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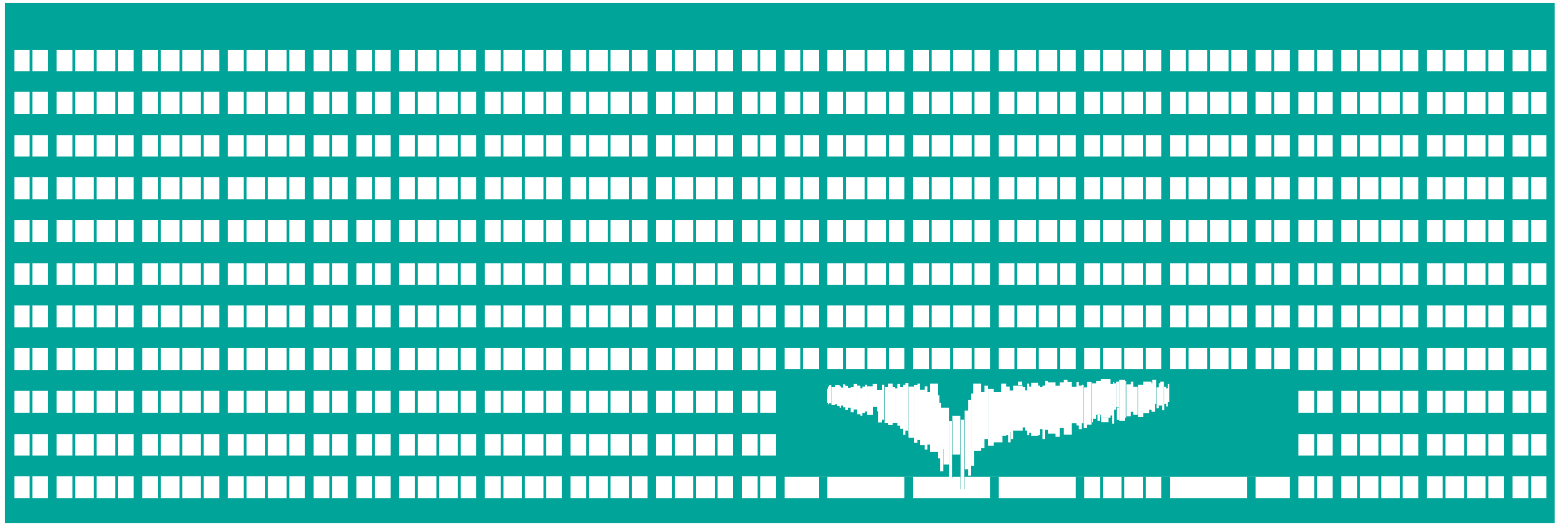


www.vsb.cz

What Is AV (Autonomous Vehicle)?

A **self-driving car**, **also known** as an **autonomous vehicle** (AV), connected and autonomous vehicle (CAV), driverless car, robo-car, or robotic car, is a vehicle that is capable of sensing its environment and moving safely with little or no human input. (Wikipedia)

A Waymo self-driving car. *Wikipedia* [online]. [cit. 2020-01-25]. Dostupné z: https://upload.wikimedia.org/wikipedia/commons/c/cf/Waymo_self-driving_car_front_view.gk.jpg

What Is AV (Autonomous Vehicle)?

https://www.youtube.com/watch?v=FDuvPOYYTY4

What Tesla See

https://www.youtube.com/watch?v=zRnSmw1i_DQ

What Is AV (Autonomous Vehicle)?

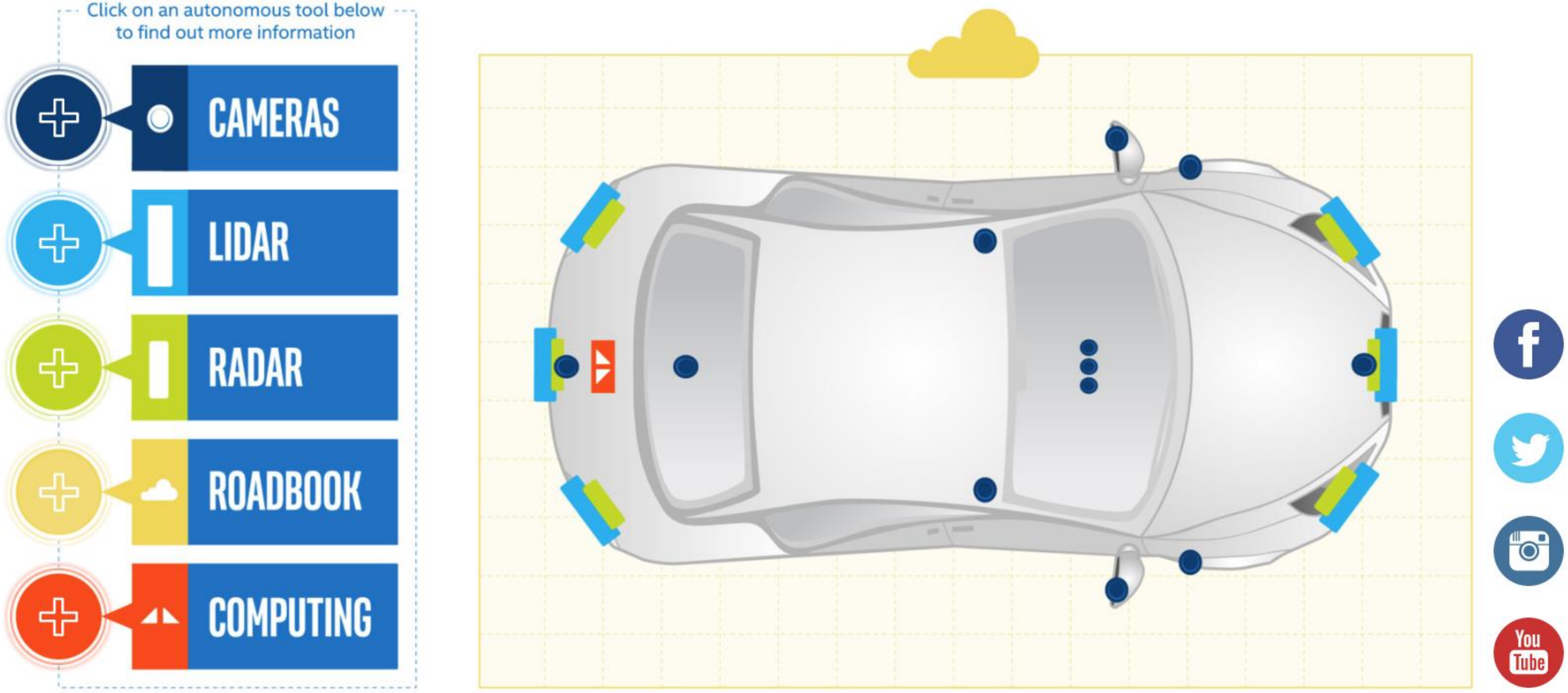
- Ground vehicles
- Autonomous aerial vehicles (drone)
- Autonomous surface vehicles

An MQ-9 Reaper unmanned aerial vehicle

An MQ-9 Reaper. *Wikipedia* [online]. [cit. 2020-01-25]. Dostupné z: https://en.wikipedia.org/wiki/File:MQ-9_Reaper_UAV_(cropped).jpg

AUTONOMOUS VEHICLE PLATFORM

The sensors, hardware and software provided by **Intel** and **Mobileye** give autonomous vehicles their ability to recognize the environment around them. This technology creates the building blocks for autonomous vehicles (AV) and includes a suite of cameras, lidar, radar, and computing and mapping technologies.



Intel Explainer: Sensors. *Businesswire* [online]. [cit. 2020-01-25]. Dostupné z: https://www.businesswire.com/news/home/20180816005108/en/Intel-Explainer-Sensors-%E2%80%93-Eyes-Ears-Autonomous https://www.youtube.com/watch?v=x7_GRigShUM


- Cameras
- Lidars
- Radars
- Maps

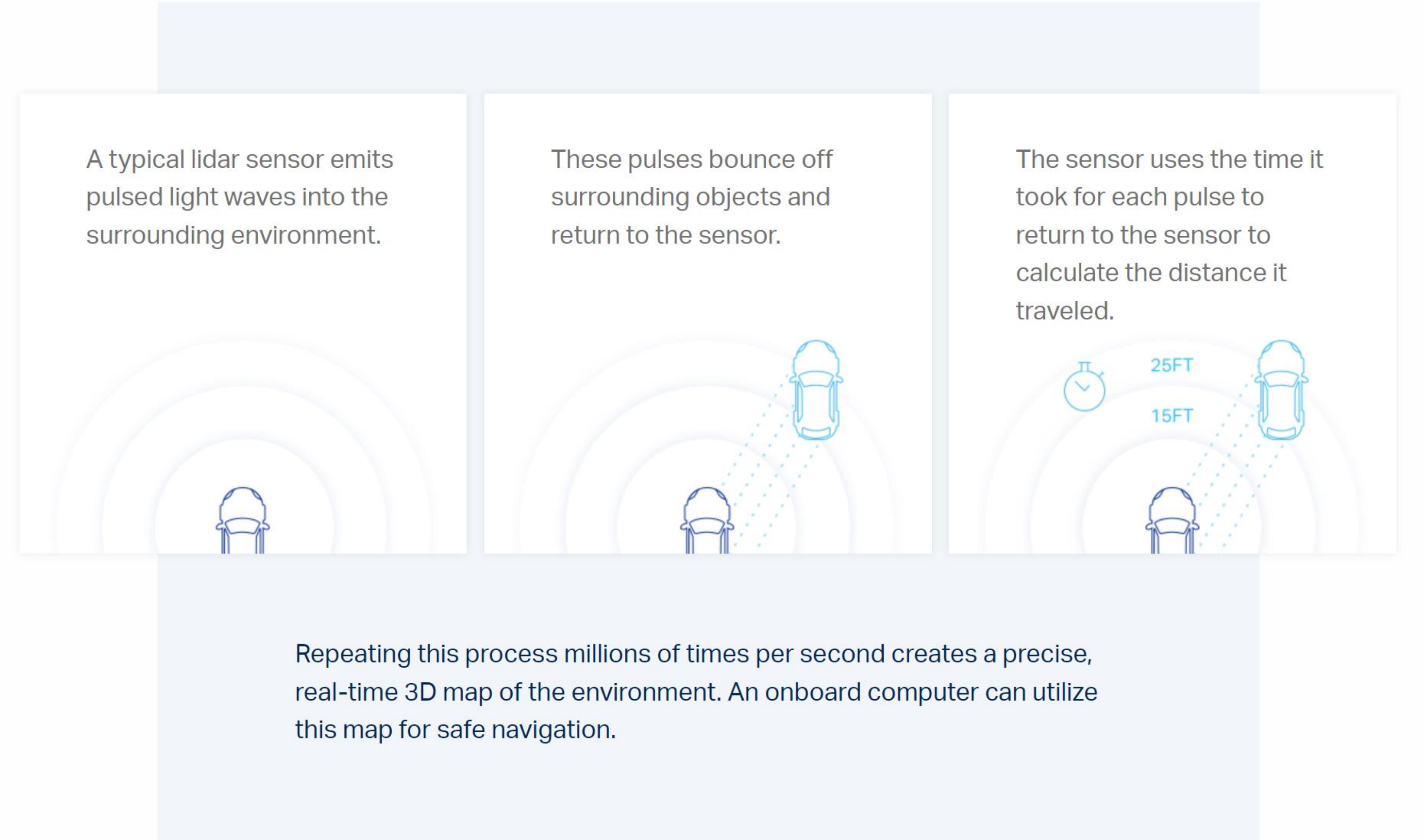
Puck Lidar Sensor. *Velodynelidar* [online]. [cit. 2020-01-25]. Dostupné z: https://eak2mvmpt4a.exactdn.com/wp-content/uploads/2019/08/Velodyne_Puck600.png?strip=all&lossy=1&ssl=1

Intel® RealSense™ Technology. *Intel* [online]. [cit. 2021-01-25]. Dostupné z: https://www.intel.com/content/www/us/en/architecture-and-technology/realsense-overview.html

https://velodynelidar.com/products/puck/

What is Lidar?

