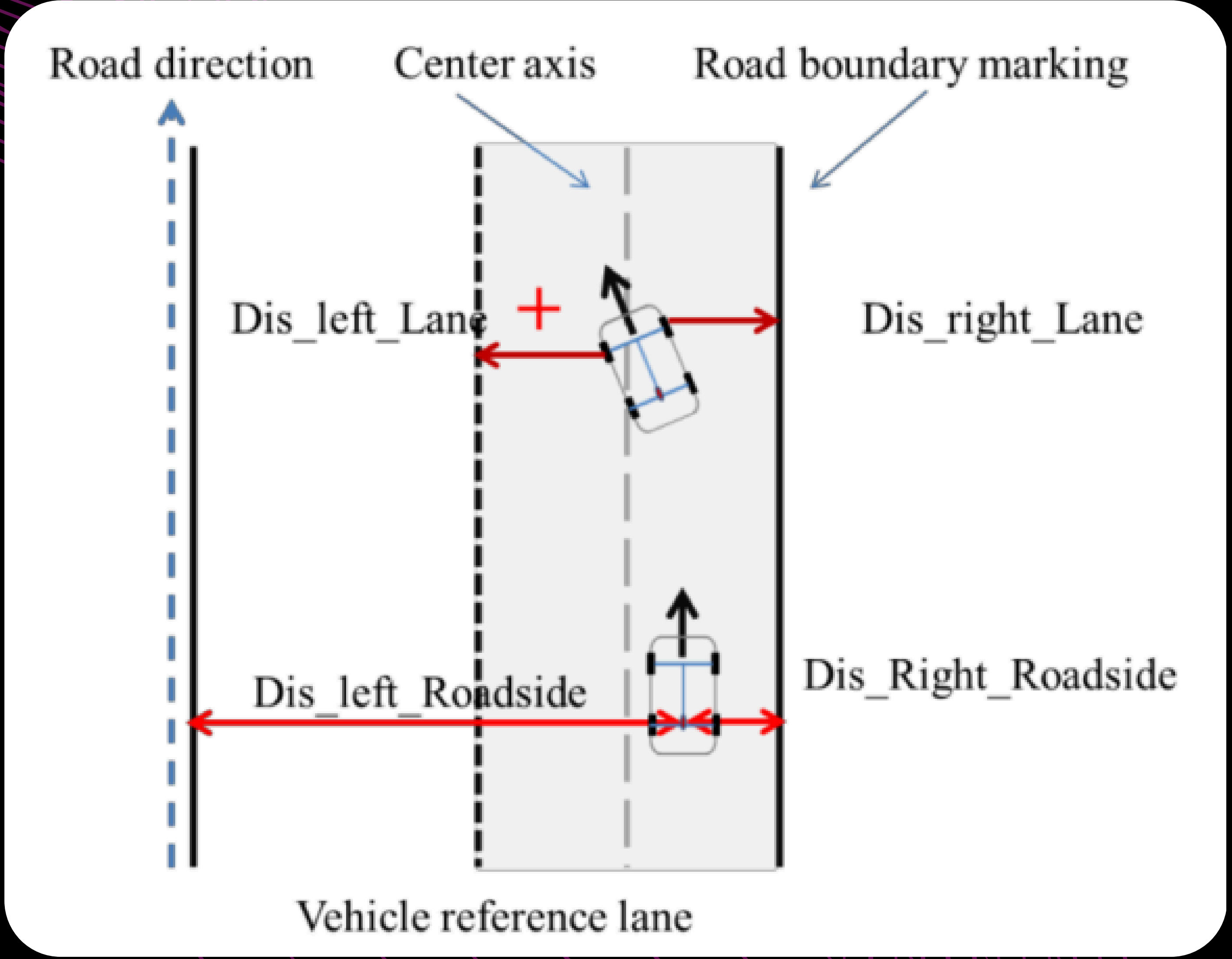
- Understand the current traffic scene situation
- Predict probability distribution of driving patterns
- Process partially observable and uncertain information

