17th of January 2021

Topic 1
Autonomous vehicles

Alina Miron

alina.miron@brunel.ac.uk

Brunel University London

References: [3]
See the full list of references on blackboard

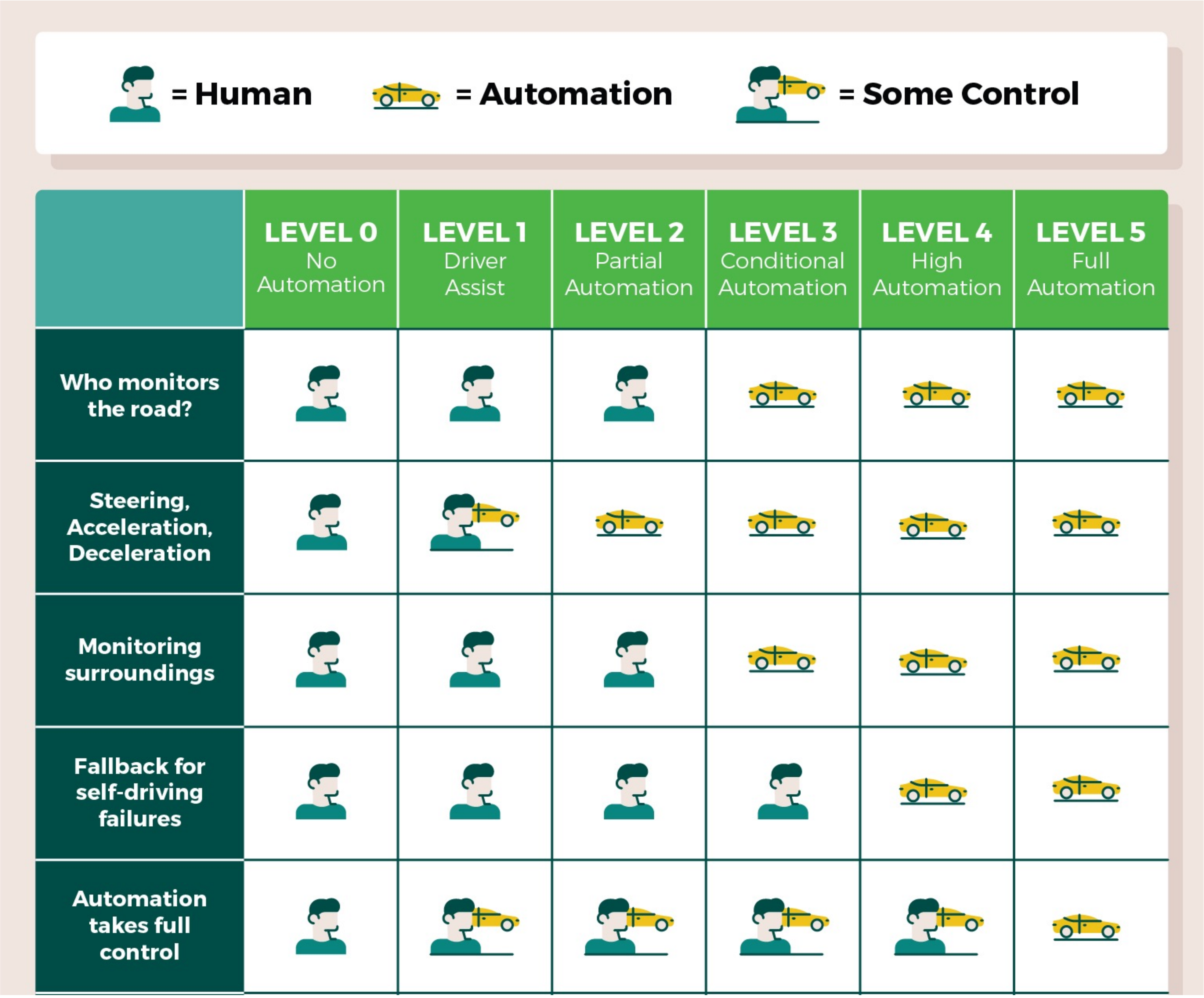
Motivation

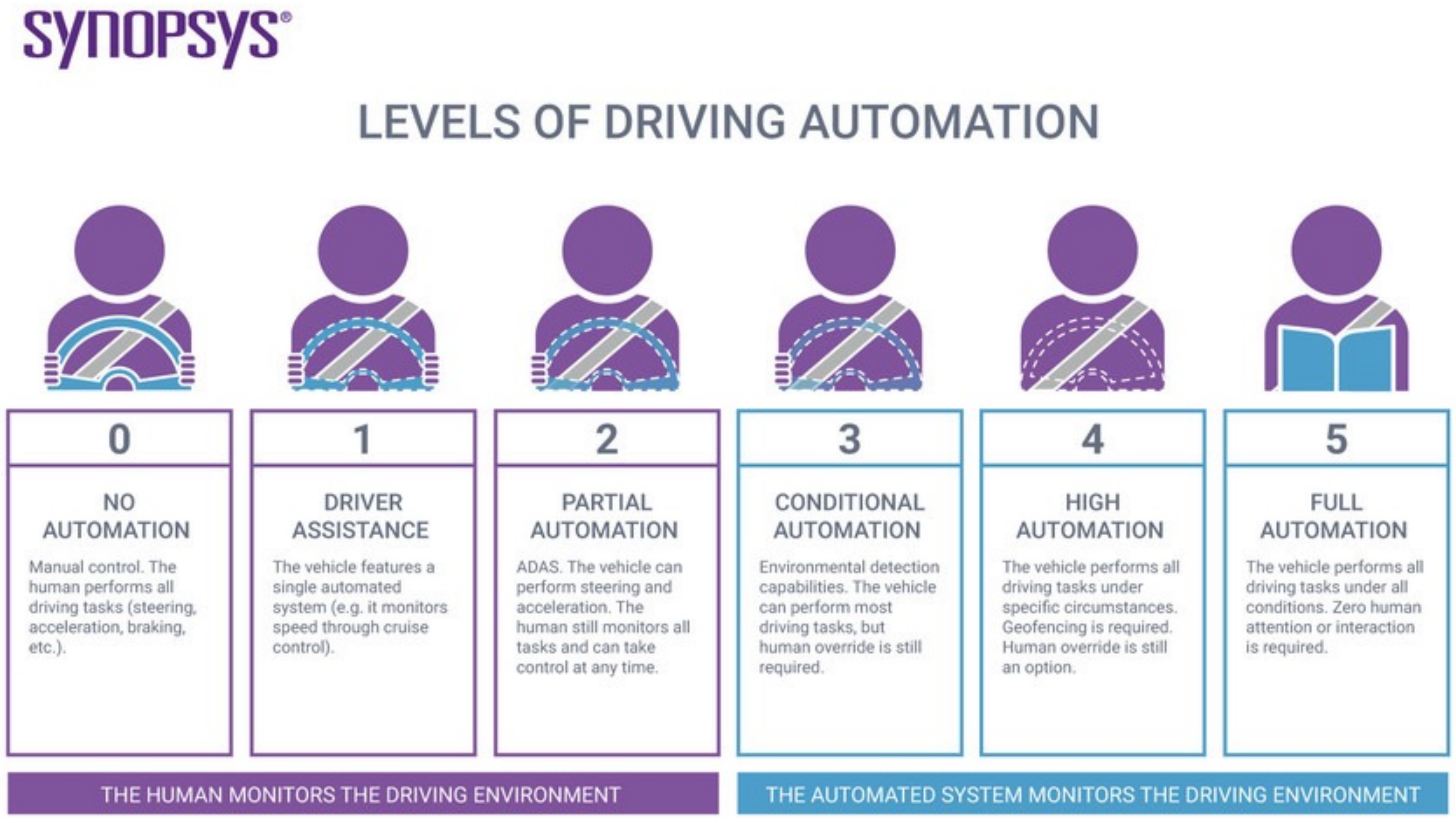
References: [2]
See the full list of references on blackboard

Motivation

References: [1]
See the full list of references on blackboard

Levels of Autonomous Driving





References: [4, 5, 6]
See the full list of references on blackboard

DARPA Grand Challenge (2004)

References: [31]
See the full list of references on blackboard

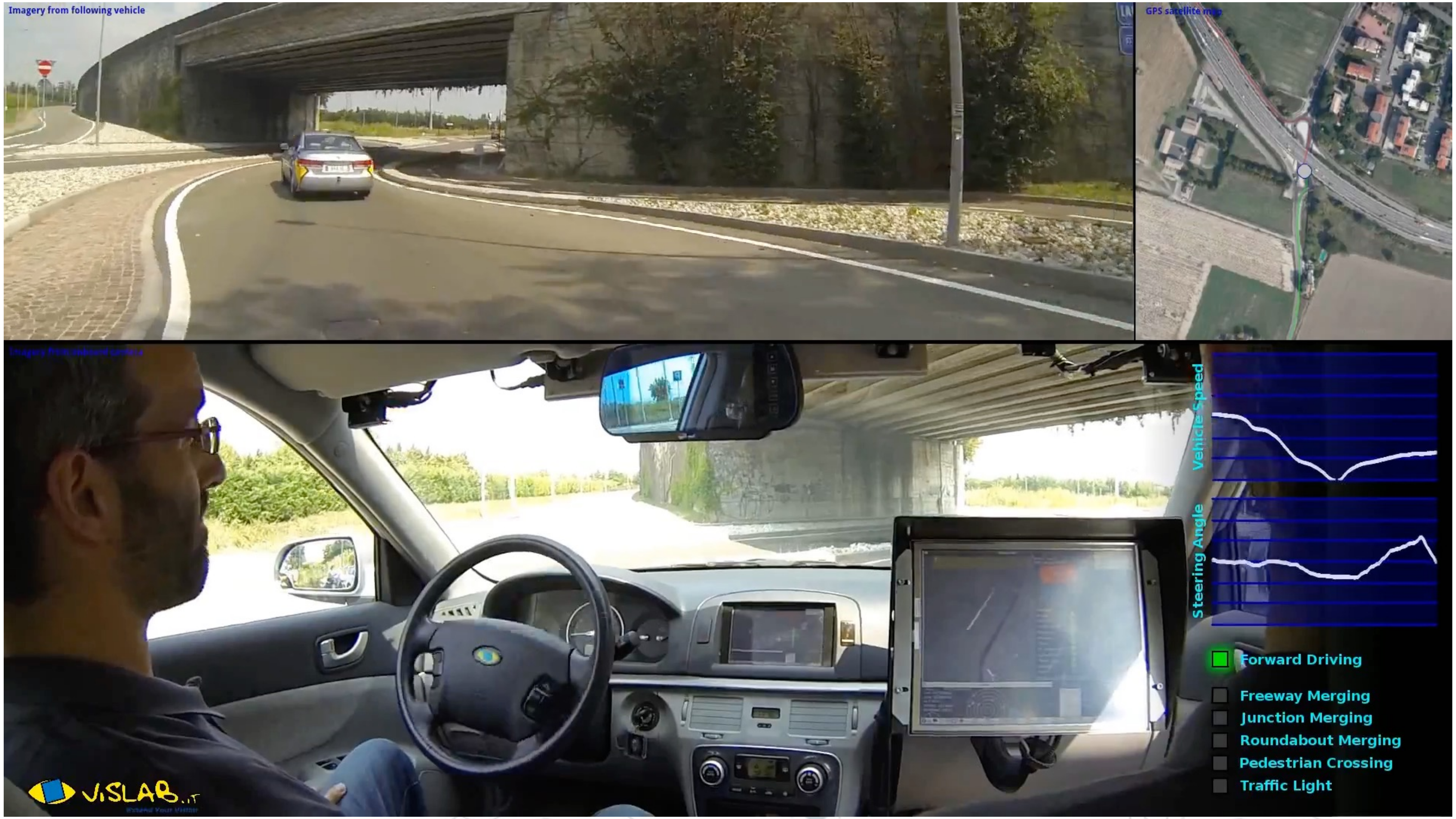
DARPA Grand Challenge (2005)

References: [30]
See the full list of references on blackboard

DARPA Grand Challenge (2007)

References: [29]
See the full list of references on blackboard

VisLab



References: [32]
See the full list of references on blackboard

Predictions

2015: The Guardian : “Self-driving cars: From 2020 you will become a permanent backseat driver “ [33]
2016: Business insider: ““10 million self-driving cars will be on the road by 2020” [34]
2018: Announcements for Consumer-Facing Fully Autonomous Vehicles

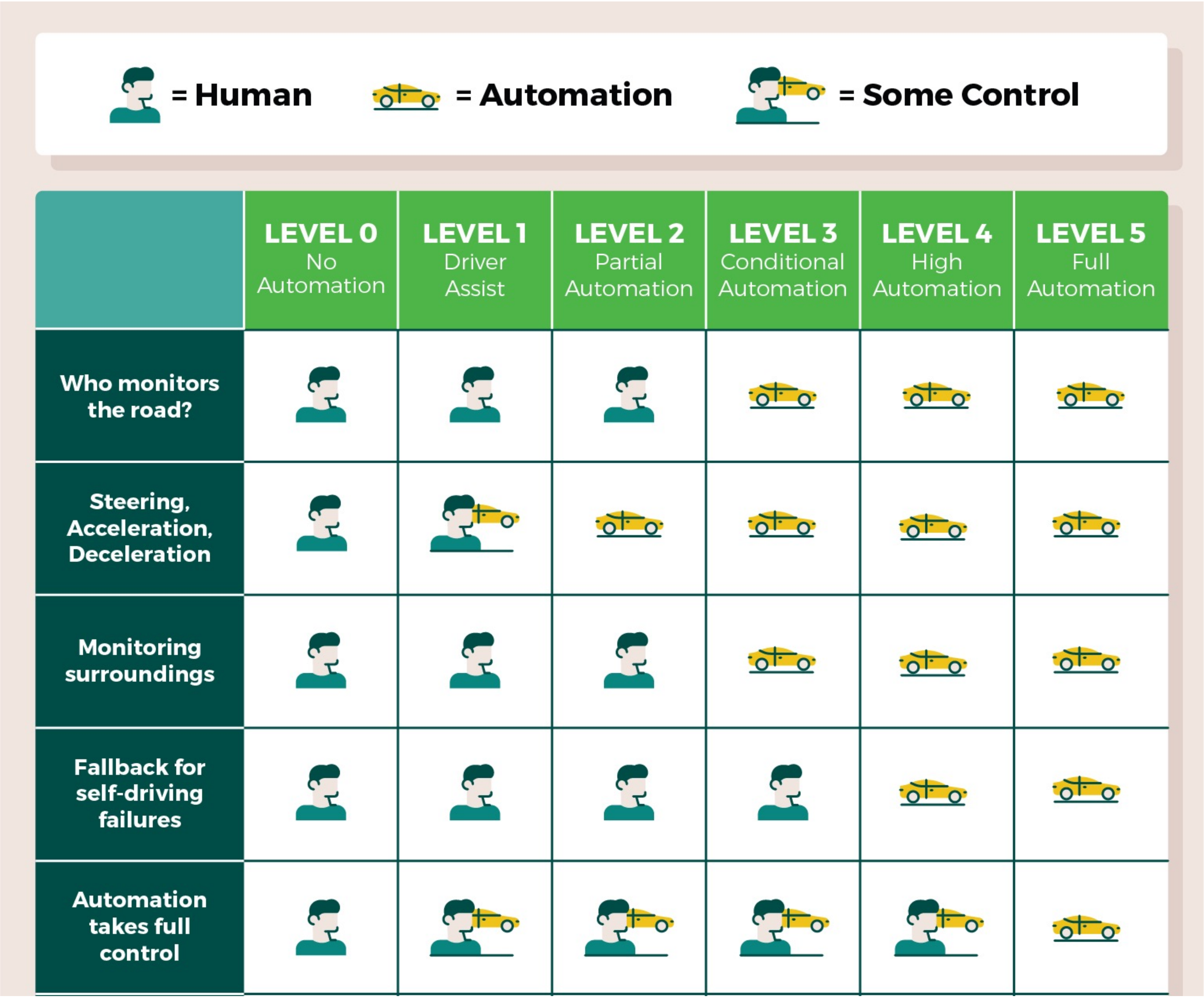
Tesla: 2019
Nissan, Honda: 2020
Toyota, Hyundai: 2020 (highway)
Renault: 2020 (urban)
Volvo: 2021 (highway)
BMW, Ford, Fiat-Chrysler: 2021
Daimler: 2020-2025

2019: Elon Musk: “A year from now, we’ll have over a million cars with full self-driving, software...everything” [35]

What do you think? When we will have autonomous vehicles?

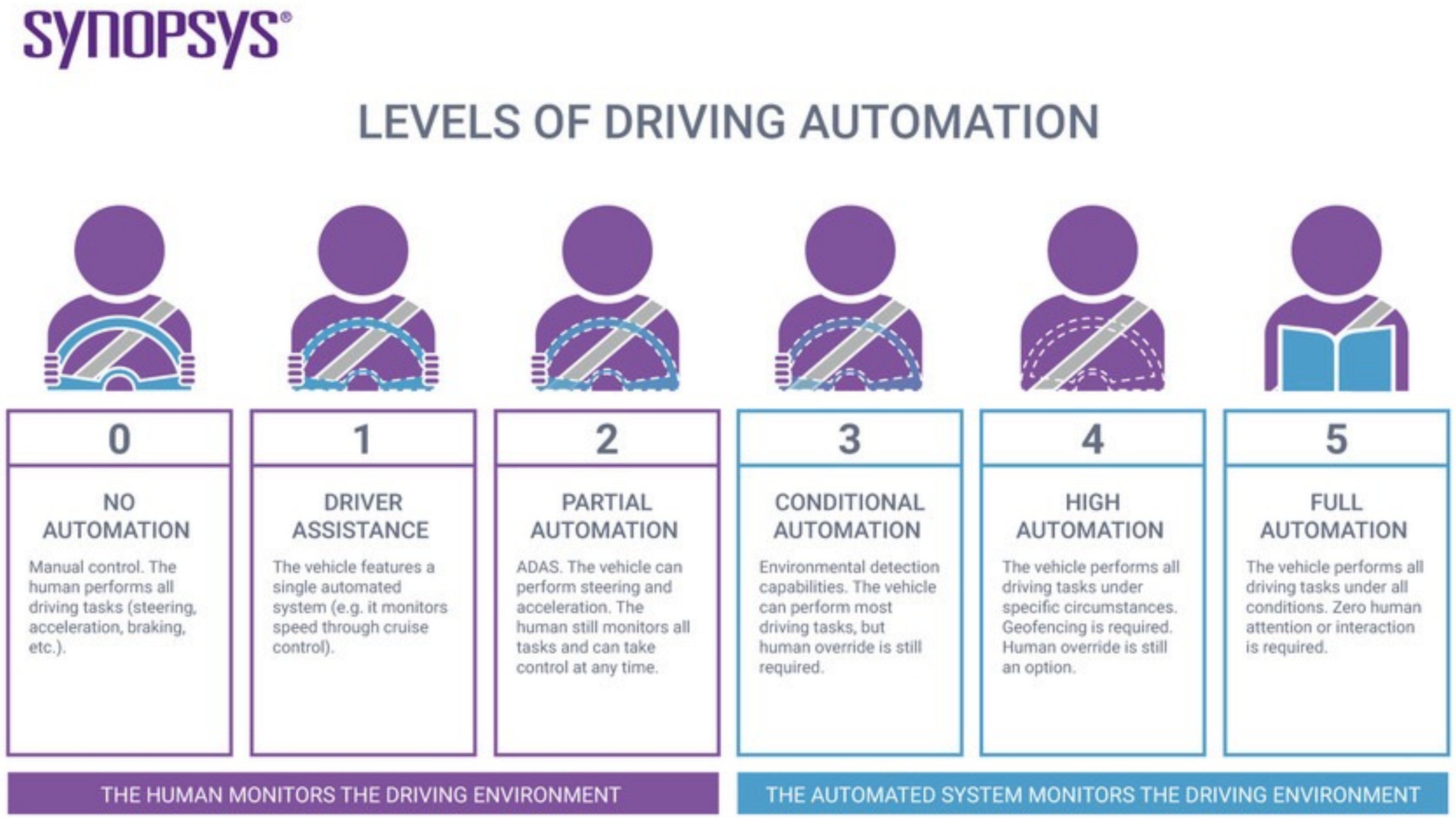
References: [7]
See the full list of references on blackboard

Levels of Autonomous Driving



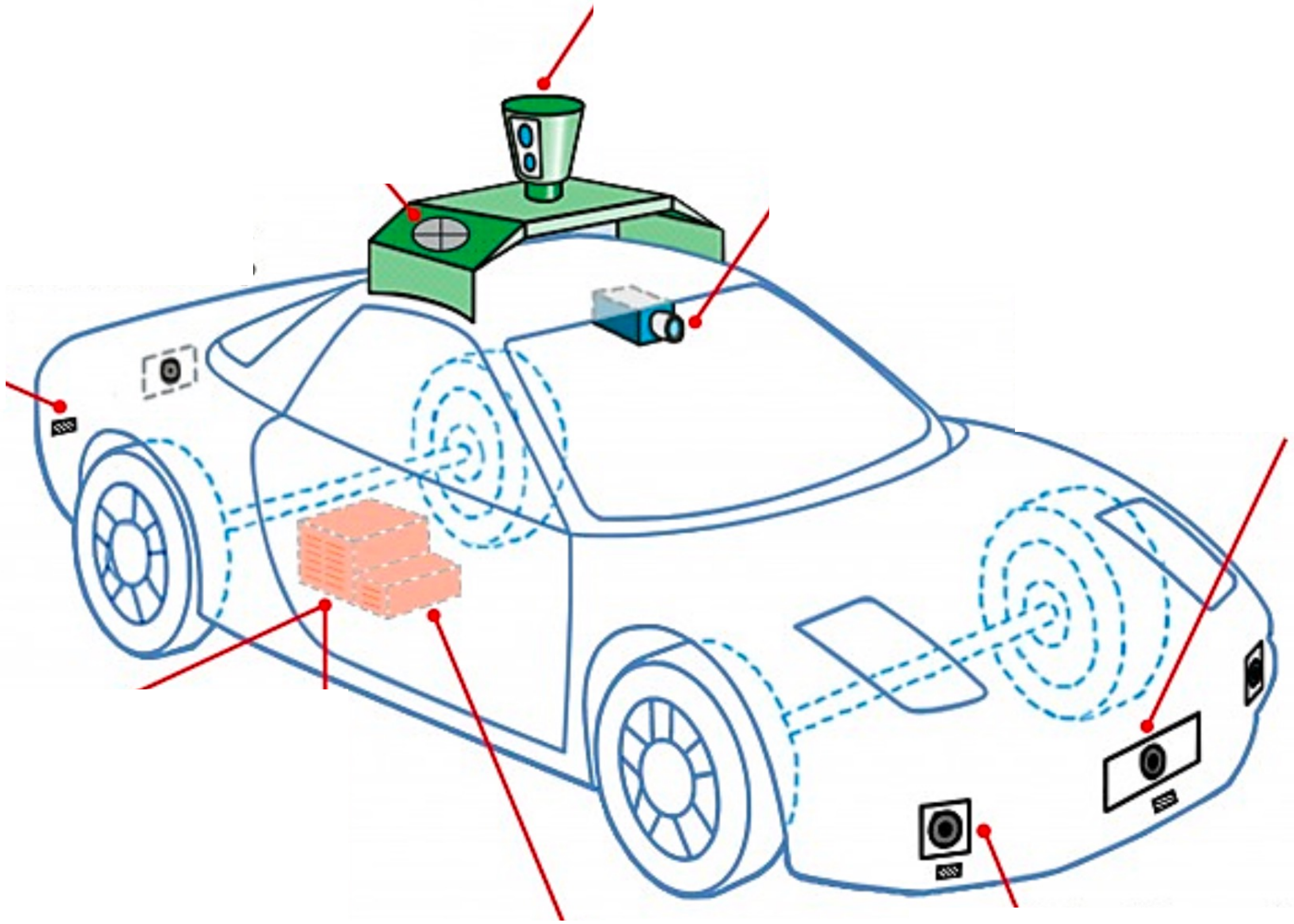
= Human = Automation = Some Control

	LEVEL 0 No Automation	LEVEL 1 Driver Assist	LEVEL 2 Partial Automation	LEVEL 3 Conditional Automation	LEVEL 4 High Automation	LEVEL 5 Full Automation
Who monitors the road?	Human	Human	Human	Automation	Automation	Automation
Steering, Acceleration, Deceleration	Human	Some Control	Automation	Automation	Automation	Automation
Monitoring surroundings	Human	Human	Human	Automation	Automation	Automation
Fallback for self-driving failures	Human	Human	Human	Human	Automation	Automation
Automation takes full control	Human	Some Control	Some Control	Some Control	Some Control	Automation



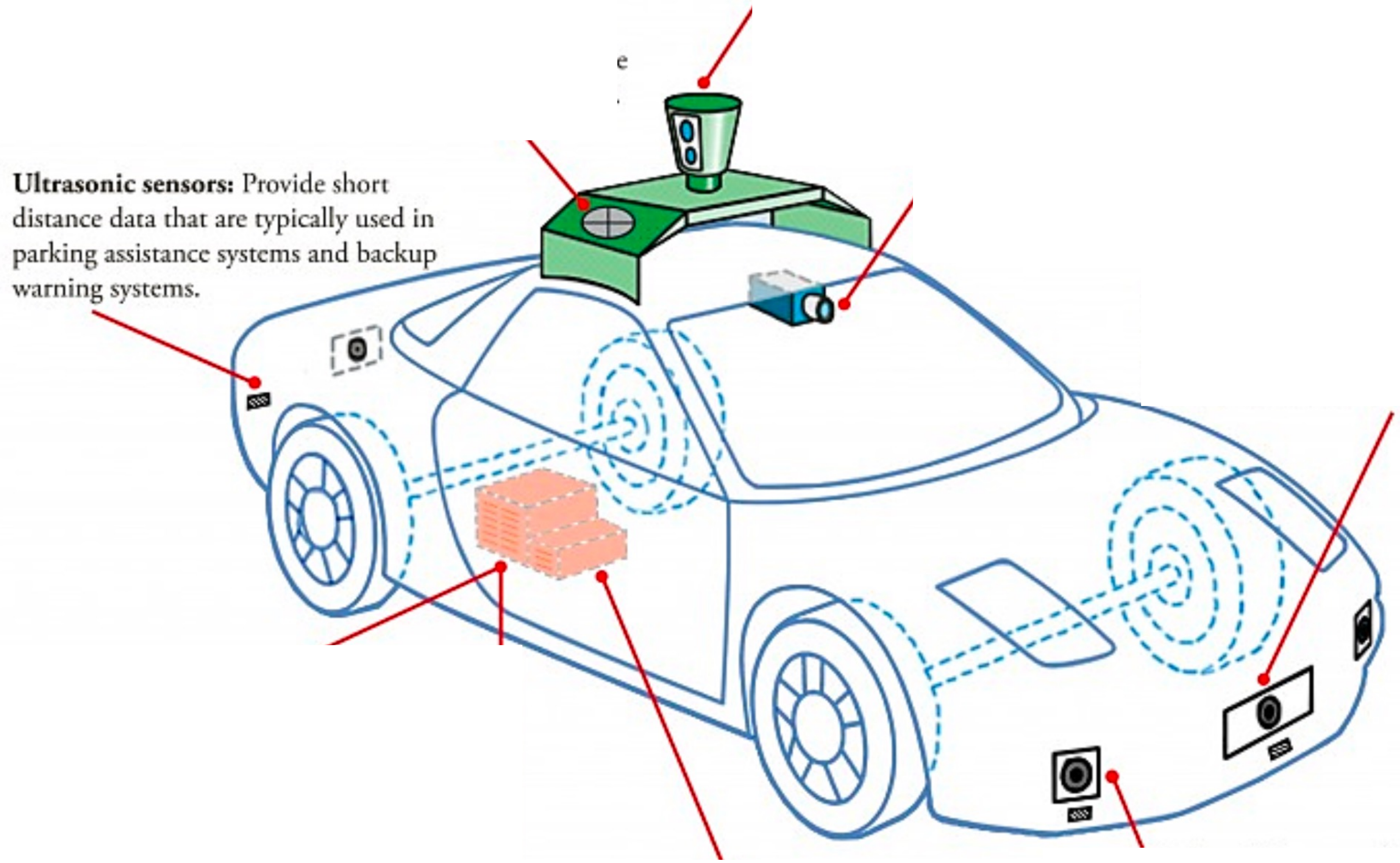
References: [4, 5, 6]
See the full list of references on blackboard