Lidar (“light detection and ranging”) uses eye-safe laser beams to “see” the world in 3D, providing machines and computers an accurate representation of the surveyed environment.

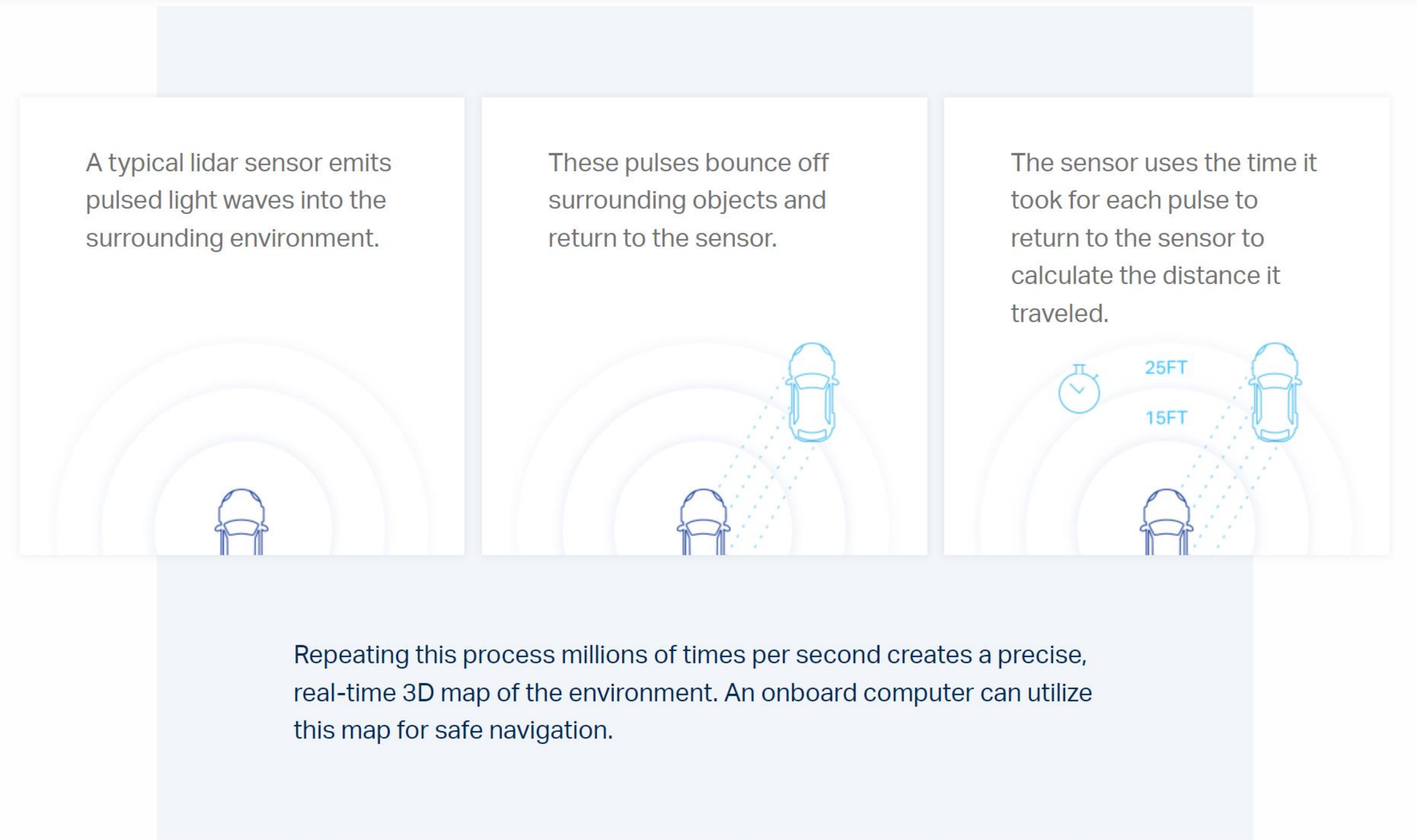


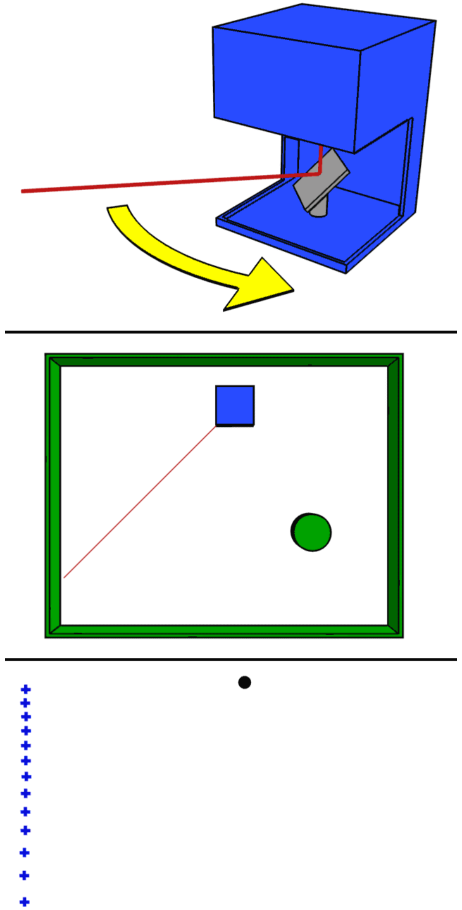
https://velodynelidar.com/what-is-lidar/

https://velodynelidar.com/products/puck/

What is Lidar?

Lidar ("light detection and ranging") uses eye-safe laser beams to "see" the world in 3D, providing machines and computers an accurate representation of the surveyed environment.





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Lidars

https://velodynelidar.com/what-is-lidar/

https://velodynelidar.com/products/puck/

Lidars

https://www.youtube.com/channel/UCKyHFNyJ3QV-1rjogCYHkRA

https://velodynelidar.com/products/puck/

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Lidars

https://www.youtube.com/c/ANYbotics/videos

https://velodynelidar.com/products/puck/

Lidars vs. Cameras

Tesla CEO Elon Musk: "Anyone relying on LiDAR is doomed"

https://www.youtube.com/watch?v=HM23sjhtk4Q

Lidars vs. Cameras

https://youtu.be/HLczErXDujI

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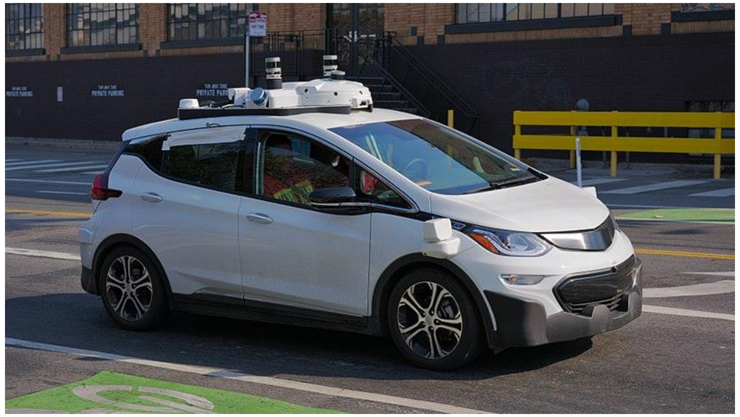
Lidar vs Camera

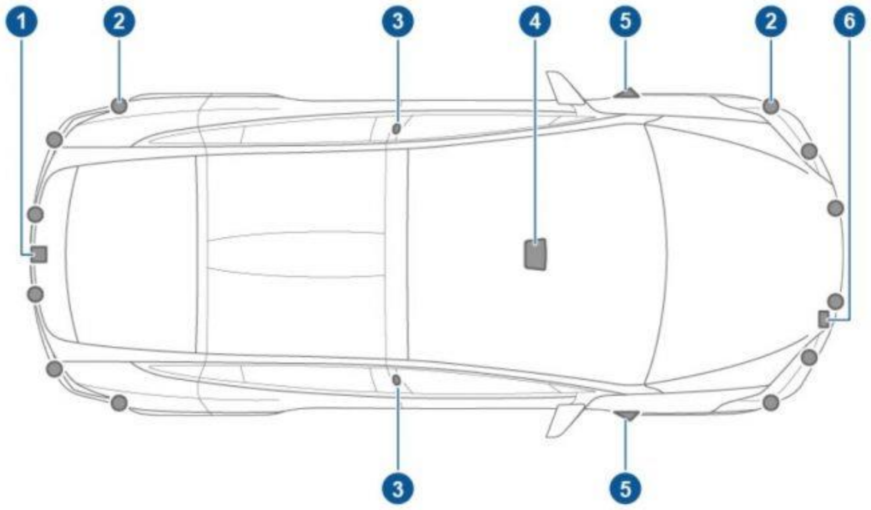
LiDAR

- cannot detect colors
- cannot interpret the text
- Impossible to identify traffic lights or road signs
- can achieve good results day and night
- high level of accuracy
- is more expensive
- requires more space
- gives self-driving cars a three-dimensional image



Camera

- can recognize colors and read road signs
- many modern AI methods to identify objects or distances
- require significantly more computing power
- camera systems are almost invisible
- challenging low-light conditions

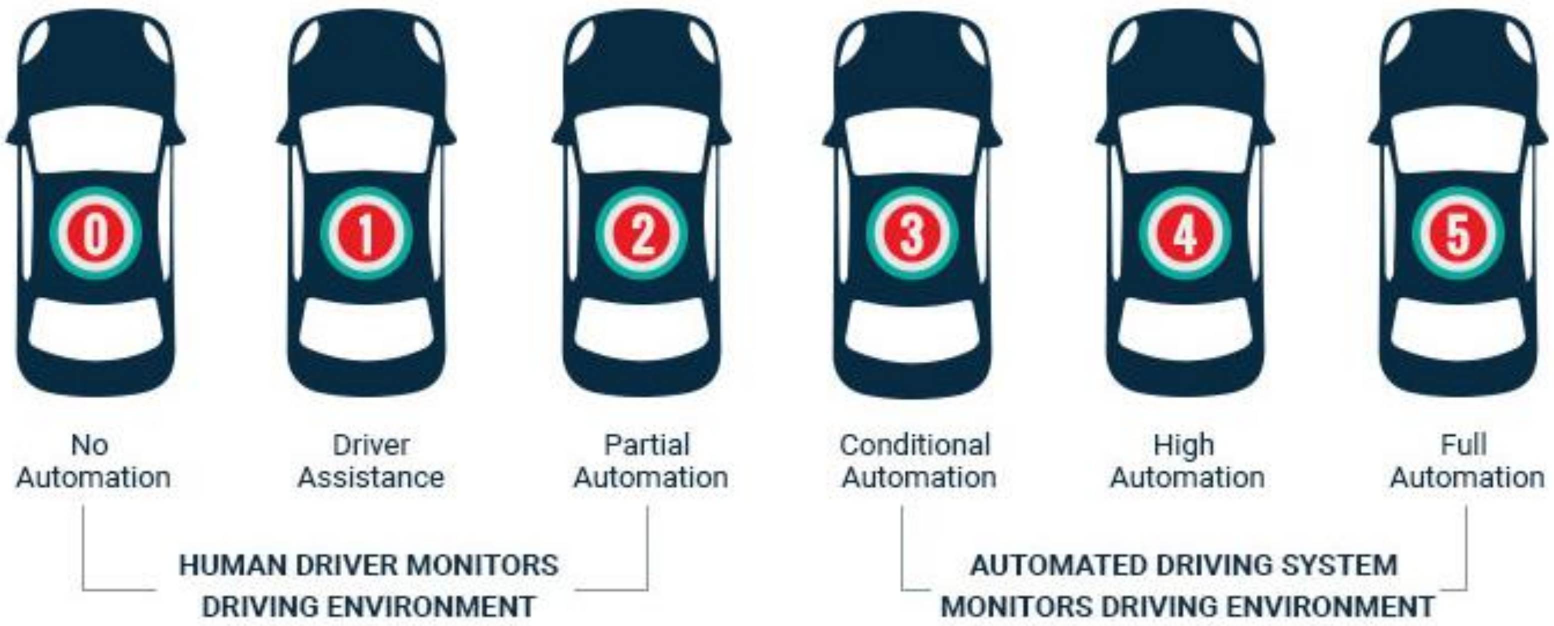


1. A camera is mounted above the rear license plate.
2. Ultrasonic sensors are located in the front and rear bumpers.
3. A camera is mounted in each door pillar.
4. Three cameras are mounted to the windshield above the rear view mirror.
5. A camera is mounted to each front fender.
6. Radar is mounted behind the front bumper on the right side of the vehicle.