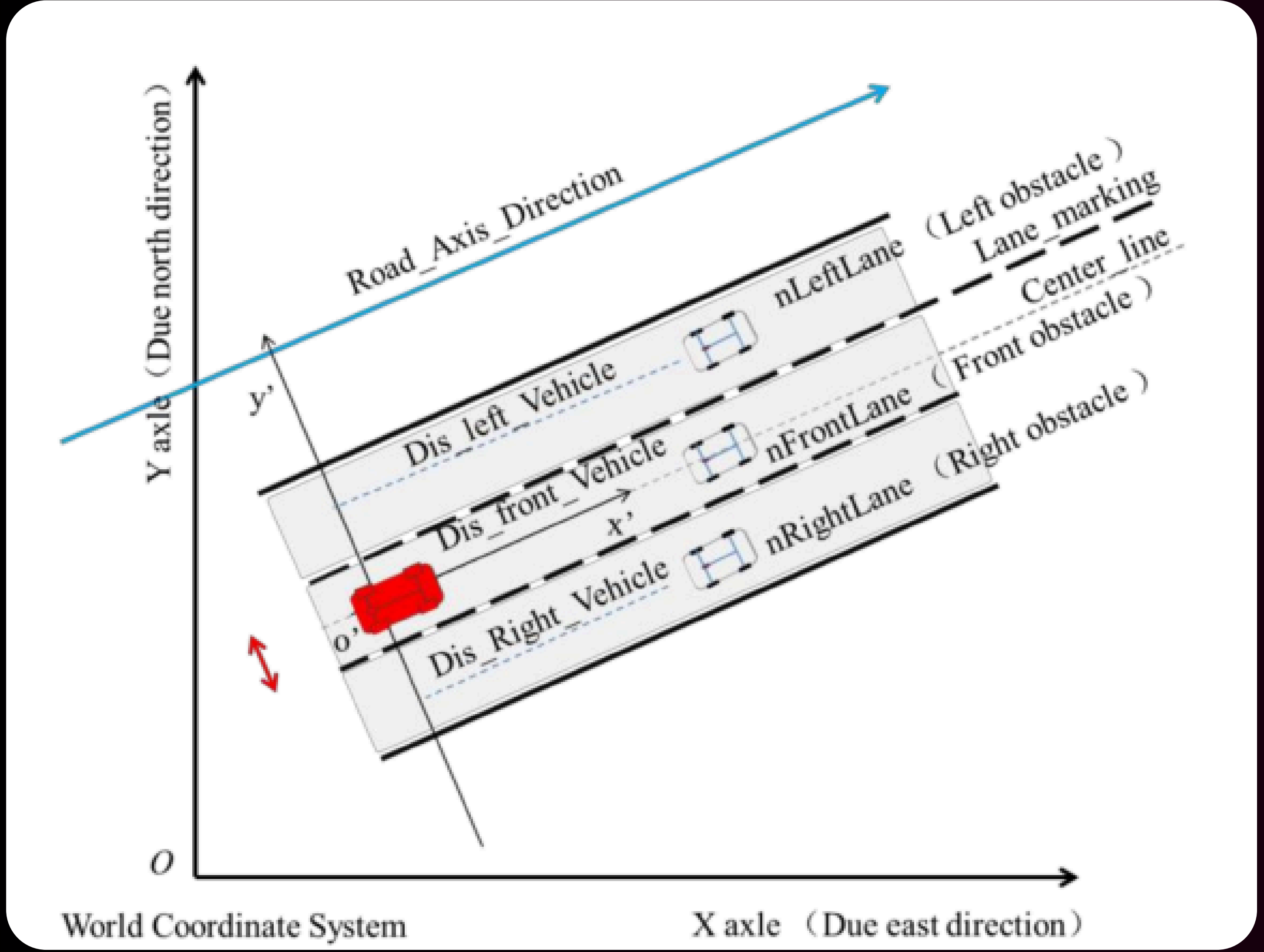
The Bayesian Driver Agent



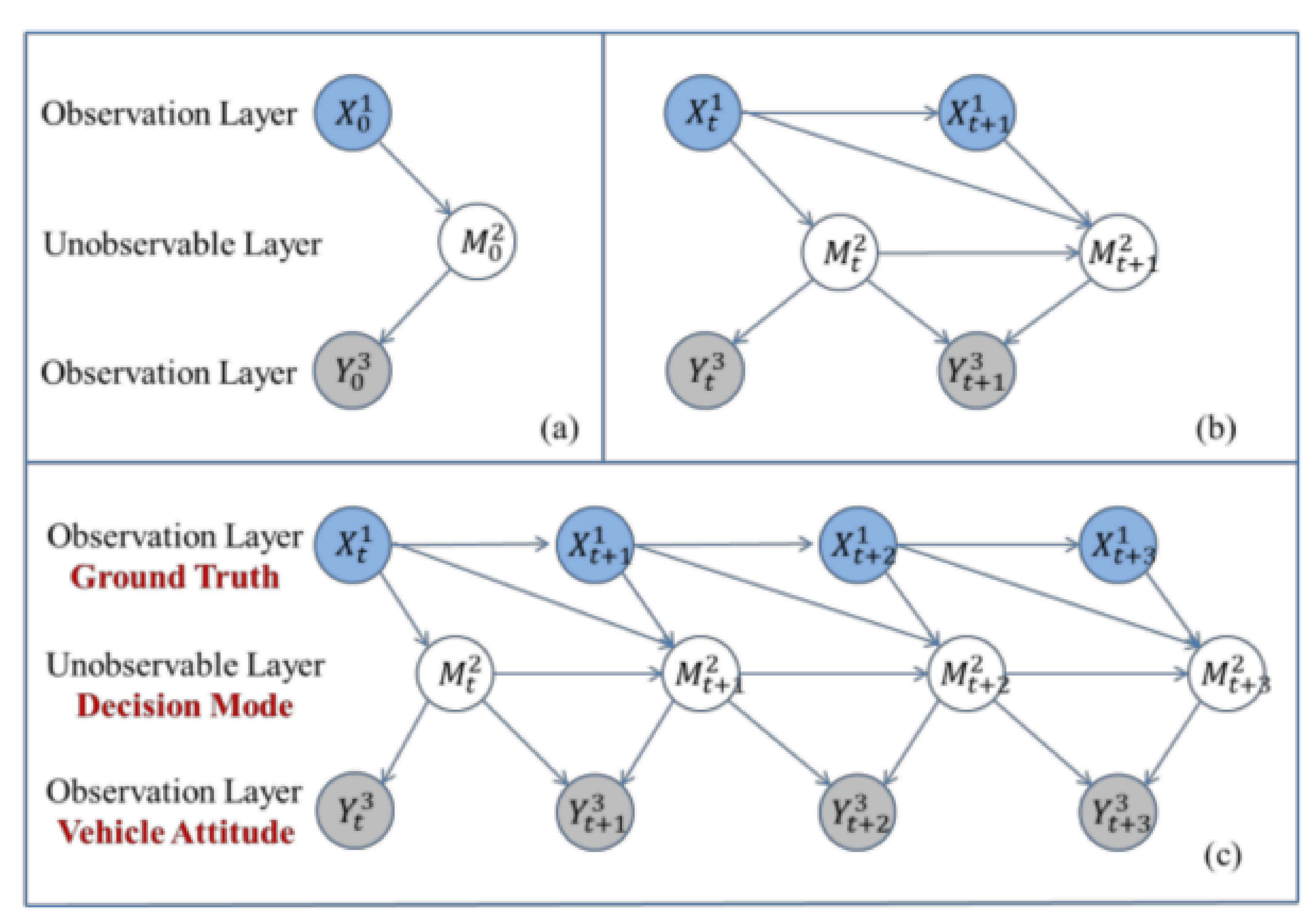
- The model should:
  - Learn the behaviors of human drivers
  - Understand the traffic situation
  - Predict the action in real time