Sensors Ecosystem



References: [11]
See the full list of references on blackboard

Sensors Ecosystem: Ultrasonic



References: [11]
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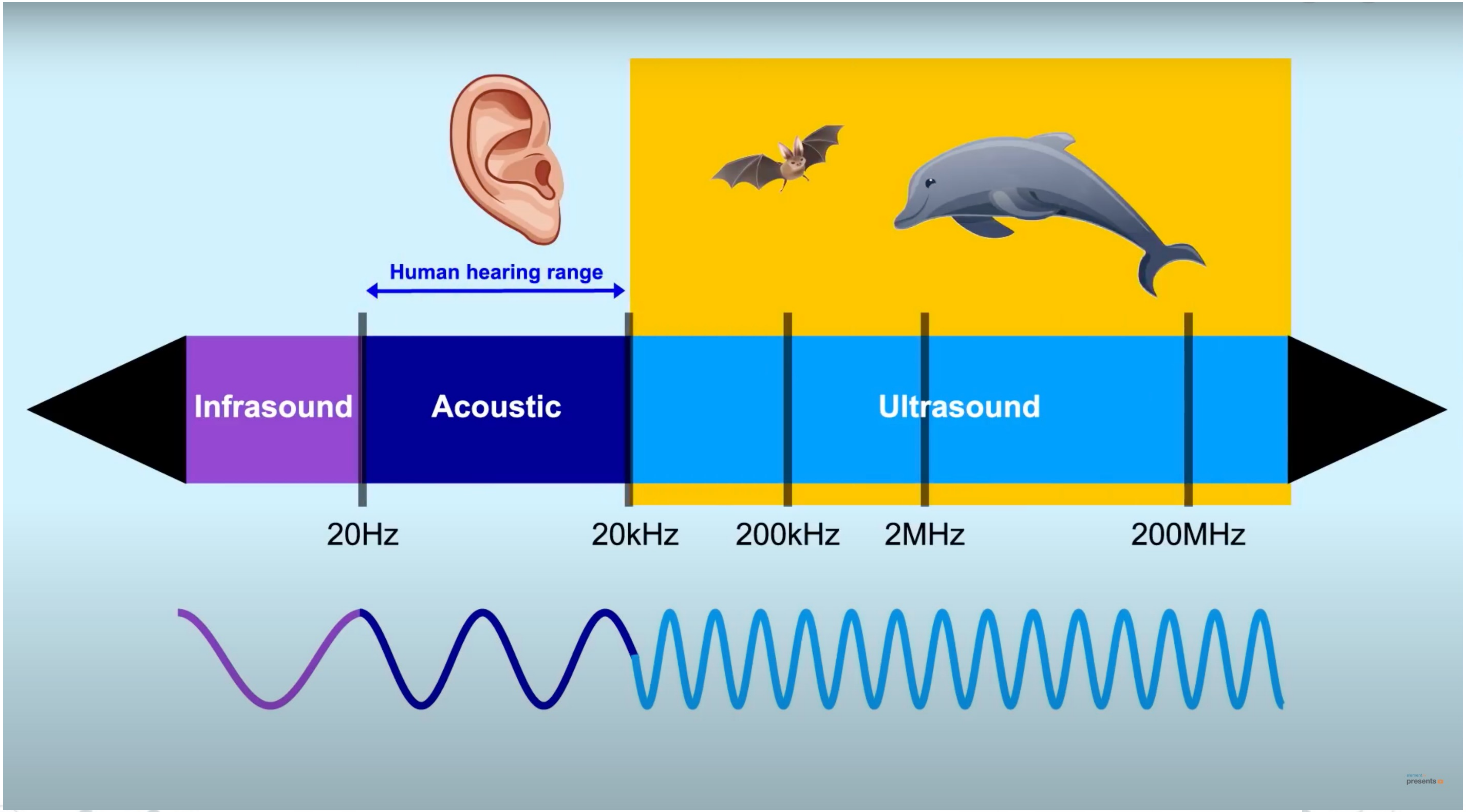


References: [12]
See the full list of references on blackboard

Ultrasonic sensor

Surround sensor for the calculation of distances to obstacles and to monitor space when parking and maneuvering

For comfortable and automated parking as well as for emergency braking functions at low speeds

- Benchmark in robustness against dirt, ice, environmental conditions and other ultrasonic systems
- Most sensitive ultrasonic system in the market (e. g. detection of low reflecting objects)
- Faster reaction time (first-time detection), therefore fast reaction on suddenly appearing obstacles (e. g. pedestrians, changing scenes)

optimum support

Basis for parking and maneuvering systems as well as automated parking

state-of-the-art

in terms of robustness, reaction time and object detection

most sensitive

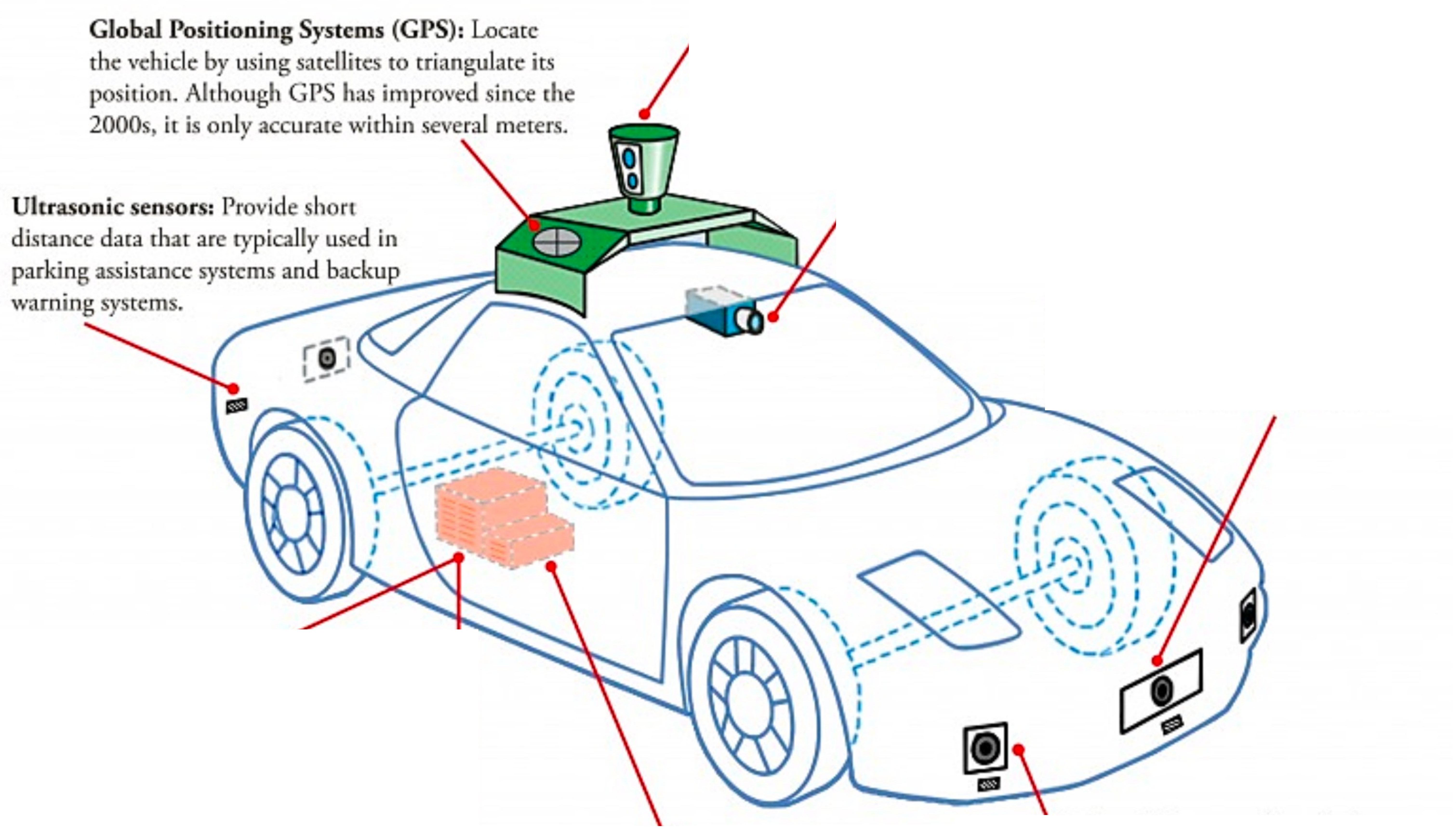
ultrasonic system in the market due to very reliable object detection

TECHNICAL CHARACTERISTICS

Min. range	15 cm (Ø 7.5 cm standard pole)
Max. range	5.5 m (Ø 7.5 cm standard pole)
Object presence detection	3 – 15 cm
Detection zone	+/-40° @ -3dB signal strength (horizontal field of view)
Opening angles	+/-25° @ -3dB signal strength (vertical)
Safety level	up to ASIL-B
Frequency	Frequency modulation
Membrane diameter	15.5 mm
Housing diameter	23 mm
Dimensions	44 mm (length) x 26 mm (width)
Weight	~ 14 g
Operating temperature	- 40° to + 85° C
Current consumption	≤ 570 mA (transmit mode) 17 mA (receive mode)
Protection class	IP64K

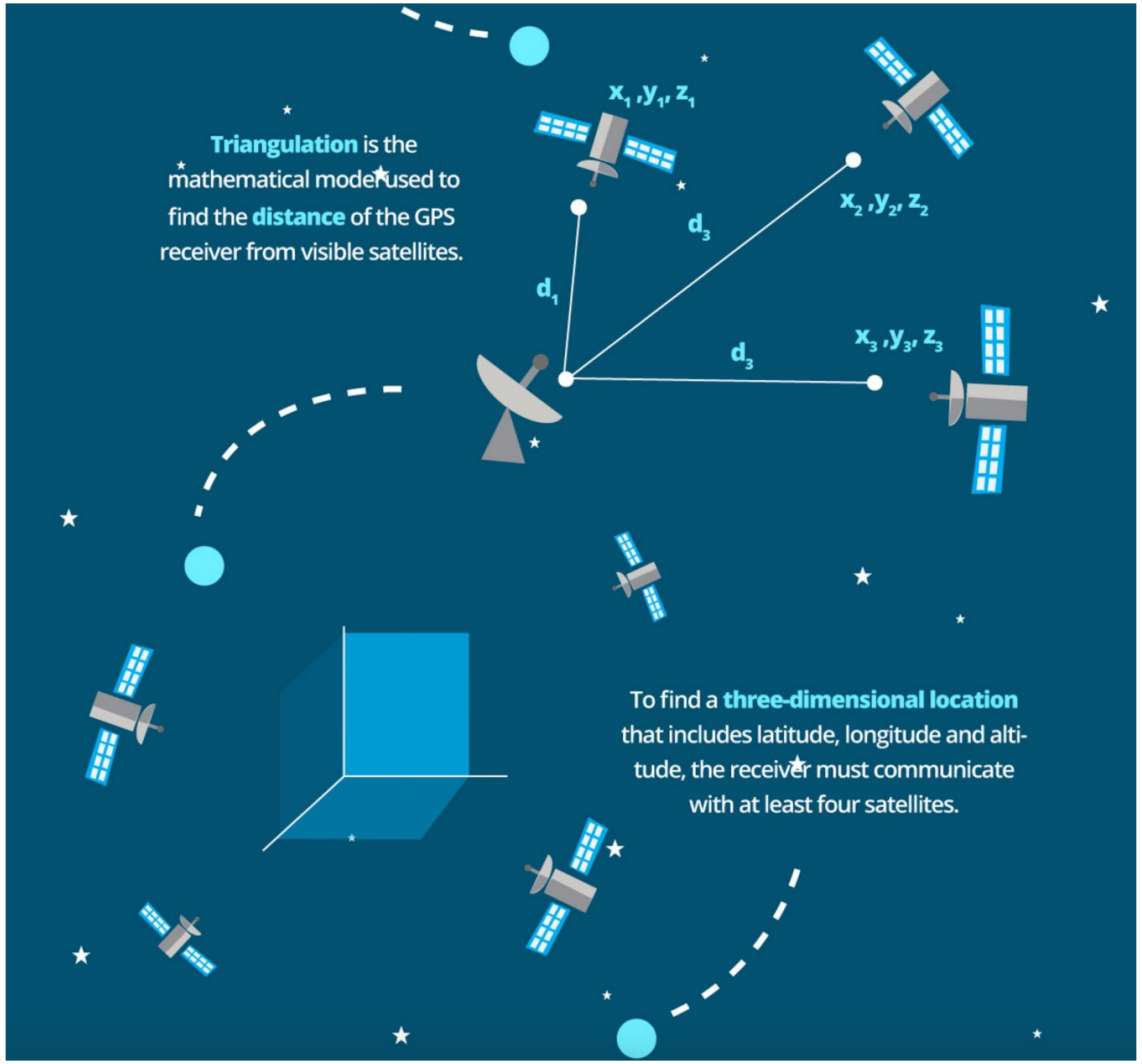
References: [12]
See the full list of references on blackboard

Sensors Ecosystem: GPS



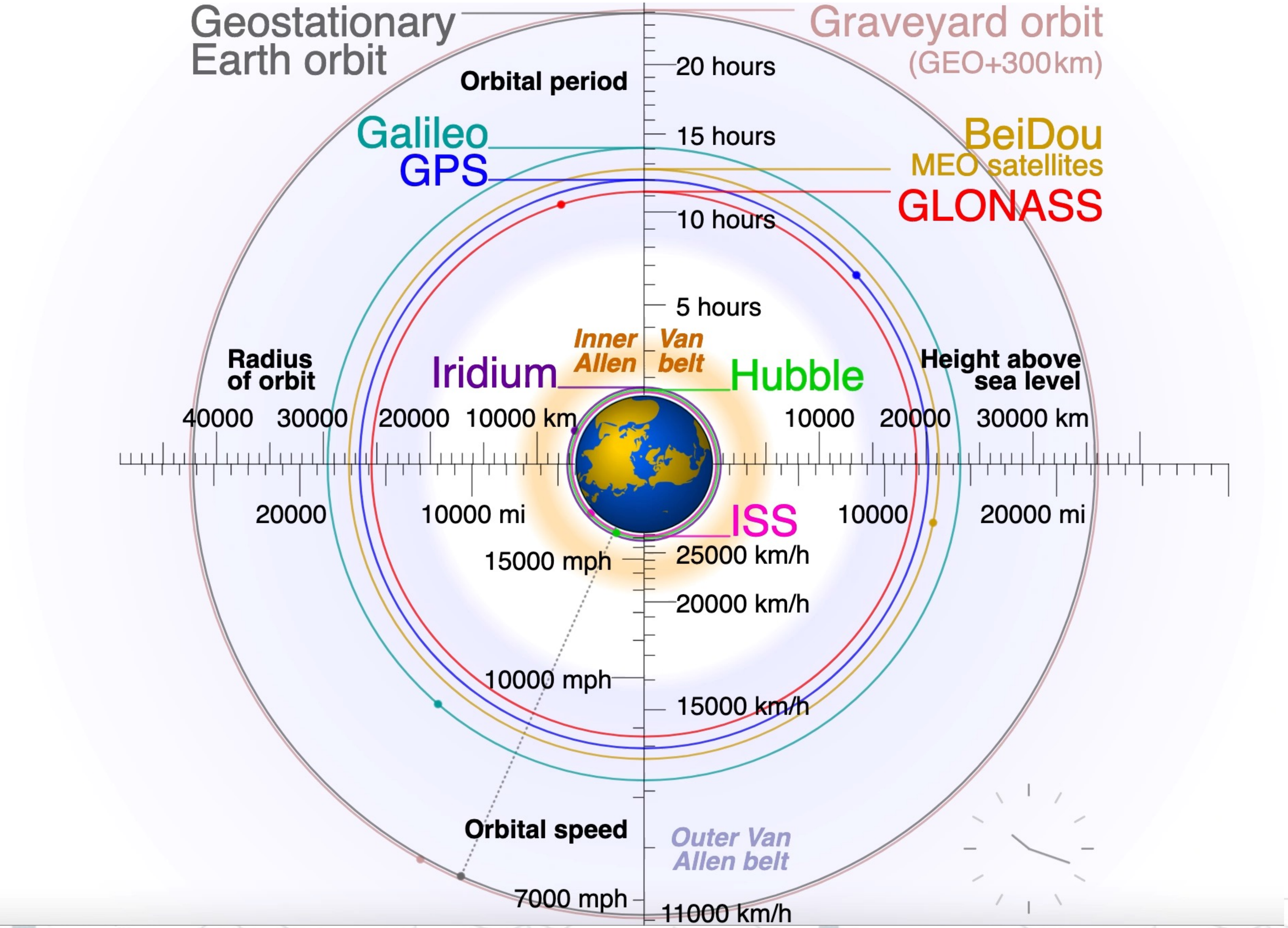
References: [11]
See the full list of references on blackboard

Sensors Ecosystem: GPS



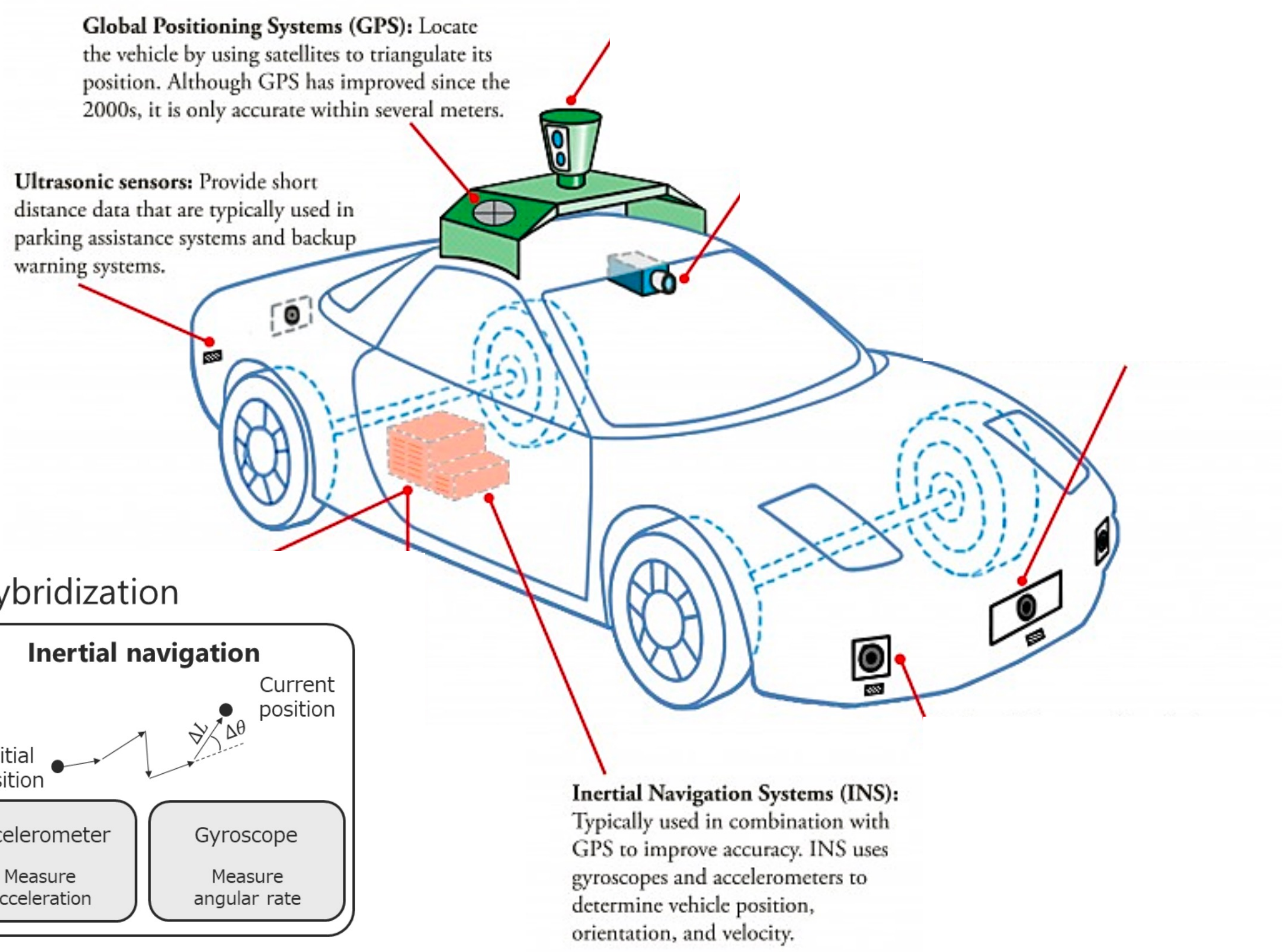
References: [14]
See the full list of references on blackboard