Model X is also equipped with high precision electrically-assisted braking and steering systems.

https://www.autopilotreview.com/lidar-vs-cameras-self-driving-cars/
https://medium.com/0xmachina/lidar-vs-camera-which-is-the-best-for-self-driving-cars-9335b684f8d
https://leddartech.com/lidar-radar-camera-demystifying-adas-ad-technology-mix/

Levels of Autonomous Cars



Levels of autonomous cars [online]. [cit. 2020-01-25]. Dostupné z: https://geospatialmedia.s3.amazonaws.com/wp-content/uploads/2018/02/bi-graphics_autonomous-cars.png

Levels of Autonomous Cars

https://www.businessinsider.com/what-are-the-different-levels-of-driverless-cars-2016-10

Zero autonomy; the driver performs all the driving, but the vehicle can aid with blind spot detection, forward collision warnings and lane departure warnings.

https://newsroom.intel.com/news/autonomous-driving-hands-wheel-no-wheel-all

Levels of Autonomous Cars

The vehicle may have some active driving assist features, but the driver is still in charge. Such assist features available in today’s vehicles include adaptive cruise control, automatic emergency braking and lane keeping.

https://newsroom.intel.com/news/autonomous-driving-hands-wheel-no-wheel-all

https://www.businessinsider.com/what-are-the-different-levels-of-driverless-cars-2016-10

Levels of Autonomous Cars

The driver still must be alert and monitor the environment at all times, but driving assist features that control acceleration, braking and steering may work together in unison so the driver does not need to provide any input in certain situations. Such automated functions available today include self-parking and traffic jam assist (stop-and-go traffic driving).
https://newsroom.intel.com/news/autonomous-driving-hands-wheel-no-wheel-all

https://www.businessinsider.com/what-are-the-different-levels-of-driverless-cars-2016-10

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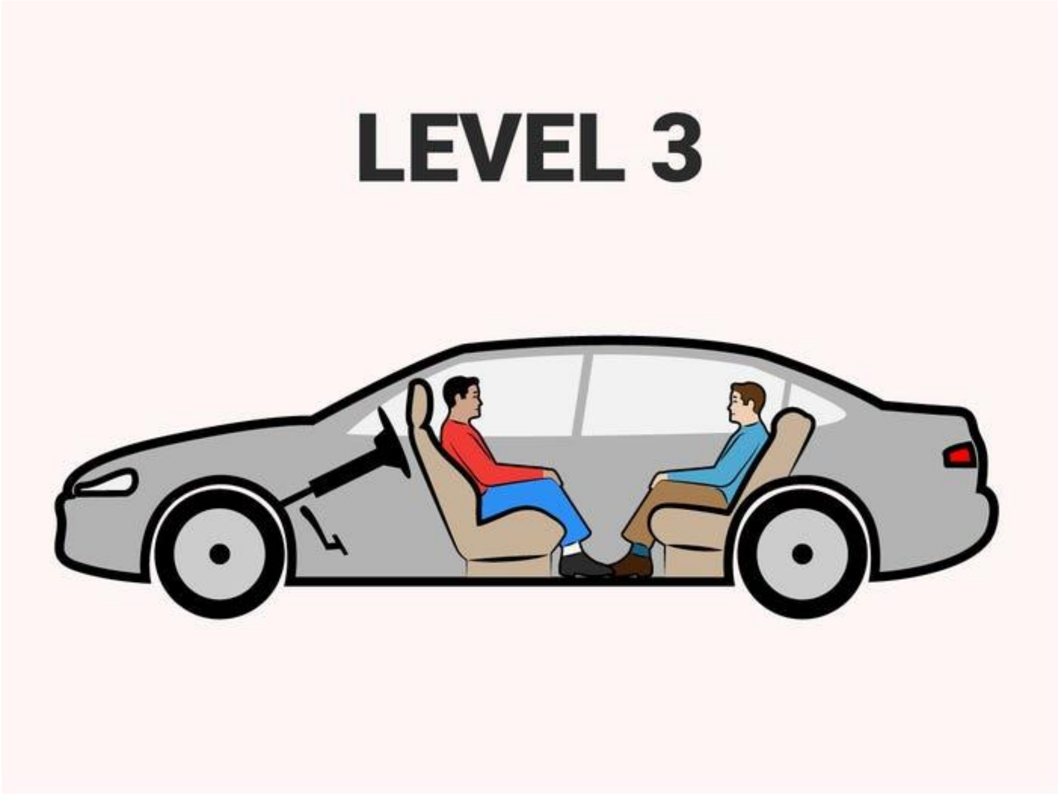
Levels of Autonomous Cars

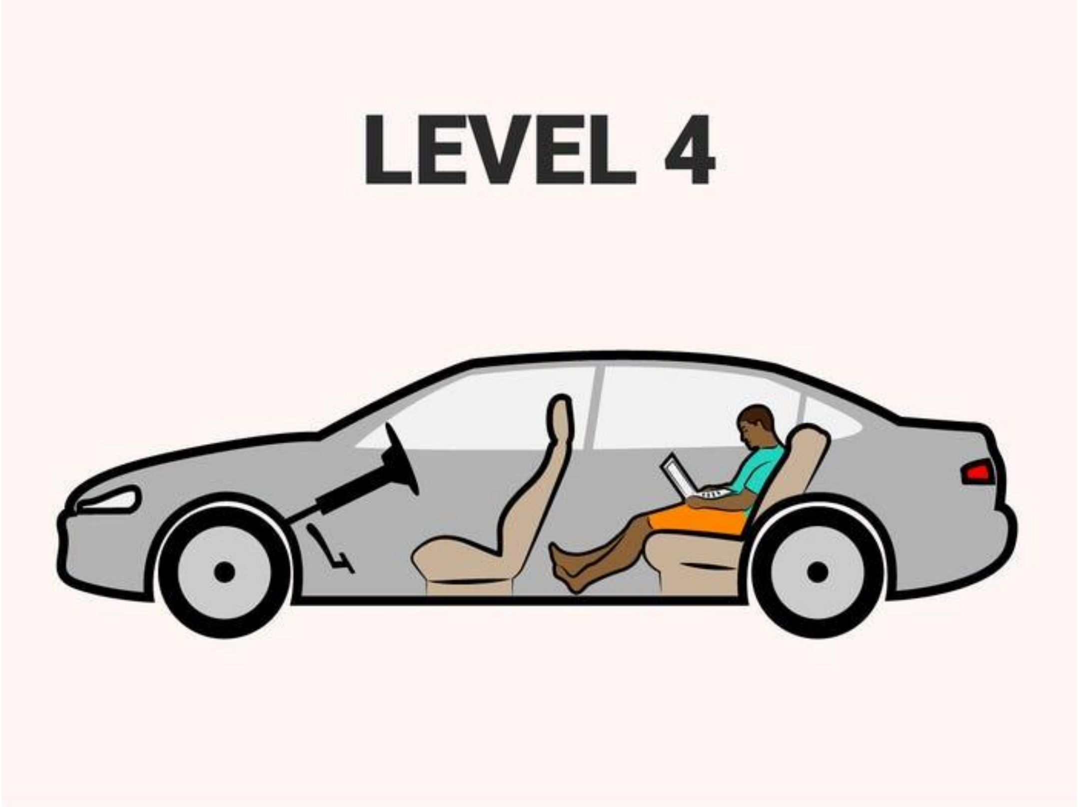
https://www.businessinsider.com/what-are-the-different-levels-of-driverless-cars-2016-10



The vehicle can itself perform all aspects of the driving task under some circumstances, but the human driver must always be ready to take control at all times within a specified notice period. In all other circumstances, the human performs the driving.

https://newsroom.intel.com/news/autonomous-driving-hands-wheel-no-wheel-all

Levels of Autonomous Cars



This is a self-driving vehicle. But it still has a driver's seat and all the regular controls. Though the vehicle can drive and "see" all on its own, circumstances such as geographic area, road conditions or local laws might require the person in the driver's seat to take over.

https://newsroom.intel.com/news/autonomous-driving-hands-wheel-no-wheel-all

https://www.businessinsider.com/what-are-the-different-levels-of-driverless-cars-2016-10

Levels of Autonomous Cars

The vehicle is capable of performing all driving functions under all environmental conditions and can operate without humans inside. The human occupants are passengers and need never be involved in driving. A steering wheel is optional in this vehicle.

https://newsroom.intel.com/news/autonomous-driving-hands-wheel-no-wheel-all

https://www.businessinsider.com/what-are-the-different-levels-of-driverless-cars-2016-10

Levels of Autonomous Cars in 2022 ???

"Mercedes-Benz is expected to launch the first mass-production **Level 3** car in 2022 using its Drive Pilot technology."