CNN Based Simulation
Perception





Dynamic Bayesian Network
Inference Functional Region



(a) Initial DBN Network; D0

(b) DBN Transition Network

(c) DBN Expanded into three time slices

The Driving Decision Node

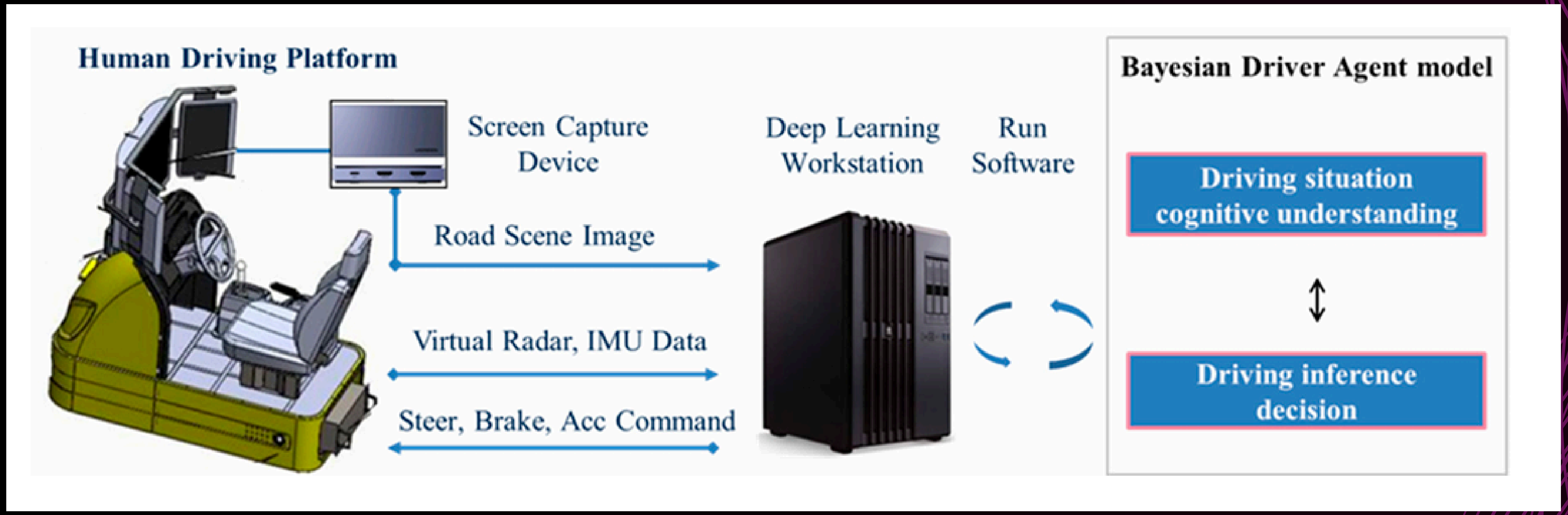
- The driving node's updated belief determines the agent's decision
- Standard variables chosen for a vector space of driving decisions

Table 4. Driving mode variable and discretization values.

