AUTONOMES FAHREN UND PERSONEN BEZOGENE DATEN

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FÜR KÜNSTLICHE INTELLIGENZ

Levels of Driving Automation

01

No Automation

Manual control. The human performs all driving taska. (steering, acceleration, braking etc.)

02

Driver Assistance

The vehicle festures a single automated sytem (e.g. it monitors speed through cruise control)

03

Partial Assistance

ADAS. The vehicle can perform steering and sccelera-tion. The human monitors all tasks and can take control at any time.

04

Conditional Automation

Environemental detection capabilities. The vehicle can perform most driving tasks, but human override is still required.

05

High Automation

The vehicle performs all driving tasksmunder specific circumstances. Geofencing is required. Human override is still an option.

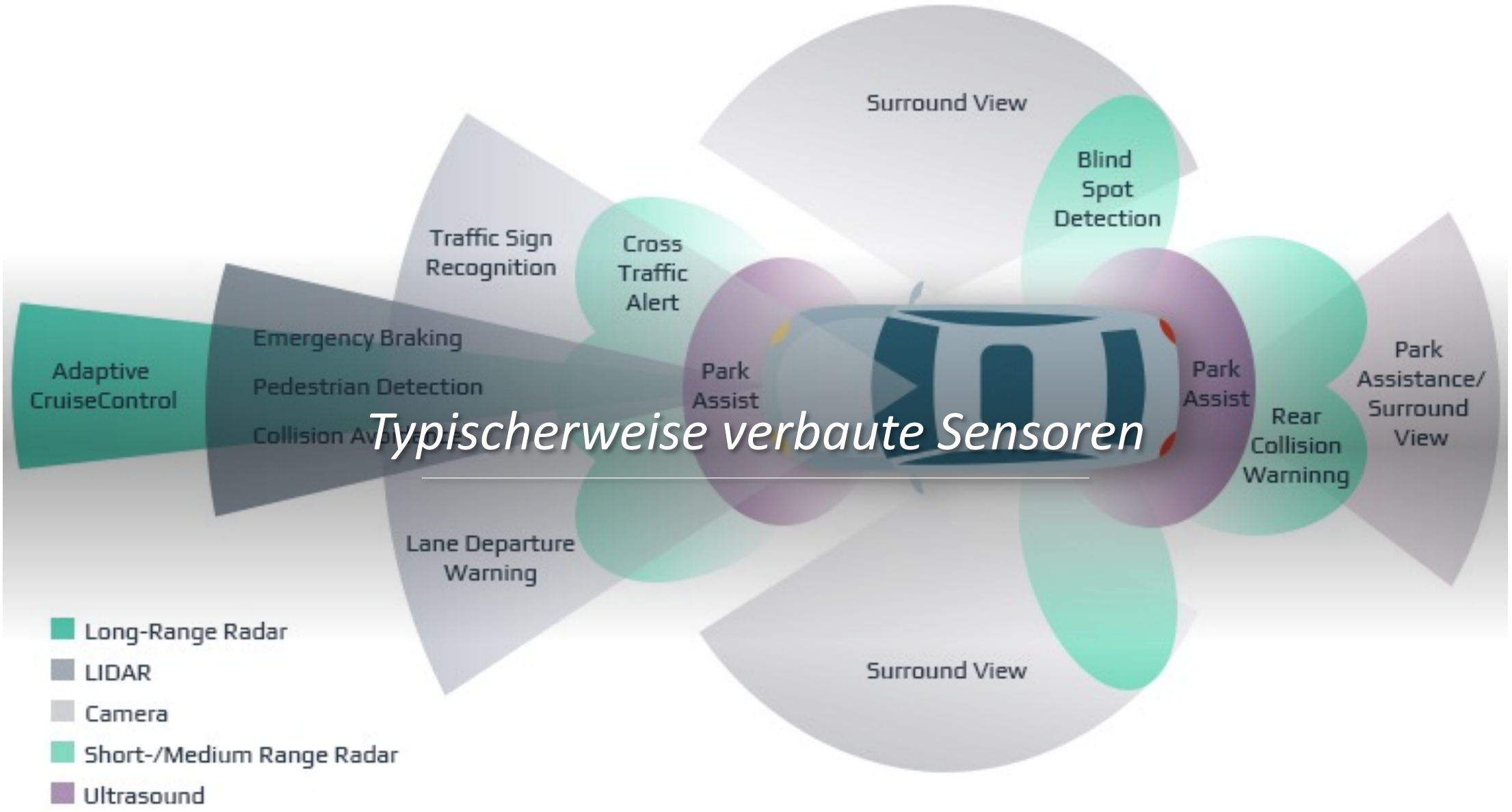
06

Full Automation

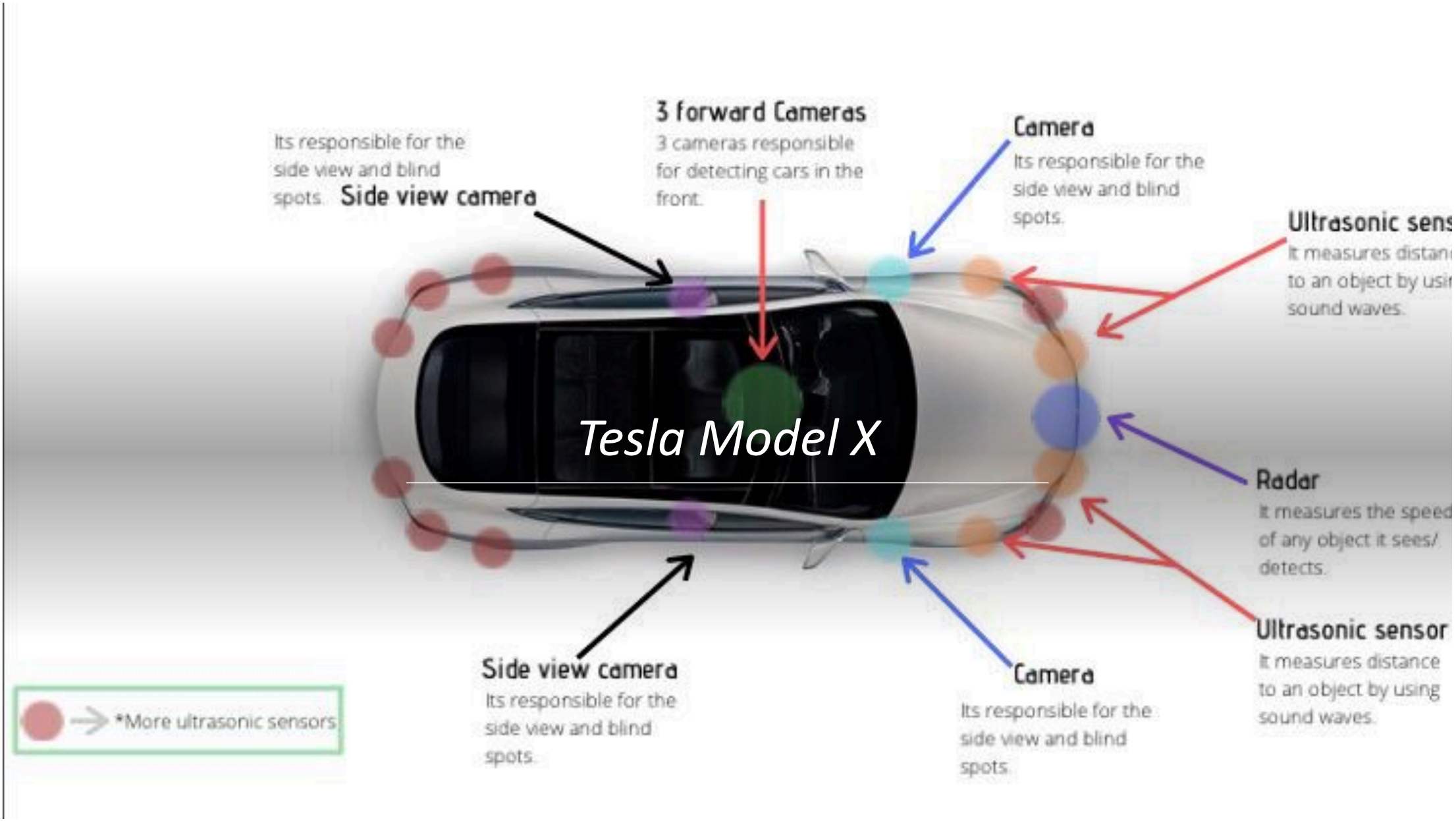
The vehicleperforms all driving tasks under all conditons. Zero human attention or interaction required.

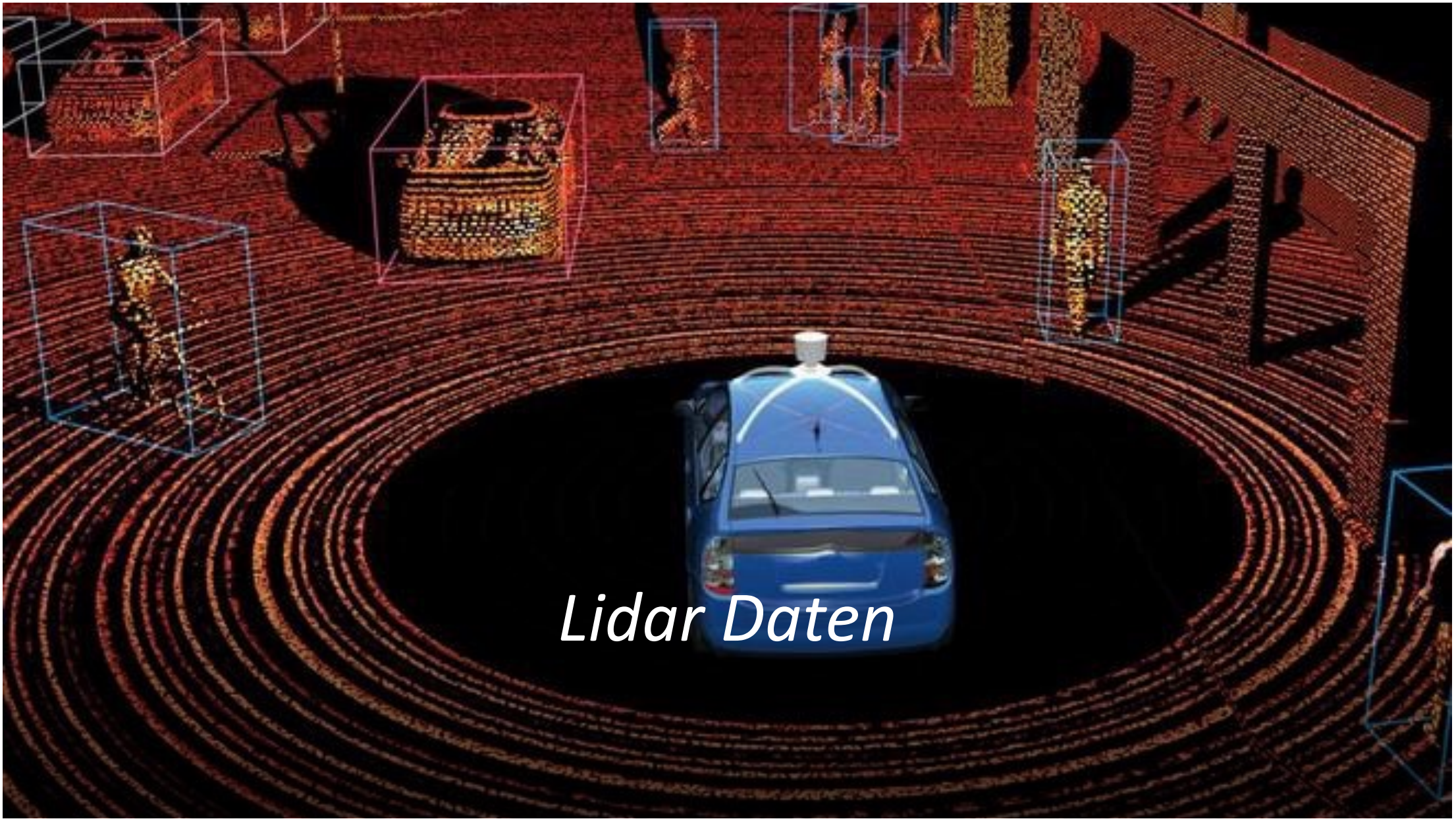
The human monitors the driving environment