Sensors Ecosystem: Satellite Navigation

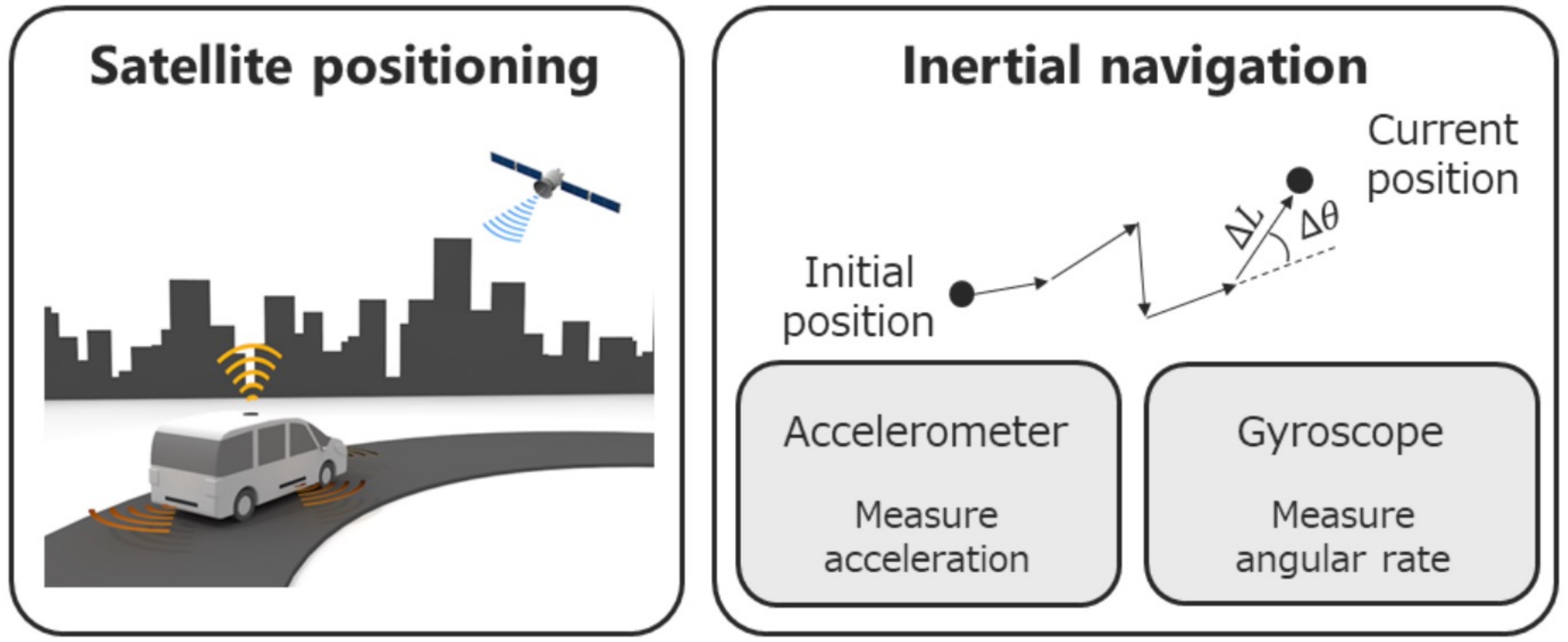


References: [14]
See the full list of references on blackboard

Sensors Ecosystem: Inertial Navigation Systems

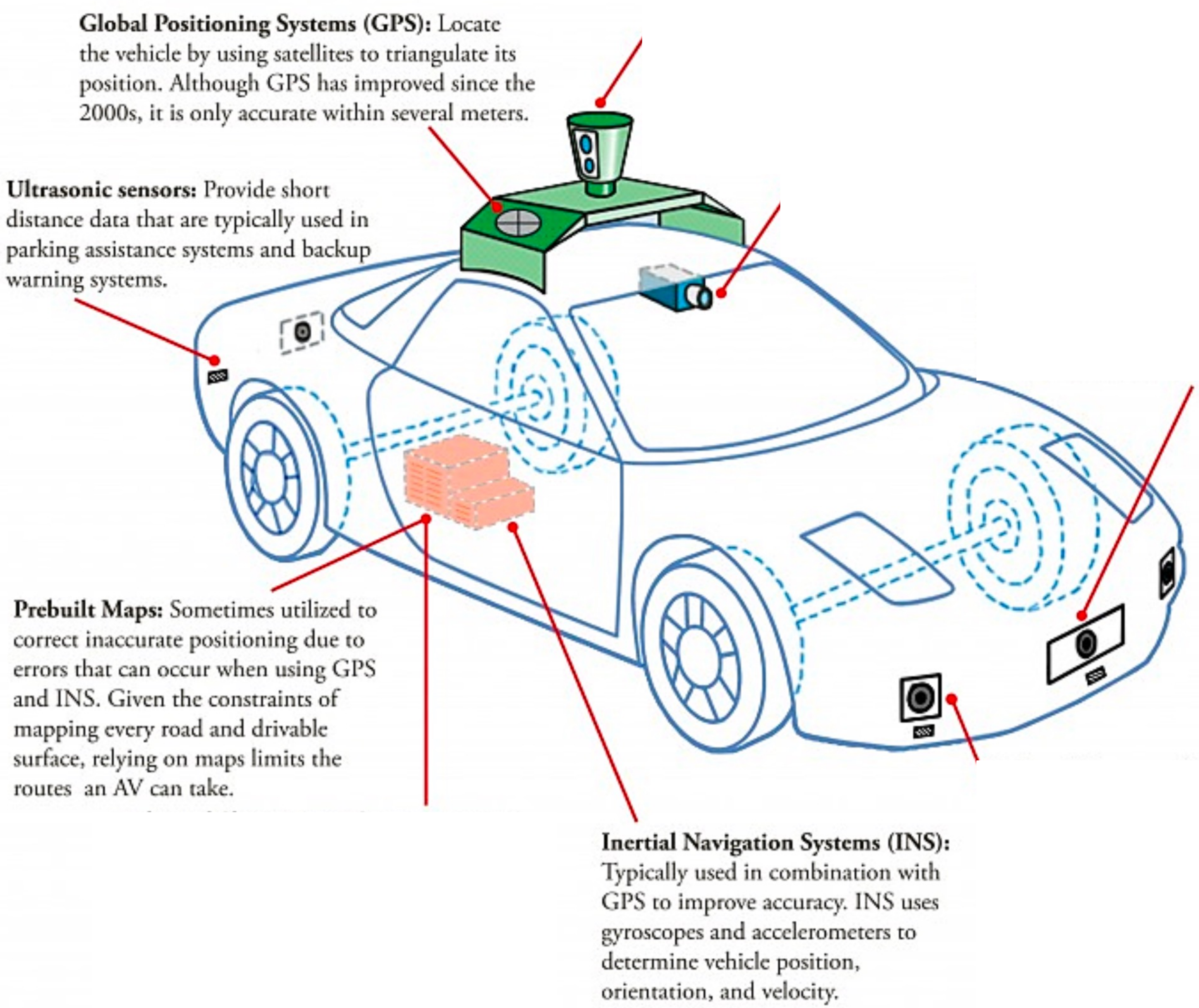


Necessity of Hybridization



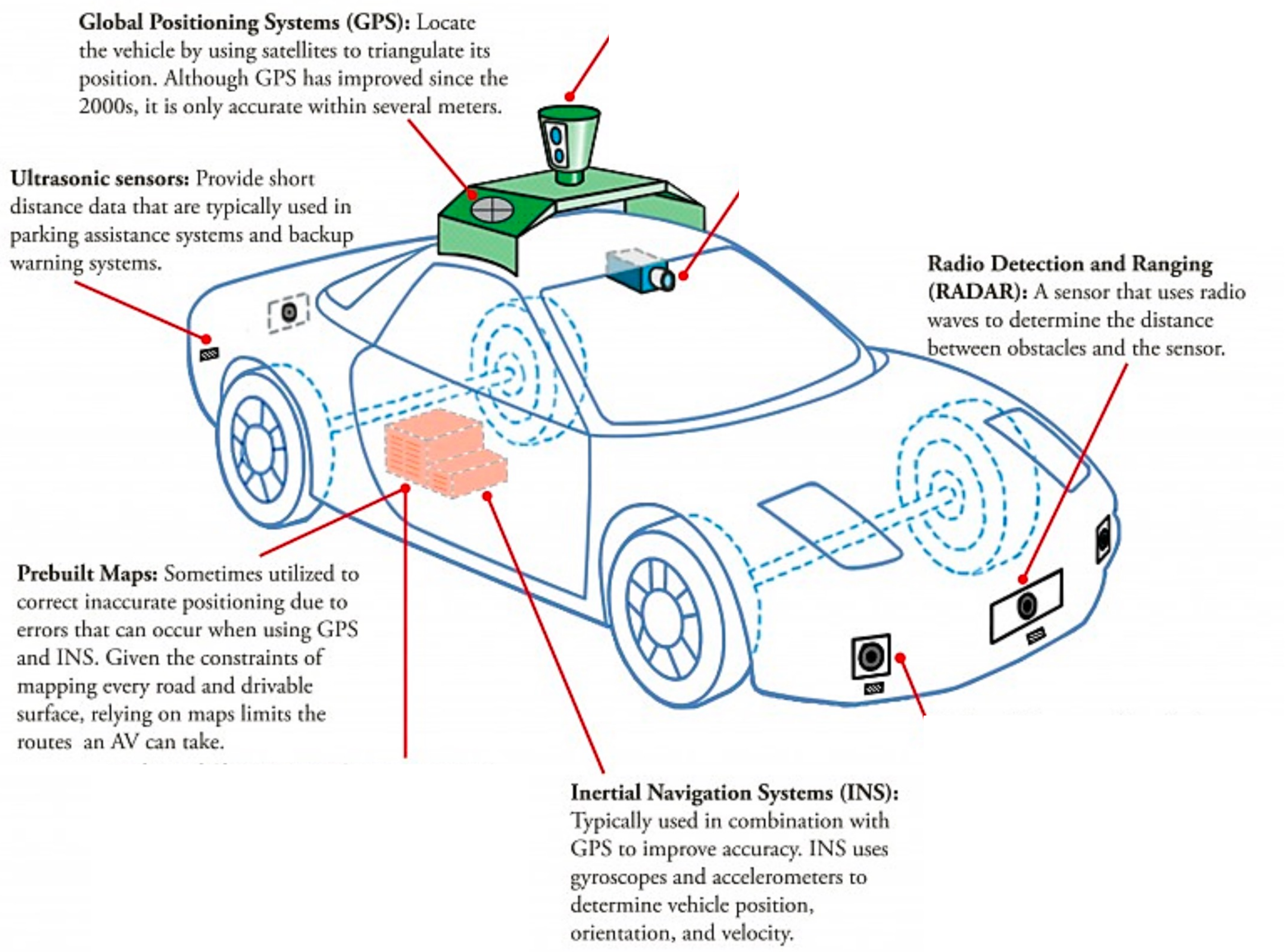
References: [11, 15]
See the full list of references on blackboard

Sensors Ecosystem: Prebuilt Maps



Sensors Ecosystem: Prebuilt Maps

Sensors Ecosystem: Radar



References: [11]
See the full list of references on blackboard

Sensors Ecosystem: Radar

BOSCH
Invented for life

Front radar

The new radar sensor generation for greater comfort, safety and automated driving

Precise, fast and robust detection of objects and people

- Detection of position, relative speed and direction of motion with only one radar measurement thanks to chirp-sequence modulation
- Suitable for NCAP (AEB Car-to-Car Rear, AEB Pedestrian, AEB Cyclist) as well as partially automated driving
- Improved comfort for adaptive cruise control (ACC) up to 210 km/h

high-precision
object detection and tracking

60 % lighter
than the preceding generation

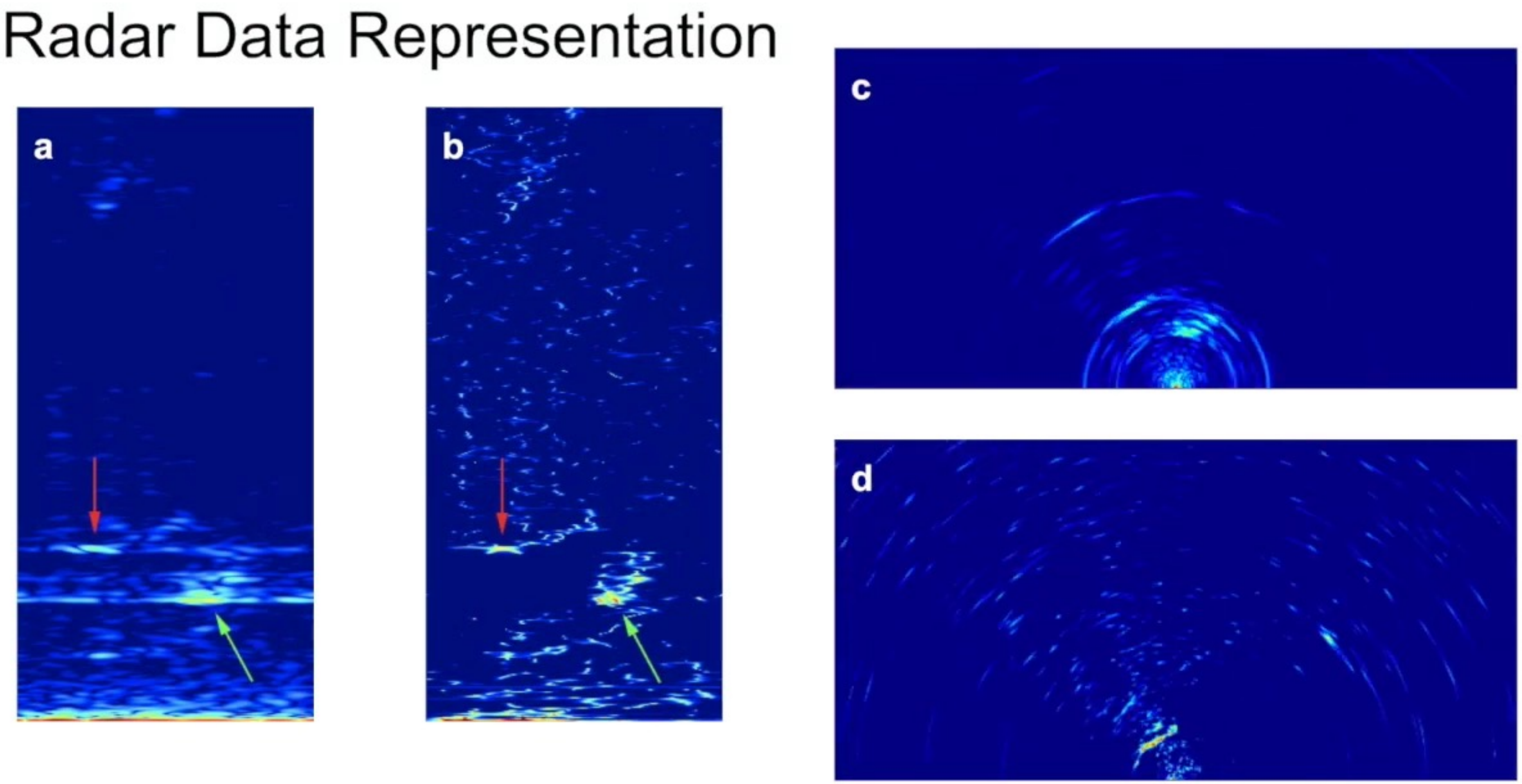
wide field of view

TECHNICAL CHARACTERISTICS

Frequency range		76 to 77 GHz
Detection range		up to 210 m
Field of view	horizontal	± 60°
	vertical	± 15°
Key performance indicators	Range accuracy, resolution	0.1 m, 0.2 m
	horizontal angle accuracy, separability	0.1°, 3.0°
	vertical angle accuracy, separability	0.2°, 6.0°
	Velocity accuracy, resolution	0.05 m/s, 0.1 m/s
Interfaces and power	Data	1 x CAN-FD, 1 x CAN-FD, Flexray or 100BaseT1 Ethernet
	Power consumption	< 4 W
Mechanics	Box size	63 x 72 x 19 mm

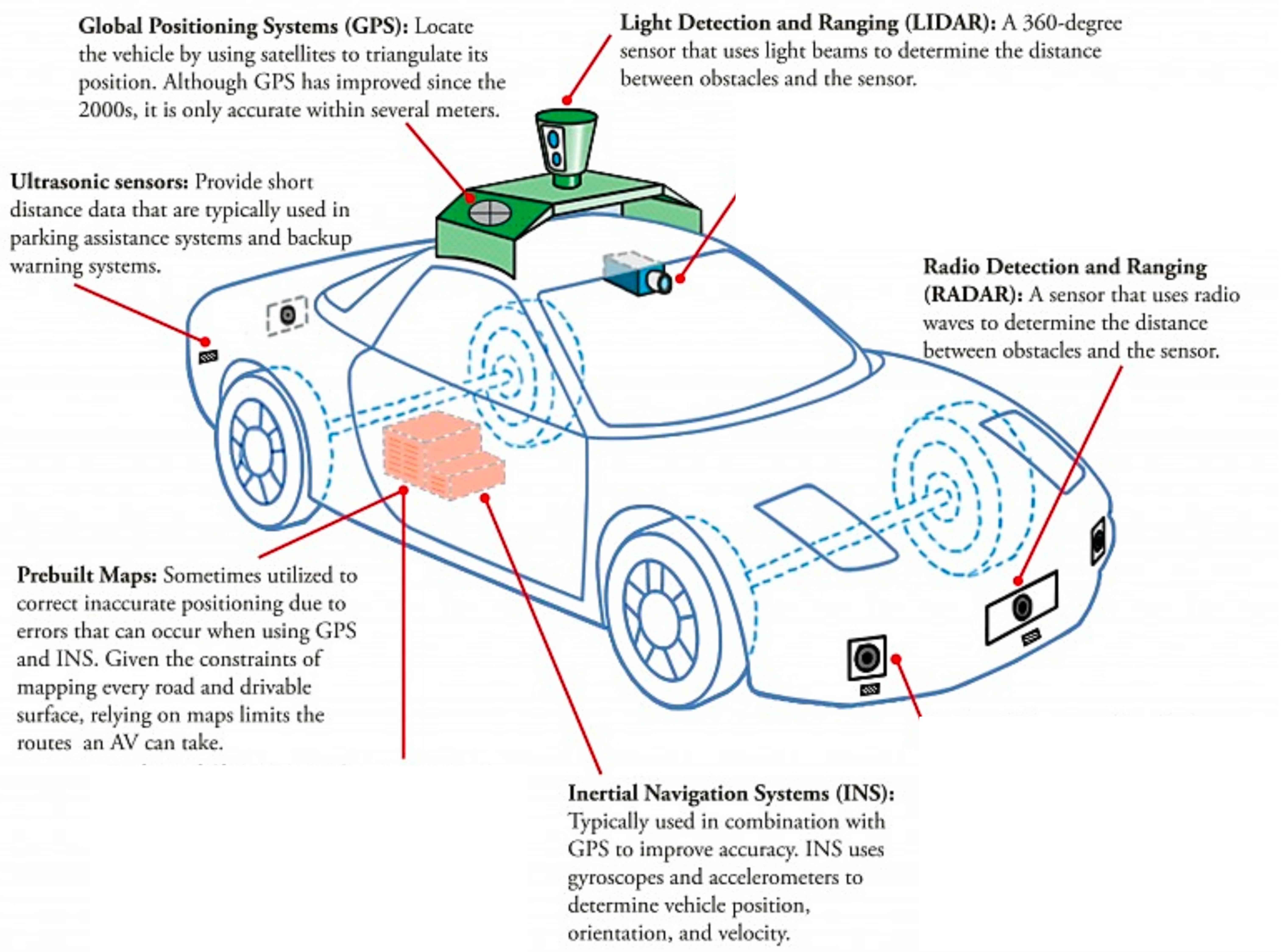
References: [18]
See the full list of references on blackboard

Sensors Ecosystem: Radar



References: [18]
See the full list of references on blackboard

Sensors Ecosystem : LIDAR

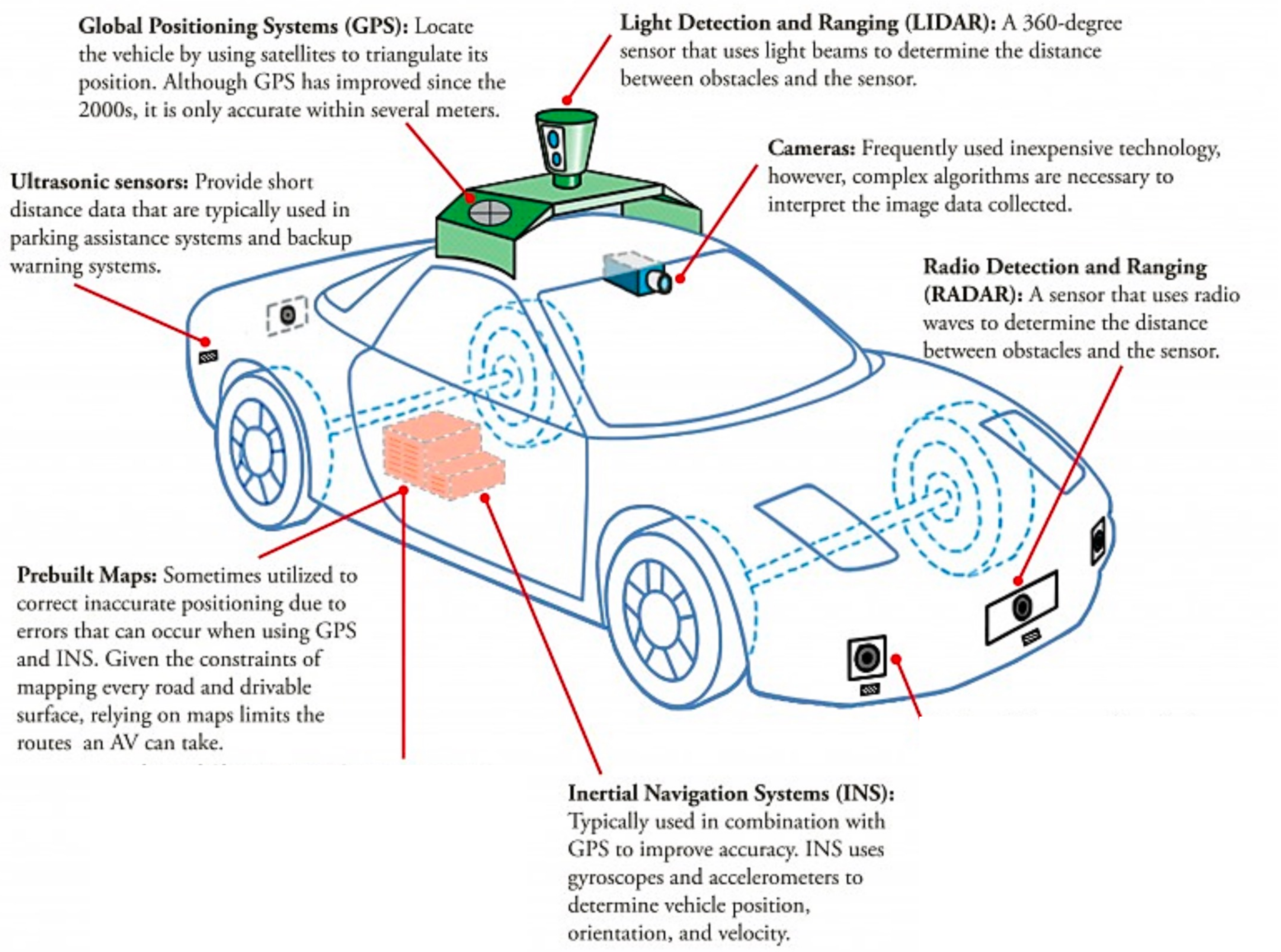


References: [11]
See the full list of references on blackboard

Sensors Ecosystem : LIDAR

References: [19]
See the full list of references on blackboard

Sensors Ecosystem : Cameras

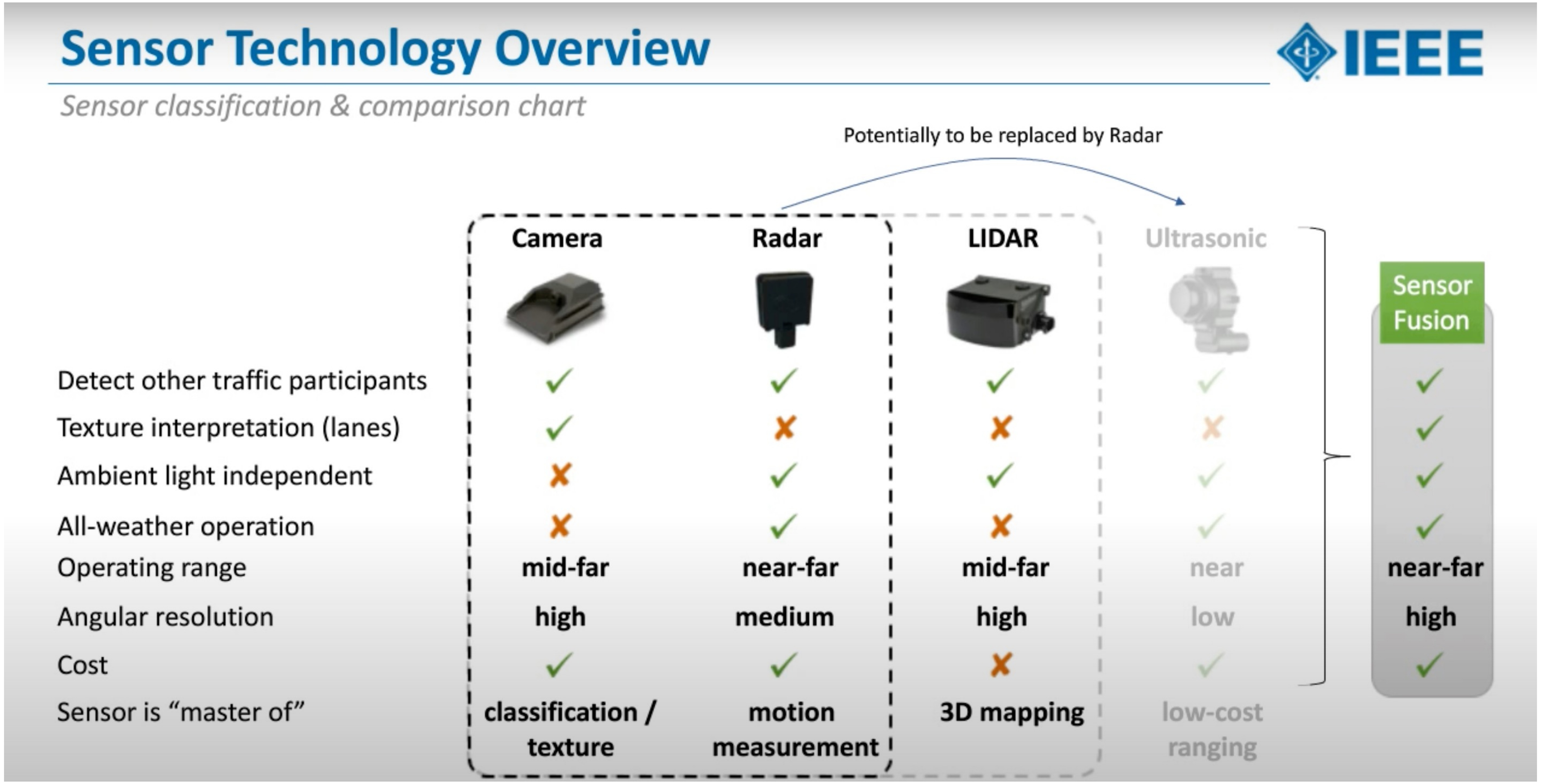


References: [11]
See the full list of references on blackboard

Sensors Ecosystem : Cameras

References: [21]
See the full list of references on blackboard

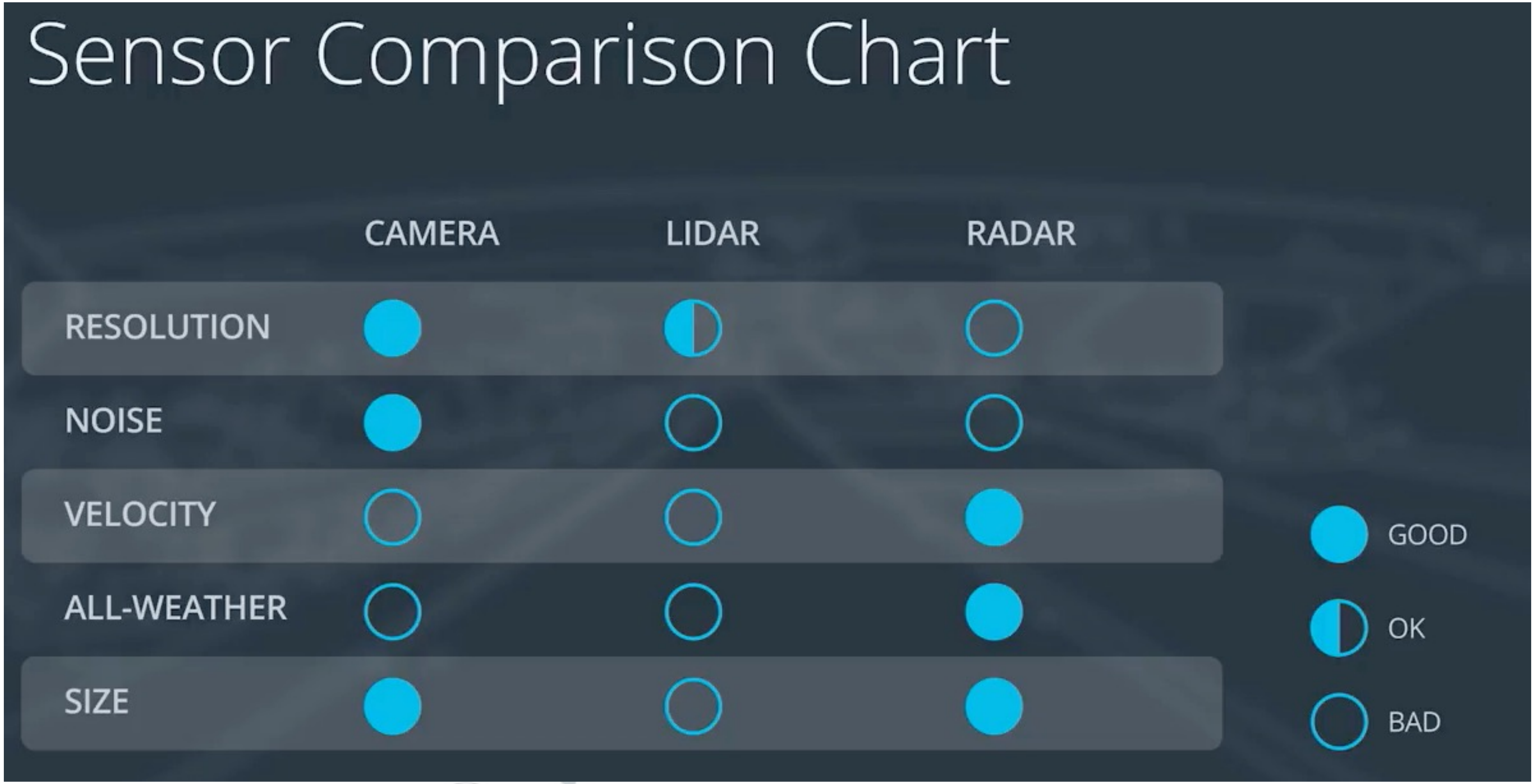
Sensors Ecosystem: CAMERA vs Radar vs LIDAR