Query Node	State Description	Discretization Value
Driving decision mode	Left_Lane_Change	1
	Lane_Keep	2
	Right_Lane_Change	3
	Drive_Free	4

Experimental Setup

- Setup consists of:
  - Driving platform (simulating car and world)
  - Input:
    - Screen capture --> road scene
    - Radar, IMU --> vehicle odometry
  - Output:
    - Steer, Brake, Accelerate



- 1000 test cases were designed with different lane scenarios -->

Data Collection

- 4 drivers drove vehicle on simulator
- For each frame, vehicle odometry was recorded
- A total of 69000 samples (frames + corresponding odometries) were obtained

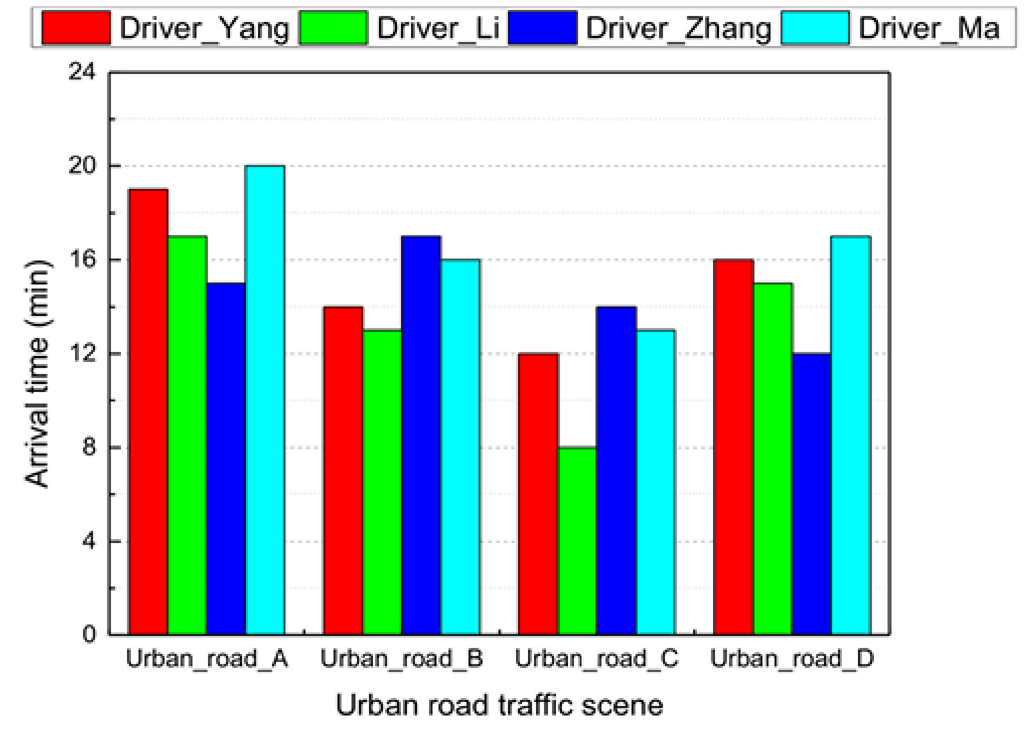


Figure 9. Histogram of the task completion time for each urban road.