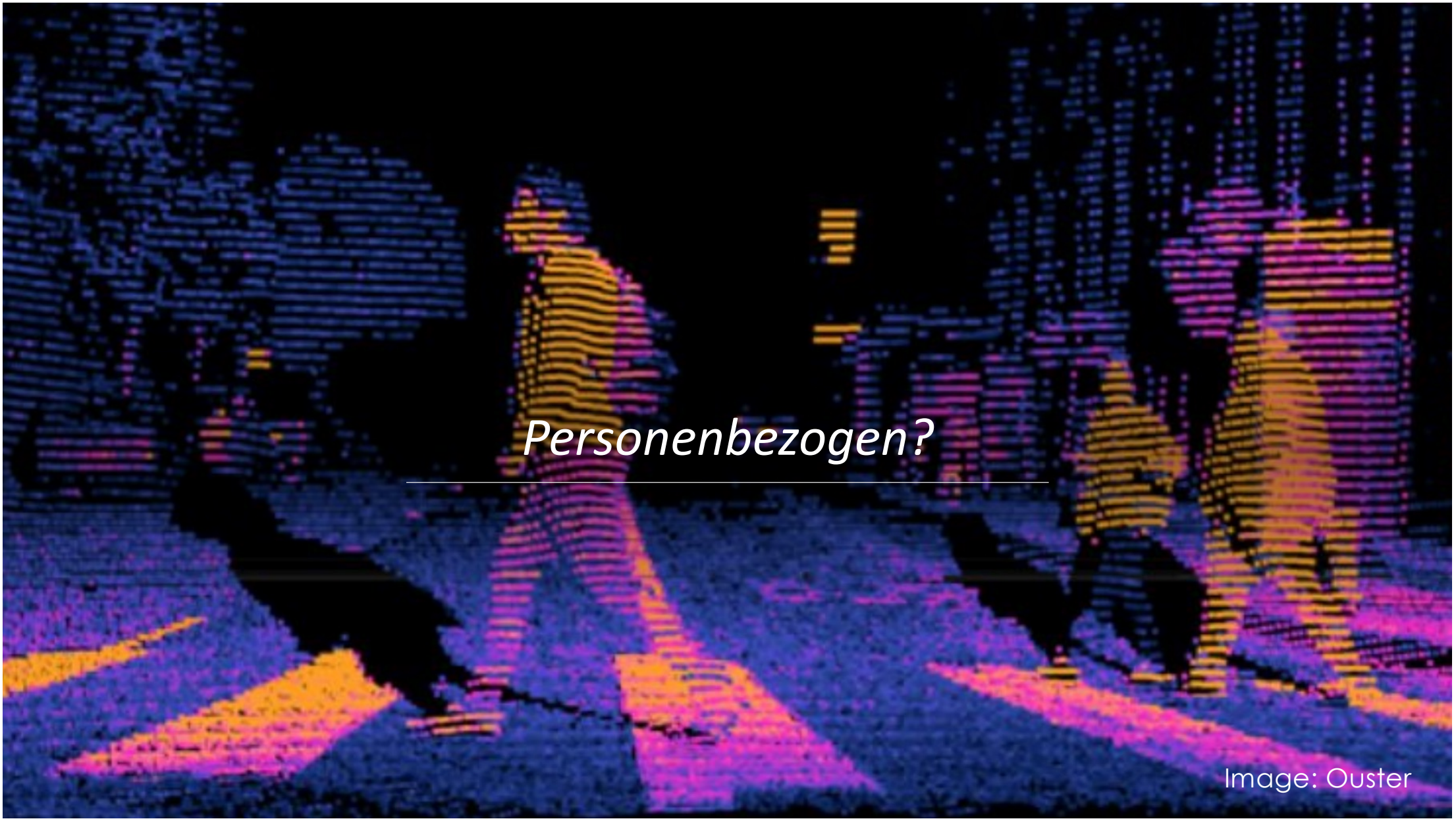
The automated system monitors the driving environment



