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[www.ofp-projekt.de](http://www.ofp-projekt.de)

## 23322: Open Fusion Platform for Automated Driving Cars Based on Nvidia DPX2



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# Agenda

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- Motivation
- Overview of the *Open Fusion Platform (OFP)* Project
- Functional Architecture
- Interface Specification
- Joint Semantic Segmentation and Detection
- Intention Prediction, Risk Assessment and Decision Making for Vehicle Guidance
- Conclusion and Outlook



# Motivation

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- Fully automated driving prototypes available but no serial production
  - High development cost on sensors, hardware and algorithm
- Advanced driver assistance systems cover only predefined situations
- Integration issues due to heterogeneous sensors and interfaces
- Actual standardization initiatives for automated driving
  - OpenDRIVE: Format specification for road networks and infrastructure
  - OpenSCENARIO: Description of dynamic contents in driving simulation applications
  - Adaptive AUTOSAR: New AUTOSAR Platform for complex fusion systems
  - EB Robinos
    - Architecture specification in environmental fusion models
    - Software for development and embedded prototyping
    - SW Modules inside environmental model and situation analysis



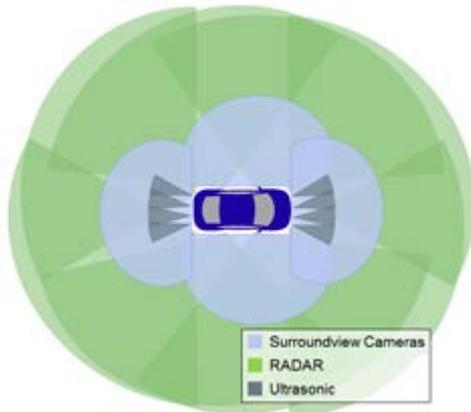


# Overview of OFP

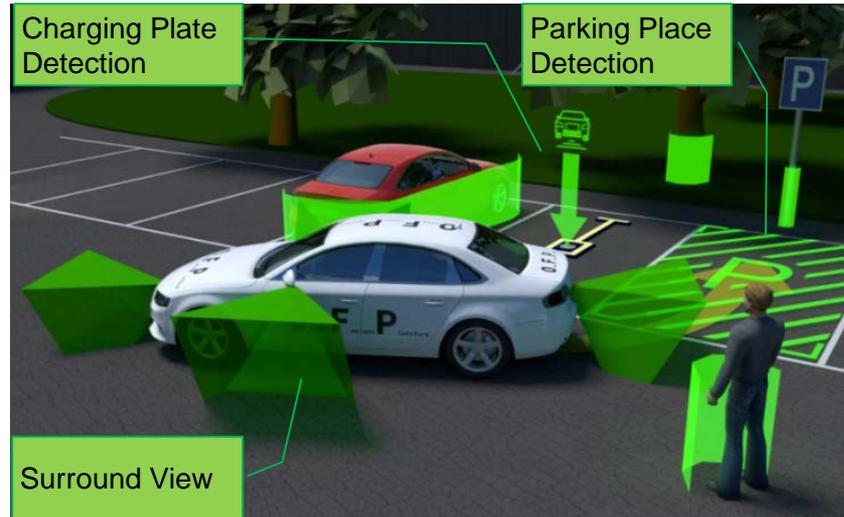
## Project Objective:

- **Create a near series fusion platform** with open interfaces, that allows a cost efficient implementation of highly and fully automated driving functions.

## Sensor Configuration



**Project Timeframe:** Jan 2016 – Dec 2018



## Use Case:

“An e-car autonomously parks and **positions** itself directly on **top** off a **parking space with a wireless charging plate**. When car is charged, it drives itself to another parking space without a charging plate.”