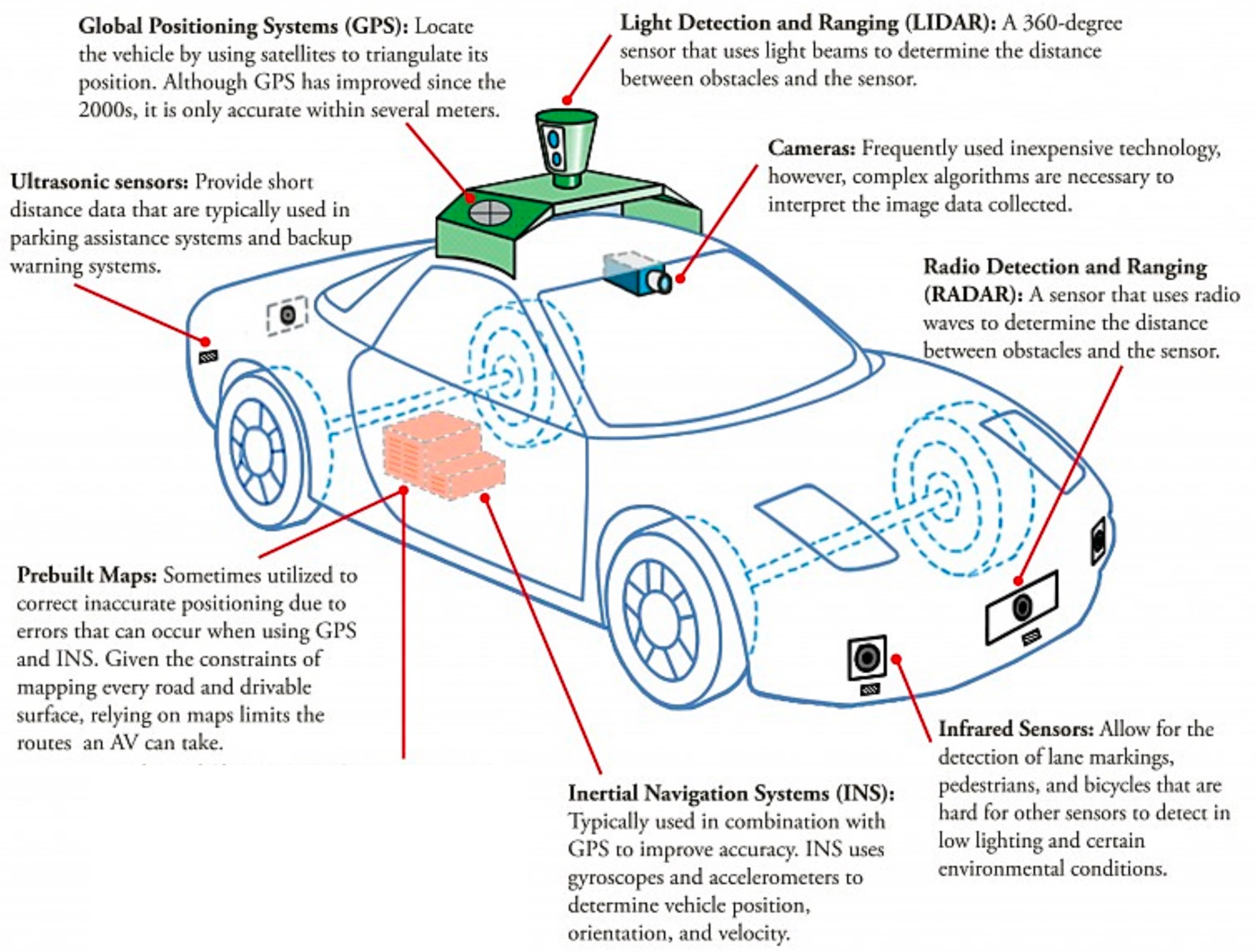
	Camera	Radar	LIDAR	Ultrasonic	Sensor Fusion
Detect other traffic participants	✓	✓	✓	✓	✓
Texture interpretation (lanes)	✓	✗	✗	✗	✓
Ambient light independent	✗	✓	✓	✓	✓
All-weather operation	✗	✓	✗	✓	✓
Operating range	mid-far	near-far	mid-far	near	near-far
Angular resolution	high	medium	high	low	high
Cost	✓	✓	✗	✓	✓
Sensor is "master of"	classification / texture	motion measurement	3D mapping	low-cost ranging	

References: [17]
See the full list of references on blackboard

Sensors comparison

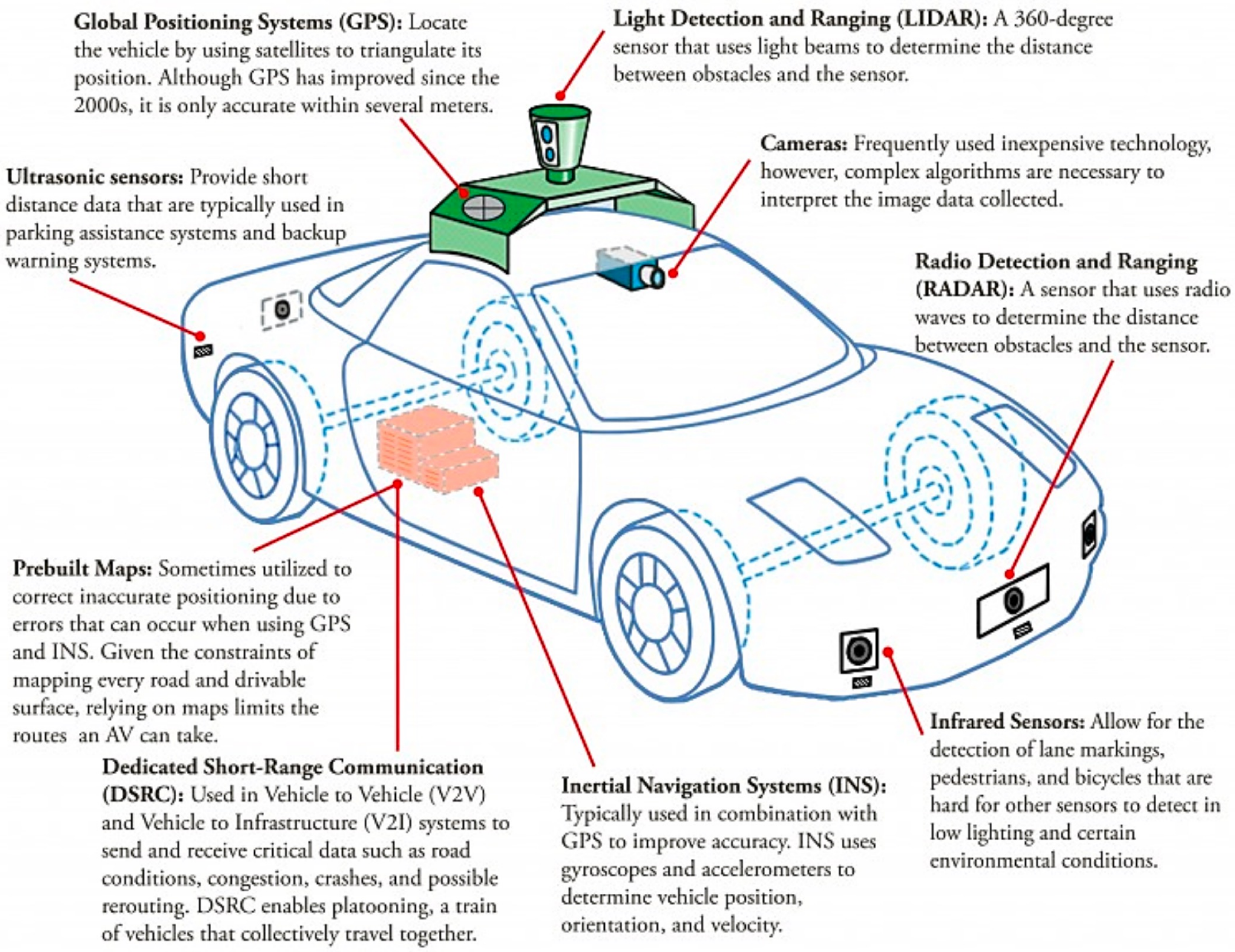


Sensors Ecosystem : Infrared sensors



References: [11]
See the full list of references on blackboard

Sensors Ecosystem: Dedicated Short-Range Communication



References: [11]
See the full list of references on blackboard

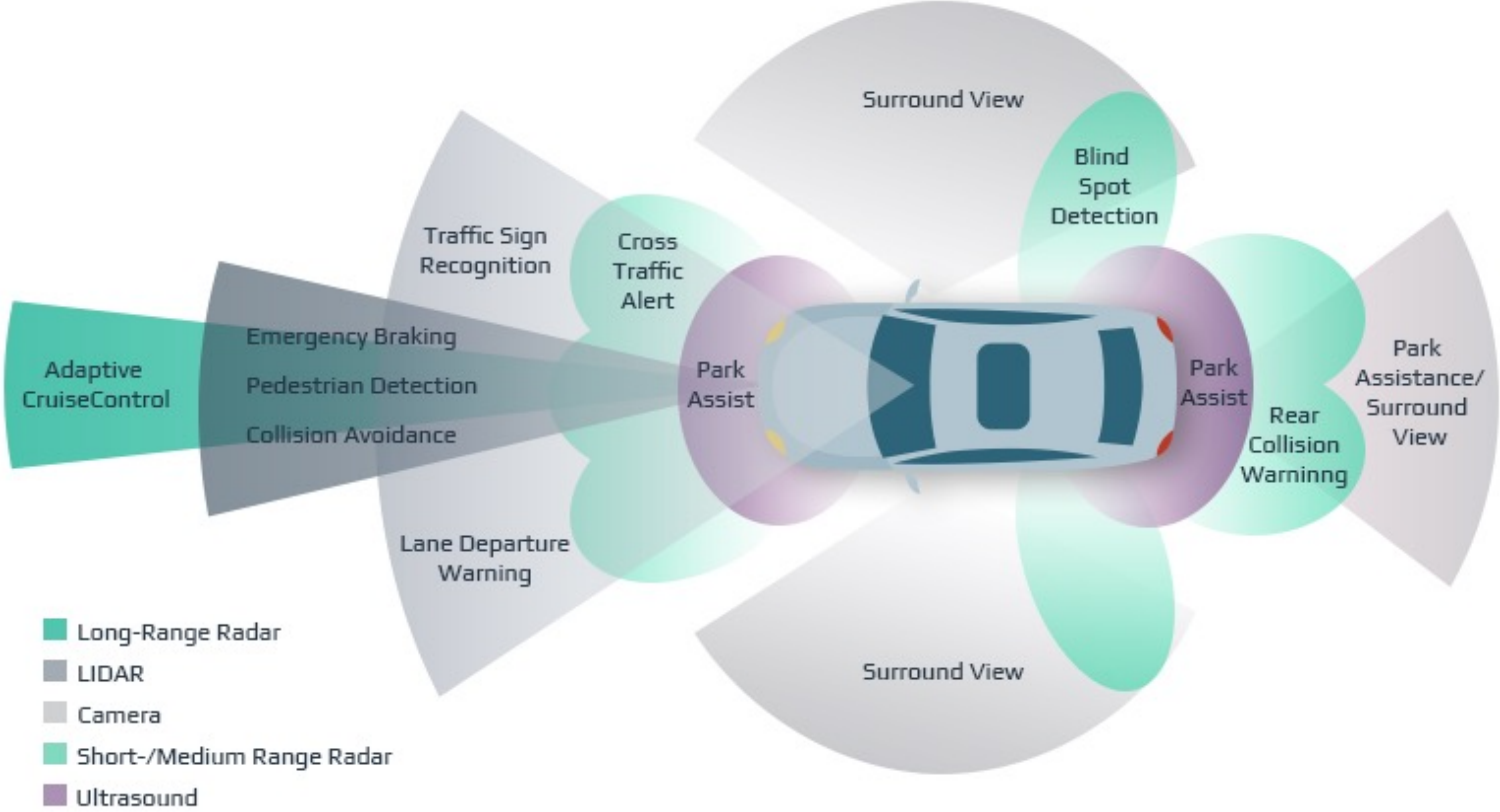
Sensors Ecosystem: Dedicated Short-Range Communication

References: [23]
See the full list of references on blackboard

Sensors Ecosystem: Dedicated Short-Range Communication

References: [22]
See the full list of references on blackboard

Sensors Ecosystem



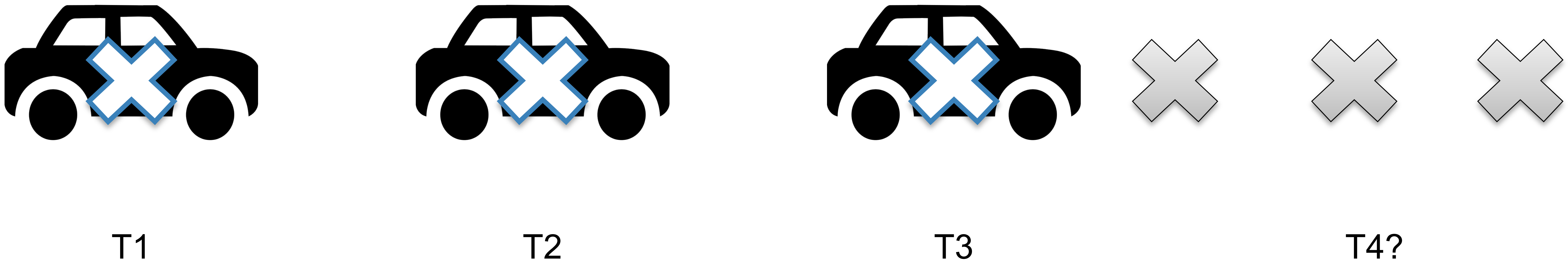
References: [27]
See the full list of references on blackboard

What is Kalman filter?

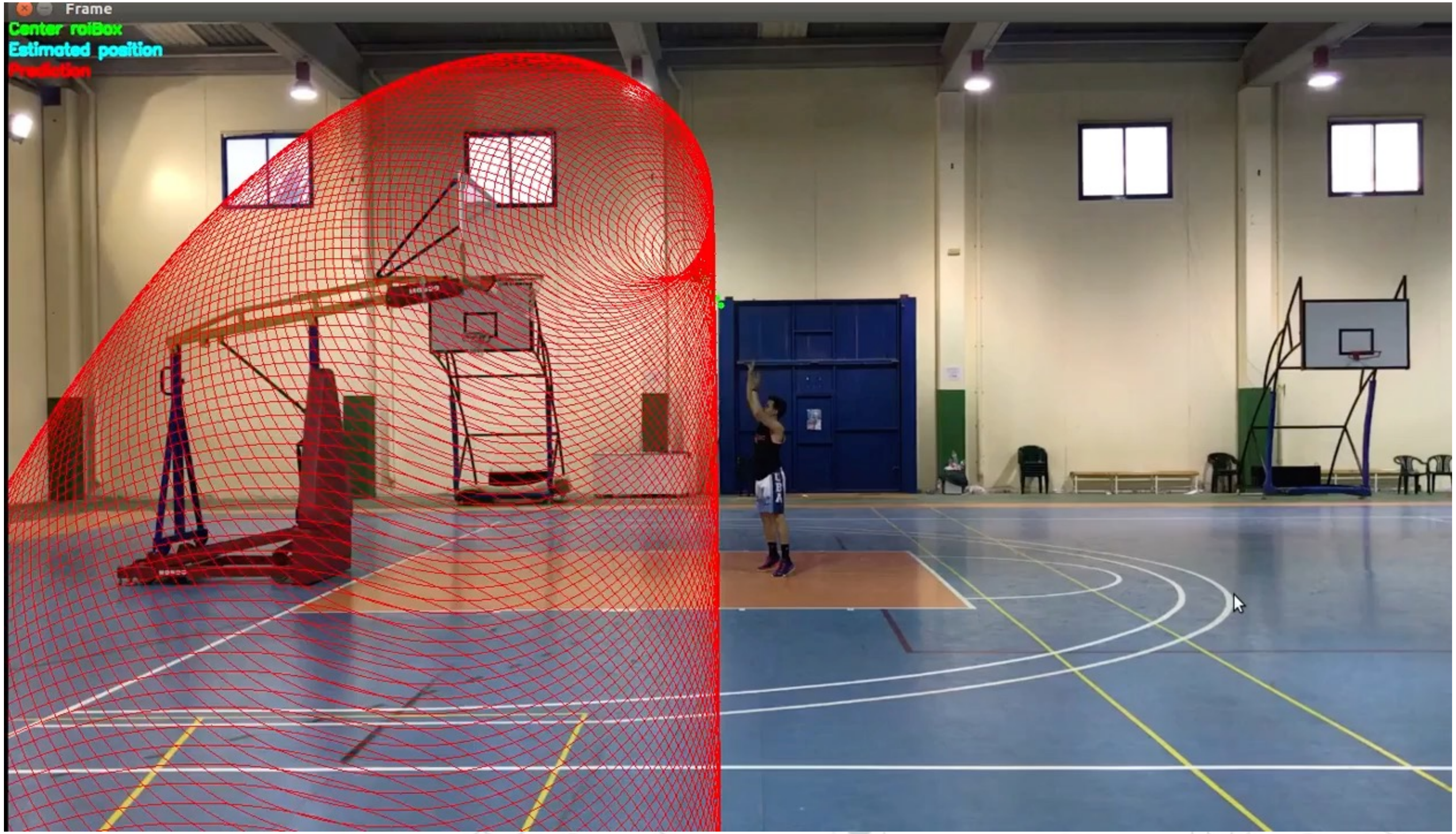
Kalman filtering is an algorithm that provides estimates of some unknown variables given the measurements observed over time.
It is regarded as the optimal solution to many tracking and data prediction tasks.

Why Kalman filter?

How to find and track: Kalman filter

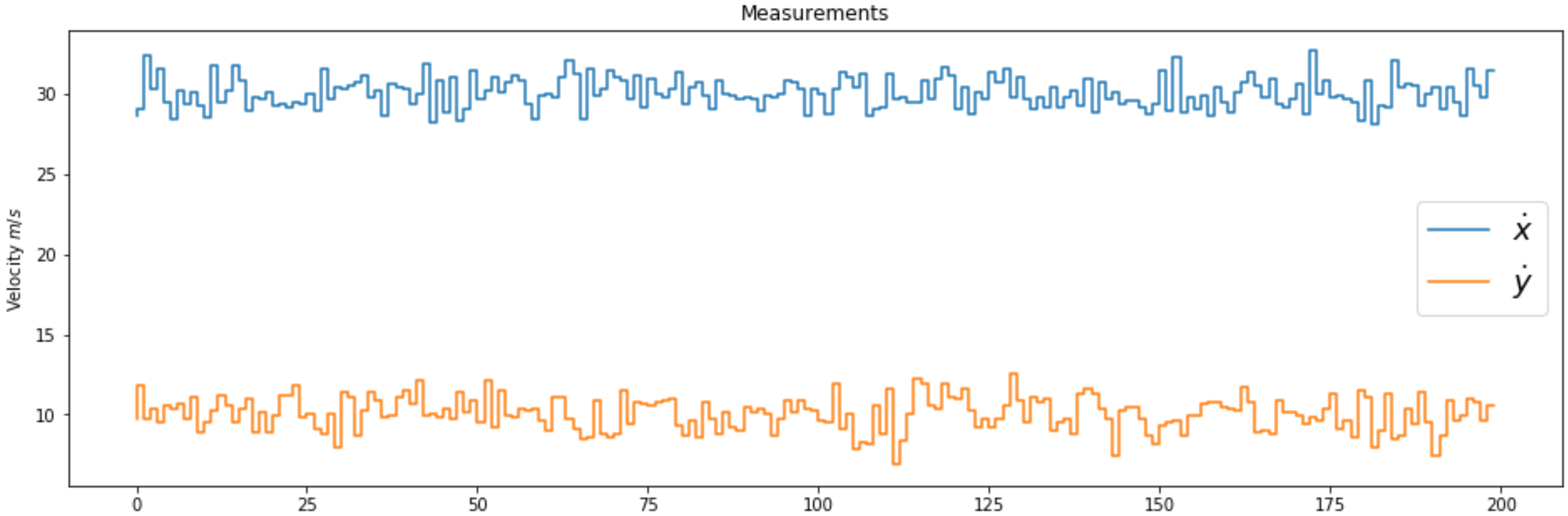


Why Kalman filter?



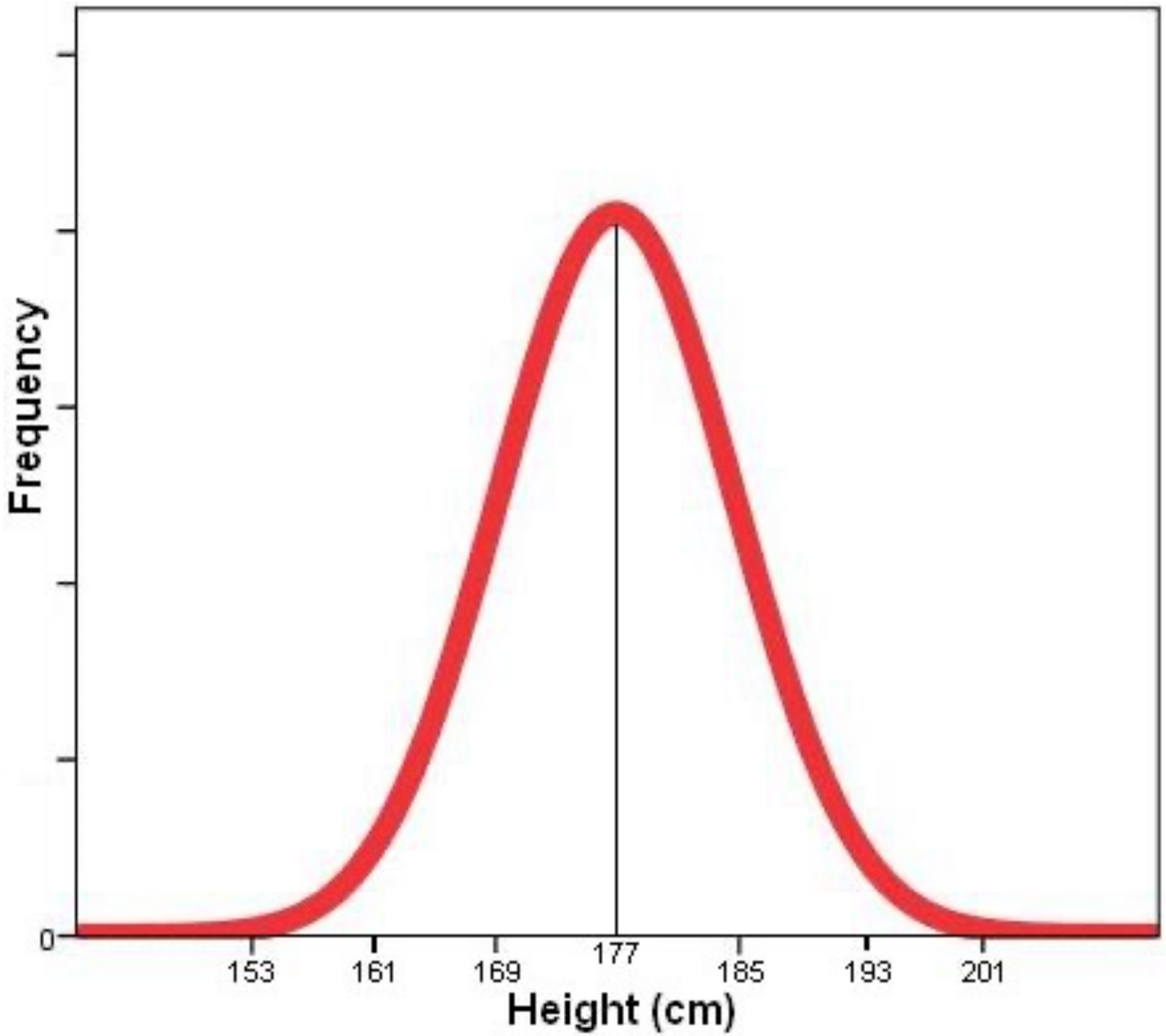
References: [37]
See the full list of references on blackboard

All measurements are noisy



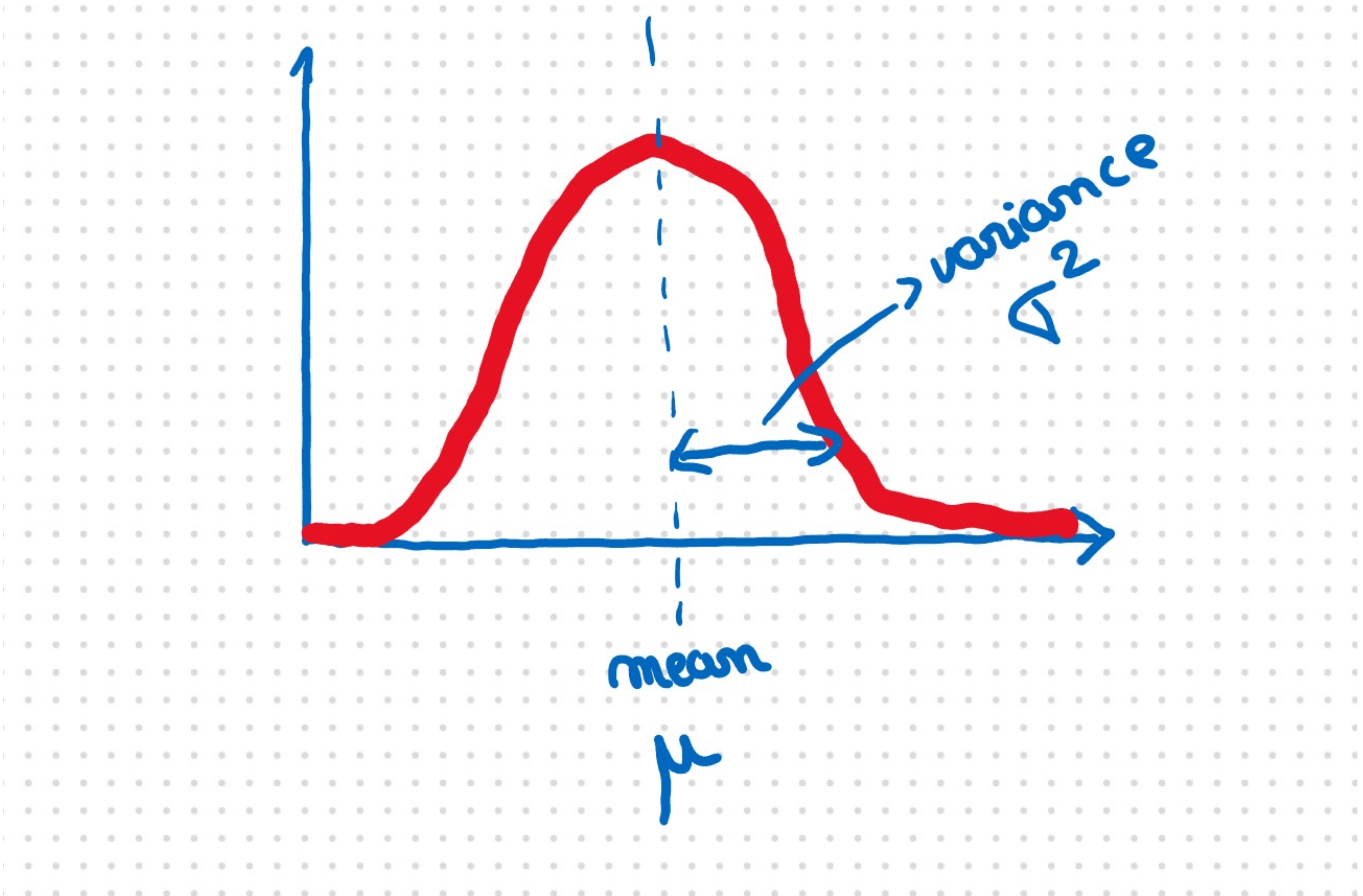
References: [36]
See the full list of references on blackboard