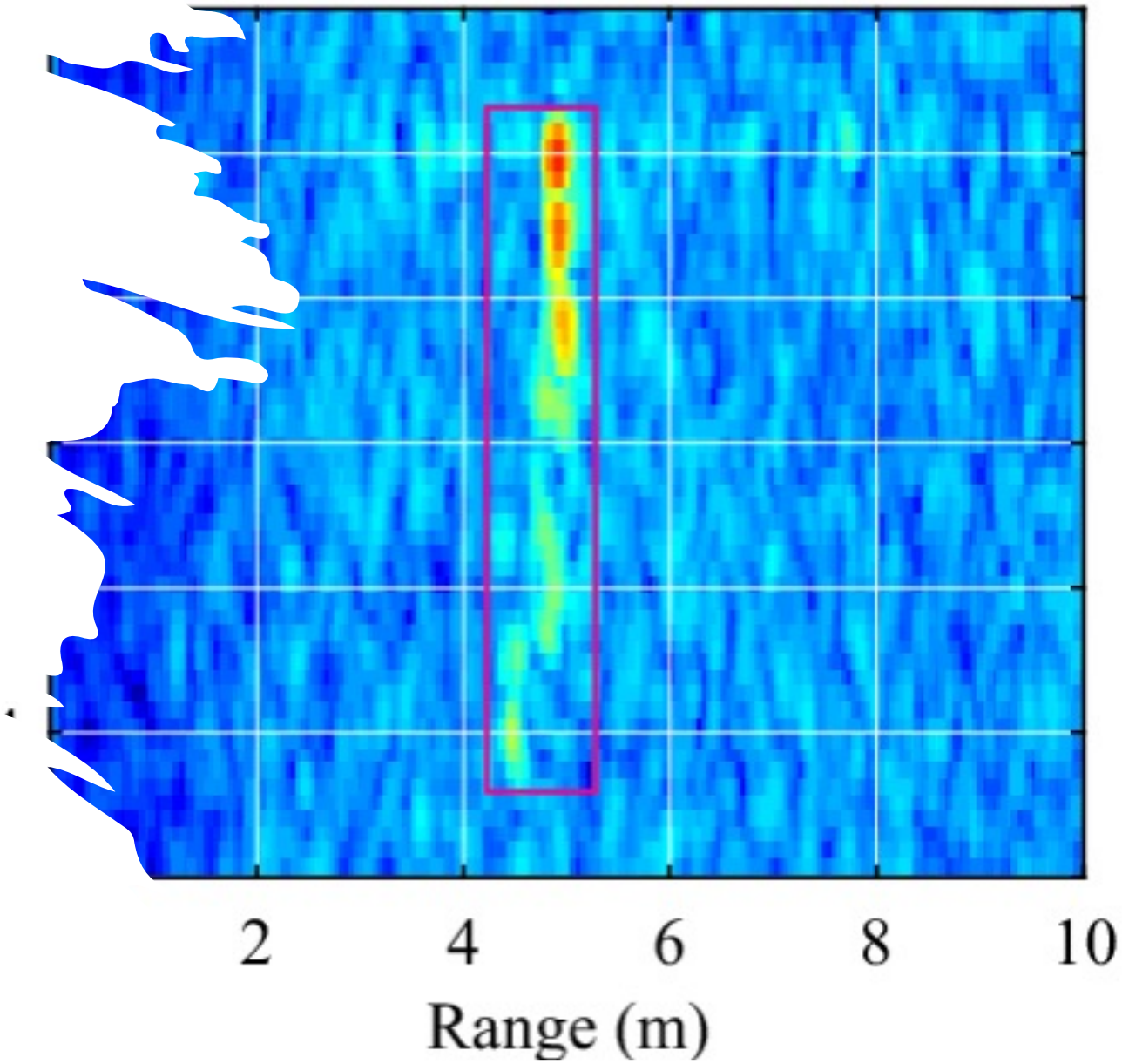
Typischerweise verbaute Sensoren


Its responsible for the side view and blind spots.
Side view camera
3 forward Cameras
3 cameras responsible for detecting cars in the front.
Camera
Its responsible for the side view and blind spots.
Ultrasonic sens
It measures distan
to an object by usi
sound waves.
Tesla Model X
Radar
It measures the speed
of any object it sees/
detects.
Ultrasonic sensor
It measures distance
to an object by using
sound waves.
Side view camera
Its responsible for the side view and blind spots.
Camera
Its responsible for the side view and blind spots.
*More ultrasonic sensors

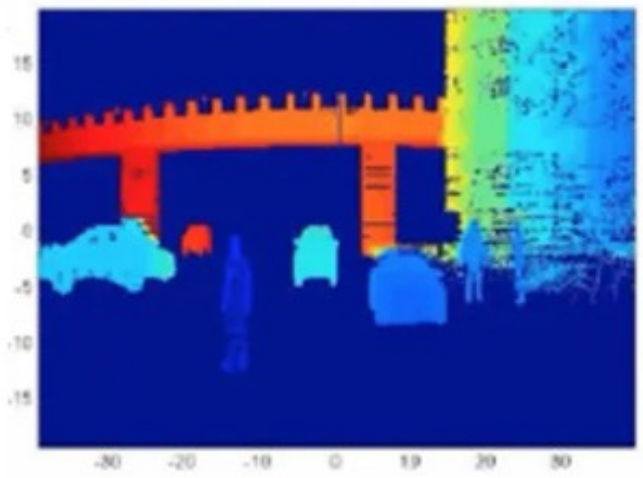

Lidar Daten


Personenbezogen?
Image: Ouster

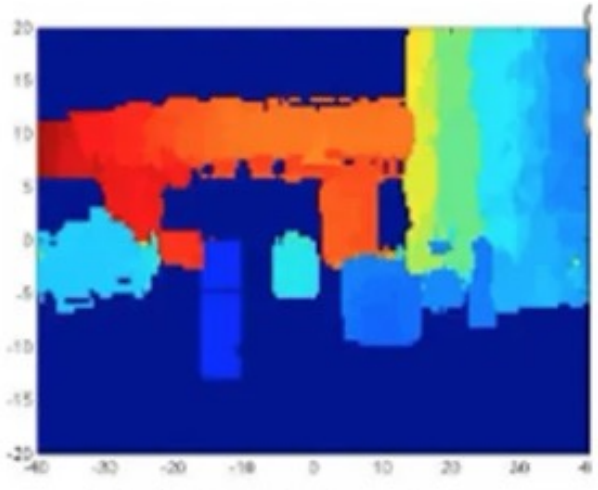
Typischer Radar



Prophet, R., Hoffmann, M., Vossiek, M., Sturm, C., Ossowska, A., Malik, W., & Lübbert, U. (2018, June). Pedestrian classification with a 79 GHz automotive radar sensor. In *2018 19th International Radar Symposium (IRS)* (pp. 1-6). IEEE.