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# Car Platforms used in OFP

**e.GO life (Electric)**



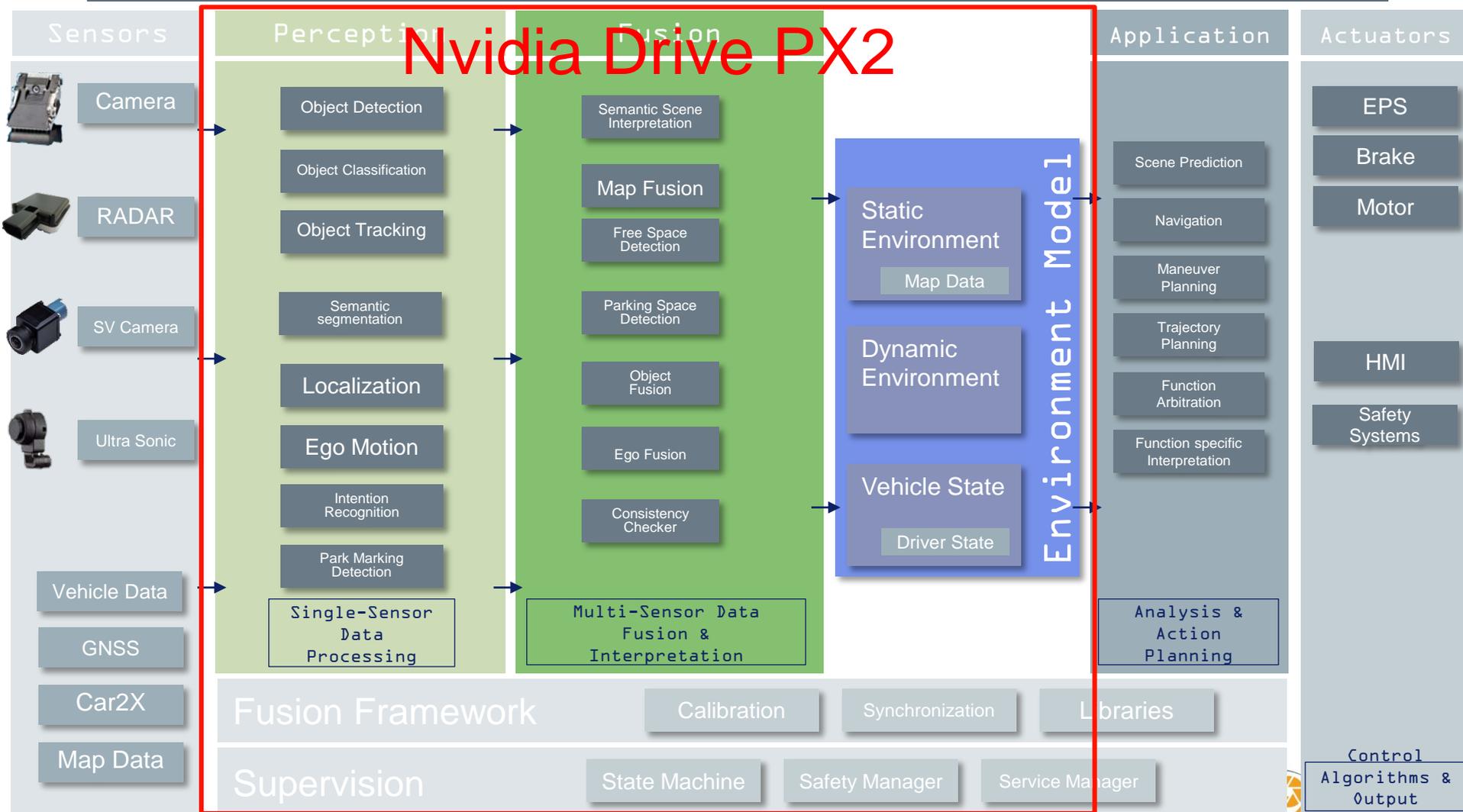
**Passat GTE (Plug-in Hybrid)**



**AUDI A6**



# Functional Architecture



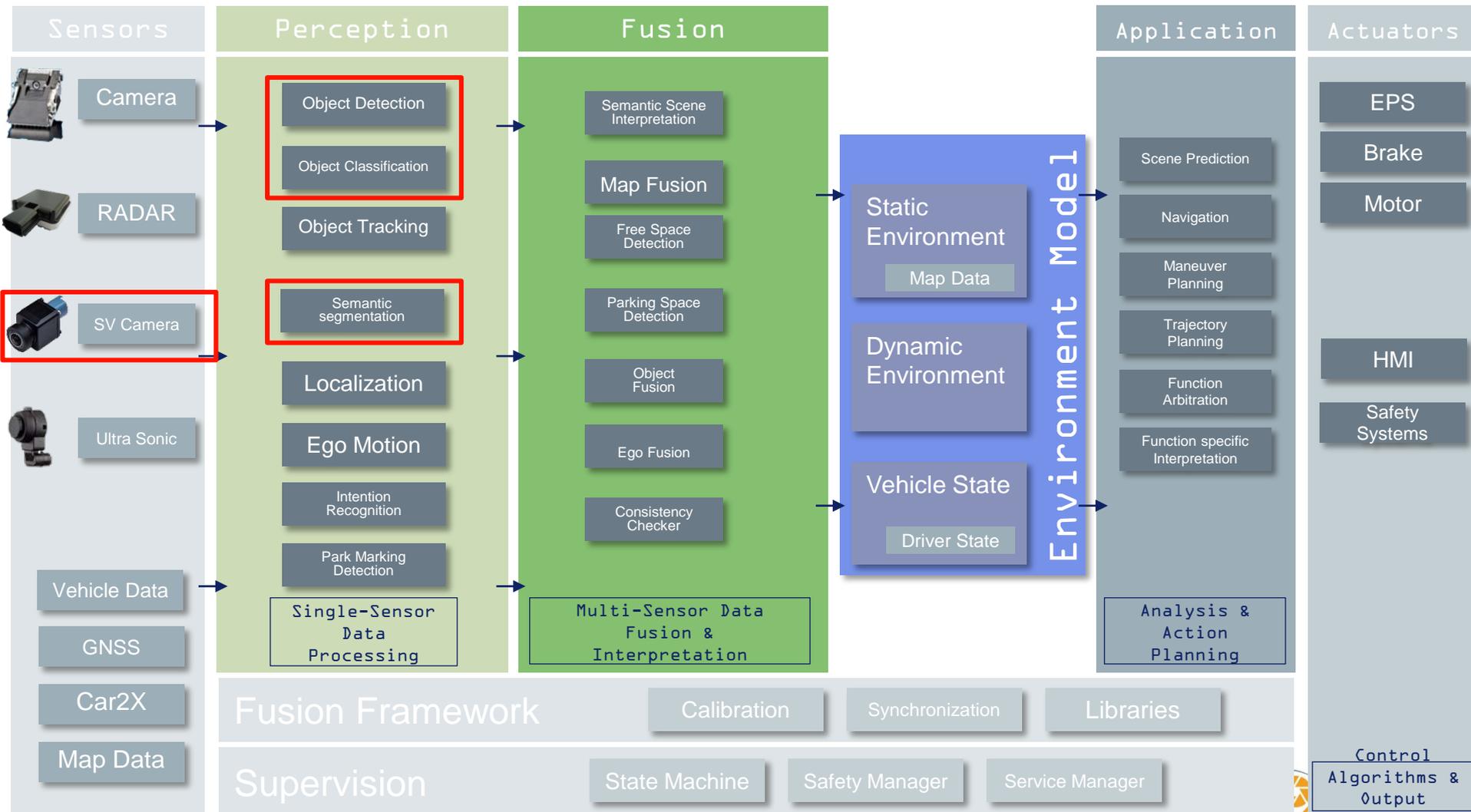
# Interface Specification

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- Hardware Interface
  - Use available standards as CAN, LVDS, etc.
- Basic Software
  - Elektrobit AdaptiveCore: Adaptive AUTOSAR implementation from Elektrobit
- Data- and timing-driven communication
- Definition of generic data types. E.g. object, ego pose and motion, image, etc.
- Software interface
  - Description of inputs and outputs using module manifest
  - Specification of a module manifest template
  - Layer specific module manifest implements the manifest template
- Interface specification available soon on the project homepage <http://www.ofp-projekt.de/ofp-project/de/Oeffentliche-Dokumente-305.html>