Recap: Gaussian distribution



References: [37]
See the full list of references on blackboard

Recap: Gaussian distribution

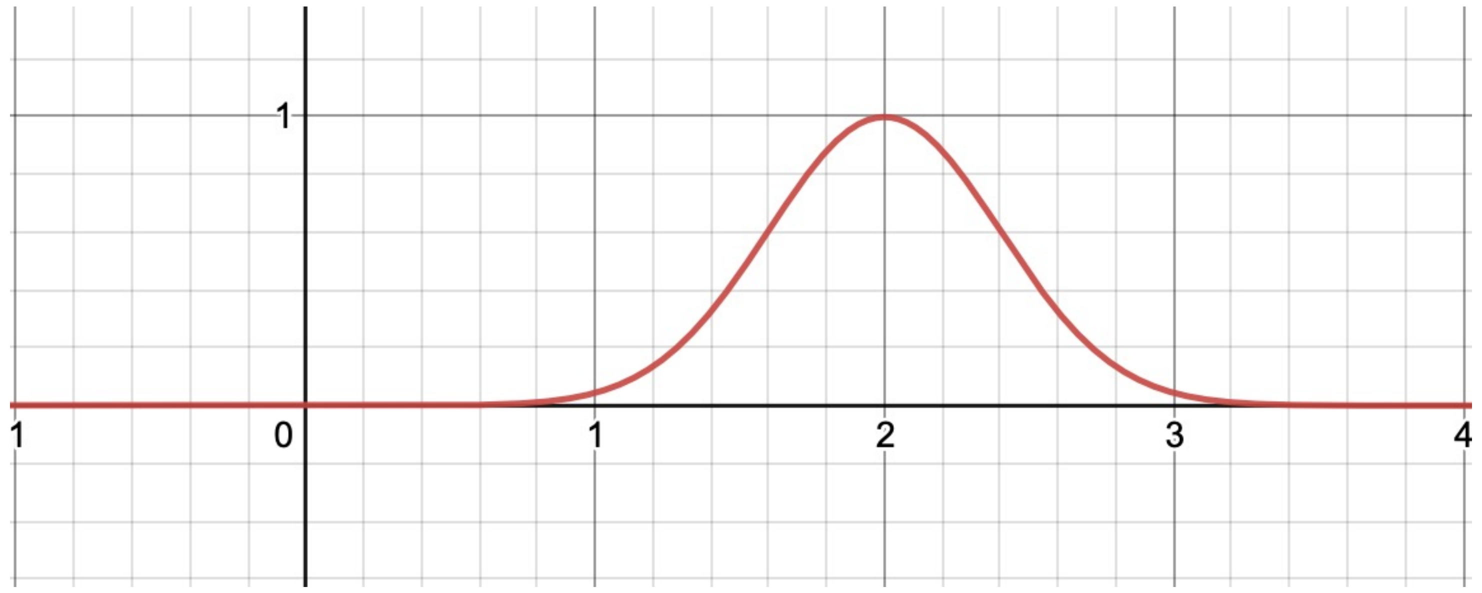


$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$

Recap: Gaussian distribution

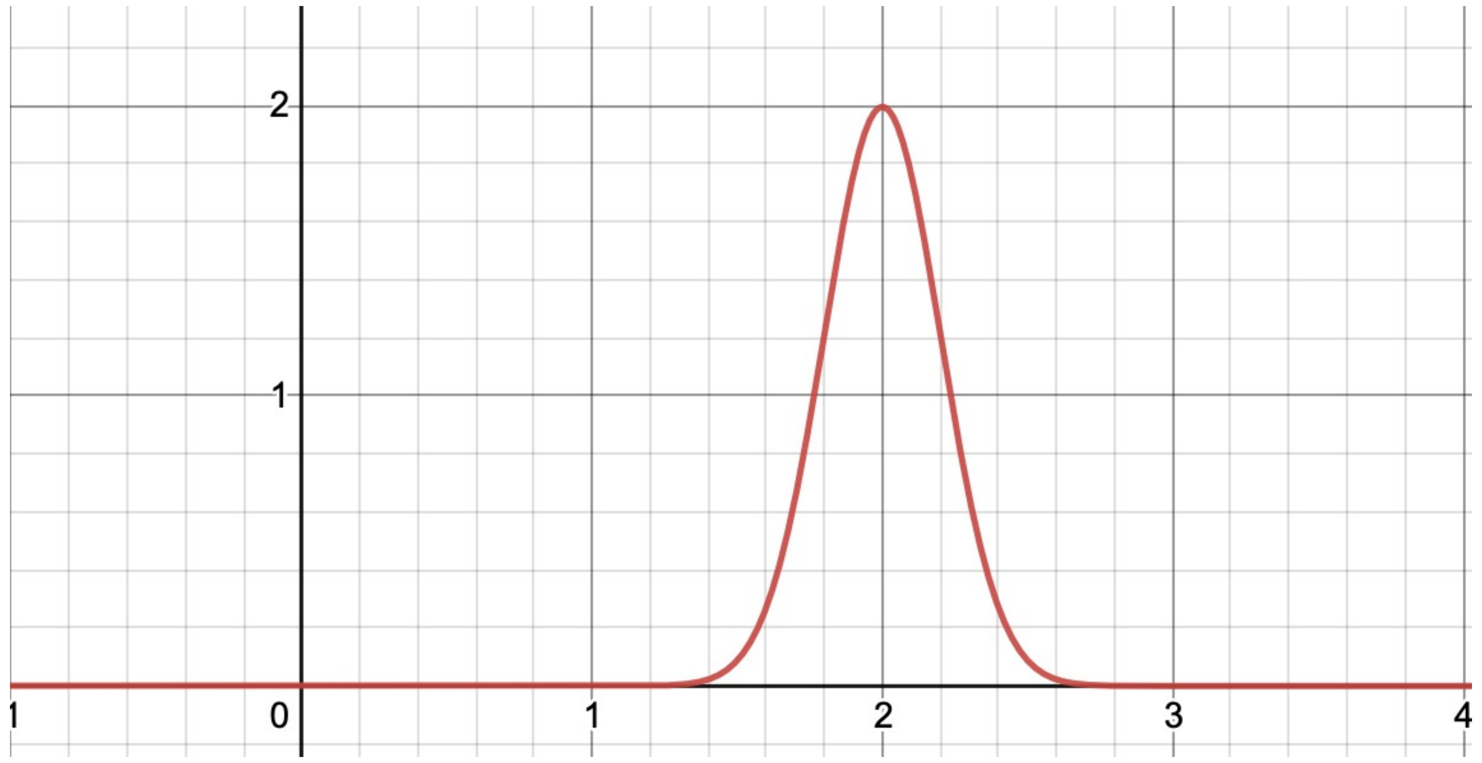
$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$

A



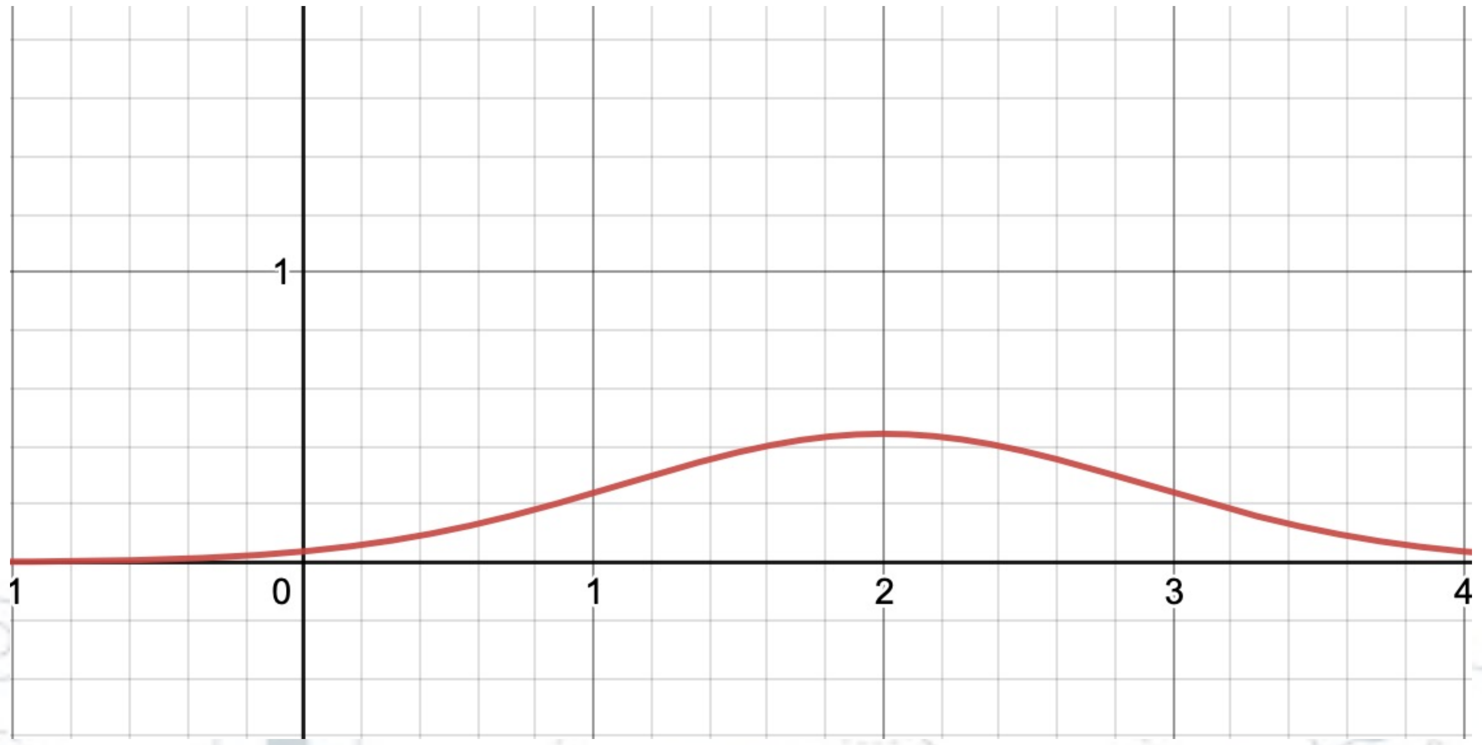
σ^2? Large Medium Small

B



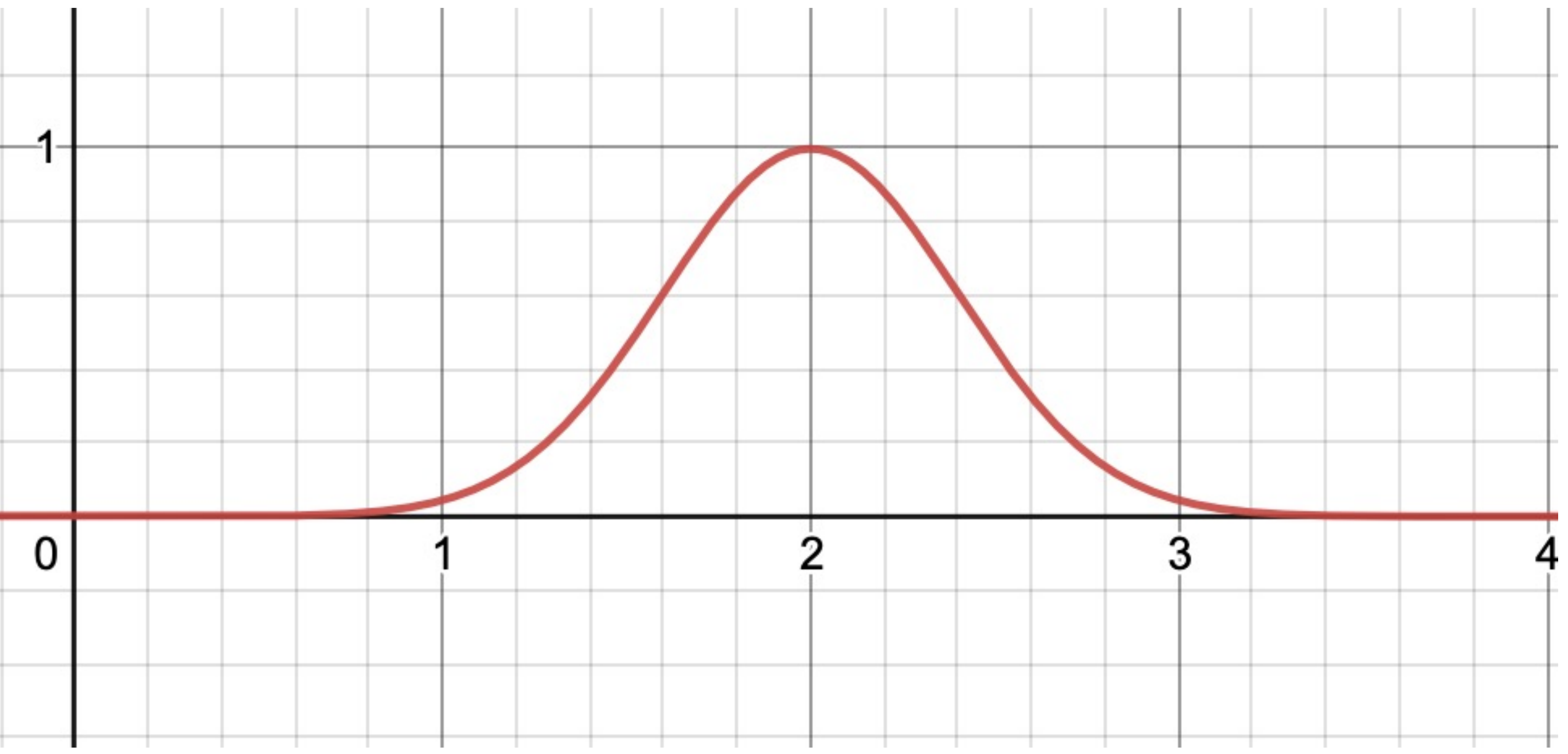
σ^2? Large Medium Small

C



σ^2? Large Medium Small

Gaussian distribution: sensor uncertainty



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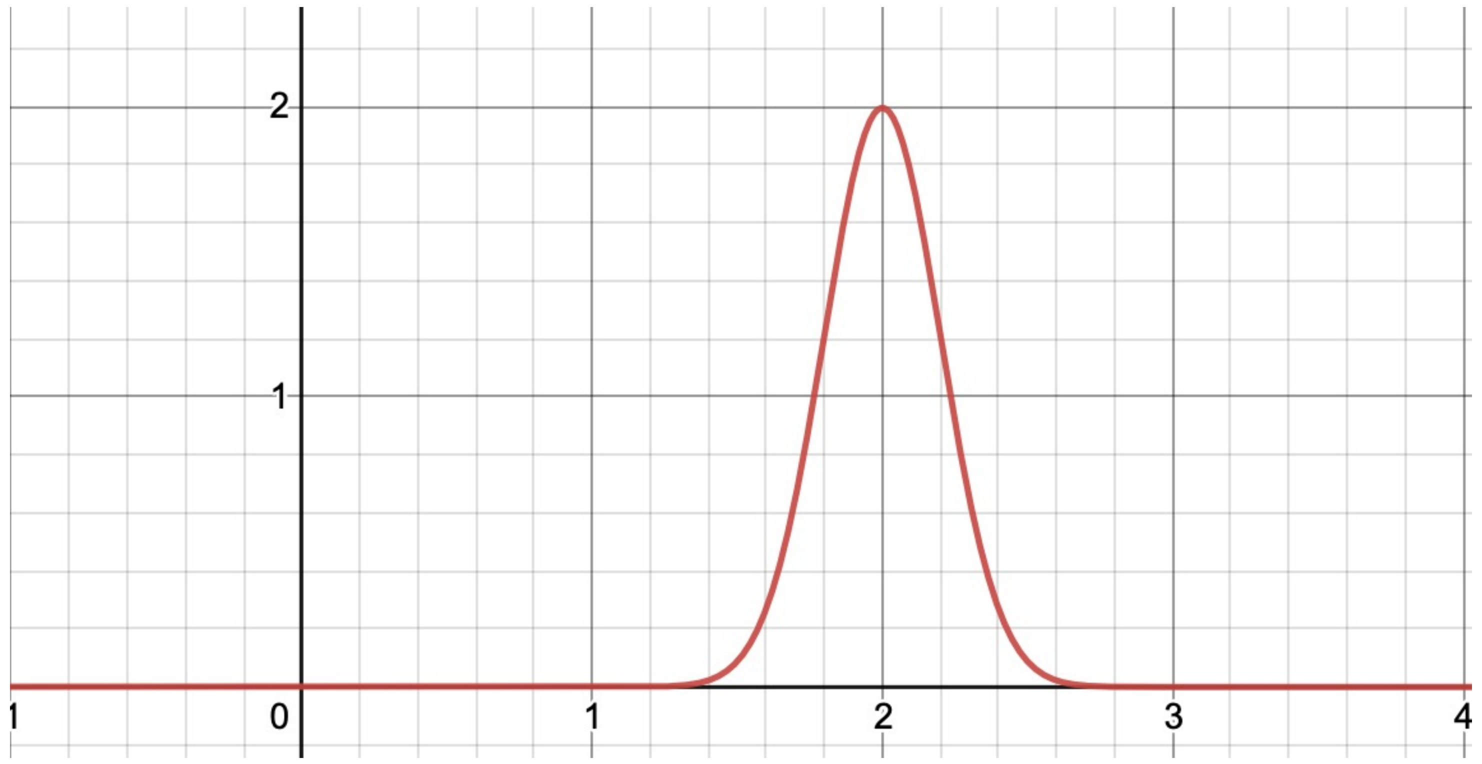

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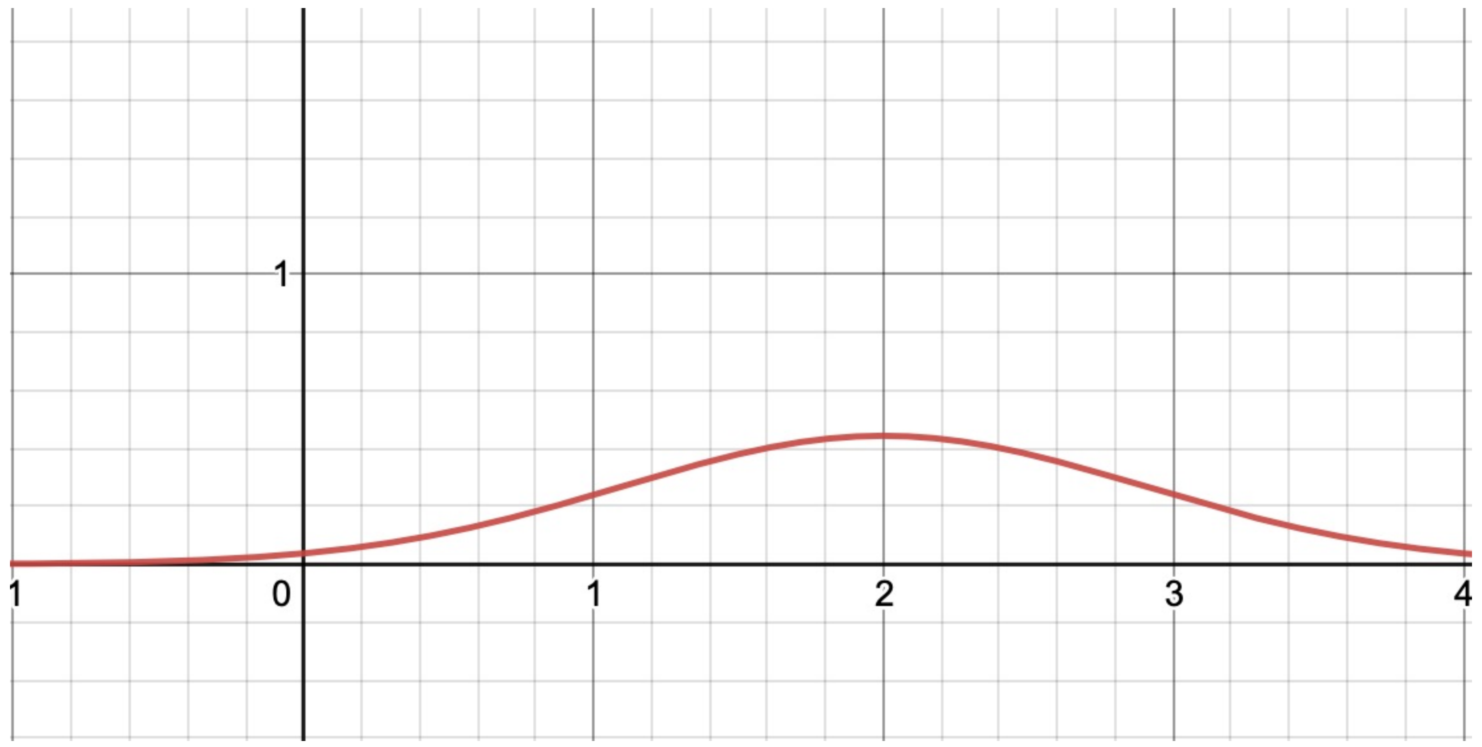


C

Gaussian distribution: sensor uncertainty

A sensor that measures 100% exactly has a variance of $\sigma^2 = 0$.
Most likely a sensor like this does not exist.

Kalman filter

Measurement update

Prediction

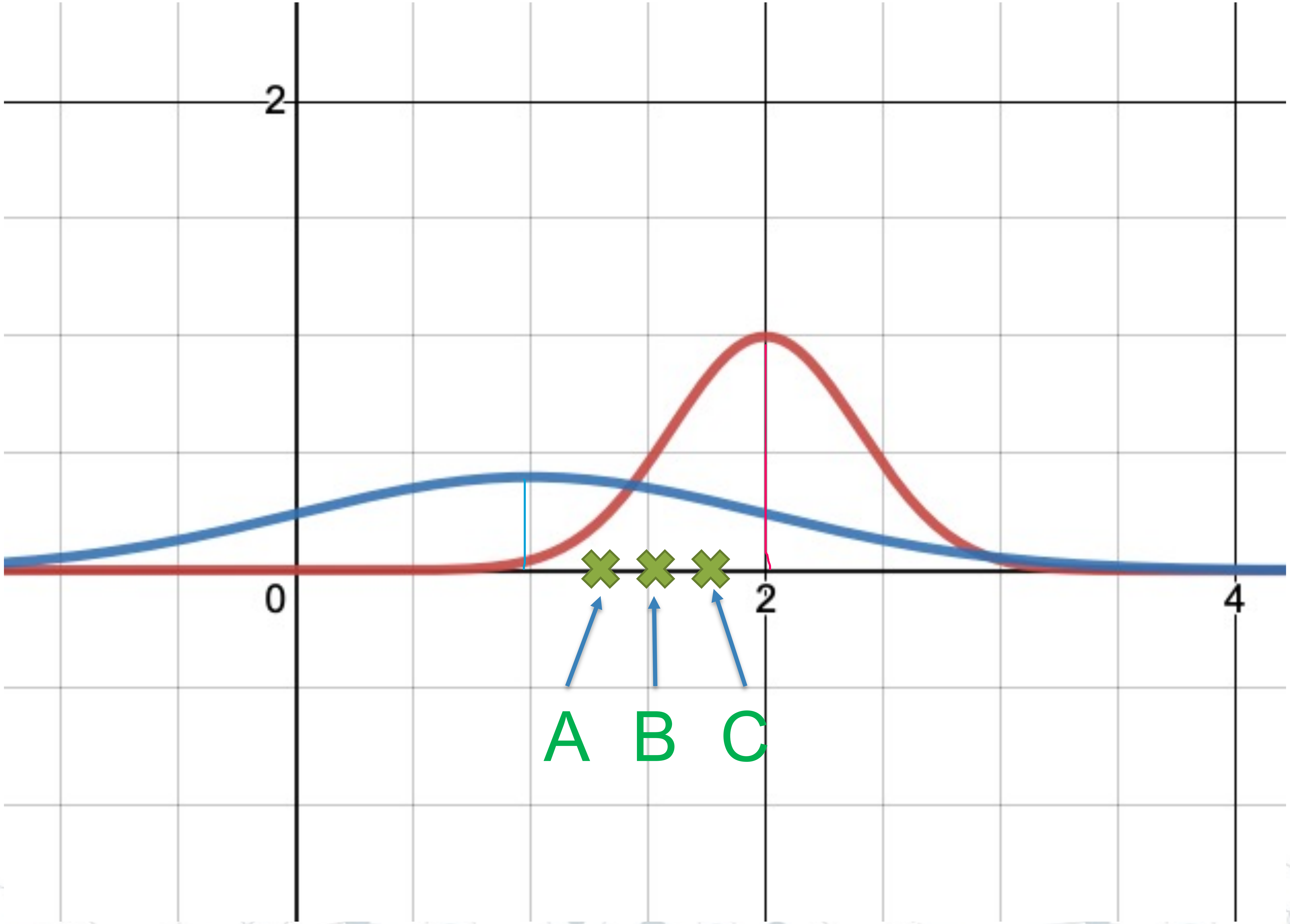
Bayes Rule

(Product)