Lidar

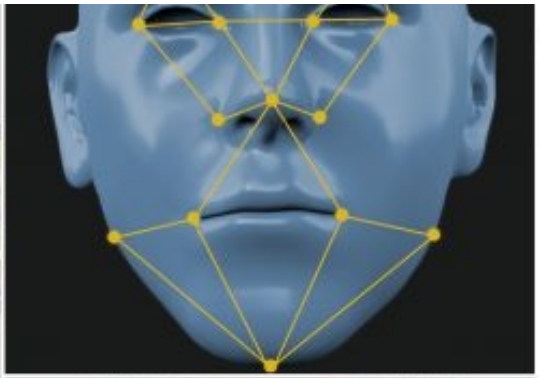


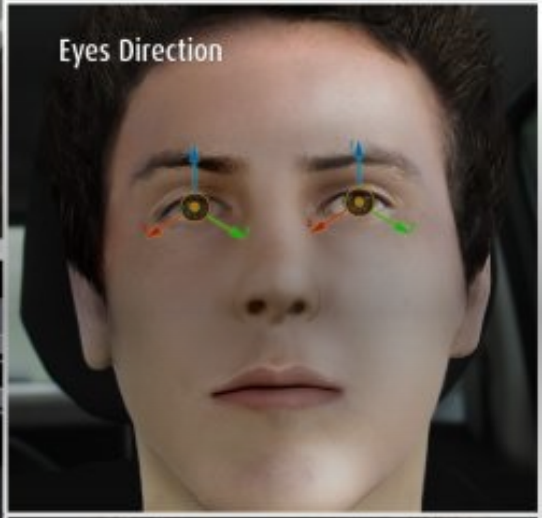
High Resolution Radar

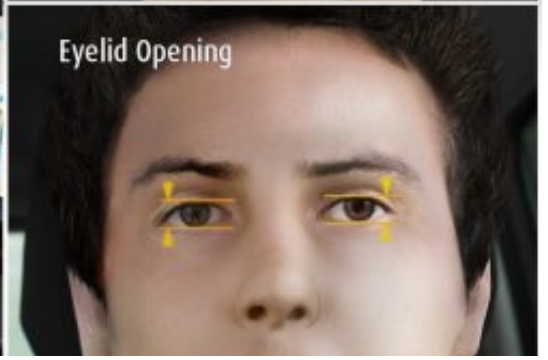
Imaging Radar

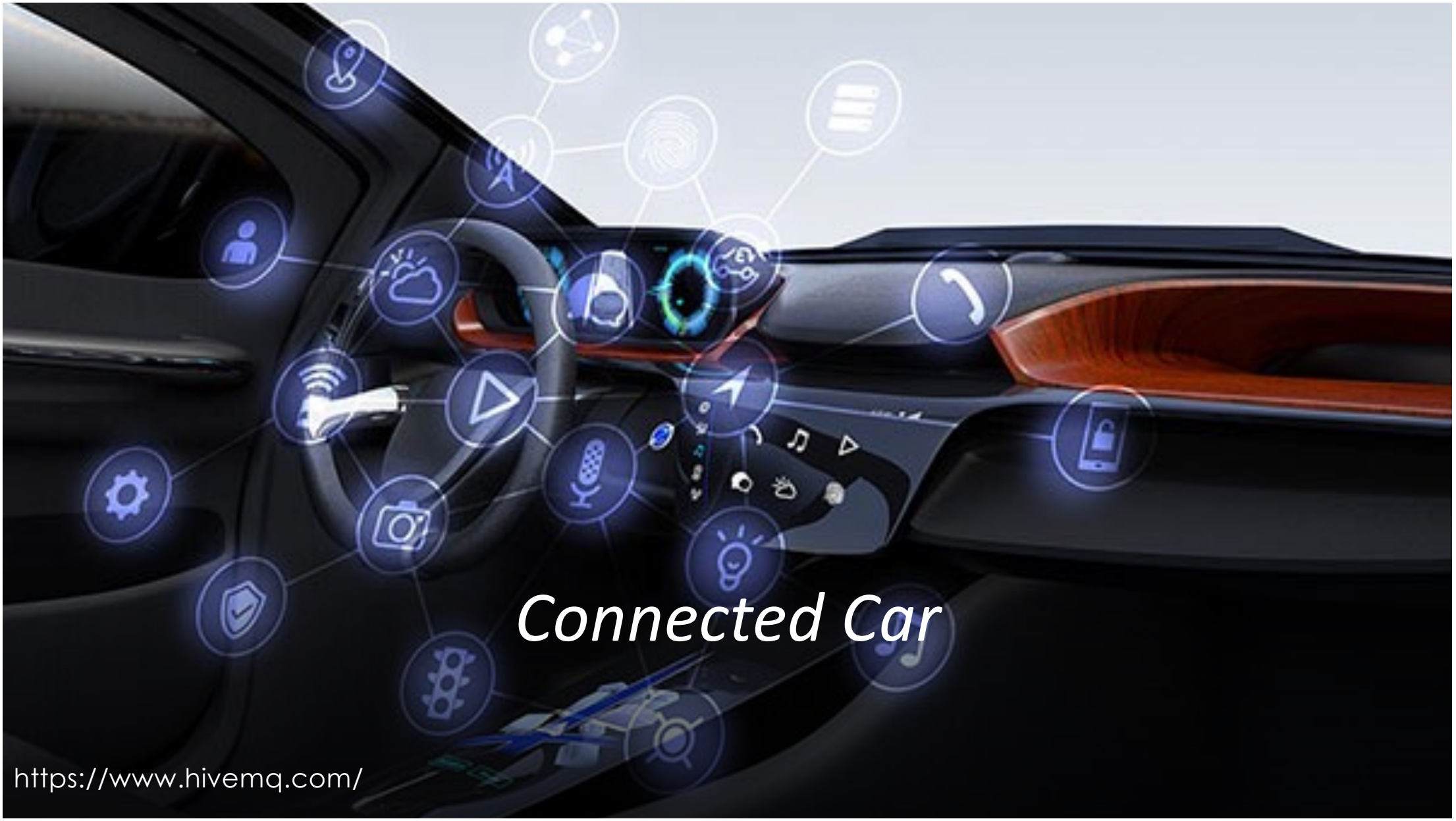
(From semiengineering.com, courtesy of NXP)