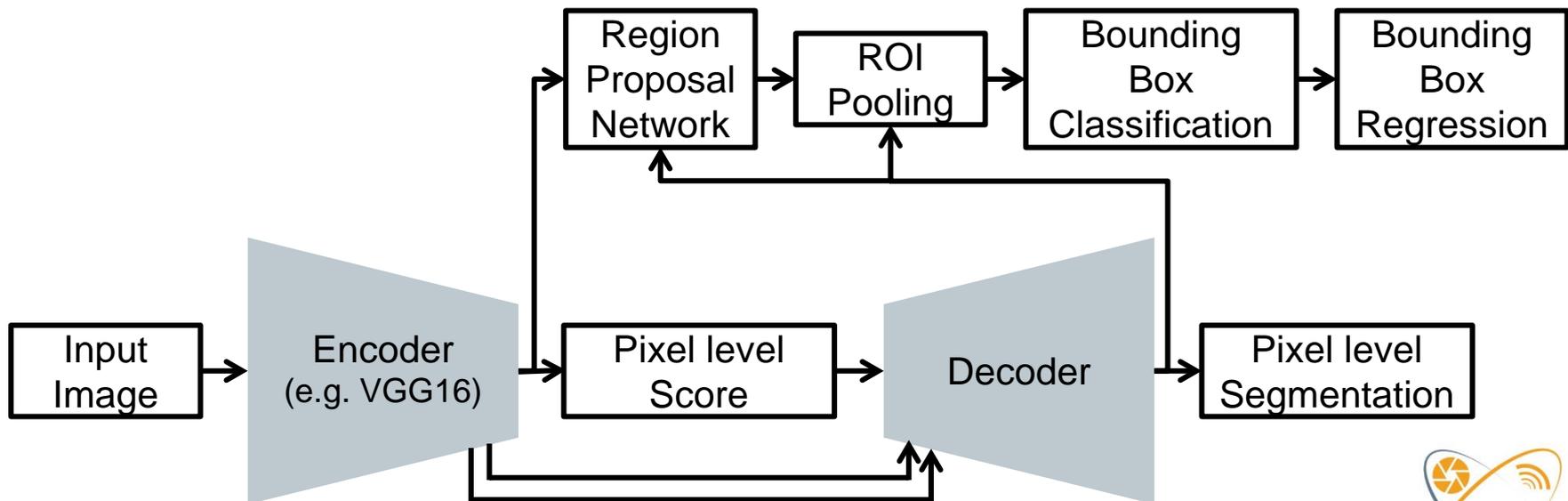


# Joint Semantic Segmentation and Object Detection Overview



# Joint Semantic Segmentation and Object Detection Model

- Sharing of features between Faster R-CNN [1] and FCN [2]
- Extension of Faster R-CNN ROI Poling with FCN score map
- Advantages
  - Reduce feed forward computation time and memory consumption
  - Improve detection while keeping the segmentation unchanged



# Joint Semantic Segmentation and Object Detection

## Training and Evaluation on Daimler Cityscapes dataset

- Training and evaluation on Daimler Cityscapes dataset [3] using GTX 1080ti GPU
- Evaluation results: Intersection Of Union (IOU) for segmentation and mean Average Precision (mAP) for detection

FCN Model	Average IOU	FR-CNN Model	AVG mAP	Overall mAP
Single	<b>0,579</b>	Single	0,32	0,327
Joint Model	0,572	Joint Model	<b>0,325</b>	<b>0,358</b>

- Complexity on GTX 1080ti, image size: 2048x1024
  - The joint-Model uses **33%** less memory and is **1,3x** slower than both single models running in parallel

Model	#Params	Runtime	Memory
Single FCN	134,5M	320ms	5,63GB
Single Faster R-CNN	136,9M	250ms	4,47GB
Joint-Model	256,9M	430ms	6,71GB



# Joint Semantic Segmentation and Object Detection

## Fine Tuning on OFP Surround View Camera Data

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- Fine tuning of the model trained on Daimler Cityscapes with OFP surround view camera data
- Complexity on GTX 1080ti, image size: 1024x440
  - The joint-Model uses **23%** less memory and is **1,08x** slower than both single models running in parallel

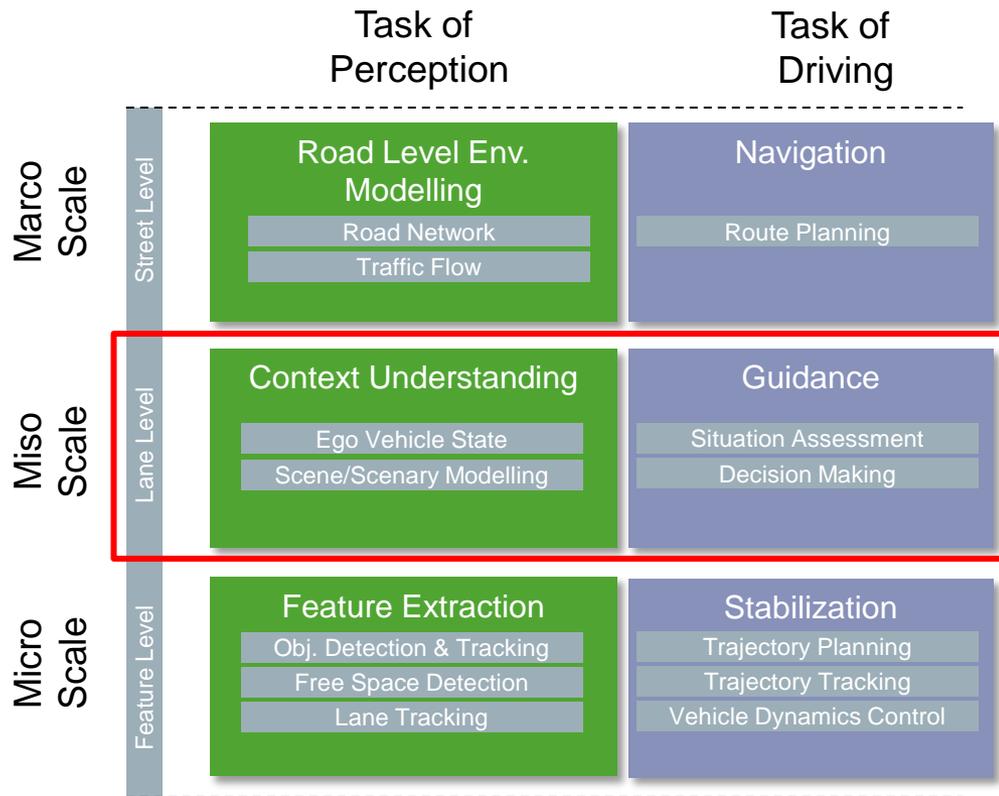
Model	Runtime	Memory
Single FCN	180ms	2,22GB
Single Faster R-CNN	112ms	1,98GB
Joint-Model	195ms	3,22GB