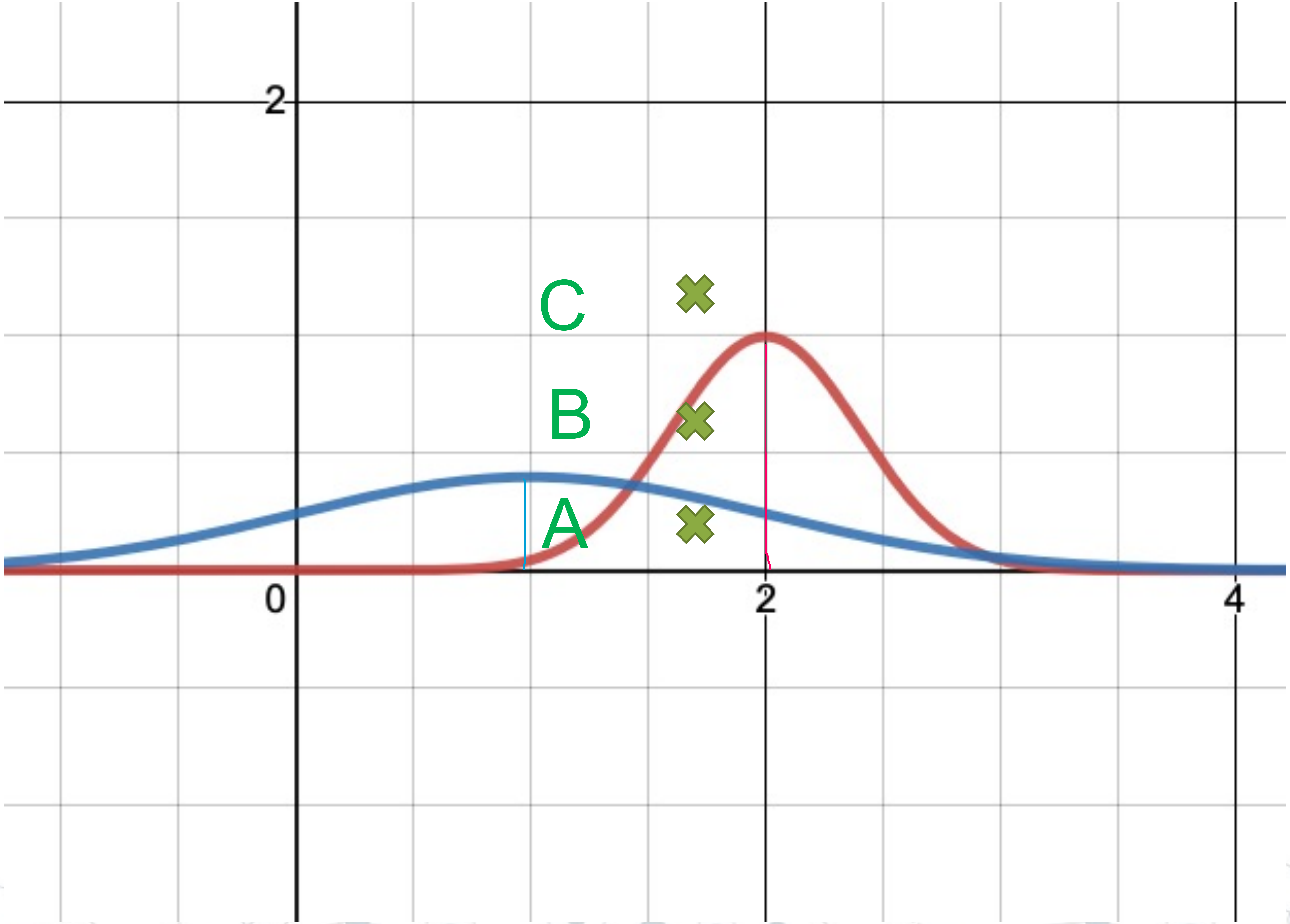
Total probability

(Addition)

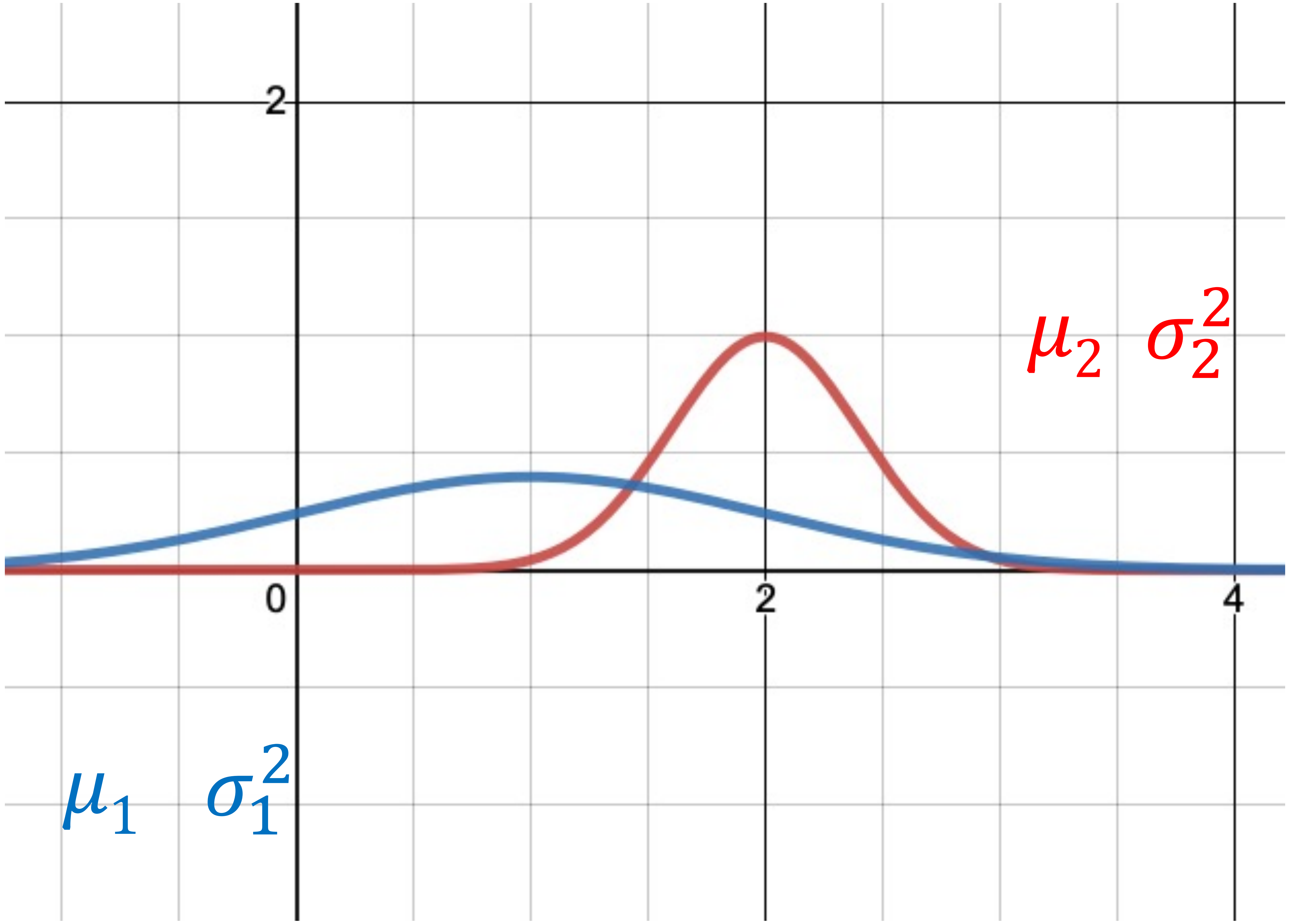
Kalman filter: Measurement update
Multiplying gaussians: Shifting the mean



Kalman filter: Measurement update
Multiplying gaussians: Where is the peak?



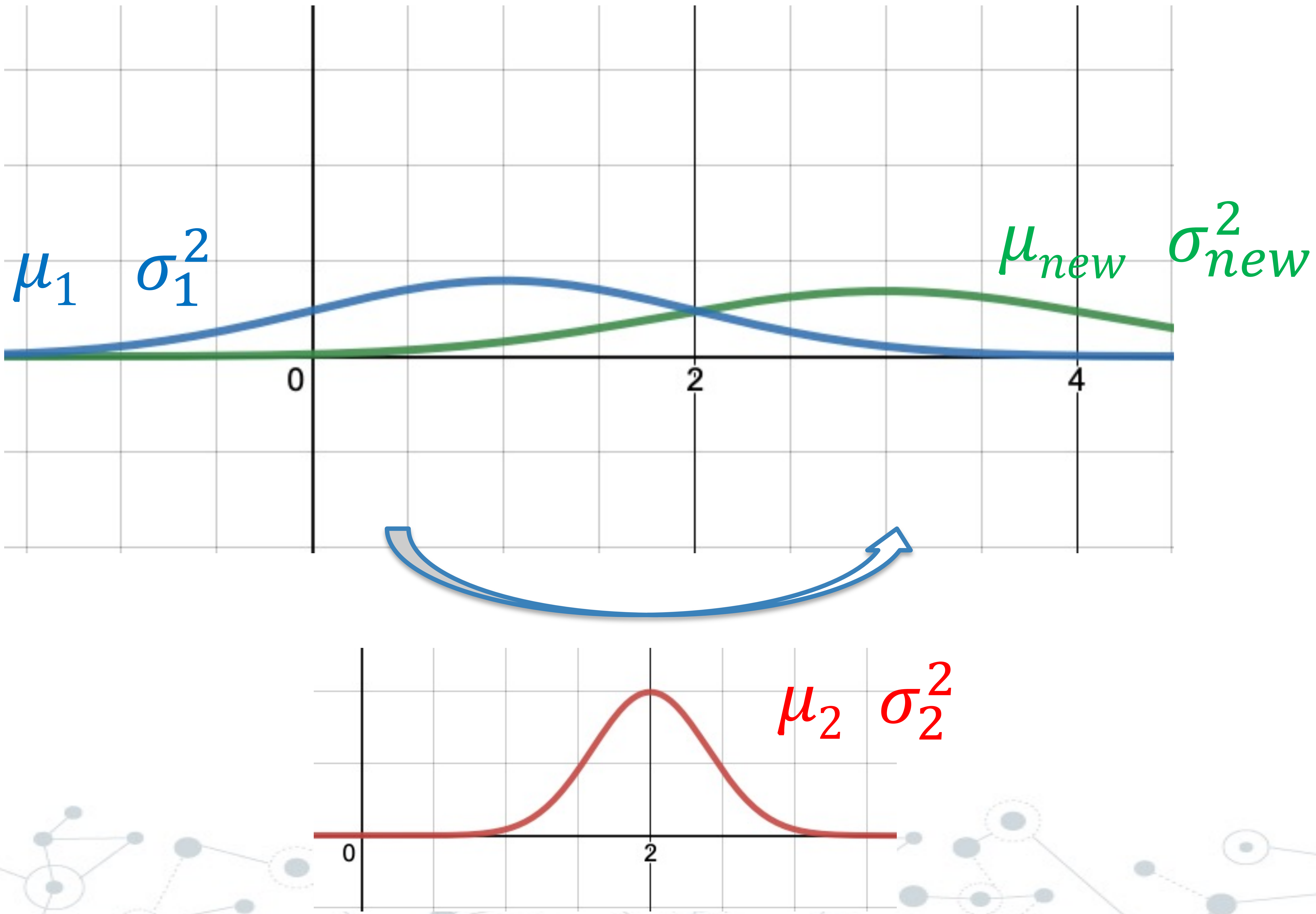
Kalman filter: Measurement update



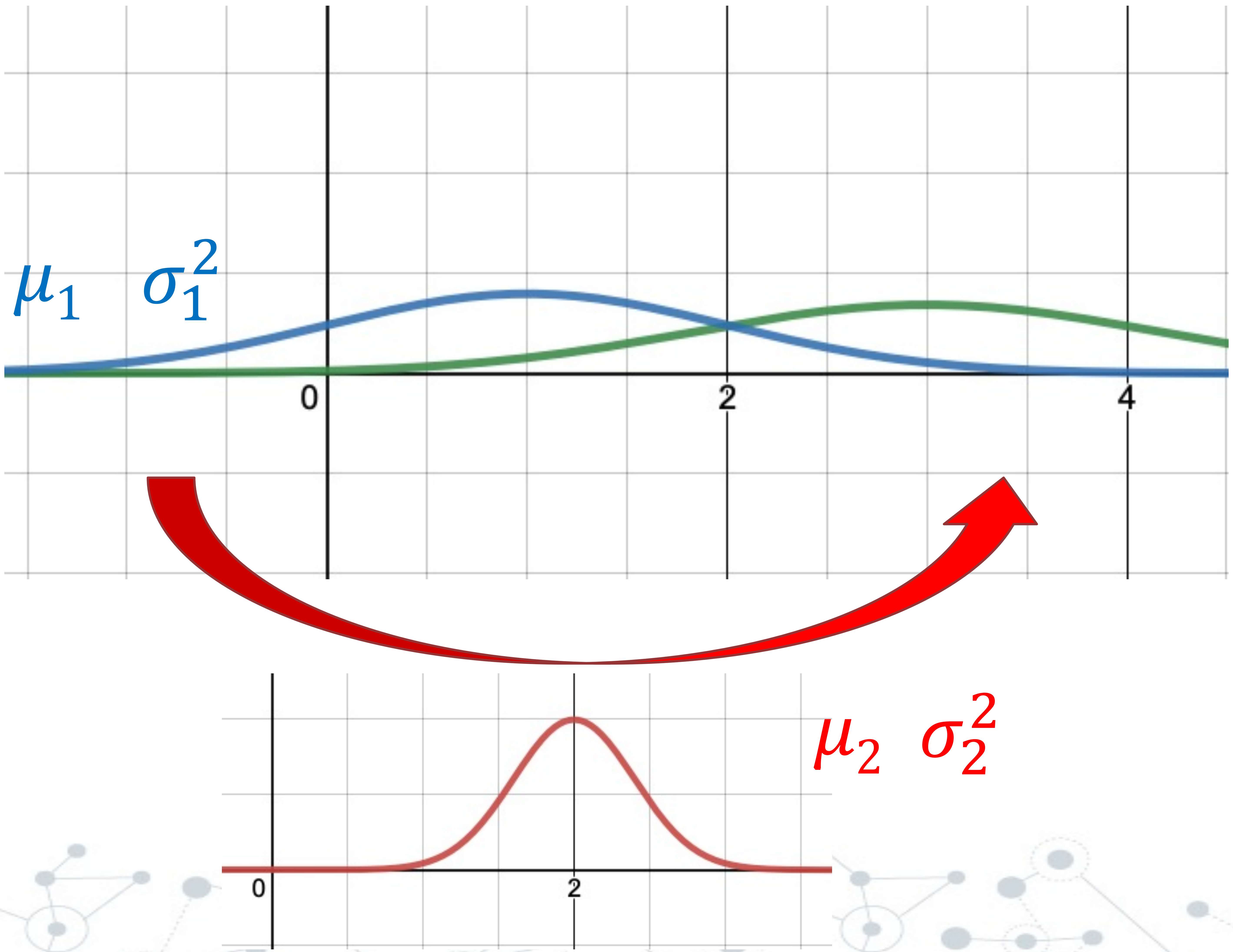
$$\mu_{new} = \frac{\sigma_2^2 * \mu_1 + \sigma_1^2 * \mu_2}{\sigma_1^2 + \sigma_2^2}$$

$$\sigma_{new}^2 = \frac{1}{\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}}$$

Kalman filter: Predicting motion



Kalman filter: Predicting motion



$$\mu_{new} = \mu_1 + \mu_2$$

$$\sigma_{new}^2 = \sigma_1^2 + \sigma_2^2$$

Kalman filter 1D: pseudocode

```
Function update(mean1, var1, mean2, var2)
Input: mean1, var1, mean2, var2

       mean_new = (var2 * mean1 + var1 * mean2)/(var1 + var2)
       var_new  = 1 / ( 1/var1 + 1/var2)

Output: mean_new, var_new
```

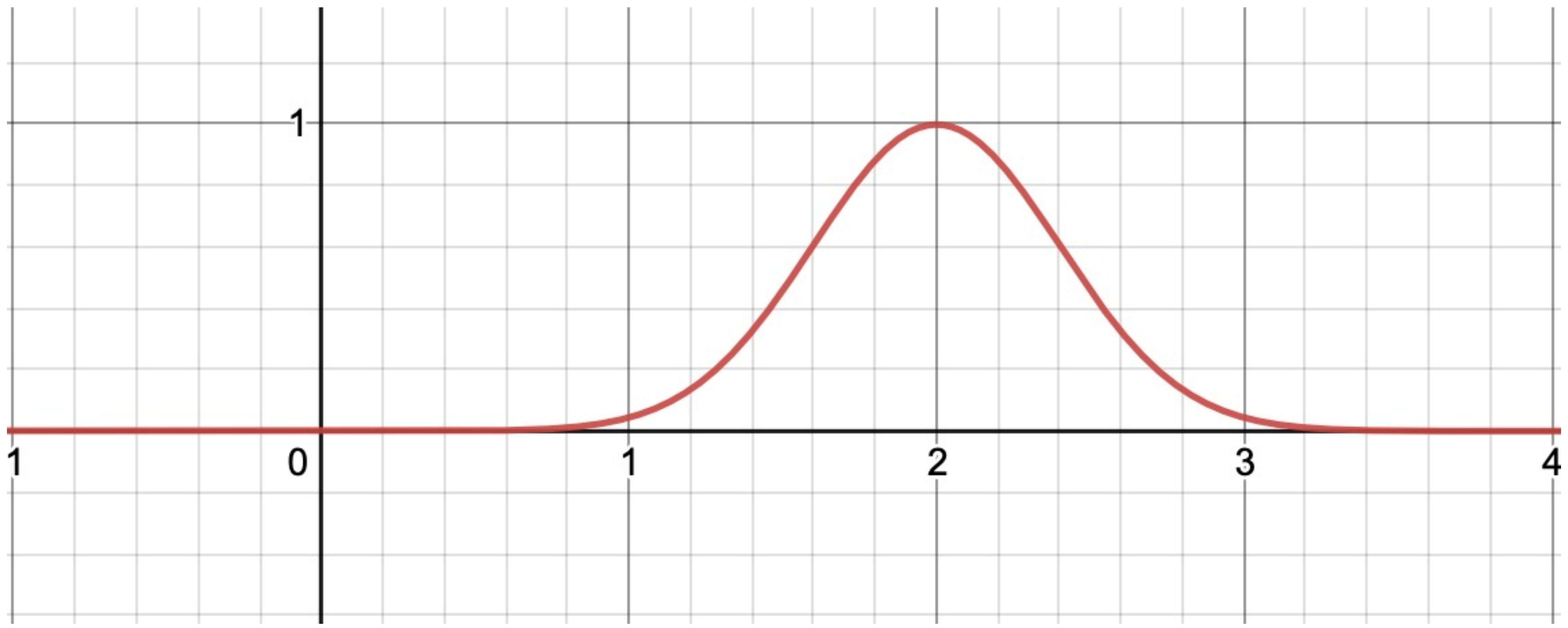
```
Function predict(mean1, var1, mean2, var2)
Input: mean1, var1, mean2, var2

       mean_new = mean1 + mean2
       var_new  = var1 + var2

Output: mean_new, var_new
```

Kalman filter multidimensions

1D Gaussian

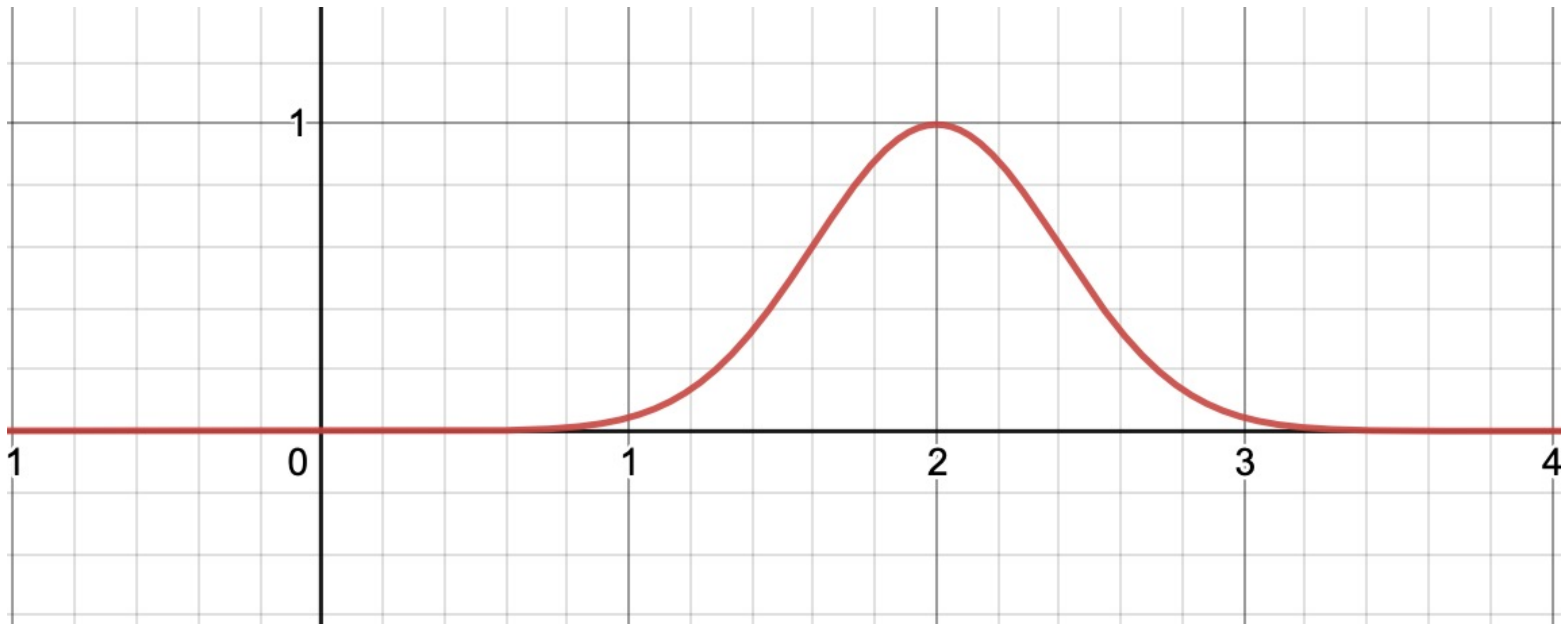


2D Gaussian

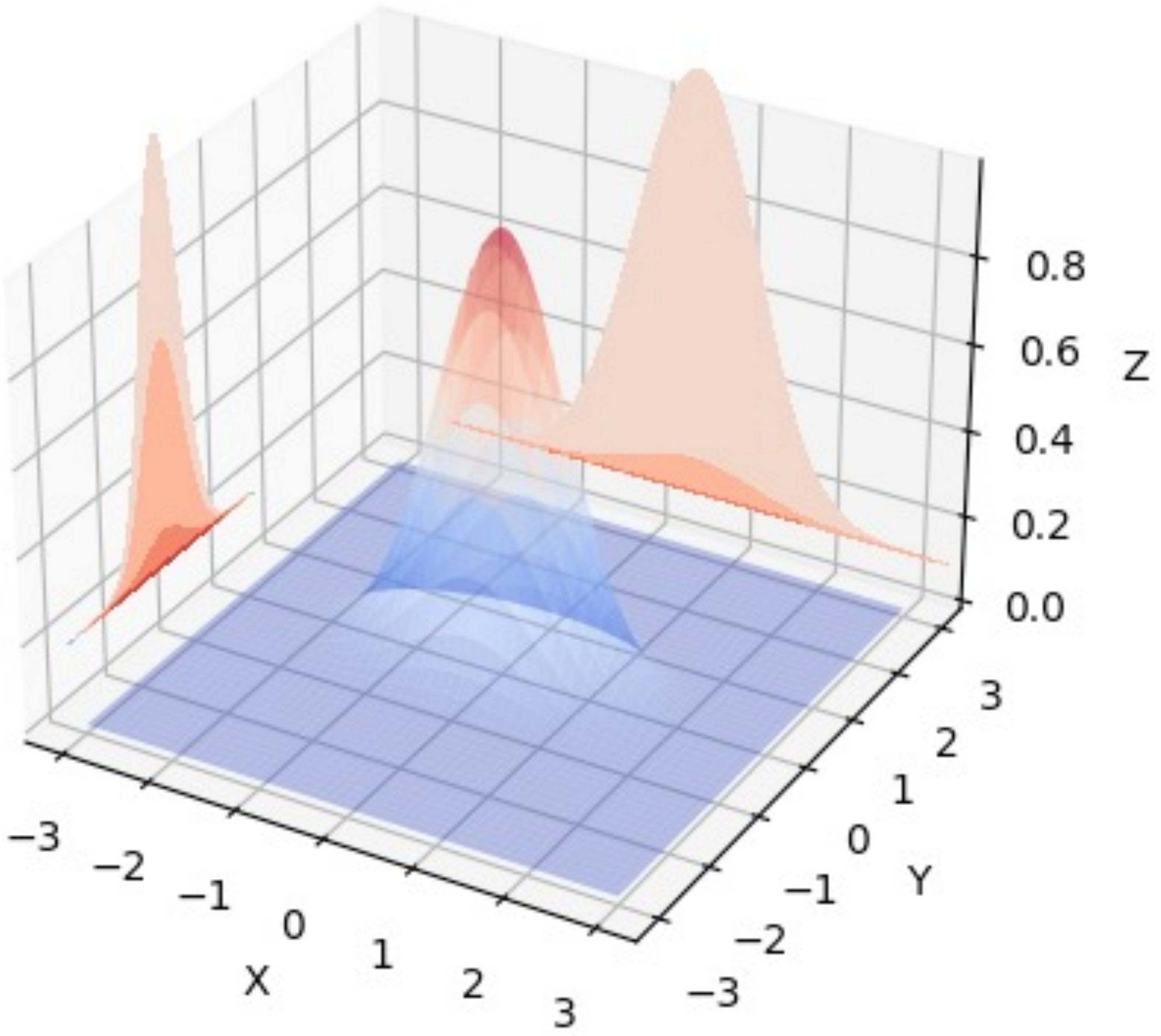
?