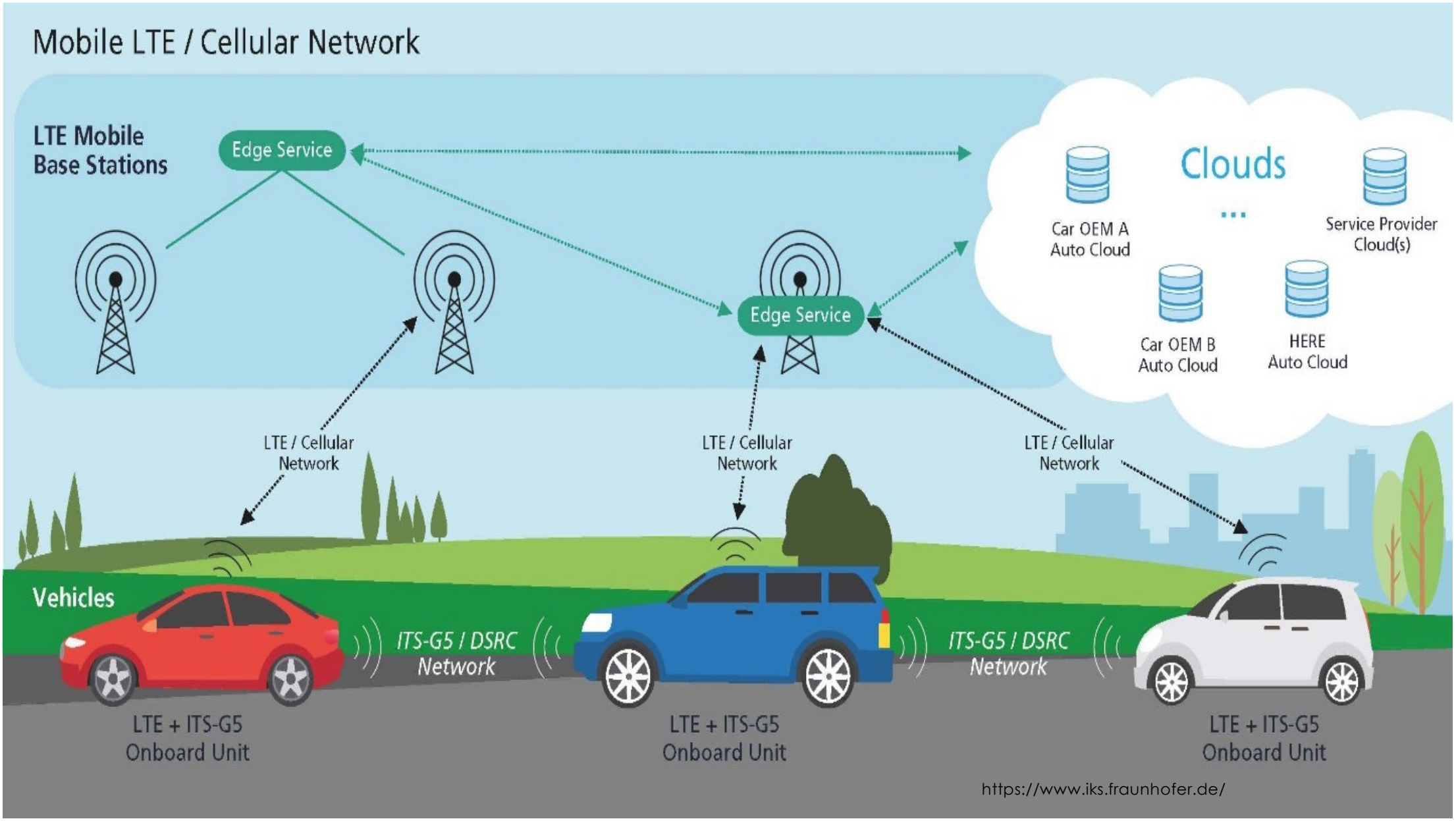
Driver Monitoring



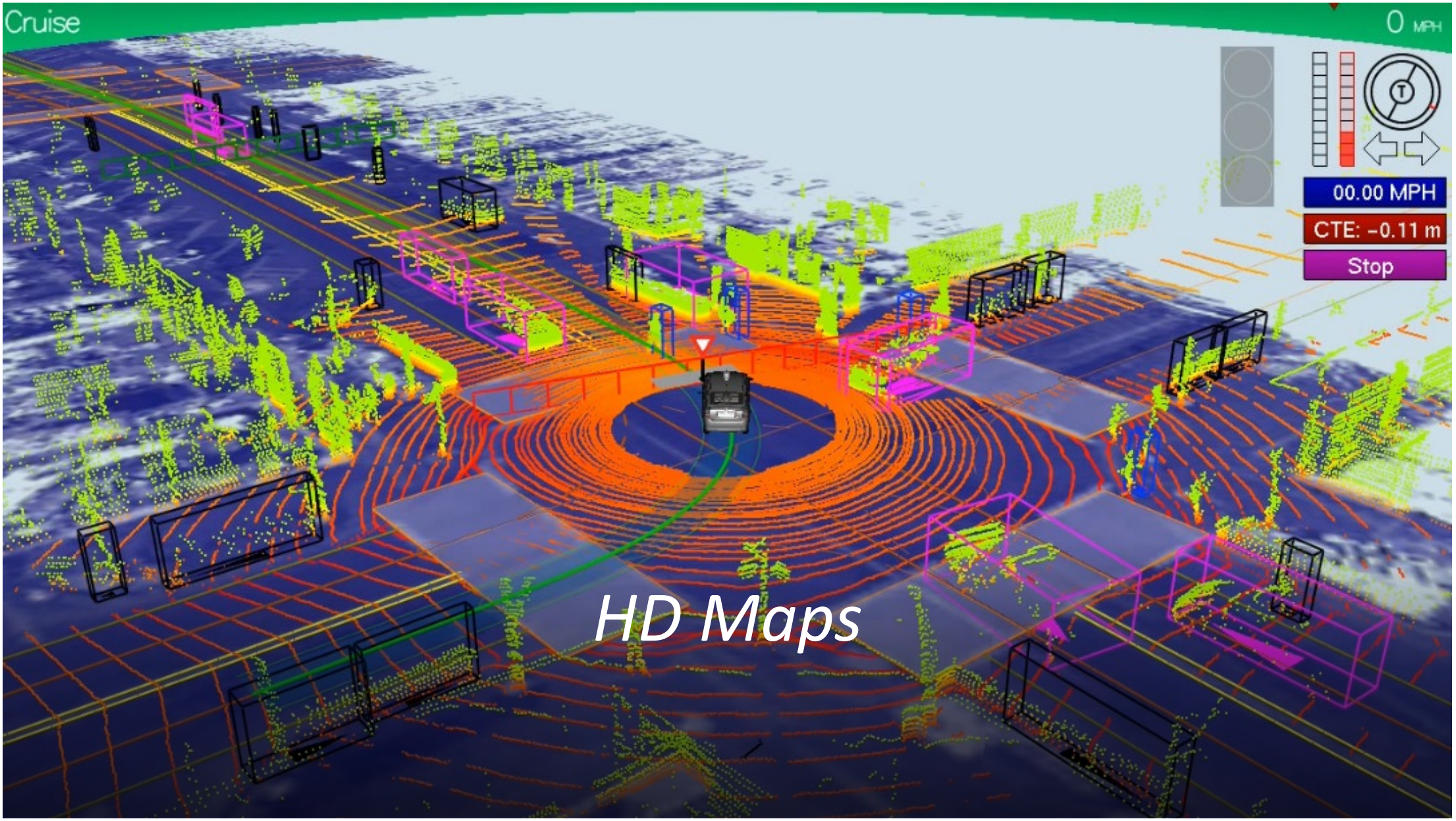





Connected Car
https://www.hivemq.com/


Mobile LTE / Cellular Network
LTE Mobile Base Stations
Edge Service
Edge Service
Clouds
...
Car OEM A Auto Cloud
Service Provider Cloud(s)
Car OEM B Auto Cloud
HERE Auto Cloud
LTE / Cellular Network
LTE / Cellular Network
LTE / Cellular Network
Vehicles
ITS-G5 / DSRC Network
ITS-G5 / DSRC Network
LTE + ITS-G5 Onboard Unit
LTE + ITS-G5 Onboard Unit
LTE + ITS-G5 Onboard Unit
https://www.iks.fraunhofer.de/