"BMW is widely expected to roll out **Level 3** technology in the new 7 Series"

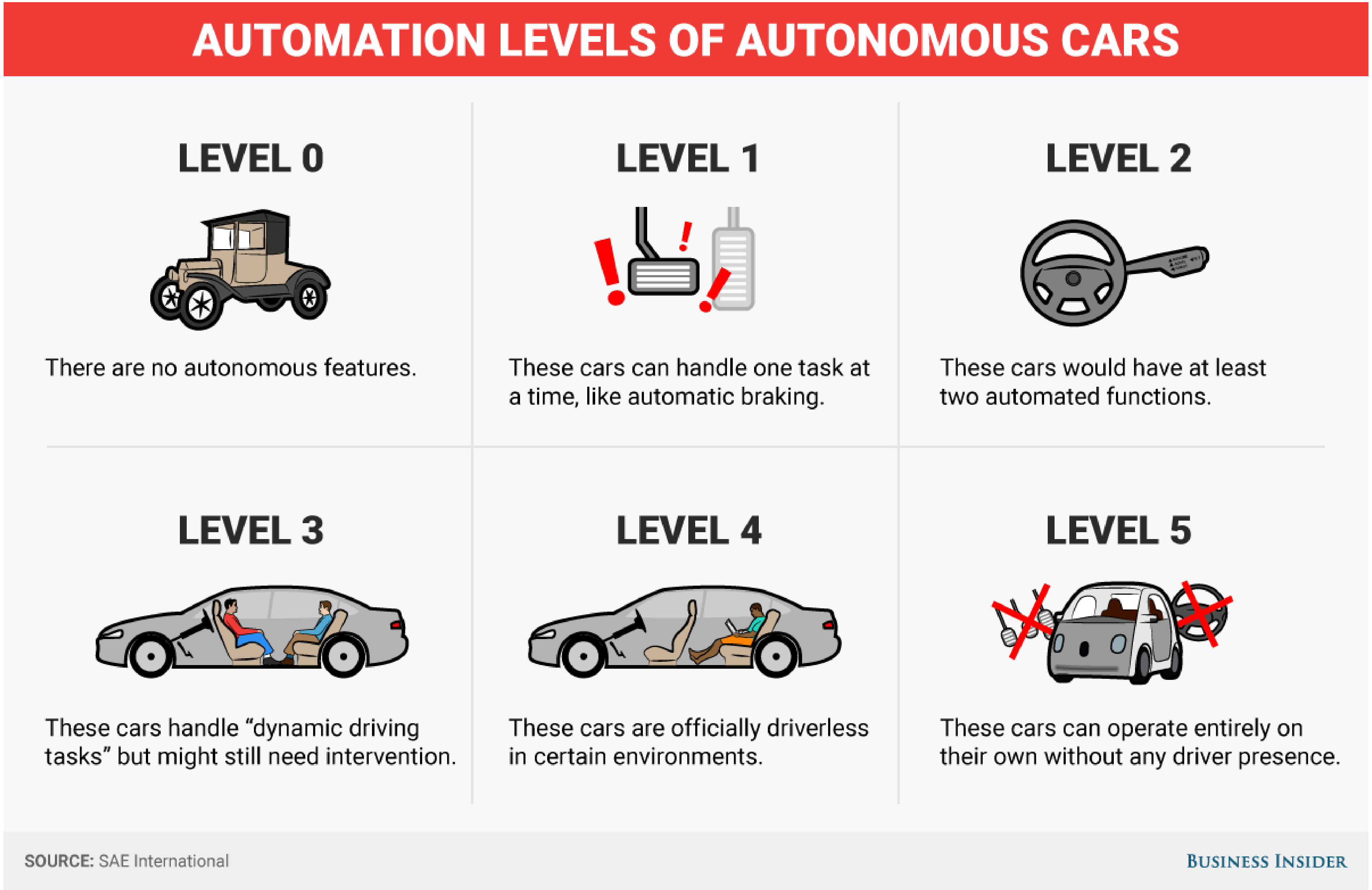
"Alphabet's Waymo recently unveiled a **Level 4** self-driving taxi service in Arizona, where they had been testing driverless cars—without a safety driver in the seat—for more than a year and over 10 million miles.."

"Tesla is likely to achieve **Level 4** autonomy in 2022, says Elon Musk, when certain milestones in the development of full self-driving (FSD) are achieved. The data show that Tesla's system performs better than a human driver for preventing accidents."

https://www.cnet.com/roadshow/news/the-most-important-self-driving-cars-of-2022/

https://www.tesmanian.com/blogs/tesmanian-blog/tesla-likely-to-achieve-level-4-autonomy-in-2022-says-elon-musk

https://www.synopsys.com/automotive/autonomous-driving-levels.html



Levels of autonomous cars [online]. [cit. 2020-01-25]. Dostupné z: https://geospatialmedia.s3.amazonaws.com/wp-content/uploads/2018/02/bi-graphics_autonomous-cars.png

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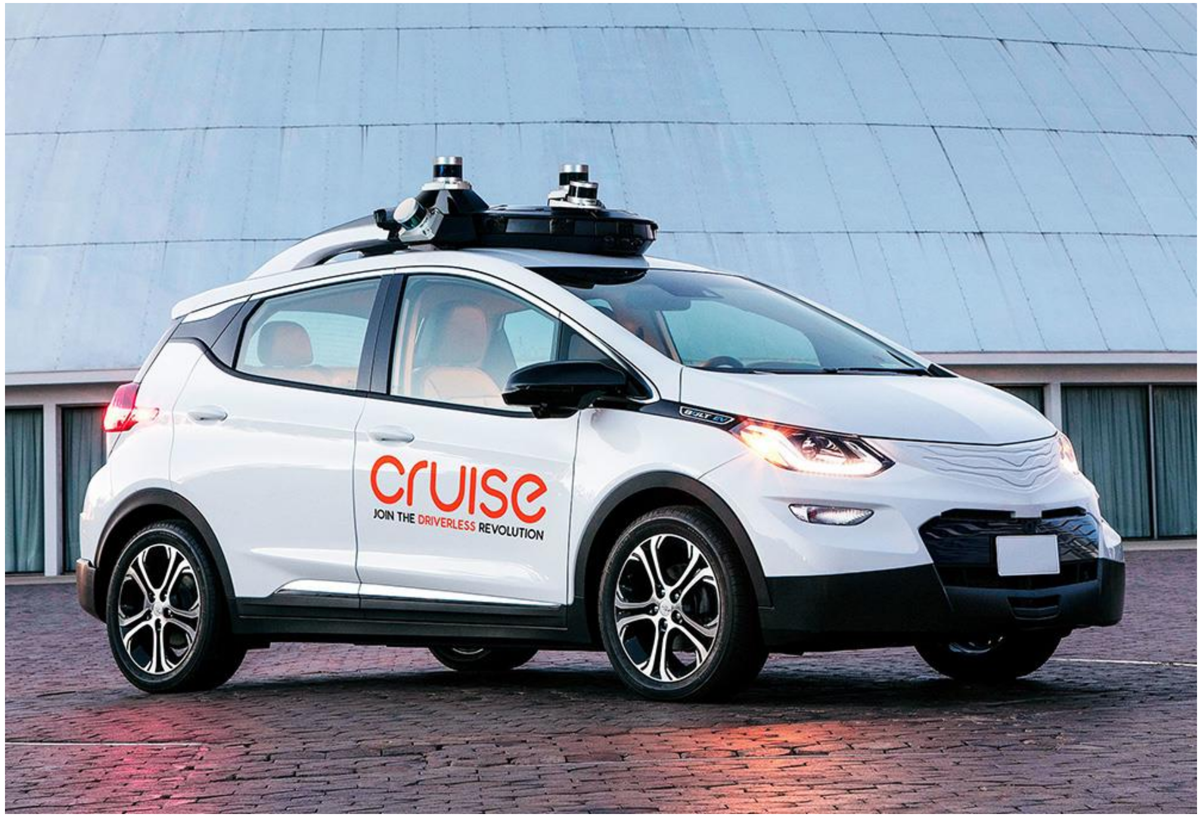
Company Scores (2019)

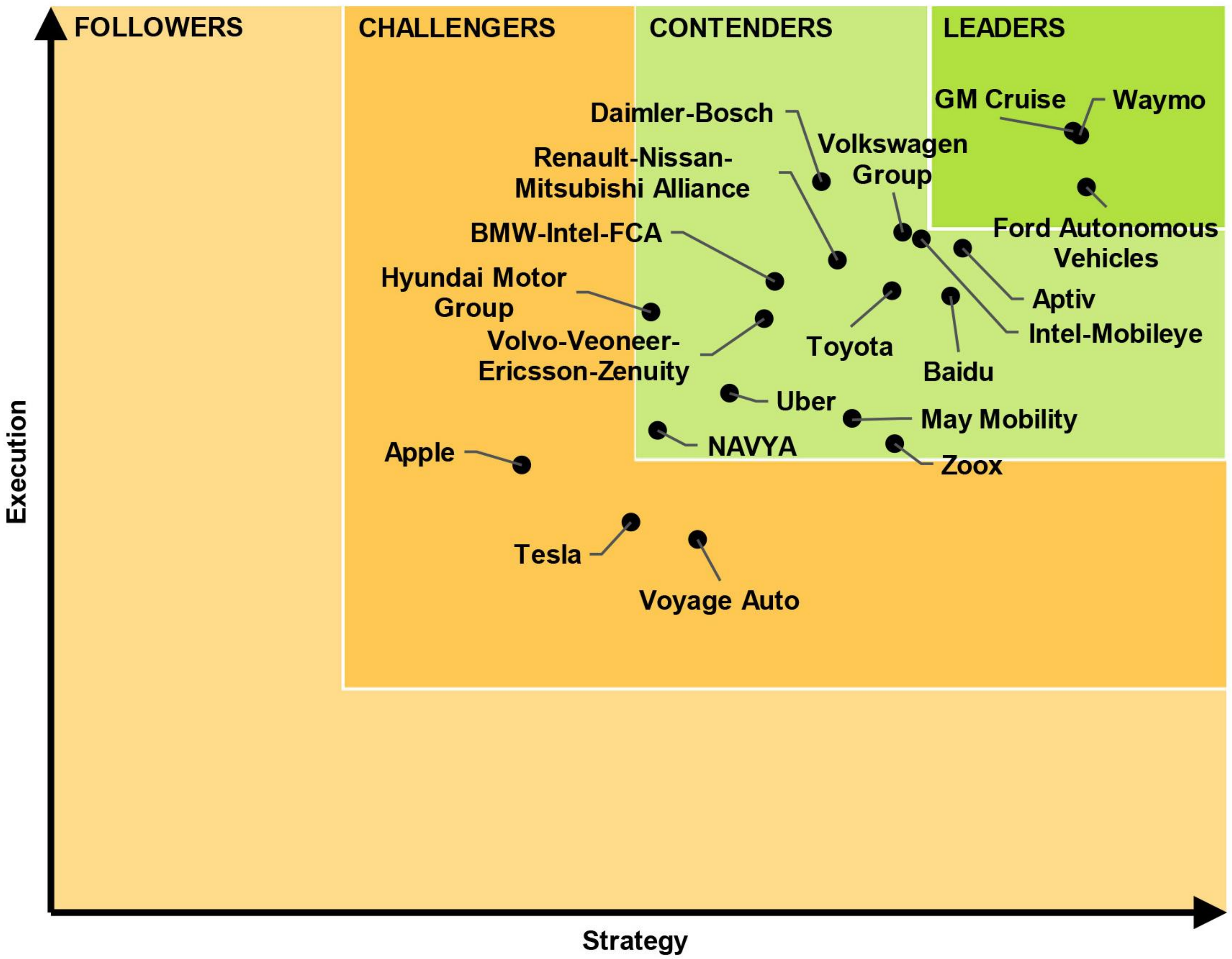
- Waymo (Google)
- GM
- Ford



Automated Driving Leaderboard. *Sae* [online]. [cit. 2020-01-25]. Dostupné z: https://www.sae.org/news/2019/03/2019-navigant-autonomous-leaderboard