Kalman filter multidimensions

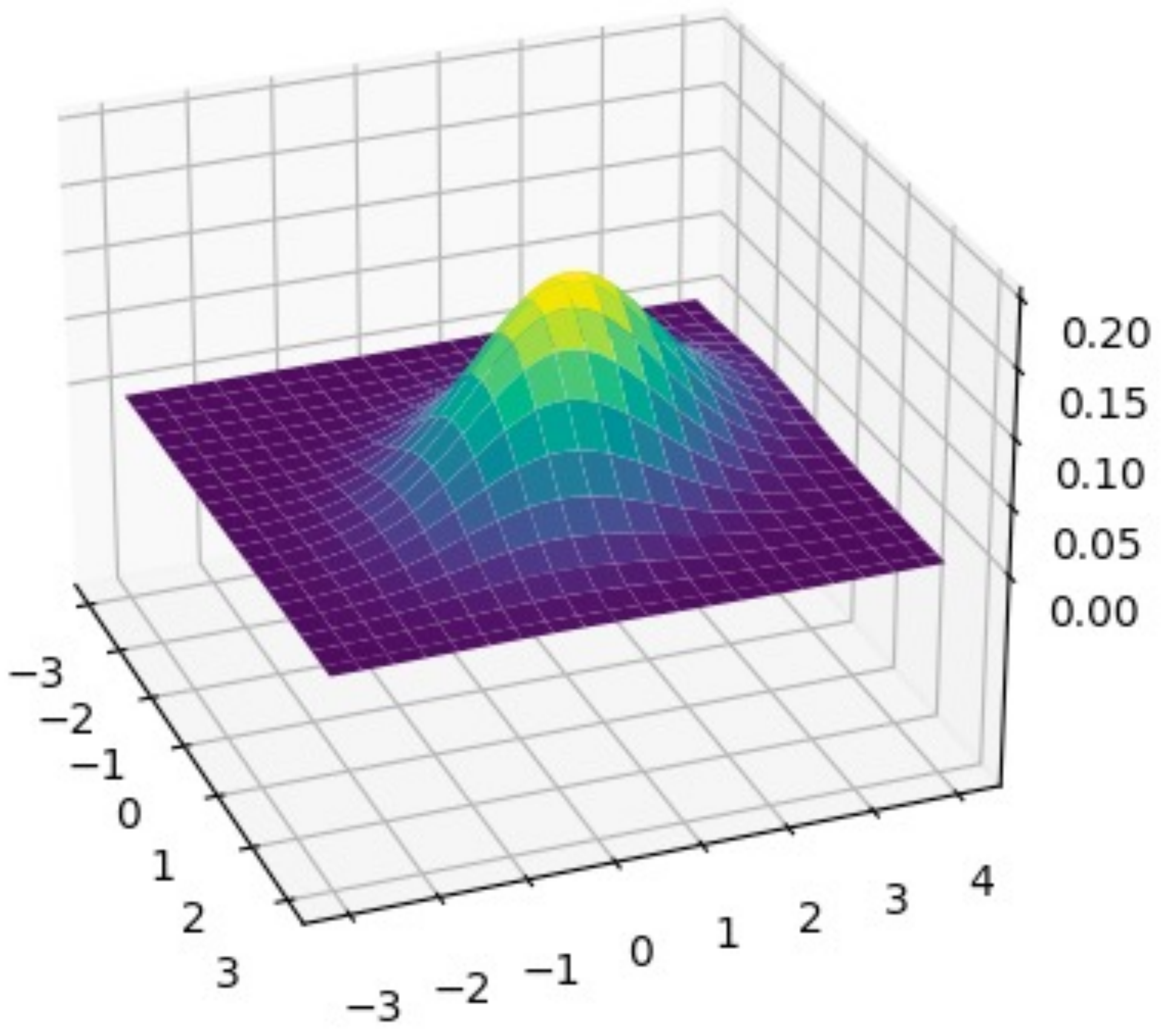
1D Gaussian



2D Gaussian



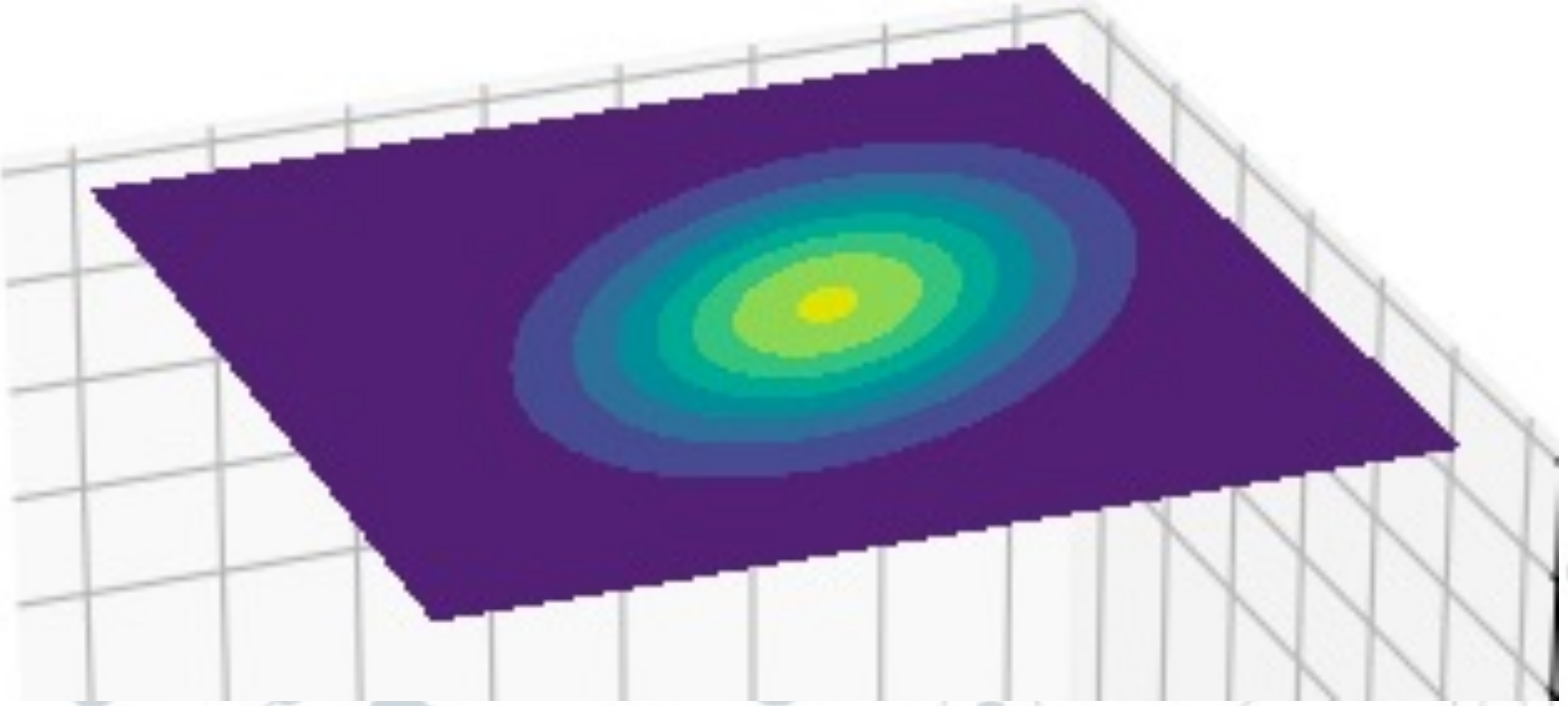
Gaussian in multidimensions: example



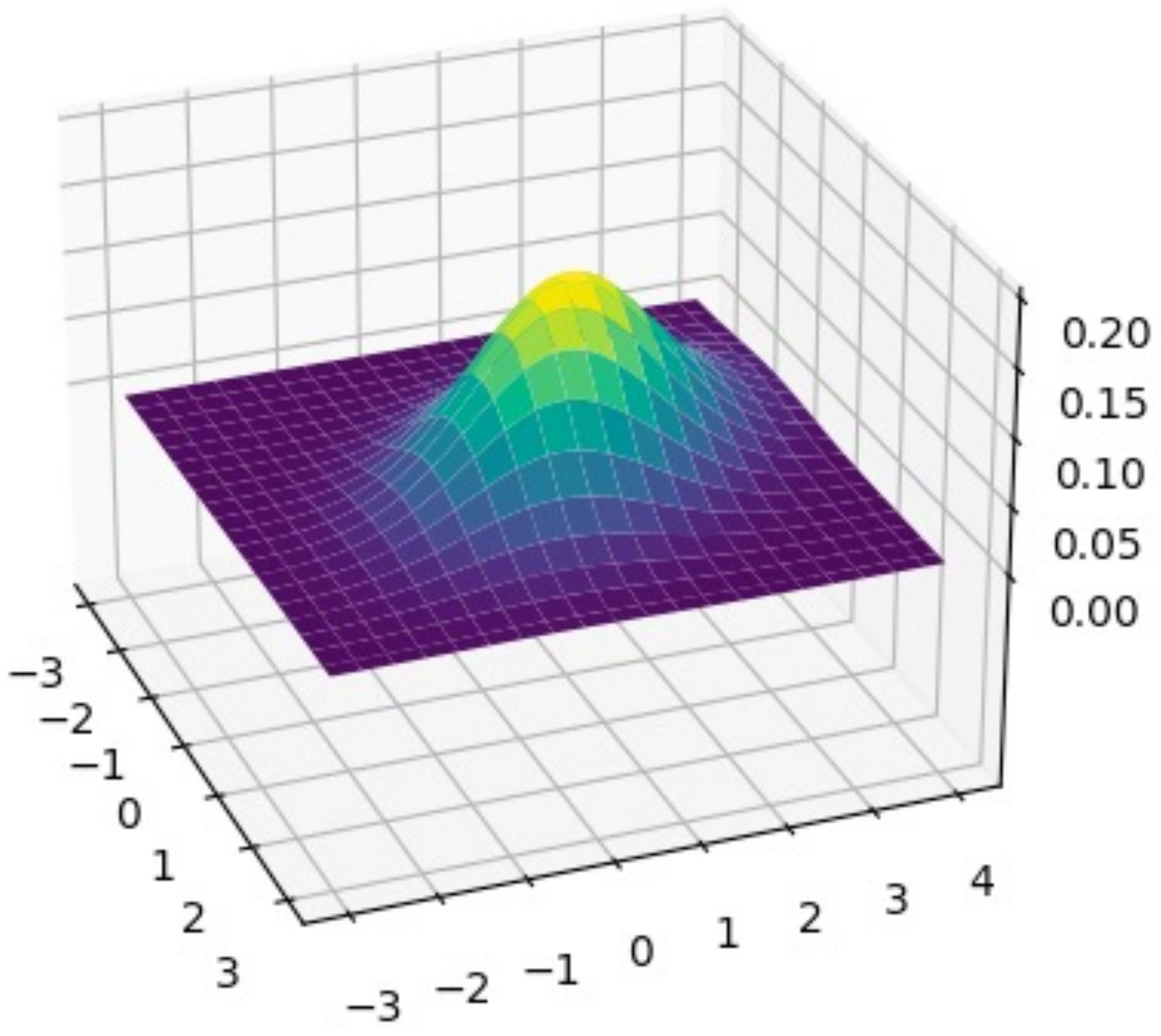
$$\mu = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\Sigma^2 = \begin{bmatrix} 1 & -0.5 \\ -0.5 & 1.5 \end{bmatrix}$$

Covariance



Gaussian in multidimensions: example



$$\mu = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

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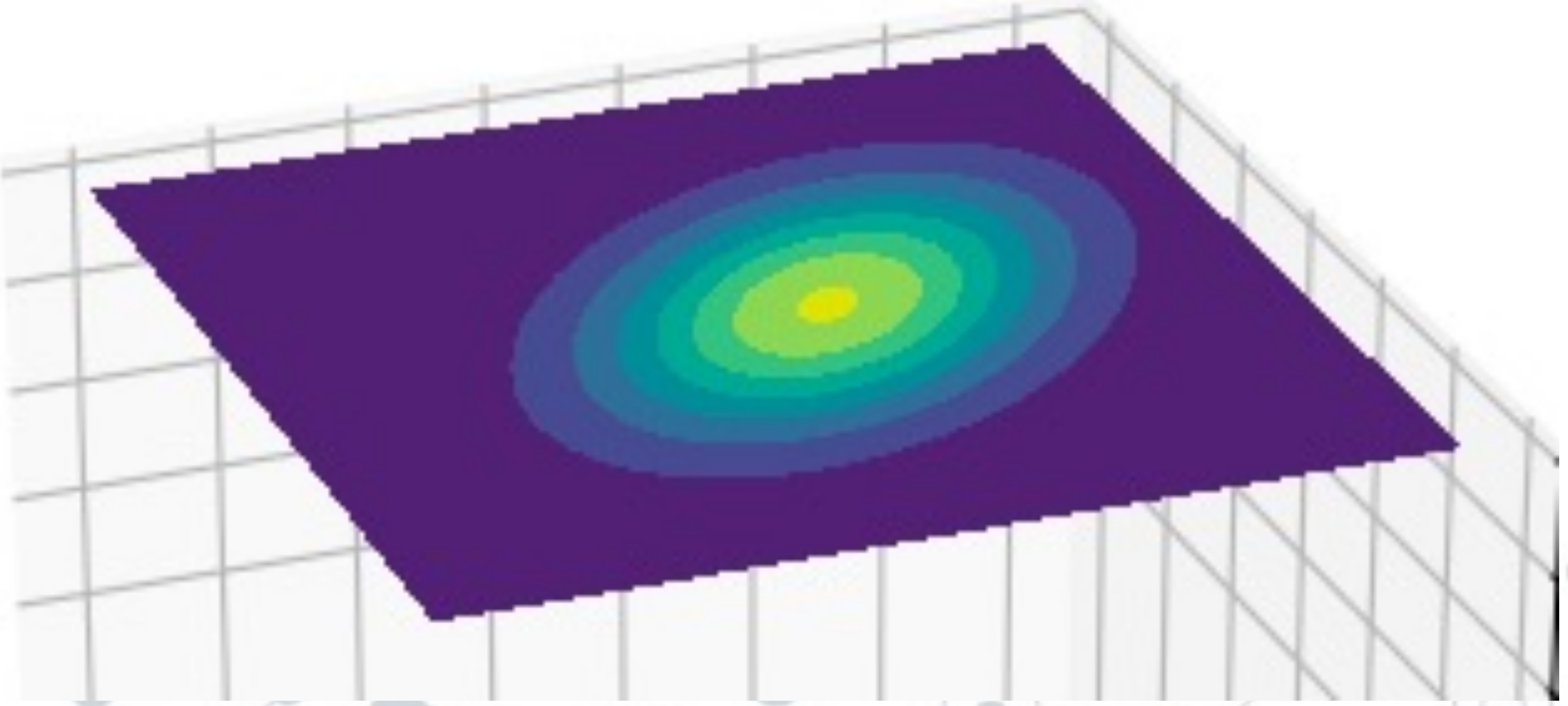
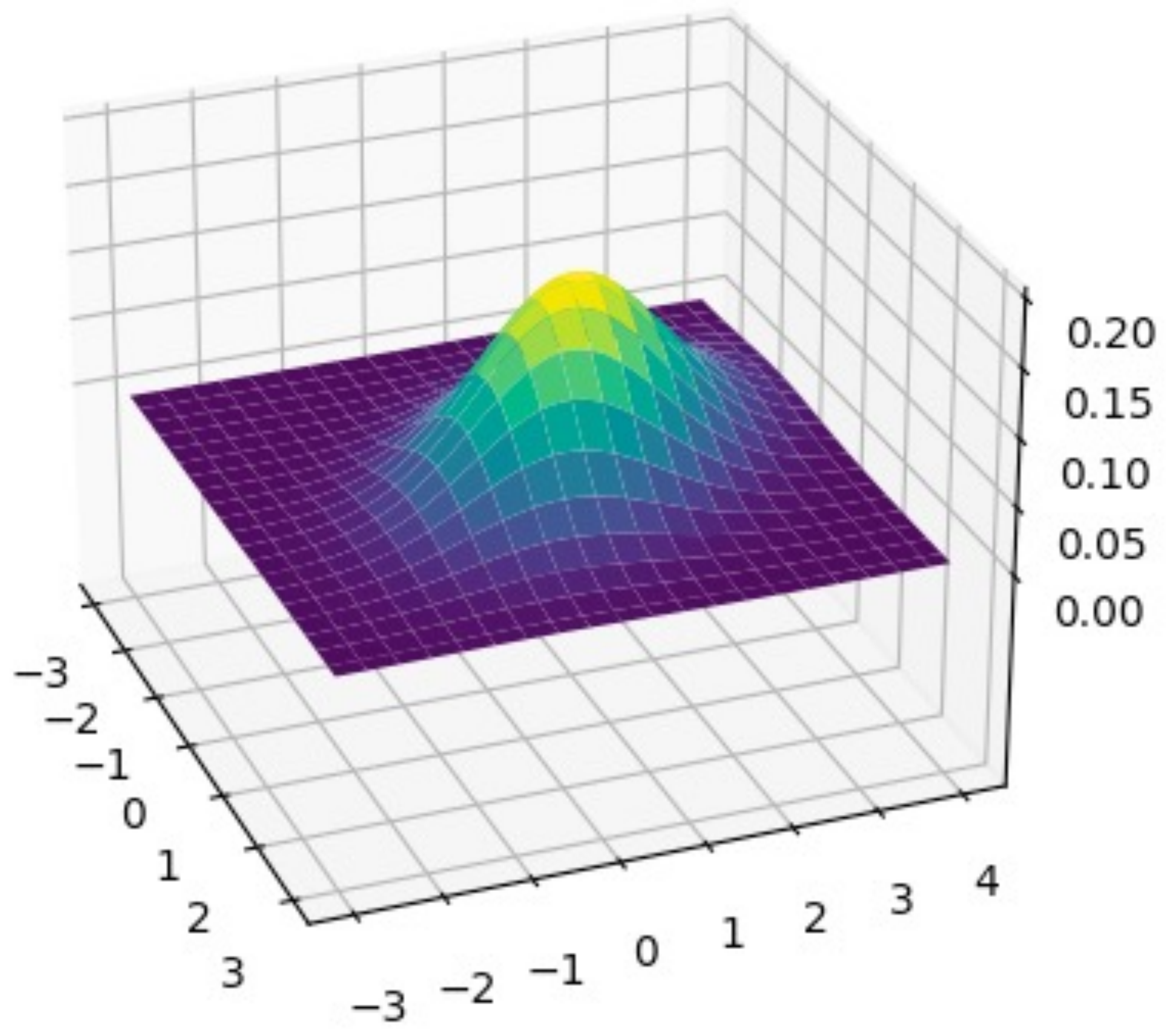
Covariance



$$p(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{\sqrt{(2\pi)^n |\boldsymbol{\Sigma}|}} \exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})\right),$$

Gaussian in multidimensions: example



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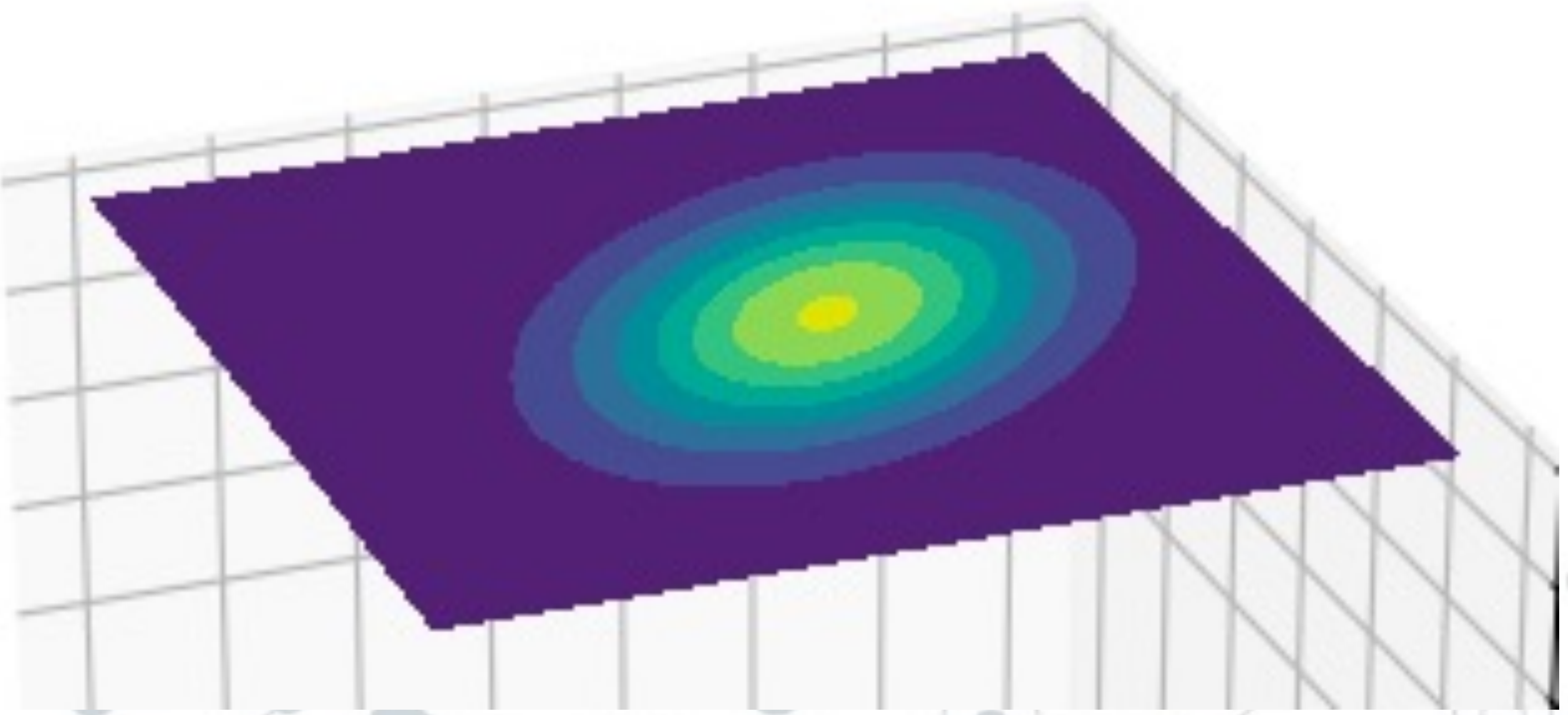
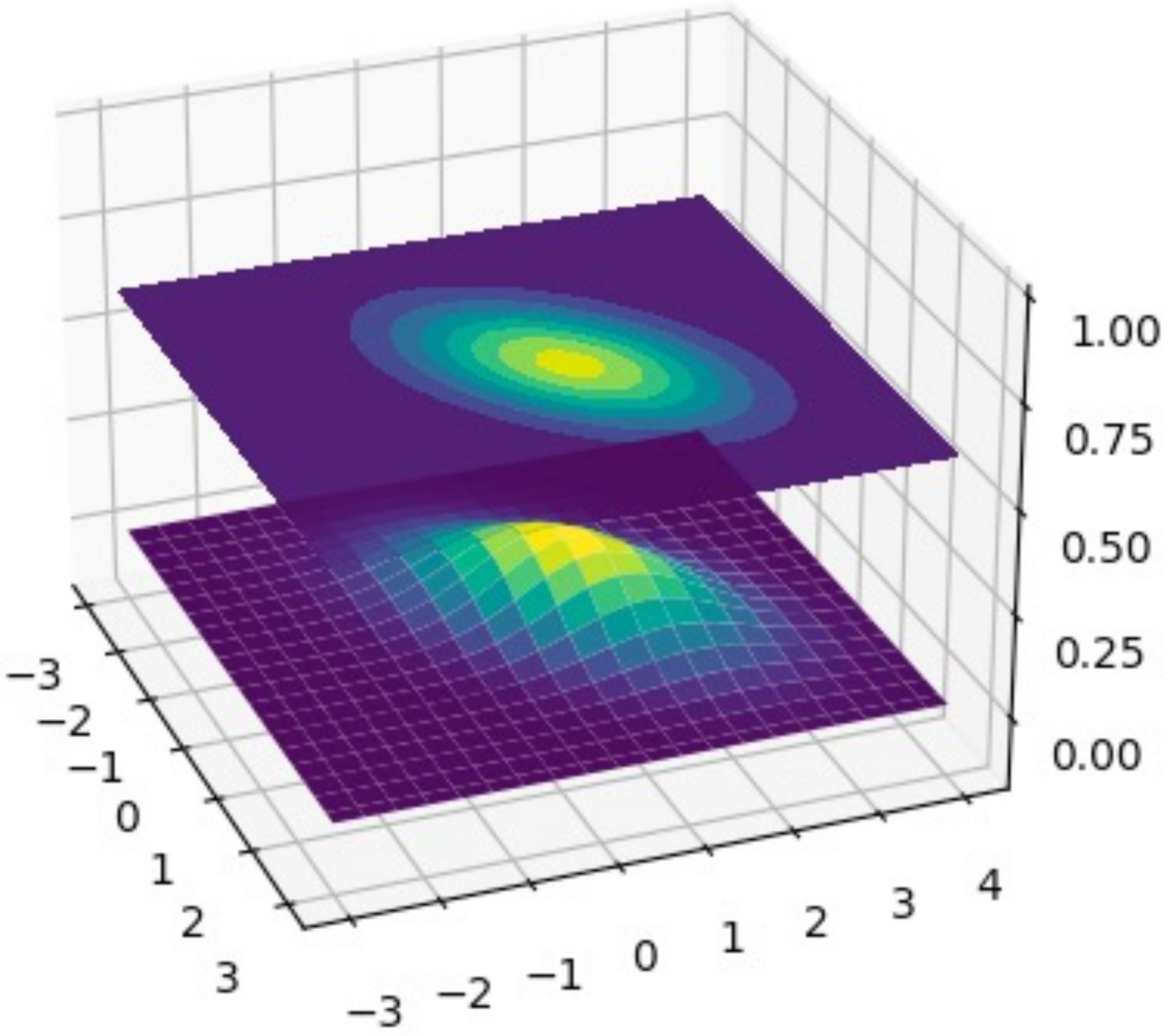
Covariance



$$\cancel{p(\boldsymbol{x};\boldsymbol{\mu},\boldsymbol{\Sigma}) = \frac{1}{\sqrt{(2\pi)^n|\boldsymbol{\Sigma}|}}\exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{\mu})^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})\right),}$$

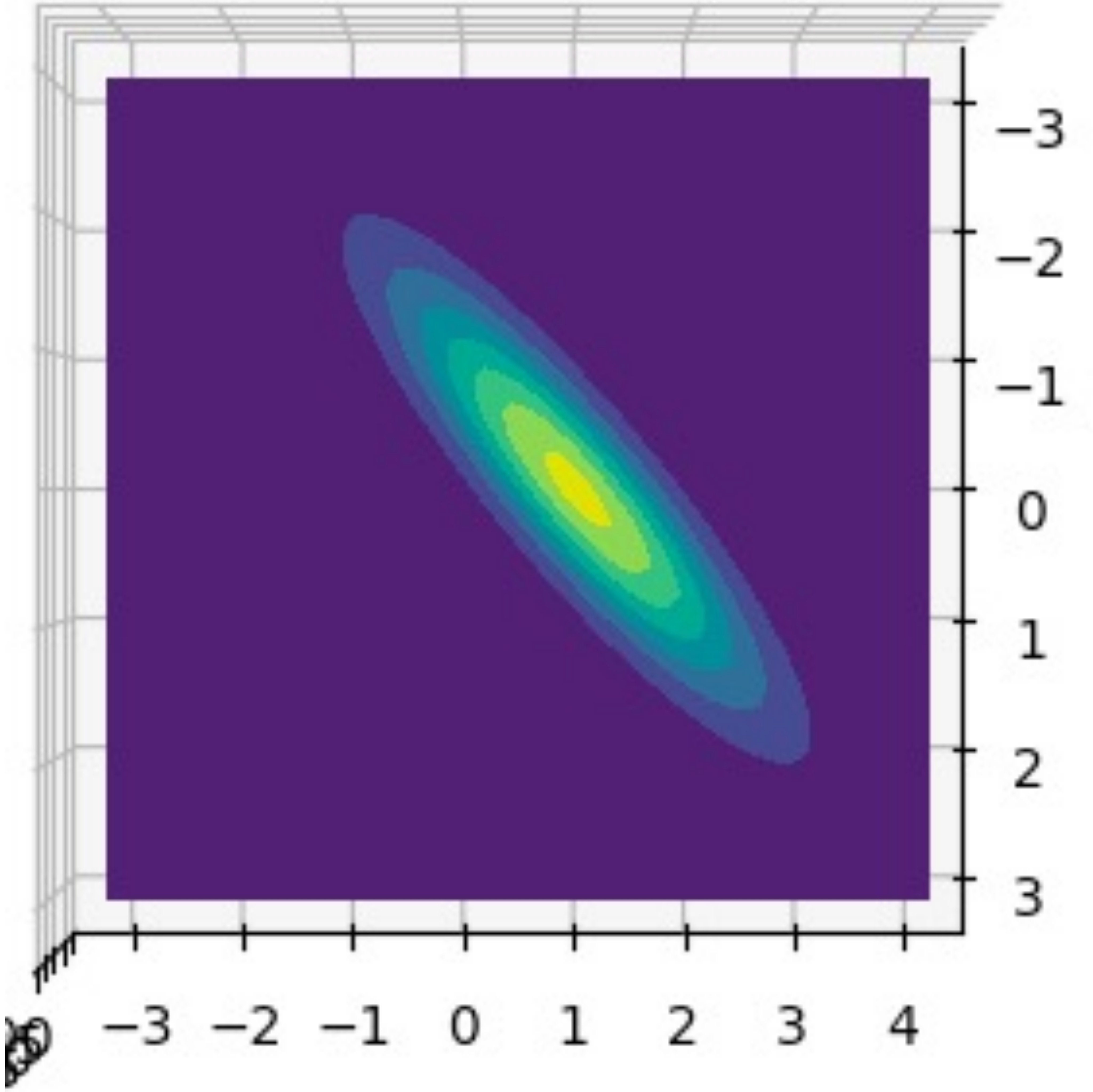
Gaussian in multidimensions: example



$$\mu = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\Sigma^2 = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