The Bayesian Network

Setup Prior Bayesian Network

Use expert knowledge to build a prioir Bayesian Network

Learn structure of Network

Build on the network structure based on sample data

Deploy Real-time

Use the Bayesian network as the driving agent

Prior Bayesian Network

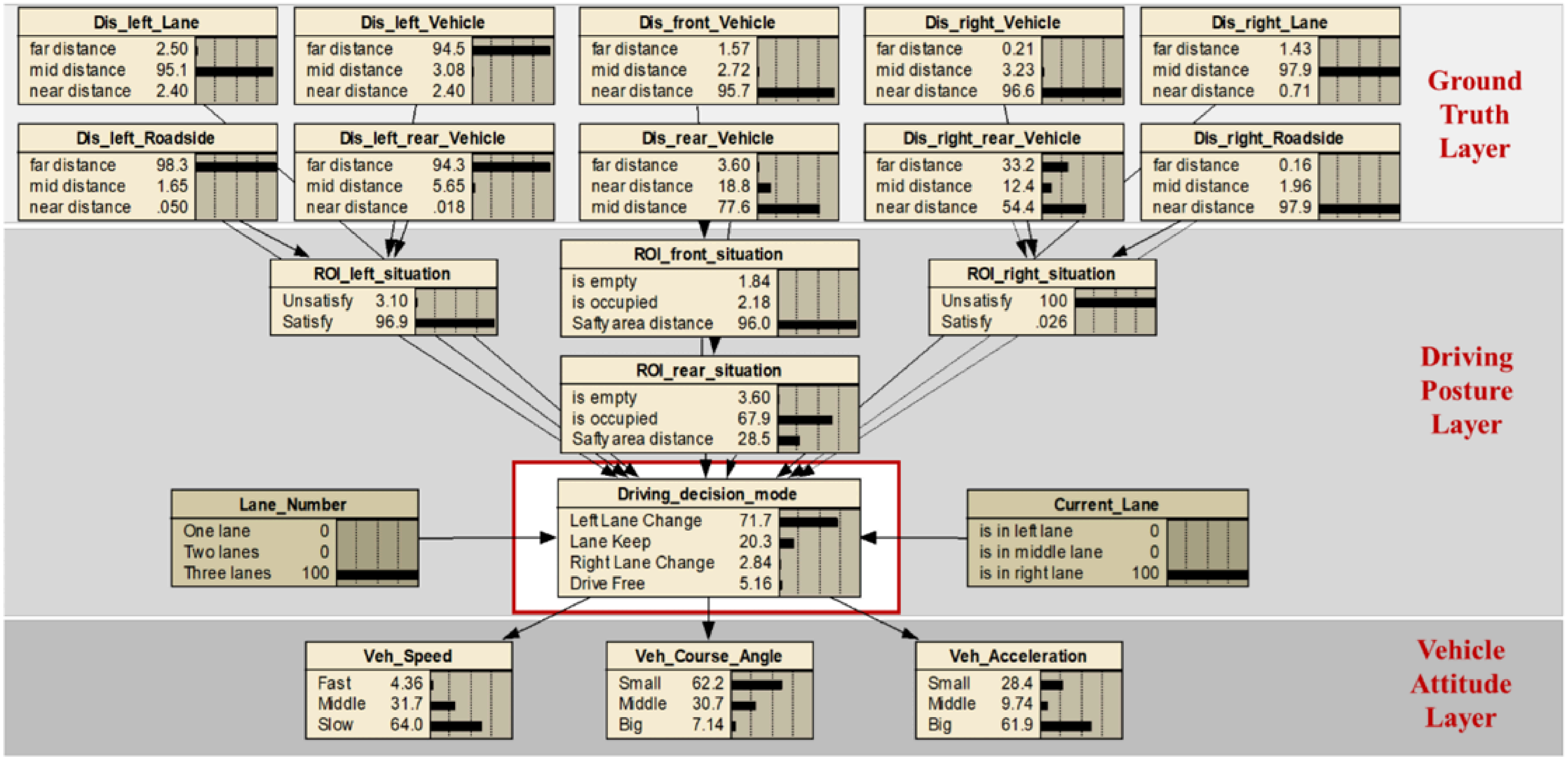


Figure 19. Architecture diagram of a priori Bayesian network.

Learned Baysian Network

Choice of Learning Algorithm

- Search space grows exponentially large
- To cater to prior knowledge
- Constrained based Greedy Search Algorithm: KB-GES
- Improves the Bayesian Information Criterion (BIC) as so:

$$BIC_0 = \sum_i \sum_j \sum_k N^0_{i,j,k} \cdot log\hat{\theta}^0_{i,j,k} - \frac{1}{2} logN \cdot \#S_0 + N \cdot \frac{1}{2} log\left(1 + \frac{e}{N}\right),$$

$$BIC_{\rightarrow} = \sum_i \sum_j \sum_k N^{\rightarrow}_{i,j,k} \cdot log\hat{\theta}^{\rightarrow}_{i,j,k} - \frac{1}{2} log \cdot \#S_{\rightarrow},$$

Algorithm 1 KB-GES based on the fusion of priori knowledge

Input: ρ : Variable order; e : Experts constraints; μ : Maximum number of parent nodes; D : Complete sample data.

Output: Optimal Bayesian network structure.

G $\leftarrow$ boundless graph composed of nodes $X_1, X_2, \ldots, X_n$

for $j = 1$ to n

  $\pi_j \leftarrow \varnothing$; $V_{old} \leftarrow BIC\left(\left(X_j, \pi_j\right) | D\right)$

  while (True)

    $i \leftarrow \mathrm{arg}max_{1 \leq i \leq j, x_i \notin \pi_j} BIC\left(\left(X_j, \pi_j \cup \{X_i\}\right) | D\right)$

    $V_{new} \leftarrow BIC\left(\left(X_j, \pi_j \cup \{X_i\}\right) | D\right)$

    $if\ (V_{old} \leftarrow V_{new}\ and\ |\pi_j| < \mu)$

      $V_{old} \leftarrow V_{new}$;

      $\pi_j \leftarrow \pi_j \cup \{X_i\}$;

      Add an edge $X_j \leftarrow X_i$ to G

    else

      break;

    end if

  end while

end for

return G

Learned Baysian Network

- Used KB-GES algorithm to learn the Bayesian Network structure
- Some connections are removed
- Some of the posture layer nodes (11,13,14) directly started affecting the decision node
- Vehicle attitude layer nodes (18,19,20) remained the same.