- [Video](#)

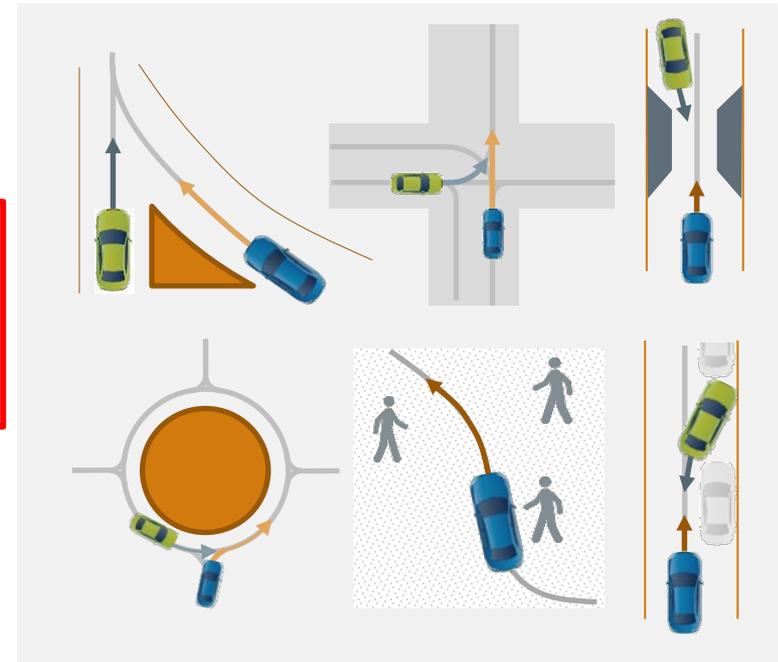


# An Abstract Functional Architecture for Automated Driving

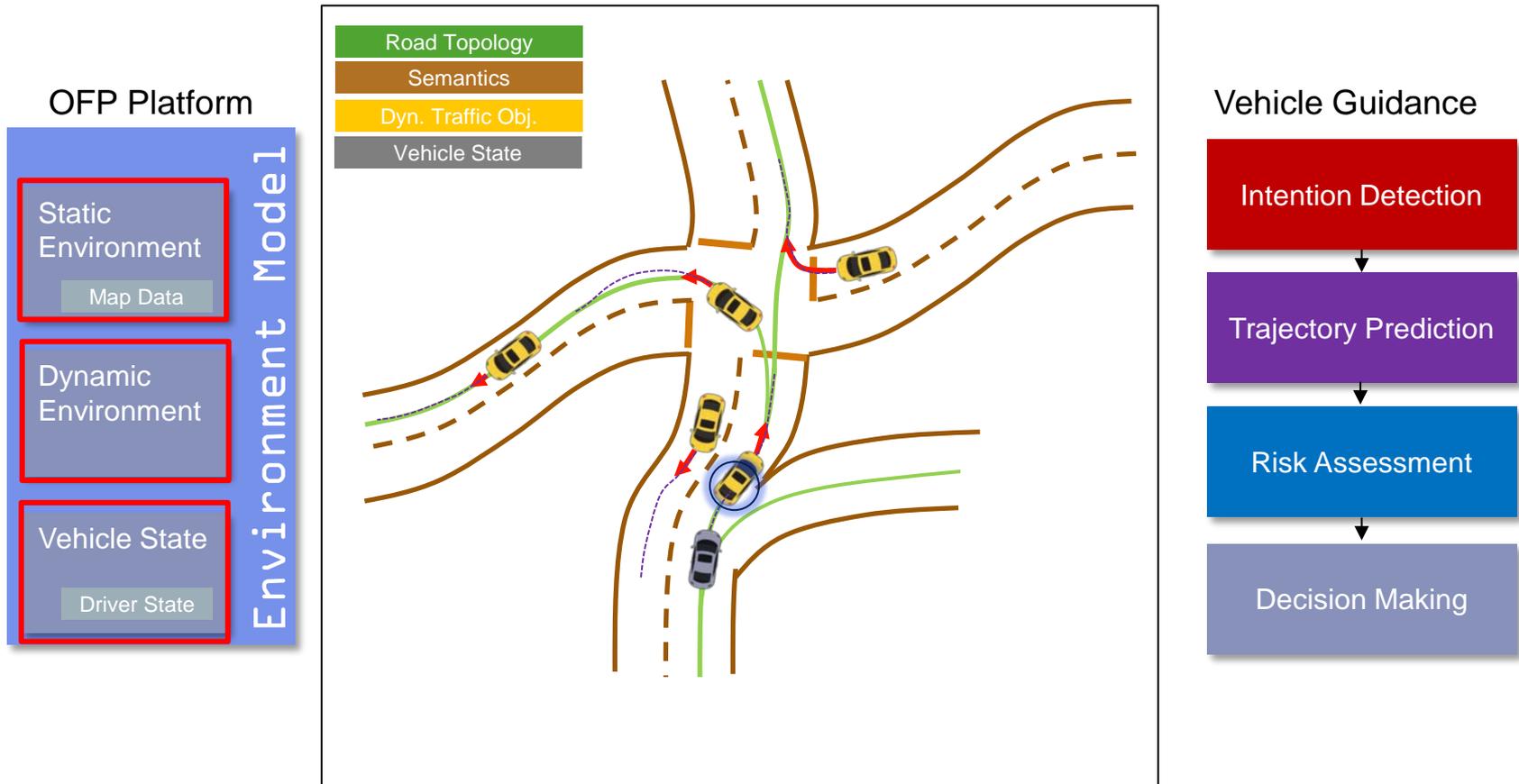
For an automated vehicle guidance, the model and understanding about the current scene and it's context are required



Addressing Scenarios



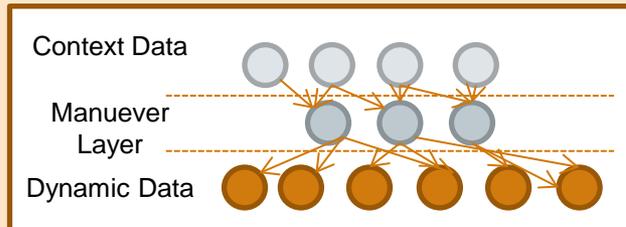
# OFP-Platform Provides us with Required Information about the Current Scene with different APIs



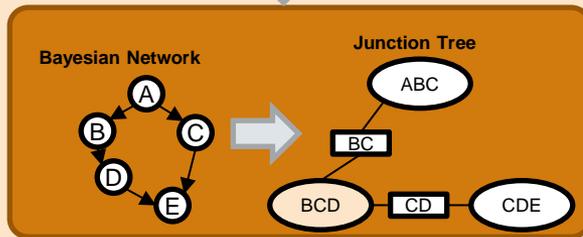
# Intention Detection and Prediction of Road Participants by Using Probabilistic Approaches such as Bayesian Network

## Approach:

Dynamic data:  $v_{lat}$ ,  $v_{long}$ ,  $a_{lat}$ ,  $a_{long}$ , ...  
 Context data:  $t_{time-to.turn}$ ,  $t_{time-to.vehicle}$ ,  $t_{time-to-line}$ ,



Conversion of Bayesian Network to Junction Tree for better calculation performance