TOMTOM ROADDNA


Cruise
0 MPH
00.00 MPH
CTE: -0.11 m
Stop
HD Maps

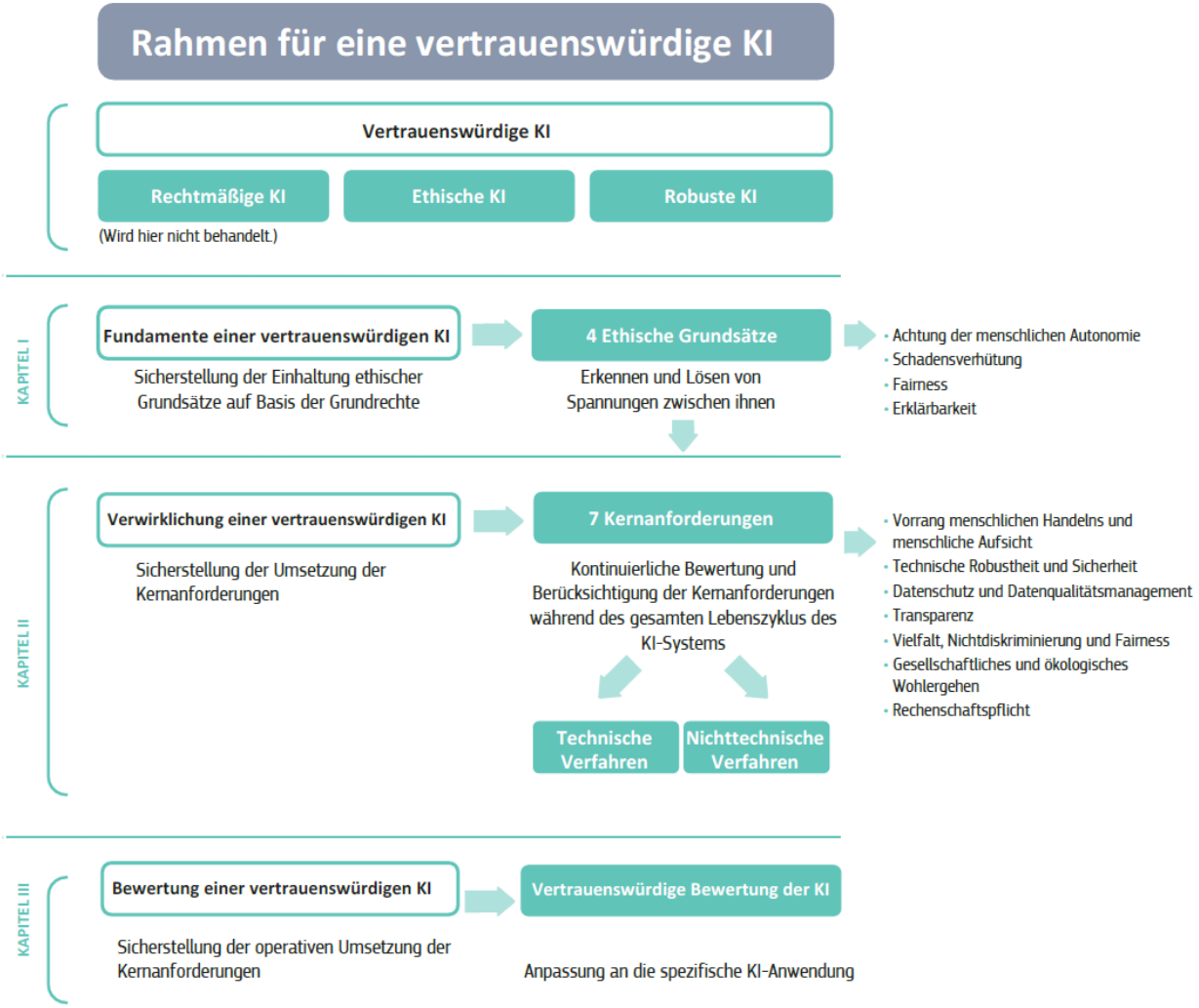


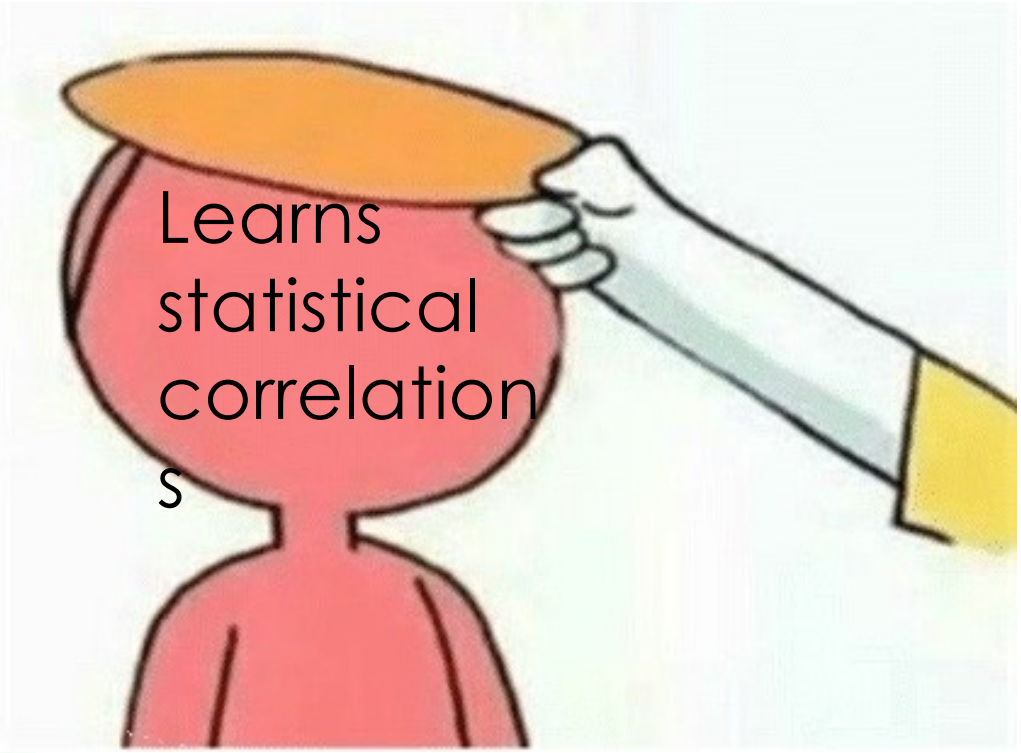
Abbildung 1: Die Leitlinien als Rahmen für eine vertrauenswürdige KI

Hey AI…

…why are your always wearing that mask?