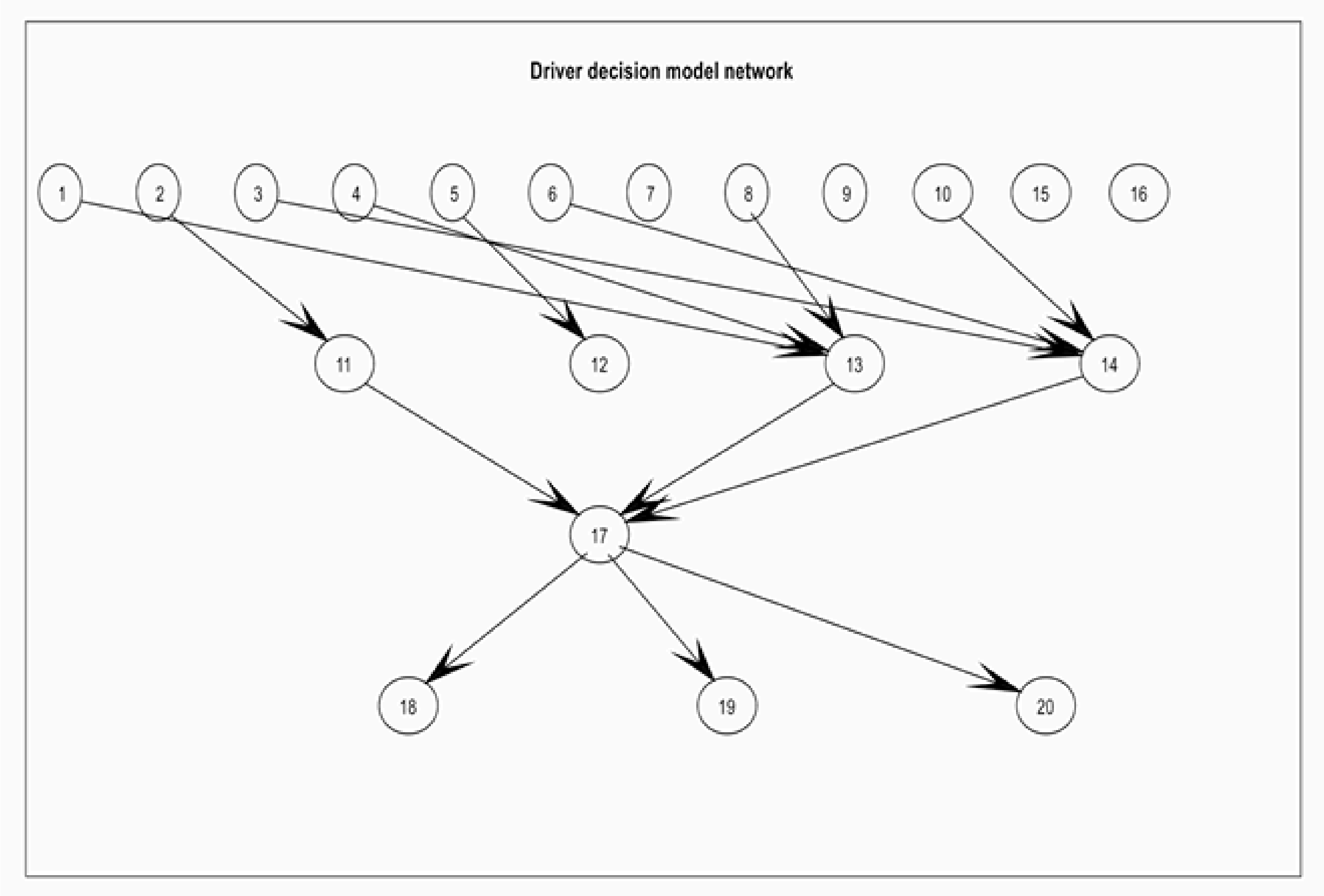


Figure 22. DBN structure learned from sample data.