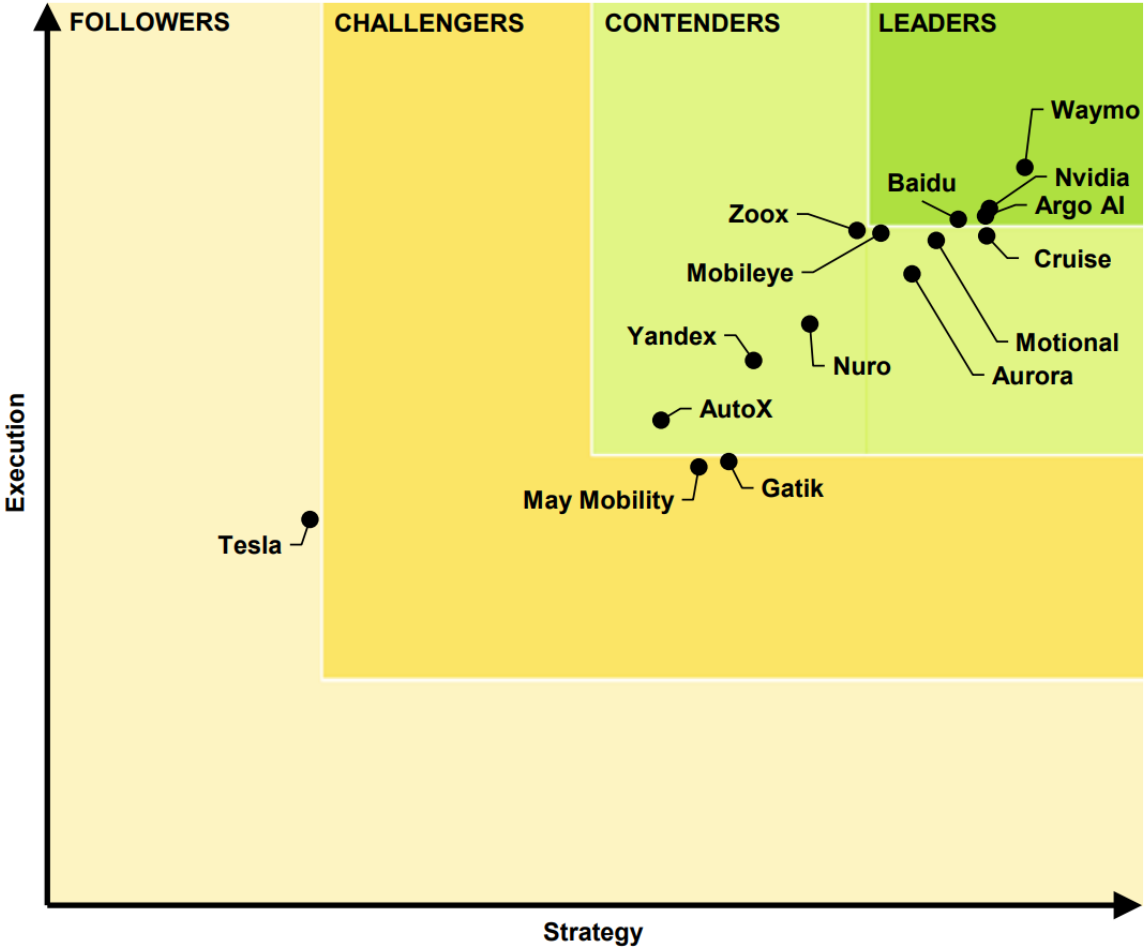
Company Scores (2019)

The Navigant Research Leaderboard Grid



Automated Driving Leaderboard. *Sae* [online]. [cit. 2020-01-25]. Dostupné z: https://www.sae.org/news/2019/03/2019-navigant-autonomous-leaderboard

Company Scores (2020)



(Source: Guidehouse Insights)

Chart 1-1 shows the ranking of each company. This year, four companies had scores that earned a place in the Leaders group: Waymo, Nvidia, Argo AI, and Baidu. Several others, including Cruise, Motional, Mobileye, Zoox, and Aurora, fell just outside of this group among the eight companies in the Contenders group. Notably, Tesla continues to rank at the bottom of this list despite getting significant press attention for its full self-driving (FSD) beta software release. Although several of the companies ranked this year have close affiliations with automakers, Tesla is the only automaker on the list and has made marketing FSD a key feature in selling vehicles. Tesla has made significant progress in strengthening several areas including staying power thanks to the runup in its stock price in the second half of 2020, but its technology is still lacking.

Guidehouse Insights Leaderboard report. *Guidehouseinsights* [online]. [cit. 2022-02-25]. Dostupné z: https://guidehouseinsights.com/reports/guidehouse-insights-leaderboard-automated-driving-systems

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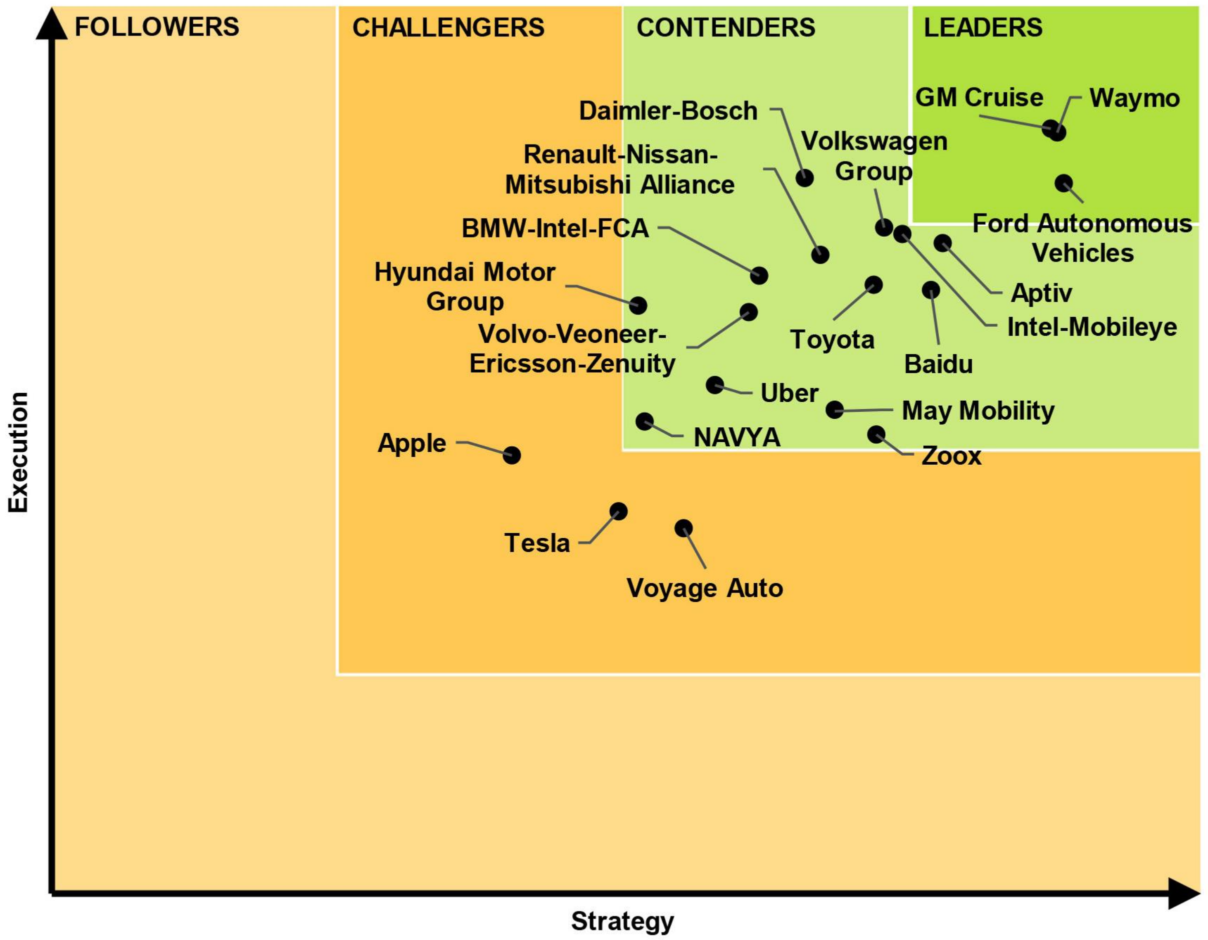
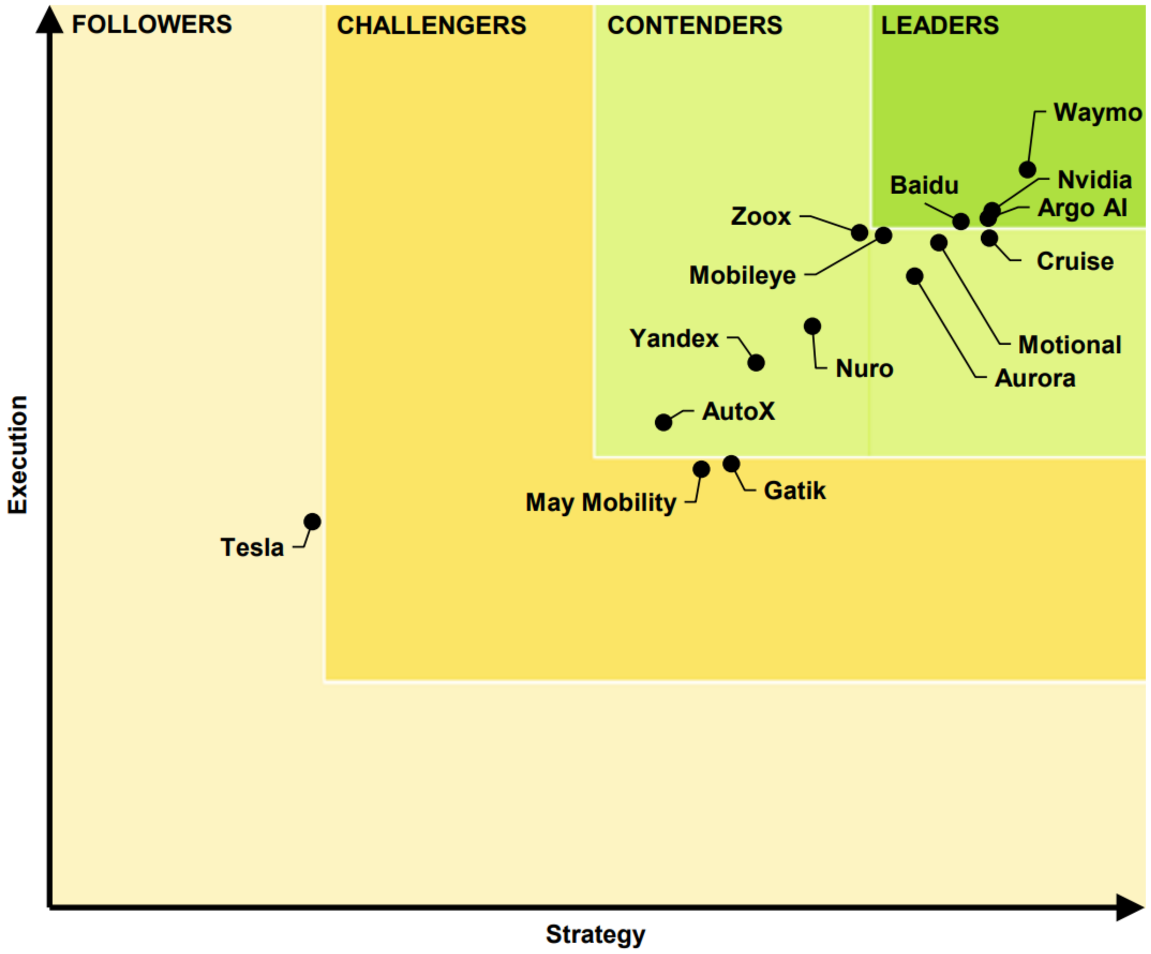
Company Scores (2019 vs 2020)

The Navigant Research Leaderboard Grid





(Source: Guidehouse Insights)

Automated Driving Leaderboard. *Sae* [online]. [cit. 2020-01-25]. Dostupné z: https://www.sae.org/news/2019/03/2019-navigant-autonomous-leaderboard
Guidehouse Insights Leaderboard report. *Guidehouseinsights* [online]. [cit. 2022-02-25]. Dostupné z: https://guidehouseinsights.com/reports/guidehouse-insights-leaderboard-automated-driving-systems

Identifying the Waymo Fully Self-Driving Vehicle

The Waymo fully self-driving Chrysler Pacifica Hybrid minivans can be easily identified by the white color with Waymo logos, roof assembly, front fender additions, or rear roof additions below.