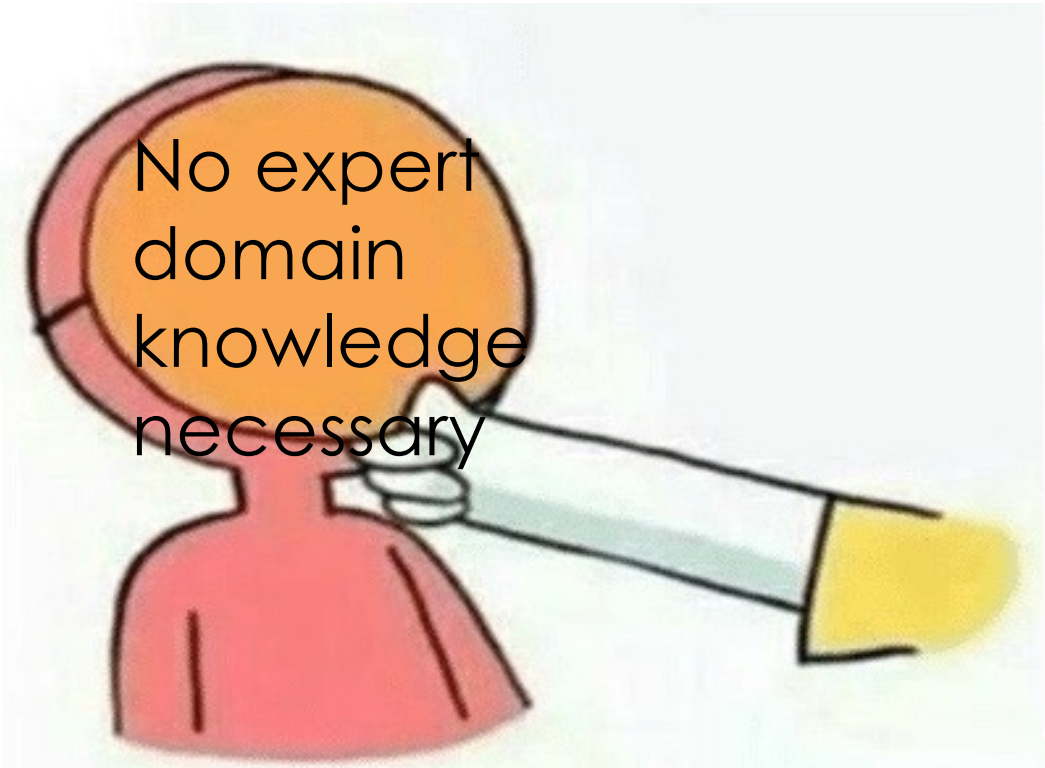
Let‘s keep that on

A Closer Look on Deep Learning



No genuine understanding

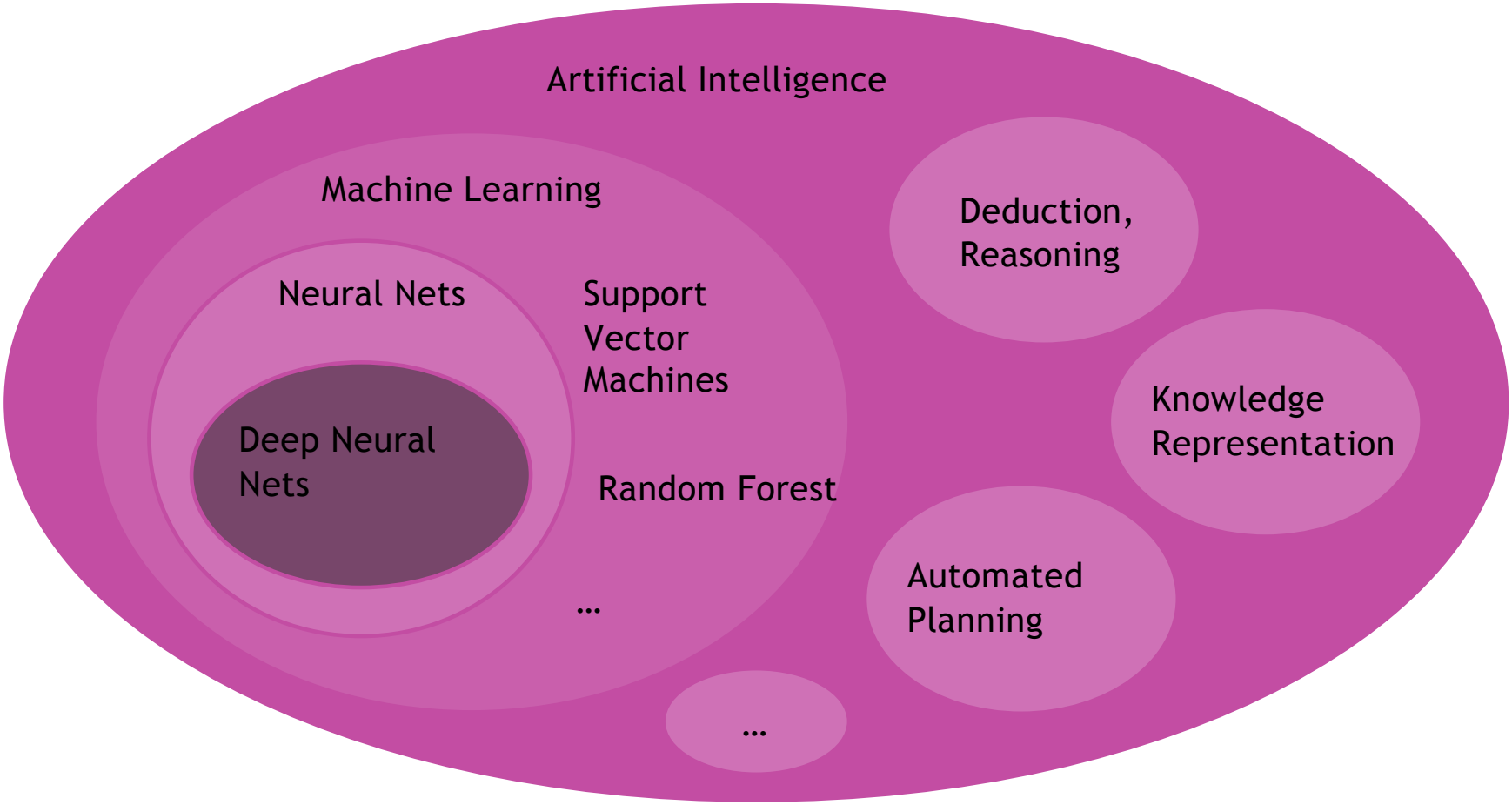
A Closer Look on Deep Learning



Easy to use, every computer science student can experiment with it

More people with less knowledge produce things that even they cannot see through

AI is not only Deep Learning



Hybrid AI Example

- Learning with **symbolic semantic prior**: Use of given or derived intermediate semantic common-sense and/or background knowledge (ontologies, rules) to improve the learning process and result.
- Learning **intermediate symbolic abstraction** for reasoning or planning: Use of data-driven learning to support semantic reasoning or planning of the hybrid system in partially observable environments, and vice versa. For example, hybrid deep reinforcement learning of guiding action policy planning in POMDPs, or, in turn, hybrid semantic rule-interposing deep reinforcement learning and planning.
- **Meta-reasoning for learning to reason** (Learning to logically reason). Learning system either observes behavior of reasoning system, or is constructed based on means of reasoning system, and learns to mimic symbolic reasoning for new symbolic queries. For data-driven deep learning transitive logical deduction or materialization of knowledge graphs is one hard challenge.

Xu, J., Zhang, Z., Friedman, T., Liang, Y., & Broeck, G. (2018, July). A semantic loss function for deep learning with symbolic knowledge. In *International Conference on Machine Learning* (pp. 5502-5511).

Van Harmelen, F., & Teije, A. T. (2019). A boxology of design patterns for hybrid learning and reasoning systems. *arXiv preprint arXiv:1905.12389*.

Ackerman, R., & Thompson, V. A. (2017). Meta-reasoning: Monitoring and control of thinking and reasoning. Trends in Cognitive Sciences, 21(8), 607-617.