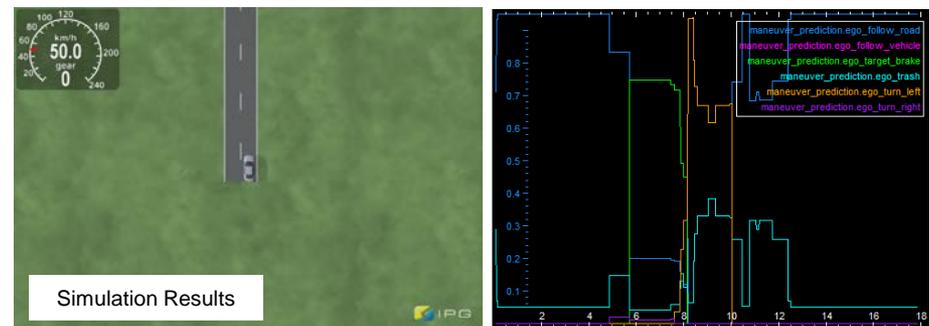


Calculation of probability of each Maneuver based using Junction Tree Algorithm

## Maneuver Catalog:

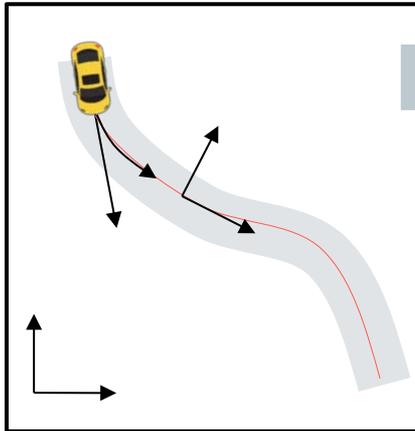


## Some Results:

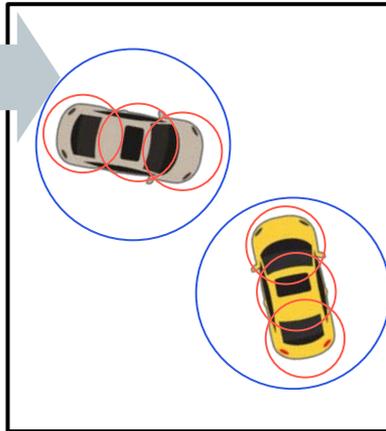


# Risk Assessment of the Scene by Calculating the Predicted Trajectory and Collision Probabilities

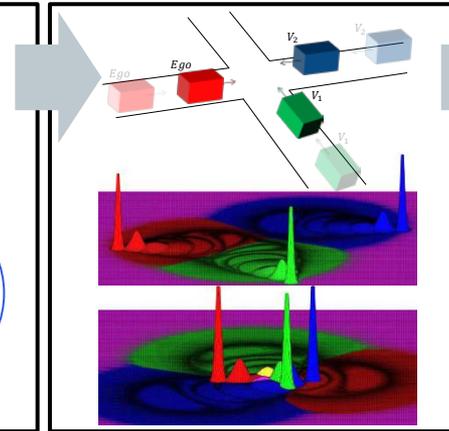
Motion Model in Road Coord. Sys.



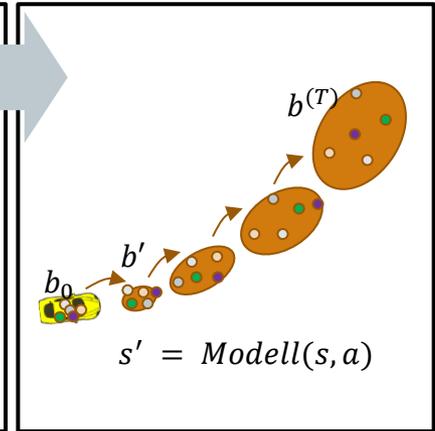
Two Step Collision Check



Calculating the Collision Probabilities



Sampling Using Monte Carlo



Motion Model



Follow Vehicle

Gap Keeping Model



Follow Road

Constant Acceleration Model



Turn

Constant Radius Model:  
Constant Velocity Model + Constant Acceleration Model



Lane Change

Half Sinus Model:  
Constant Velocity Model



Target Brake

Constant Acceleration Model (Considering the Distance to Obstacle)



Trash

Constant Acceleration Model + Constant Yaw Rate Model



# Decision Making under Uncertainties by Using POMDP-Approach

## POMDP

**Partially Observable Markov Decision Process:**

- $S = \{s\} = \{x, y, v_x, v_y\}$  (States)
- $A = \{a\} = \{Acc, CV, Dec\}$  (Actions)
- $T = P(s'|s, a)$  (Transition)
- $R = R(b, a)$  (Rewards)
- $Z = \{z\}$  (Measurements)
- $O = P(z|s', a)$  (Observation)
- $\gamma \in ]0; 1[$  (Discount factor)