During driverless testing and operation, Waymo's vehicles are fully self-driving at all times, and will not have any person in the driver's seat either steering or otherwise controlling the vehicle.

Waymo Fully Self-Driving. *Thedrive* [online]. [cit. 2022-02-25]. Dostupné z: https://s3.amazonaws.com/the-drive-staging/message-editor%2F1540065806515-waymo1.jpg

Waymo Fully Self-Driving. *Thedrive* [online]. [cit. 2020-01-25]. Dostupné z: https://guidehouseinsights.com/reports/guidehouse-insights-leaderboard-automated-driving-systems

https://waymo.com/

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https://www.youtube.com/watch?v=DJlcdH6iuAk

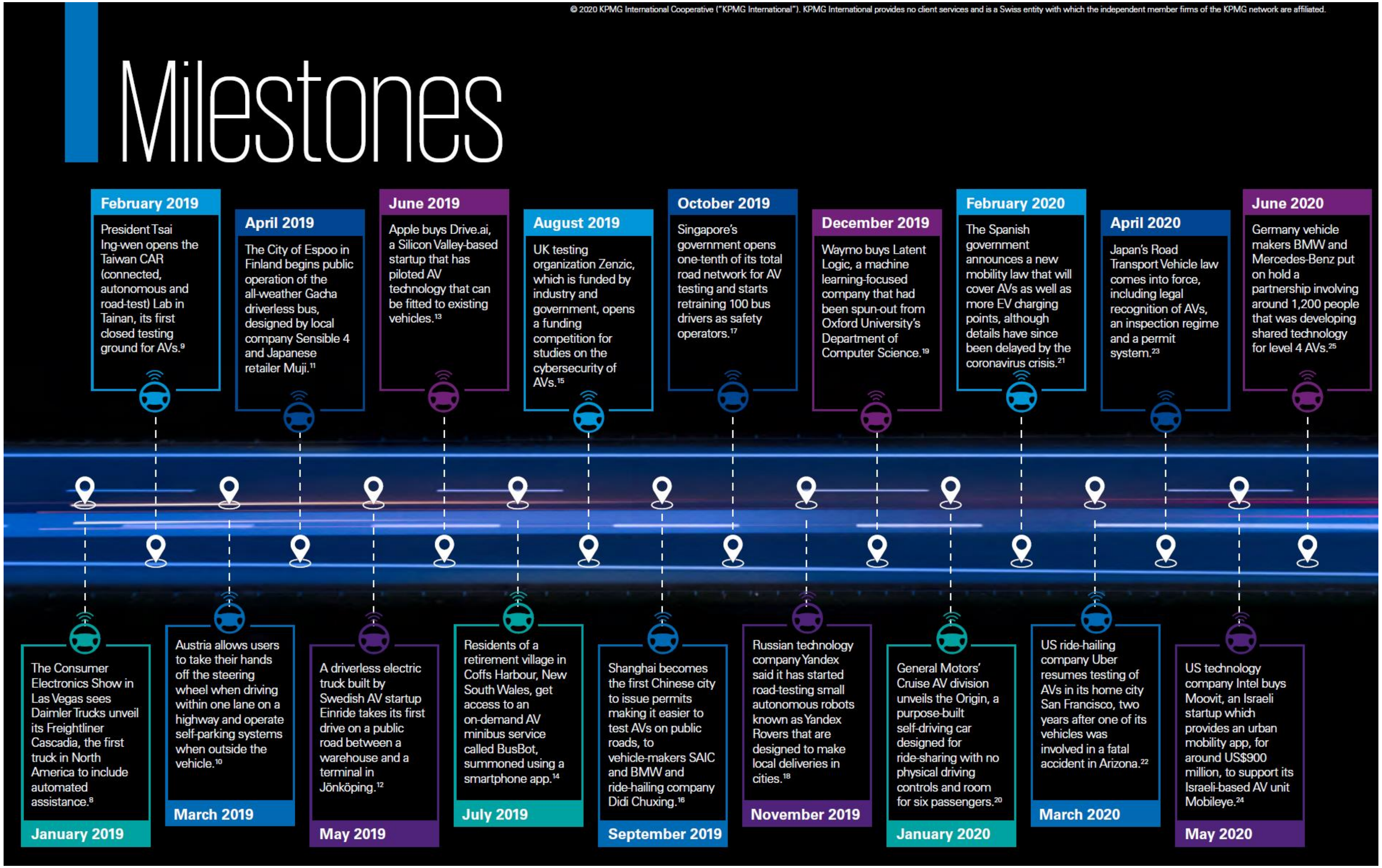
https://www.youtube.com/watch?v=O8TSA-X9UIU

The Autonomous Vehicles Readiness Index

Index results

Country or jurisdiction	Rank 2020	Rank 2019	2020 score
Singapore	1	2	25.45
The Netherlands	2	1	25.22
Norway	3	3	24.25
United States	4	4	23.99
Finland	5	6	23.58
Sweden	6	5	23.17
South Korea	7	13	22.71
United Arab Emirates	8	9	22.23
United Kingdom	9	7	21.36
Denmark	10	n/a	21.21
Japan	11	10	20.88
Canada	12	12	20.68
Taiwan	13	n/a	19.97
Germany	14	8	19.88
Australia	15	15	19.70
Israel	16	14	19.40
New Zealand	17	11	19.19
Austria	18	16	19.16
France	19	17	18.59
China	20	20	16.42
Belgium	21	n/a	16.23
Spain	22	18	16.15
Czech Republic	23	19	13.99
Italy	24	n/a	12.70
Hungary	25	21	11.66
Russia	26	22	11.45
Chile	27	n/a	11.28
Mexico	28	23	7.42
India	29	24	6.95
Brazil	30	25	5.49

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html



Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html

https://www.daimlertruck.com/innovation/safe-automated/autonomous-driving-daimler-trucks.html

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html

https://en.wikipedia.org/wiki/Einride

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html

https://www.youtube.com/c/Einride

https://www.youtube.com/watch?v=Vf44Pw3BqUI

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Executive summary

Methodology

The 2020 edition of the AVRI assesses 30 countries and jurisdictions. This includes the addition of five new countries and jurisdictions to the roster from 2019, and can explain some of the downward movement of some countries as a result. The AVRI uses 28 different measures, organized into four pillars: policy and legislation, technology and innovation, infrastructure and consumer acceptance. Four of the variables are scored for this index by KPMG International and ESI ThoughtLab and 24 draw on existing research by KPMG International and other organizations. Full details are in the Appendix.

P. 12 Singapore (1st)

— For the first time Singapore leads the AVRI, overtaking the Netherlands for the top-ranked position and leading on both the consumer acceptance and policy and legislation pillars.

— The city-state has expanded AV testing to cover all public roads in western Singapore and aims to serve three areas with driverless buses from 2022.

— The number of charging points will increase from 1,600 to 28,000 by 2030 with incentives for buying EVs, although the government is also phasing in a usage tax to compensate for loss of fuel excise duties. Given they will be mostly electric, such moves are vital in enabling AV implementation.

P. 13 The Netherlands (2nd)

— The Netherlands retains top ranking on the infrastructure pillar, leading on EV charging stations per capita and second only to Singapore on road quality.

— An extensive series of pilots means that 81 percent of people live near AV testing sites. However, tests on truck platooning in July 2019 found challenges in keeping vehicles connected at all times.

— 2019 saw the Netherlands extending its use of smart road furniture, including traffic lights that send their statuses wirelessly to AVs in 60 new areas of the country.

P. 14 Norway (3rd)

— Norway extended its use of AVs in 2019, with several bus routes in Oslo now driverless, and the speed limit for driverless vehicles on roads increasing from 16kph to 20kph.

— A majority of passenger vehicles bought in Norway in 2019 were battery or plug-in hybrids, as a result of high taxes on internal combustion vehicles and fuels and subsidies for EVs.

— The country is testing AVs in extreme weather, with pilots of driverless trucks, cars and buses on the snow-bound Svalbard islands in the Arctic Circle.

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html

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Also noted

— South Korea climbs six places to 7th in this edition of the AVRI, the biggest rise of any country. The government published a national strategy for AVs in October 2019, with the goal of reducing road deaths by three-quarters.

— The UK leads on a new AVRI measure of cybersecurity, with AV testing body Zenzic funding seven projects in this field.

— Israel retains its leadership of the technology pillar, leading on both AV-related companies and investments scaled by population.

New to AVRI

— Denmark is the highest-rated of the five countries and jurisdictions joining this edition of the AVRI, occupying the 10th spot. It allows AV tests on any public road and its first driverless bus service started running in March 2020 in Aalborg.

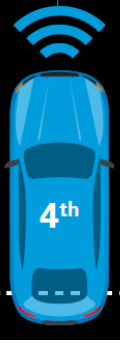
— Taiwan, the second highest at 13th, has a focus on testing AVs on its challenging mixed-use roads. Taipei is planning to start a night-time trial of driverless buses partly to tackle a shortage of drivers.

— Belgium, entering at 21st, ran its first demonstration of an AV bus at Brussels airport in May 2019, operated by Flemish regional transport authority De Lijn.

— Italy, placed 24th, introduced rules and an observatory for AV testing in 2018, with tests beginning in Parma and Turin in 2019.

— Chile, at 27th, has made use of AVs in mining for several years and in January 2020 started Latin America's first public pilot in a park in central Santiago.

P. 15 United States



— The US is second only to Israel on technology and innovation, with 420 AV company headquarters, 44 percent of all of those tracked in this research.

— American technology companies, including Apple and Google's Waymo unit, and vehicle makers such as General Motors and Ford, continue to dominate AV development. GM's Cruise division unveiled the Origin, a purpose-built self-driving car designed for ride-sharing.

— Cities including Detroit and Pittsburgh are undertaking innovative work to introduce and promote AVs (both are profiled in the Cities to watch section).