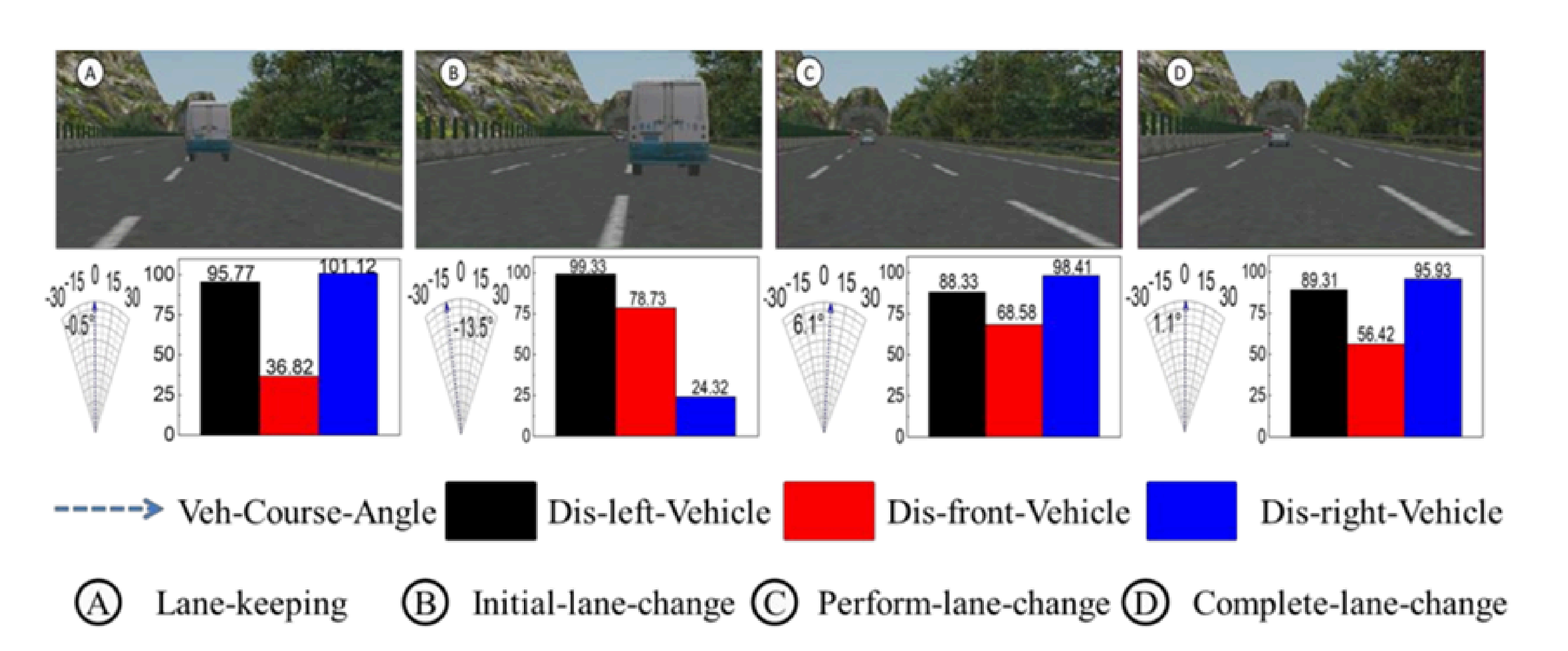
Using the trained Bayesian Network

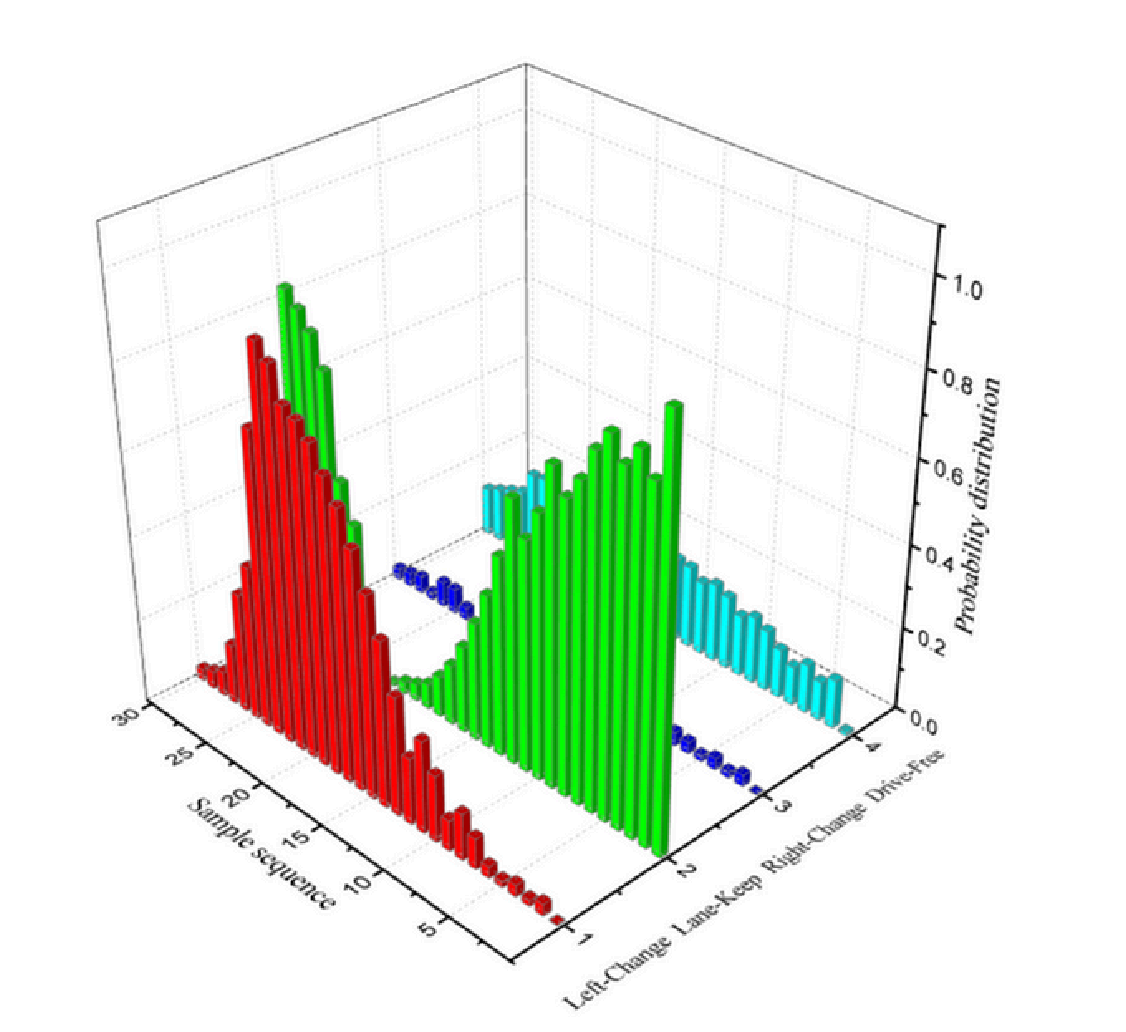
- The purpose is to select the right decision with maximum probability in the Drive_Mode node.
- Given real time data from the input, and the previous nodes, we want the updated belief about the decision at each time step
- Message Passing algorithm is used for belief propogation

$$\mathrm{Bel}(\mathrm{Drive\_Mode}) = \alpha\lambda(\mathrm{Drive\_Mode})\pi(\mathrm{Drive\_Mode}), \tag{21}$$