Gaussian in multidimensions: example



$$\mu = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

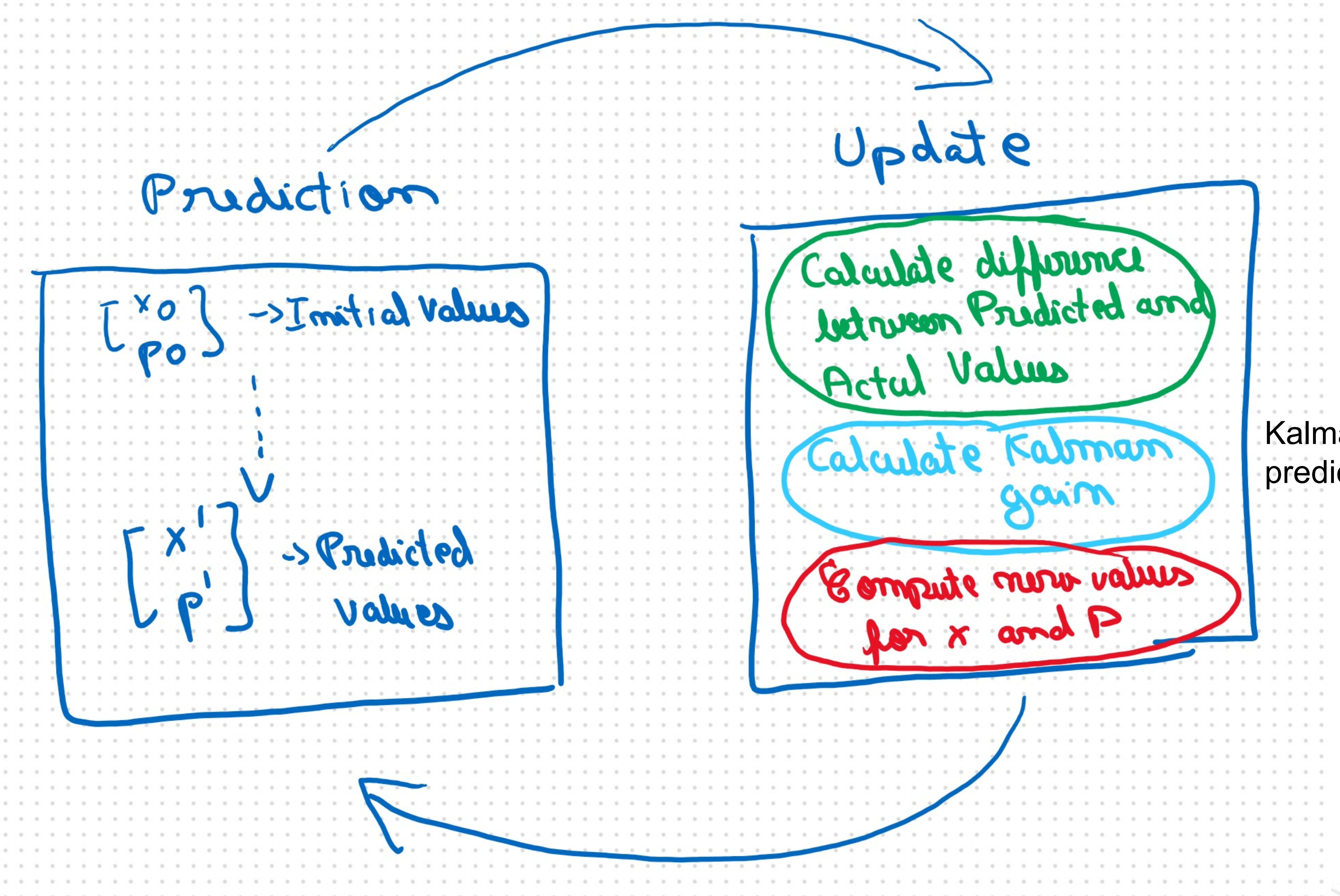
$$\Sigma^2 = \begin{bmatrix} 1 & 0.9 \\ 0.9 & 1 \end{bmatrix}$$

Kalman filter multidimension

Time Update *(prediction)*	**Measurement Update** *(correction)*
$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k$	$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1}$
$P_k^- = A P_{k-1} A^T + Q$	$\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$
	$P_k = (I - K_k H) P_k^-$

References: [39]
See the full list of references on blackboard

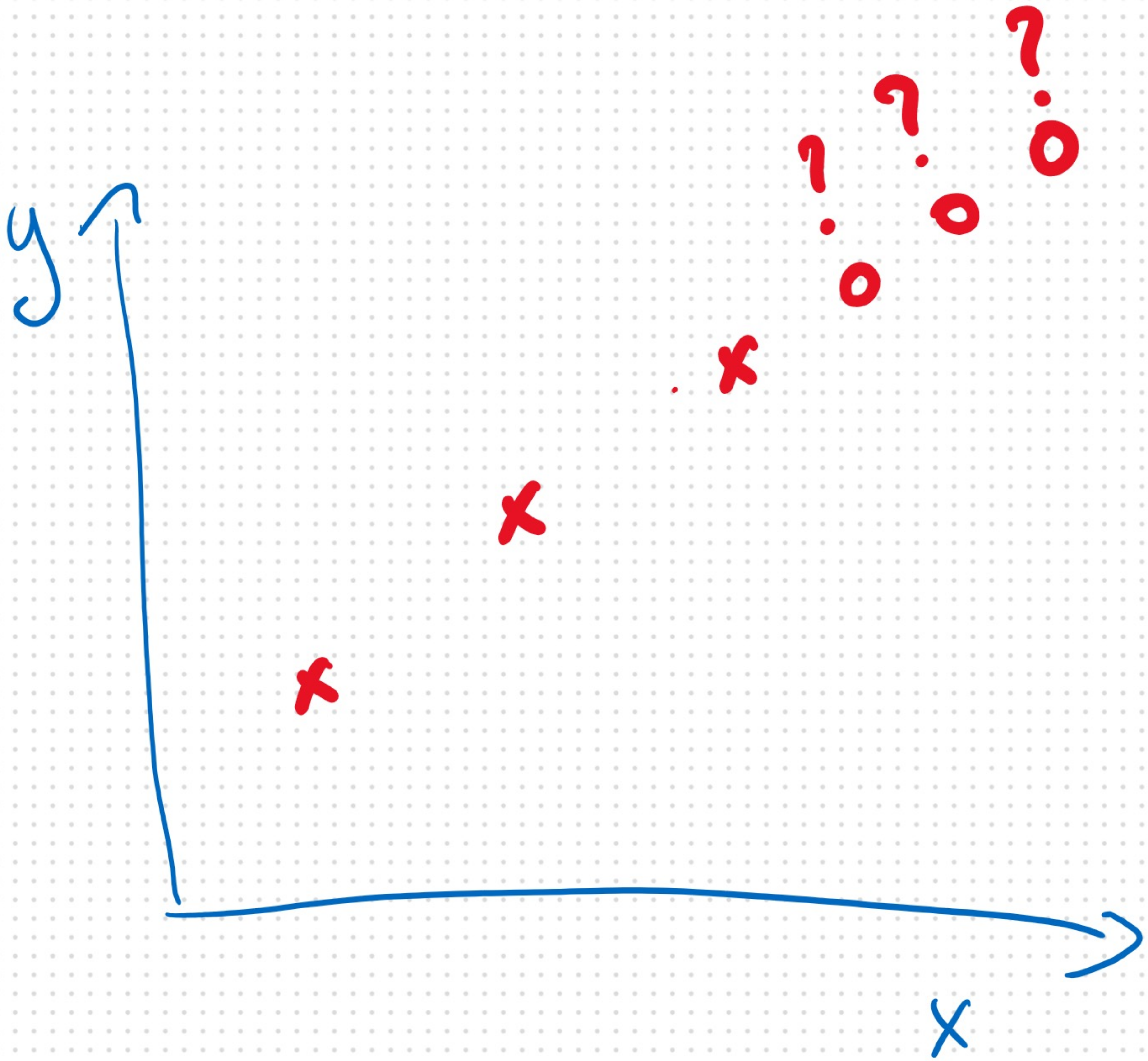
Kalman filter multidimension



Kalman gain = error in prediction / (error in prediction + error in measurement)

References: [39]
See the full list of references on blackboard

Kalman prediction



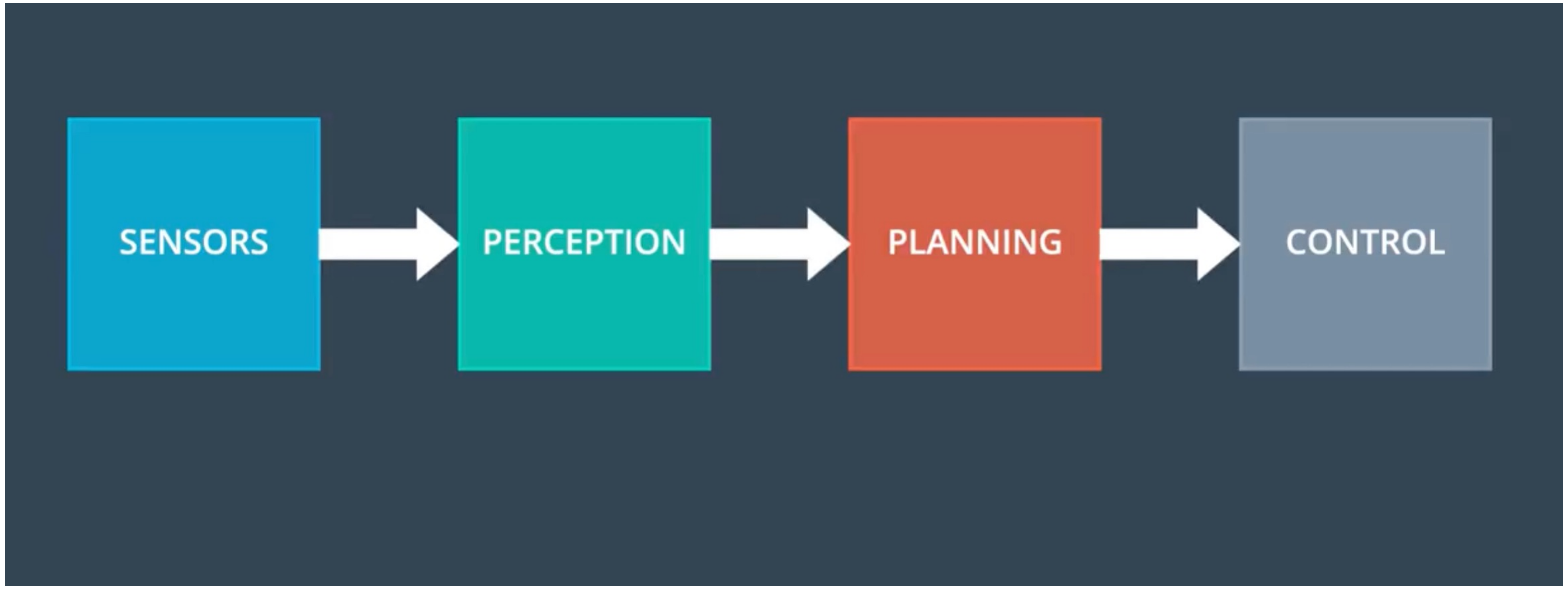
Kalman prediction: car localisation

Radar position estimation – red dots
LIDAR position estimation – blue dots

Position estimate using Kalman filter on sensor data fusion – green dots

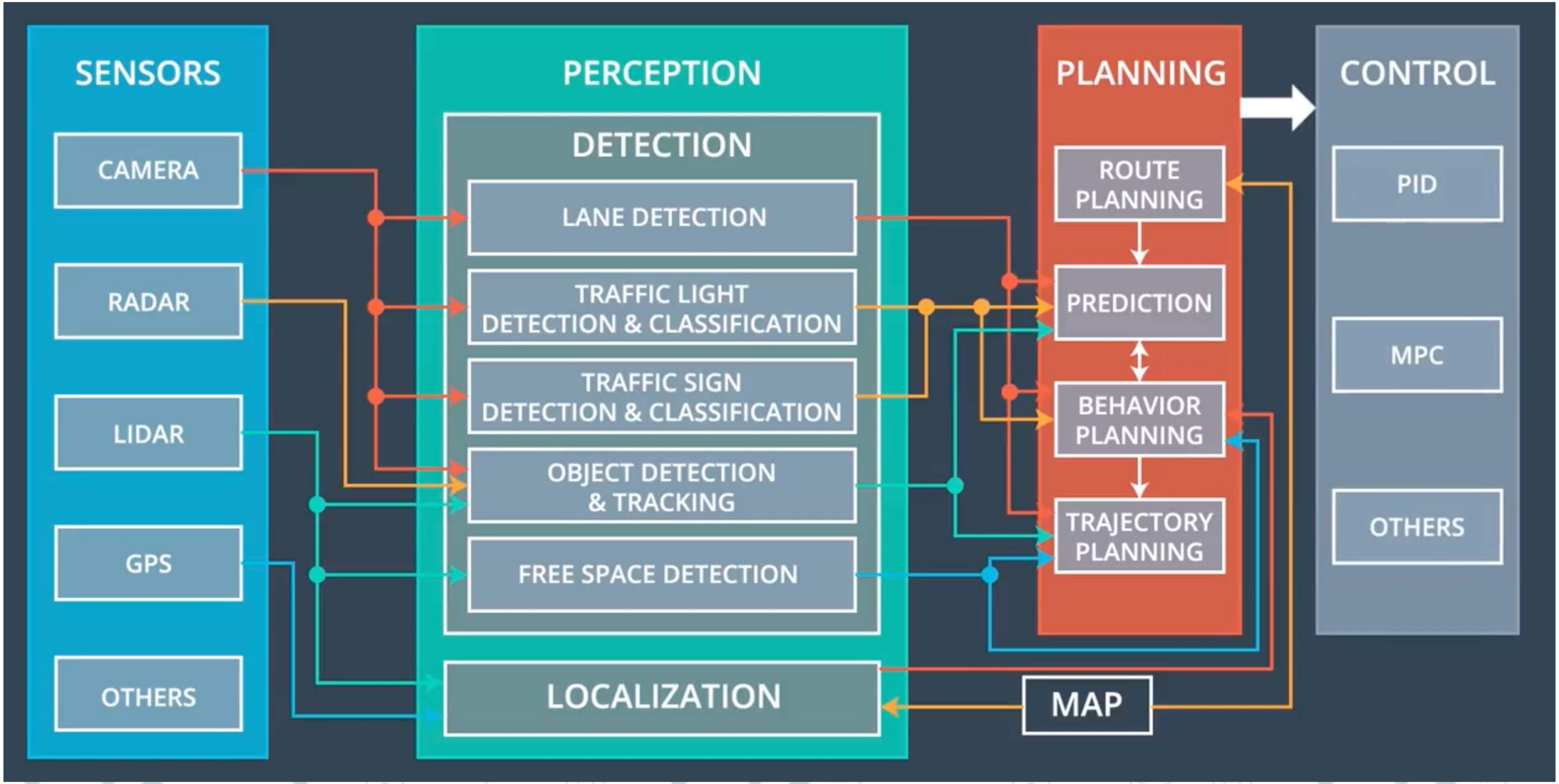
References: [43]
See the full list of references on blackboard

Autonomous car architecture



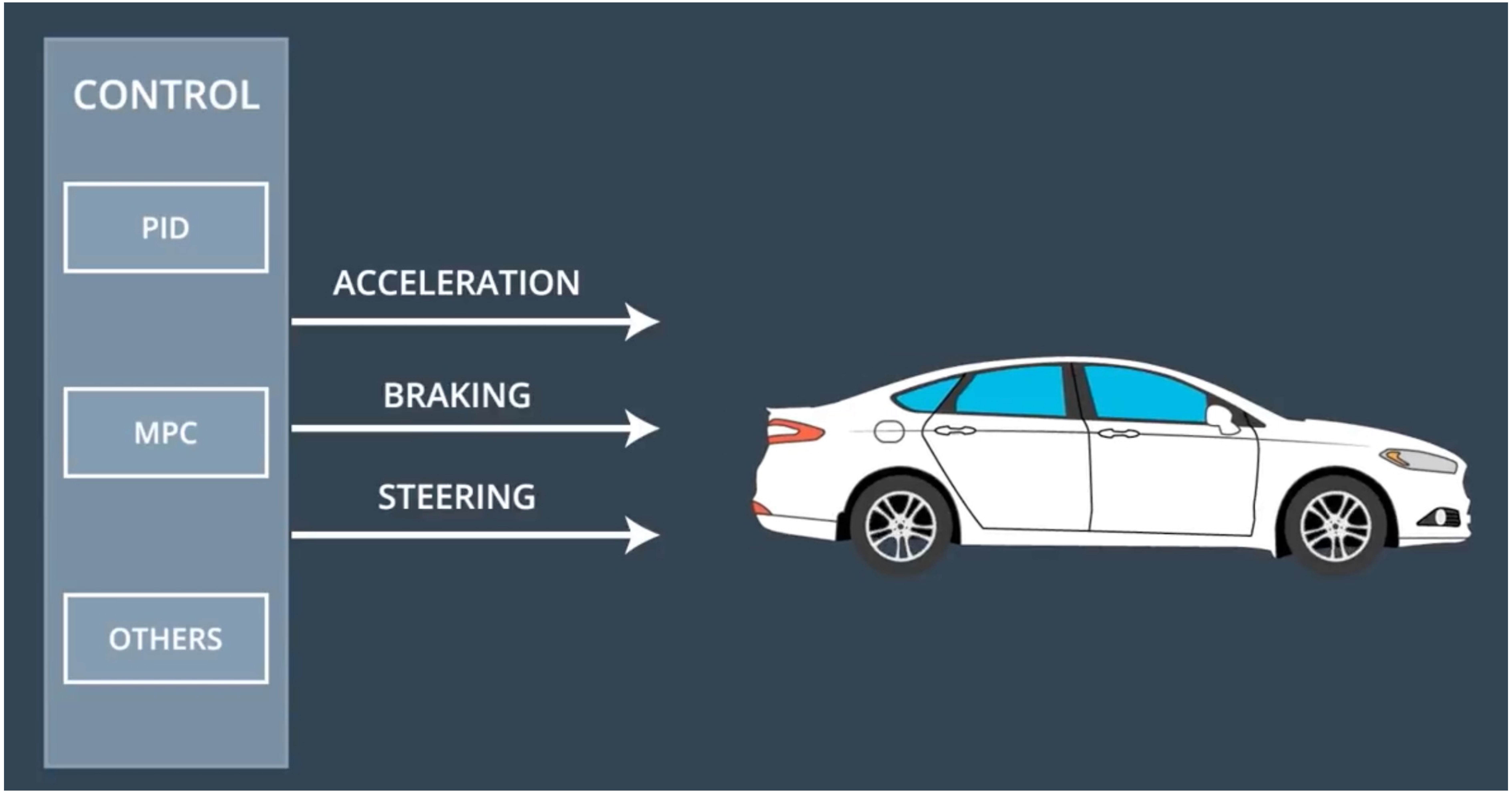
References: [40]
See the full list of references on blackboard

Autonomous car architecture: example



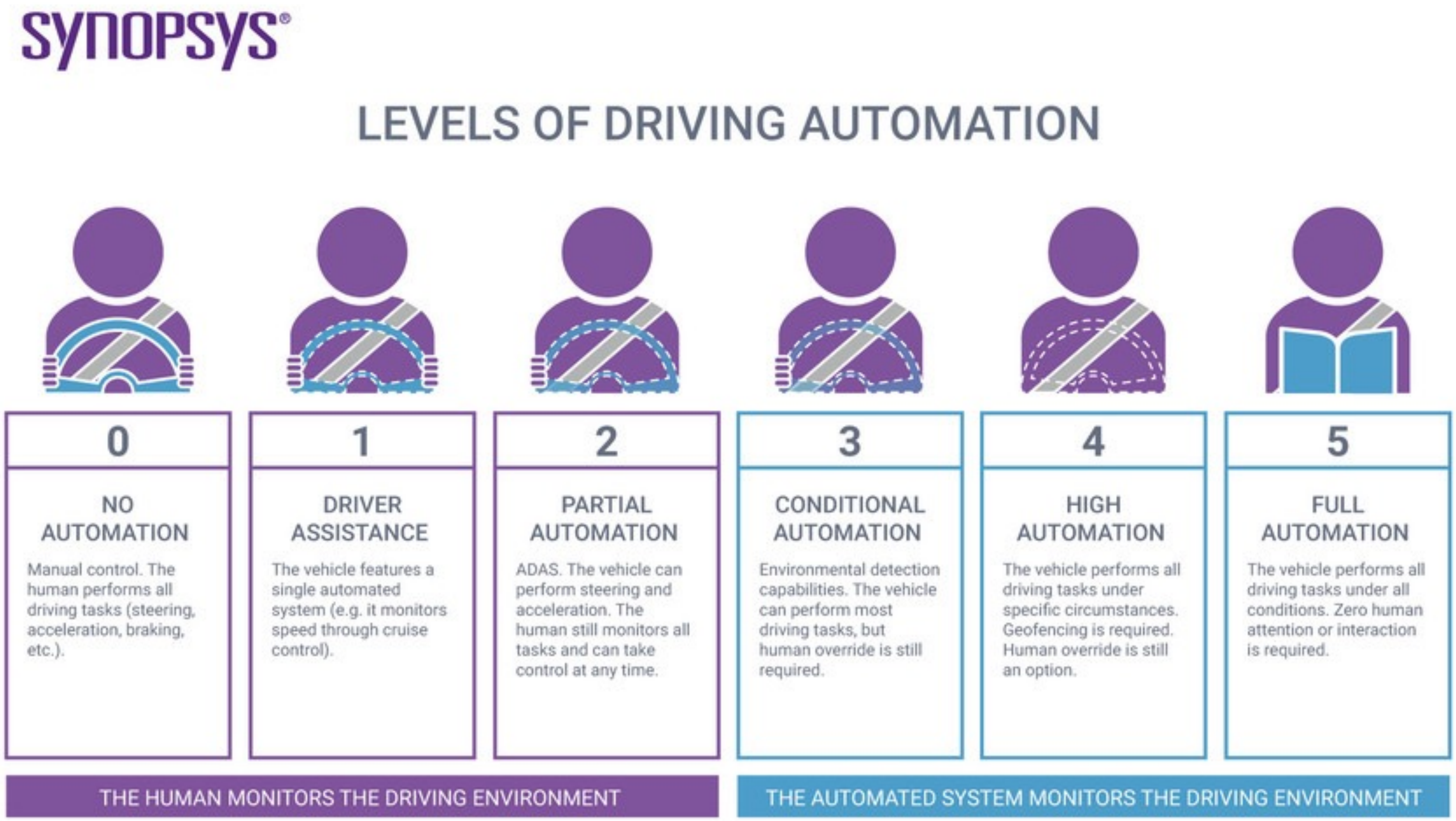
References: [40]
See the full list of references on blackboard

Autonomous car architecture



References: [40]
See the full list of references on blackboard

Mixing humans and automation…



Mixing humans and automation…

References: [24]
See the full list of references on blackboard

Mixing humans and automation…

References: [25]
See the full list of references on blackboard

Mixing humans and automation…

References: [26]
See the full list of references on blackboard

Incidents & Fatalities:

References: [8]
See the full list of references on blackboard

Incidents & Fatalities:

References: [9]
See the full list of references on blackboard

Incidents & Fatalities: Tesla Auto pilot (Level 2 Automation)

Date	City/County	State	Notes/Refs
Jan 22, 2018	Culver City	California	Tesla struck a stationary fire truck on southbound I-405.
May 29, 2018	Laguna Beach	California	Tesla struck a stationary patrol vehicle on Laguna Canyon Road at 11:07 am.
Dec 7, 2019	Norwalk	Connecticut	Tesla struck a stationary police cruiser with its emergency lights flashing on I-95 near exit 15. Driver stated he had been checking on his dog in the back seat.
Dec 29, 2019	Cloverdale	Indiana	Tesla struck a stationary fire truck on I-70 near mile marker 38; passenger in Tesla was killed.
Jan 22, 2020	West Bridgewater	Massachusetts	Tesla struck a stationary patrol vehicle at 10 pm on Route 24. Driver stated that Autopilot was engaged.
Jul 14, 2020	Cochise County	Arizona	Tesla struck a stationary patrol vehicle at 3 am on I-10 near Benson, Arizona.
Aug 26, 2020	Charlotte	North Carolina	Tesla struck a stationary patrol vehicle on I-64W near the border of Nash and Franklin counties. Driver was watching a movie.
Feb 27, 2021	Montgomery County	Texas	Tesla struck a stationary police cruiser at 1:15 am on the Eastex Freeway near East River Road.
Mar 17, 2021	Lansing	Michigan	Tesla struck a stationary patrol car at 1:10 am on I-96 in Eaton County.
May 19, 2021	Miami	Florida	Tesla struck a stationary Florida Department of Transportation road ranger truck at 5:30 am on I-95
Jul 10, 2021	San Diego	California	Tesla struck a stationary patrol car at 1:45 am on State Route 56.
Aug 28, 2021	Orlando	Florida	Tesla struck a stationary patrol car at 5 am on I-4.

References: [7]
See the full list of references on blackboard

Mixing humans and automation…

Shared Autonomy vs Full Autonomy

	Performance Level Required	
	Shared Autonomy	Full Autonomy
Sensor Robustness [2]	Good	Exceptional
Mapping [23]	Good	Exceptional
Localization [17]	Good	Exceptional
Scene Perception [7]	Good	Exceptional
Motion Control [4]	Good	Exceptional
Behavioral Planning [21]	Good	Exceptional
Safe Harbor	Good	Exceptional
External HMI [14]	Good	Exceptional
Teleoperation* [9]	Good	Exceptional
Vehicle-to-Vehicle* [16]	Good	Exceptional
Vehicle-to-Infrastructure* [19]	Good	Exceptional
Driver Sensing [13]	Exceptional	Good
Driver Communication	Exceptional	Good
Driver Collaboration	Exceptional	Good
Personalization	Exceptional	Good

References: [41]
See the full list of references on blackboard

Connected and Autonomous Vehicles: London

London trials

CAVs have attracted investment worldwide and small scale trials are already taking place in London. Many trials are part funded through the Government and others are privately funded.

Previous trials

- DRIVEN (Oxbotica)
- CAPRI (AECOM)
- GATEway (Transport Research Laboratory)
- Nissan (Nissan)
- Streetwise (FiveAI)

Current trials

- Smart Mobility Living Lab London (Transport Research Laboratory)
- Wayve (Wayve)
- Endeavour (Oxbotica)
- ServeCity (Nissan)
- Kar-Go (Academy of Robotics)

References: [42]
See the full list of references on blackboard

Thank you!