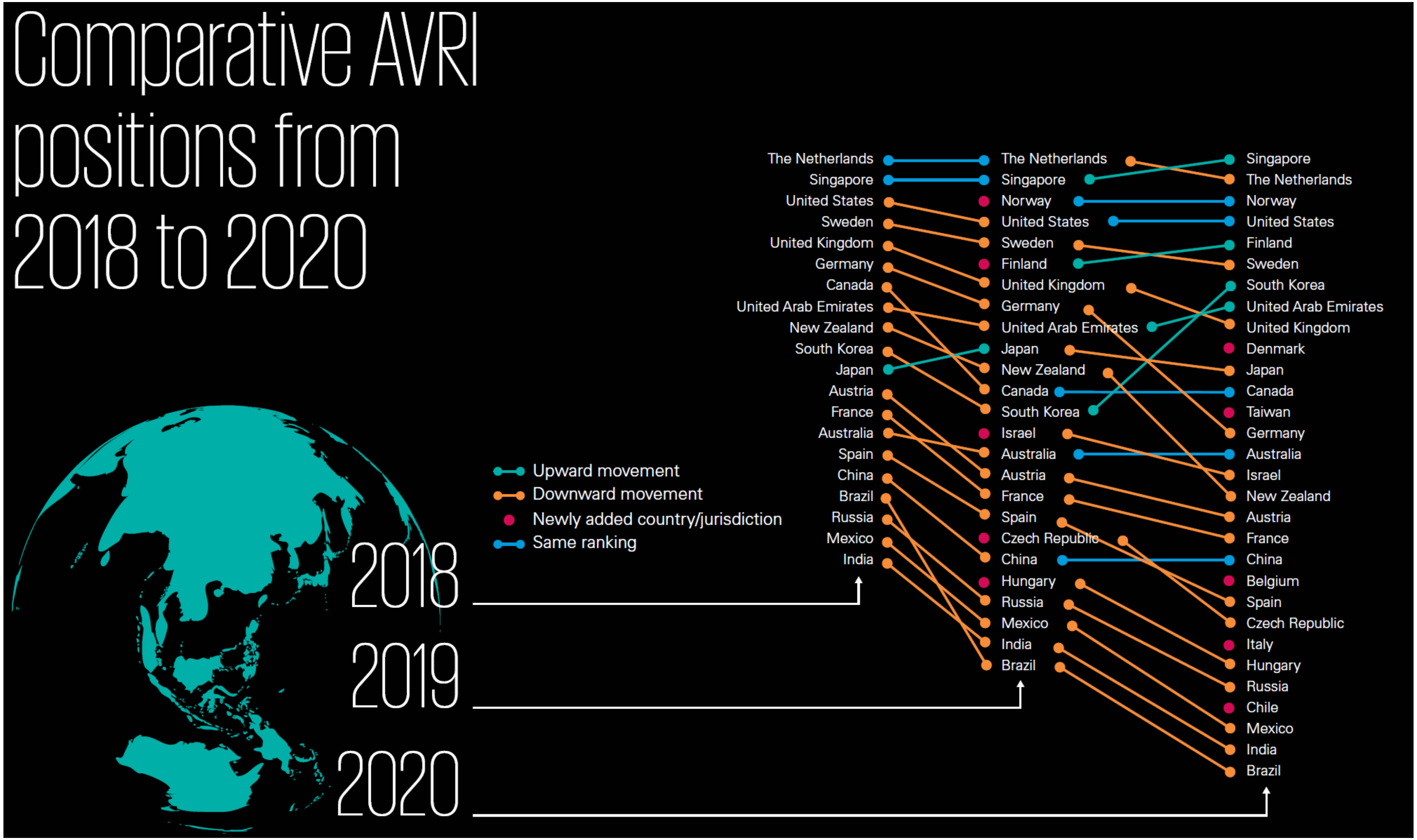
P. 16 Finland

— Finland has the highest ratings for AV-specific regulations and for the efficiency of its legal system in challenging regulations, and its entire road network is open for AV trials.

— Helsinki (profiled in Cities to watch) and its neighbor Espoo both run public AV bus services, with the latter using an all-weather vehicle designed by local company Sensible 4.

— Finland also leads on measures of digital skills, benefiting from a breadth of talented engineers, many of whom have notable experience having been part of Nokia's legacy. It also makes the greatest use of ride-hailing services.

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html



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23 | Czech Republic

22	25	24	22
Policy and legislation	Technology and innovation	Infrastructure	Consumer acceptance

The Czech Republic is one of the five countries receiving the top rating for government-funded AV pilots, and testing is the country's main area of strength. 2020 should see construction start on German vehicle maker BMW's EUR300 million (US$340 million) AV test site at Sokolov, around 300km (190 miles) from the company's main development site in Munich. BMW plans to open the site, which will have around 100km of road allowing tests of city, highway and rural roads, in the second half of 2022. It will create around 700 jobs and has established a cooperation agreement with the University of West Bohemia.[103]

The country has several other test facilities under development. Czech investment group Accolade is planning to build on a site near Stříbro, which is similarly near the German border, to be used by companies developing AV technologies. It plans to open in 2022 at a cost of EUR180 million (US$200 million), which will also offer a range of road environments including European cities that do not use right-angled grids of roads.[104] Czech-based vehicle maker Skoda, part of Germany's Volkswagen, is working on a site while German safety company TÜV and French vehicle part maker Valeo Group are both looking to convert disused airfields.

"Our strength is that the automotive industry is already here," says Pavel Kliment, Partner, KPMG in the Czech Republic, with the country making vehicles for a number of companies. "That's why there is the focus on test sites." There is less research and development work, although there are good examples, such as German vehicle maker Porsche, another Volkswagen unit, and Italian parts maker Marelli have research partnerships with the Czech Technical University in Prague.[105]

Aside from testing, Kliment says that the Czech Republic lacks a legal framework for the use of AVs. The technology attracts attention when there is a significant announcement, such as when BMW detailed its test site plans in January 2020. "There are a lot of positive things happening, but it's not a strategic issue," he says. "I expect the importance will gradually grow over time, particularly when the test sites are completed."

Government-funded AV pilots

Top performing countries and jurisdictions

- Canada
- Czech Republic
- Singapore
- South Korea
- Taiwan

Source: KPMG International (2020)

> "Our strength is that the automotive industry is already here. That's why there is the focus on test sites."

Pavel Kliment
Partner
KPMG in the Czech Republic

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html

The Autonomous Vehicles Readiness Index

- Policy and legislation
- Technology and innovation
- Infrastructure
- Consumer acceptance

Autonomous Vehicles Readiness Index: AVRI [online]. [cit. 2020-01-25]. Dostupné z: https://home.kpmg/xx/en/home/insights/2020/06/autonomous-vehicles-readiness-index.html

Policy and legislation pillar scores breakdown by variable

	Position	AV Regulations	Government-funded AV Pilots	AV-focused agency	Future orientation of government	Efficiency of legal system in challenging regulations	Government readiness for change	Data-sharing environment	Pillar 1 score (unadjusted)
1	**Singapore**	1.000	1.000	1.000	1.000	0.673	1.000	0.411	**6.084**
2	**United Kingdom**	0.929	0.857	0.857	0.534	0.668	0.780	1.000	**5.626**
3	**The Netherlands**	1.000	0.929	0.714	0.639	0.825	0.780	0.688	**5.576**
4	**Finland**	1.000	0.857	0.714	0.718	1.000	0.780	0.451	**5.521**
5	**New Zealand**	0.929	0.714	0.929	0.573	0.792	0.829	0.743	**5.509**
6	**United States**	0.857	0.929	0.714	0.763	0.792	0.634	0.771	**5.461**
7	**Germany**	0.786	0.857	0.857	0.604	0.747	0.829	0.621	**5.301**
8	**United Arab Emirates**	0.857	0.714	0.929	0.880	0.865	0.951	0.081	**5.278**
9	**Canada**	0.786	1.000	0.714	0.502	0.614	0.756	0.870	**5.242**
10	**Norway**	0.929	0.857	0.643	0.575	0.629	0.854	0.674	**5.161**
11	**Austria**	0.857	0.857	0.929	0.502	0.568	0.610	0.629	**4.952**
12	**Denmark**	0.714	0.643	0.857	0.589	0.666	0.829	0.633	**4.931**
13	**Taiwan**	0.857	1.000	0.786	0.334	0.425	0.659	0.860	**4.920**
14	**France**	0.786	0.857	0.714	0.481	0.615	0.585	0.815	**4.854**
15	**Sweden**	0.714	0.714	0.714	0.564	0.624	0.878	0.625	**4.834**
16	**South Korea**	0.857	1.000	0.857	0.488	0.346	0.463	0.766	**4.777**
17	**Australia**	1.000	0.571	0.714	0.409	0.516	0.707	0.765	**4.683**
18	**Japan**	0.571	0.857	0.571	0.505	0.642	0.659	0.691	**4.496**
19	**Israel**	0.714	0.786	0.643	0.532	0.603	0.488	0.331	**4.097**
20	**Belgium**	0.929	0.714	0.714	0.271	0.565	0.512	0.319	**4.024**
21	**China**	0.786	0.929	0.643	0.490	0.535	0.561	0.000	**3.944**
22	**Czech Republic**	0.857	1.000	0.714	0.186	0.222	0.512	0.309	**3.800**
23	**Spain**	0.857	0.571	0.714	0.163	0.322	0.317	0.668	**3.614**
24	**Chile**	0.429	0.571	0.429	0.435	0.435	0.439	0.346	**3.083**
25	**Hungary**	0.643	0.857	1.000	0.266	0.000	0.244	0.046	**3.056**
26	**Russia**	0.571	0.286	0.857	0.367	0.240	0.293	0.360	**2.973**
27	**Italy**	0.857	0.643	0.643	0.000	0.056	0.293	0.452	**2.943**
28	**India**	0.000	0.000	0.000	0.536	0.514	0.341	0.288	**1.679**
29	**Mexico**	0.143	0.143	0.143	0.168	0.194	0.098	0.670	**1.557**
30	**Brazil**	0.286	0.143	0.143	0.011	0.119	0.000	0.488	**1.190**

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Technology and innovation pillar scores breakdown by variable

	Position	Industry partnerships	AV technology firm headquarters	AV-related patents	Industry investments in AV	Availability of the latest technologies	Innovation capability	Cybersecurity	Assessment of cloud computing, AI and IoT	Market share of electric cars	Pillar 2 score (unadjusted)
1	**Israel**	0.750	1.000	0.052	1.000	0.946	0.716	0.679	0.551	0.029	**5.722**
2	**United States**	1.000	0.122	0.298	0.370	0.931	0.939	0.989	1.000	0.033	**5.681**
3	**Japan**	0.917	0.022	1.000	0.055	0.843	0.808	0.889	0.707	0.017	**5.258**
4	**Germany**	1.000	0.078	0.849	0.124	0.751	1.000	0.822	0.574	0.052	**5.250**
5	**Norway**	0.917	0.053	0.012	0.000	0.971	0.576	0.915	0.764	1.000	**5.209**
6	**Sweden**	0.833	0.203	0.352	0.051	0.937	0.826	0.737	0.805	0.201	**4.946**
7	**South Korea**	1.000	0.026	0.856	0.023	0.633	0.826	0.874	0.551	0.043	**4.832**
8	**Finland**	0.833	0.171	0.017	0.035	1.000	0.752	0.837	0.705	0.123	**4.475**
9	**United Kingdom**	0.833	0.104	0.113	0.011	0.855	0.806	1.000	0.676	0.057	**4.456**
10	**The Netherlands**	0.667	0.066	0.032	0.103	0.907	0.763	0.900	0.701	0.265	**4.403**
11	**Singapore**	0.833	0.133	0.020	0.004	0.771	0.738	0.928	0.717	0.085	**4.230**
12	**France**	0.833	0.043	0.116	0.029	0.735	0.783	0.972	0.567	0.049	**4.127**
13	**Canada**	1.000	0.085	0.012	0.073	0.782	0.711	0.915	0.488	0.047	**4.114**
14	**Taiwan**	0.833	0.007	0.094	0.000	0.551	0.851	0.856	0.736	0.018	**3.946**
15	**Denmark**	0.667	0.015	0.011	0.000	0.740	0.761	0.829	0.800	0.074	**3.896**
16	**Austria**	0.667	0.087	0.036	0.044	0.685	0.722	0.772	0.450	0.065	**3.527**
17	**Australia**	0.500	0.034	0.045	0.007	0.576	0.609	0.911	0.545	0.020	**3.248**
18	**Belgium**	0.417	0.032	0.007	0.001	0.808	0.652	0.746	0.521	0.057	**3.242**
19	**New Zealand**	0.667	0.019	0.010	0.000	0.743	0.409	0.692	0.567	0.048	**3.155**
20	**China**	1.000	0.002	0.045	0.014	0.023	0.503	0.777	0.446	0.103	**2.913**
21	**Italy**	0.833	0.008	0.012	0.000	0.330	0.519	0.796	0.360	0.016	**2.875**
22	**United Arab Emirates**	0.833	0.008	0.000	0.005	0.787	0.221	0.731	0.193	0.085	**2.864**
23	**Spain**	0.500	0.015	0.013	0.000	0.462	0.492	0.924	0.338	0.025	**2.769**
24	**Hungary**	0.667	0.037	0.006	0.026	0.371	0.111	0.742	0.103	0.033	**2.095**
25	**Czech Republic**	0.583	0.007	0.008	0.000	0.543	0.325	0.215	0.335	0.009	**2.025**
26	**Russia**	0.333	0.004	0.007	0.001	0.000	0.235	0.794	0.058	0.001	**1.432**
27	**Chile**	0.333	0.004	0.001	0.000	0.554	0.000	0.000	0.190	0.001	**1.084**
28	**India**	0.167	0.001	0.001	0.000	0.122	0.190	0.540	0.000	0.000	**1.020**
29	**Mexico**	0.000	0.000	0.001	0.000	0.269	0.025	0.345	0.122	0.001	**0.763**
30	**Brazil**	0.167	0.001	0.001	0.000	0.046	0.144	0.232	0.144	0.001	**0.736**