Scenario: Changing to left-lane

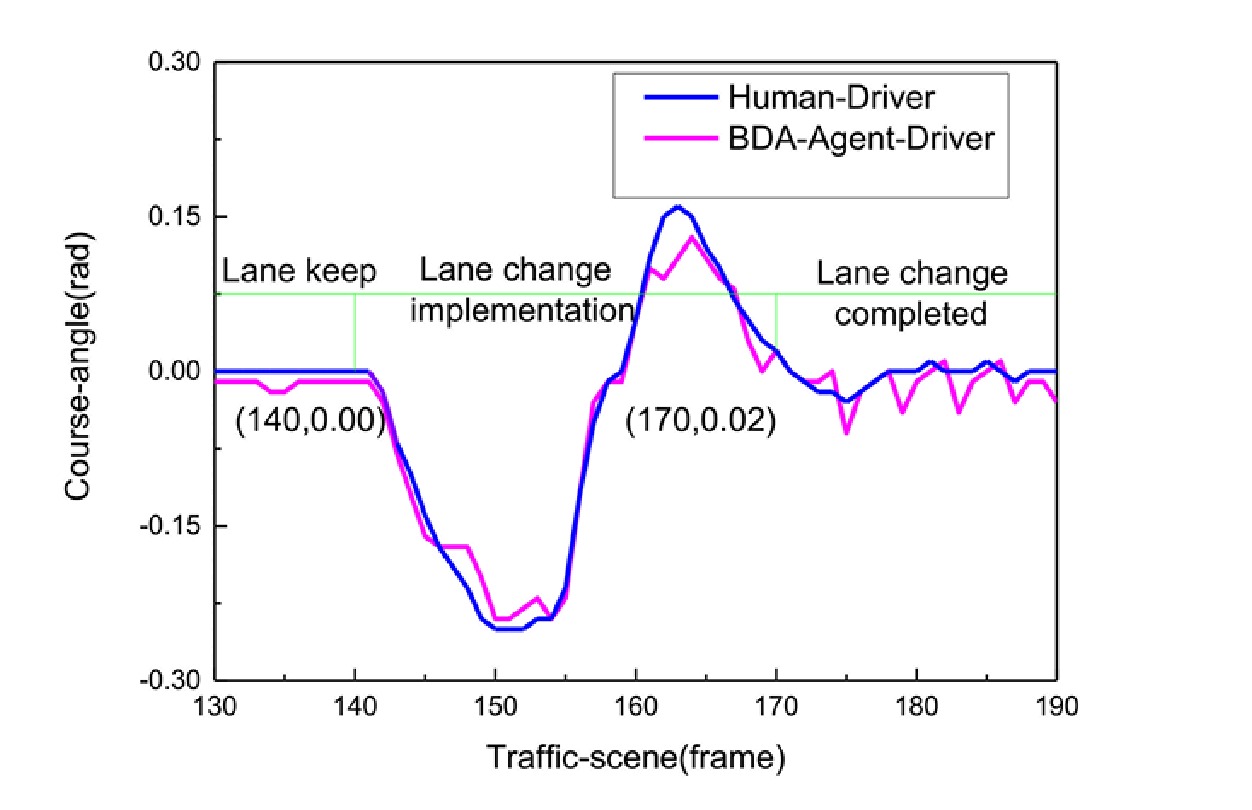
- One scenario is changing to left lane
- The vehicle is at the rightmost lane initially
- A car is present in the current
- Vehicle decides and steers to left-lane to avoid vehicle.





Comparison with Human-Driver

- The steering angle for Bayesian Driver model and human driver was compared
- The interclass correlation between the two was found to be 0.984
- The degree of variation between BDA and human driver was found to be significantly consistent.



Conclusion and Future work

- The BDA model can effectively predict the decision intention of human drivers, this enables autonomous agents to complete a series of basic driving tasks without human intervention.
- The Bayesian network can transfer human skills to the intelligent assistance system. Modeling of driving behavior based on BNs makes the decision model interpretable
- Overcomes the unexplainable characterstics of end-to-end models
- **Limitations:**
  - Only 5 urban scenes are considered. Can be generalized to incorporate more data.
  - Model can be transformed to virtual to a realistic setting.
  - Reinforcement learning can be used incorporated to optimize the driving decision.

References

[1] “A Bayesian Driver Agent Model for Autonomous Vehicles System Based on Knowledge-Aware and Real-Time Data.” Accessed: Nov. 20, 2024. [Online]. Available: https://www.mdpi.com/1424-8220/21/2/331

Appendix

Dynamic Bayesian Network
Inference Functional Region

- Initial network B0; prior probability distribution on X_t^i
- State transition network B->, transition probability distribution
- Joint Probability Distribution on an arbitrary node:

$$P\left(X_{1:T}^{(1:N)}\right) = \prod_{i=1}^{N} P_{B_0}\left(X_1^i \mid P_a\left(X_1^i\right)\right) \times \prod_{t=2}^{T} \prod_{i=1}^{N} P_{B_\rightarrow}\left(X_t^i \mid P_a\left(X_t^i\right)\right).$$

Finding the best BN for the data

- Find the best possible network structure (S_DBN) that fits the sample Data D

$$P(S_{DBN}|D) = \frac{P(S_{DBN})P(D|S_{DBN})}{P(D)}.$$

- Data likelihood can be found with relevant network parameter θ

$$P(D|S_{DBN}) = \int P(D|S_{DBN},\theta)P(\theta|S_{DBN})d\theta.$$

$$logP(D|S_{DBN}) = log\ P(D|S_{DBN},\hat{\theta_S}) - \frac{1}{2}\log N * \#S,$$

$$\#S = \frac{\pi_i(\gamma_i - 1)}{2},$$