## Action Set A

- $a_0$ : Acceleration
- $a_1$ : Deceleration
- $a_2$ : Constant Velocity

## State S

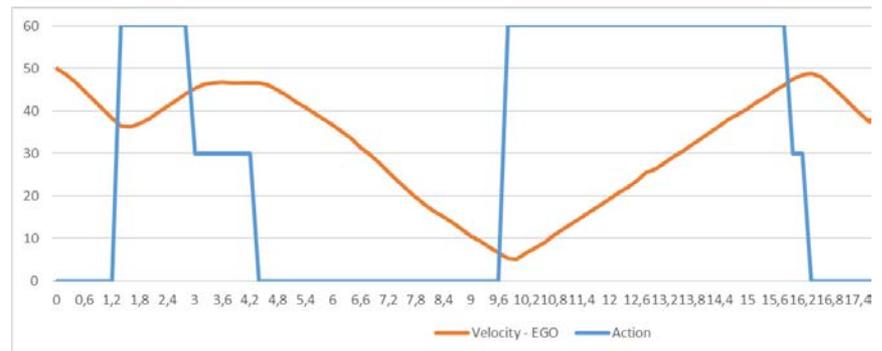
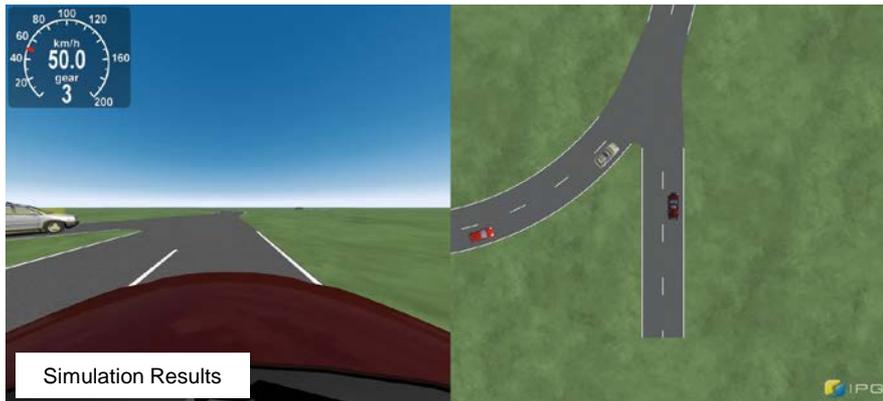
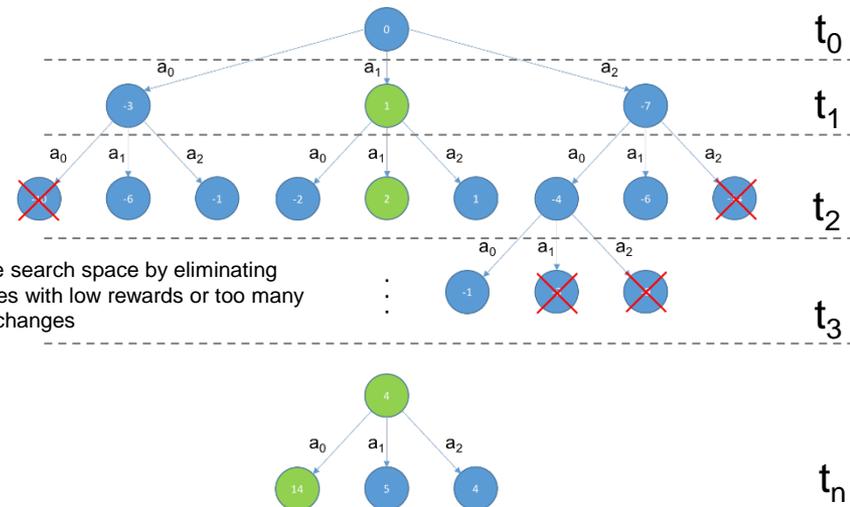
### Ego Vehicle

- Position  $(x, y)$
- Velocity  $(V_x, V_y)$

### Road Participants

- Position  $(x, y)$
- Velocity  $(v_x, v_y)$
- Intention Model

## Evolution of the Scene in each frame



# Conclusion and Outlook

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- Open fusion platform based on Nvidia DPX2
- Functional architecture as a layer model
- Interface specification based on available standards and generic data types
- Joint learning of semantic segmentation and detection improves the detection
- Automated vehicle guidance using environment model from OFP platform
- Next steps
  - Integration into the DPX2 and test with live data
  - Fine tuning of the models
  - Validation of the algorithms in real scenarios



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# Literature

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2. Evan Shelhamer, Jonathan Long, Trevor Darrell: Fully Convolutional Networks for Semantic Segmentation. CoRR abs/1605.06211 (2016)
3. Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., Schiele, B.: The Cityscapes Dataset for Semantic Urban Scene Understanding. In: Proc. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016)