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Infrastructure pillar scores breakdown by variable

	Position	EV charging stations	4G coverage	Quality of roads	Technology infrastructure change readiness	Mobile connection speed (0.5 weight)	Broadband (0.5 weight)	Pillar 3 score (unadjusted)
1	**The Netherlands**	1.000	0.832	0.993	0.622	0.755	0.792	**4.221**
2	**South Korea**	0.060	1.000	0.838	0.689	0.959	0.917	**3.525**
3	**Norway**	0.808	0.929	0.448	0.467	0.728	0.958	**3.495**
4	**United Arab Emirates**	0.010	0.636	0.869	1.000	1.000	0.833	**3.431**
5	**Singapore**	0.095	0.739	1.000	0.756	0.578	1.000	**3.379**
6	**Japan**	0.078	0.957	0.894	0.689	0.272	0.958	**3.233**
7	**Austria**	0.166	0.611	0.871	0.844	0.498	0.708	**3.095**
8	**Sweden**	0.290	0.771	0.669	0.578	0.473	0.958	**3.023**
9	**United States**	0.070	0.839	0.714	0.600	0.393	0.917	**2.878**
10	**Denmark**	0.158	0.682	0.744	0.556	0.491	0.875	**2.823**
11	**Finland**	0.068	0.714	0.653	0.644	0.483	0.833	**2.738**
12	**Australia**	0.010	0.743	0.557	0.578	0.693	1.000	**2.735**
13	**Canada**	0.074	0.689	0.587	0.378	0.788	0.917	**2.580**
14	**Taiwan**	0.024	0.588	0.754	0.533	0.453	0.865	**2.558**
15	**Spain**	0.062	0.639	0.782	0.533	0.327	0.750	**2.555**
16	**United Kingdom**	0.141	0.543	0.538	0.689	0.313	0.750	**2.442**
17	**France**	0.150	0.364	0.704	0.533	0.467	0.792	**2.381**
18	**Belgium**	0.192	0.746	0.399	0.333	0.516	0.708	**2.283**
19	**Germany**	0.165	0.264	0.666	0.600	0.328	0.667	**2.192**
20	**New Zealand**	0.021	0.250	0.420	0.711	0.522	0.917	**2.121**
21	**Hungary**	0.023	0.782	0.293	0.333	0.433	0.542	**1.919**
22	**China**	0.079	0.581	0.456	0.267	0.751	0.250	**1.884**
23	**Italy**	0.024	0.339	0.406	0.622	0.318	0.625	**1.863**
24	**Czech Republic**	0.033	0.754	0.261	0.289	0.496	0.542	**1.856**
25	**Israel**	0.108	0.000	0.537	0.578	0.146	0.833	**1.712**
26	**Chile**	0.002	0.257	0.638	0.422	0.117	0.542	**1.648**
27	**Russia**	0.001	0.157	0.136	0.622	0.117	0.625	**1.287**
28	**Mexico**	0.007	0.368	0.434	0.200	0.218	0.333	**1.284**
29	**India**	0.000	0.764	0.437	0.000	0.000	0.000	**1.202**
30	**Brazil**	0.001	0.089	0.000	0.311	0.171	0.417	**0.695**

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Consumer acceptance pillar scores breakdown by variable

	Position	Population living near test areas	Civil society technology use	Consumer ICT adoption	Digital skills	Individual readiness	Online ride-hailing market penetration	Pillar 4 score (unadjusted)
1	**Singapore**	1.000	0.514	0.906	0.910	0.715	0.828	**4.873**
2	**Finland**	0.364	0.886	0.796	1.000	0.673	1.000	**4.718**
3	**Sweden**	0.353	1.000	0.918	0.941	0.641	0.524	**4.377**
4	**United Arab Emirates**	0.210	0.543	0.985	0.814	1.000	0.719	**4.271**
5	**Norway**	0.342	0.857	0.840	0.805	0.705	0.528	**4.078**
6	**United States**	0.324	0.914	0.695	0.818	0.636	0.682	**4.069**
7	**The Netherlands**	0.811	0.814	0.728	0.926	0.624	0.131	**4.034**
8	**Denmark**	0.574	0.729	0.843	0.849	0.734	0.199	**3.927**
9	**Australia**	0.365	0.786	0.684	0.705	0.719	0.412	**3.670**
10	**South Korea**	0.216	0.514	1.000	0.694	0.690	0.483	**3.597**
11	**Israel**	0.562	0.643	0.585	0.880	0.472	0.412	**3.553**
12	**United Kingdom**	0.305	0.714	0.674	0.674	0.541	0.607	**3.515**
13	**Canada**	0.477	0.729	0.629	0.724	0.444	0.453	**3.457**
14	**New Zealand**	0.342	0.757	0.751	0.672	0.583	0.315	**3.420**
15	**Taiwan**	0.465	0.171	0.827	0.748	0.749	0.435	**3.396**
16	**China**	0.043	0.571	0.764	0.573	0.419	0.993	**3.364**
17	**Spain**	0.000	0.329	0.759	0.457	0.676	0.539	**2.761**
18	**Japan**	0.302	0.286	0.891	0.490	0.709	0.000	**2.678**
19	**France**	0.284	0.386	0.685	0.512	0.407	0.348	**2.622**
20	**Russia**	0.000	0.329	0.740	0.678	0.394	0.442	**2.583**
21	**Germany**	0.096	0.529	0.624	0.722	0.483	0.127	**2.581**
22	**Czech Republic**	0.000	0.500	0.598	0.617	0.364	0.416	**2.494**
23	**Belgium**	0.000	0.657	0.575	0.635	0.485	0.116	**2.468**
24	**Austria**	0.000	0.457	0.552	0.617	0.504	0.333	**2.463**
25	**Chile**	0.000	0.257	0.511	0.429	0.612	0.367	**2.176**
26	**Italy**	0.125	0.271	0.534	0.396	0.464	0.000	**1.790**
27	**Mexico**	0.000	0.100	0.377	0.245	0.375	0.464	**1.561**
28	**Hungary**	0.000	0.114	0.529	0.322	0.221	0.266	**1.451**
29	**Brazil**	0.104	0.000	0.428	0.000	0.306	0.476	**1.314**
30	**India**	0.000	0.157	0.000	0.490	0.000	0.427	**1.074**

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What is Object Detection?

- It is clear that the images contain many objects of interest. The goal of the object detection
  systems is to find the location of these objects in the images (e.g. cars, faces, pedestrians).

- For example, the vehicle detection systems are crucial for traffic analysis or intelligent scheduling, the people detection systems can be useful for automotive safety, and the face detection systems are a key part of face recognition systems.

What is Object Detection?

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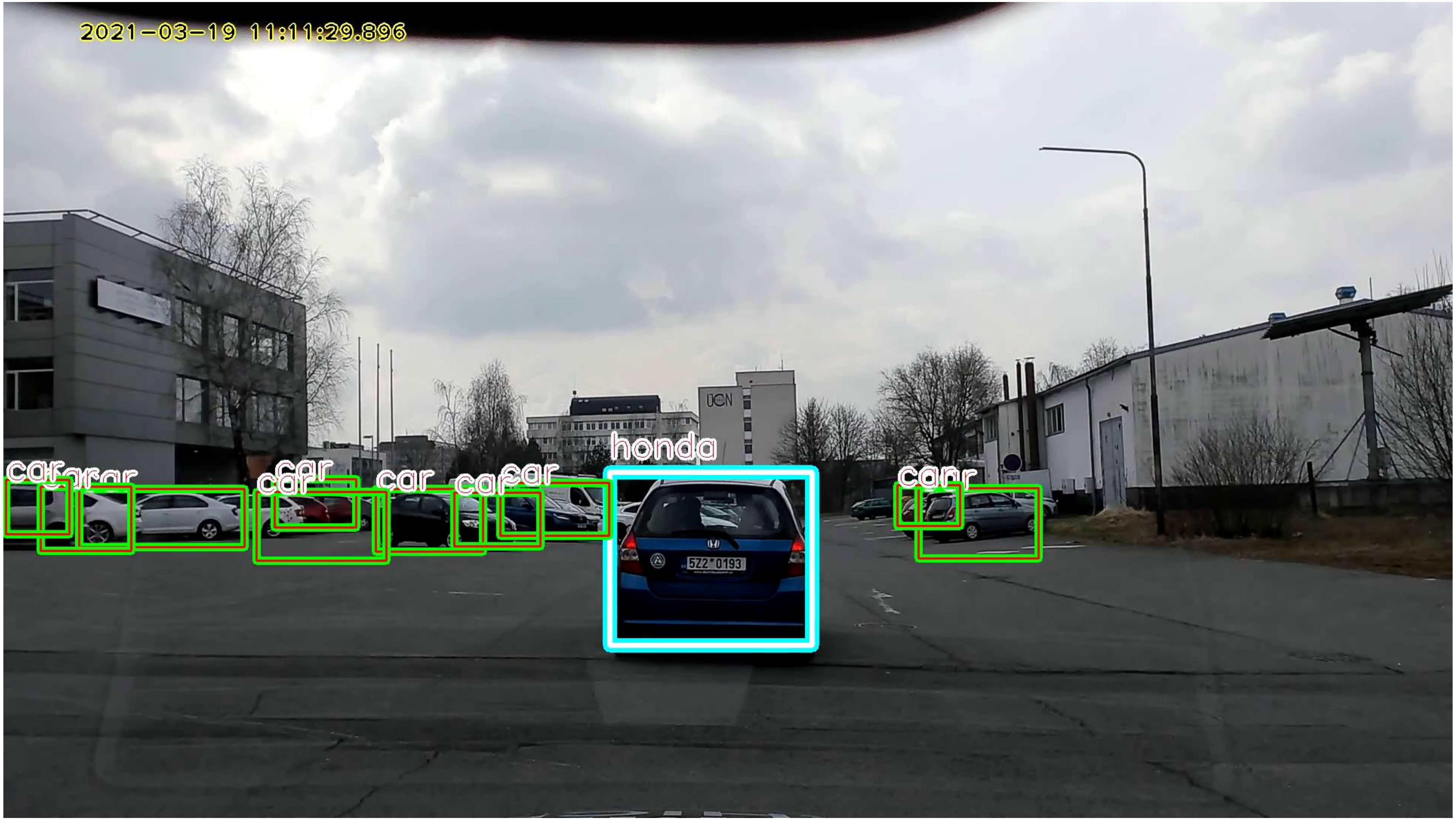
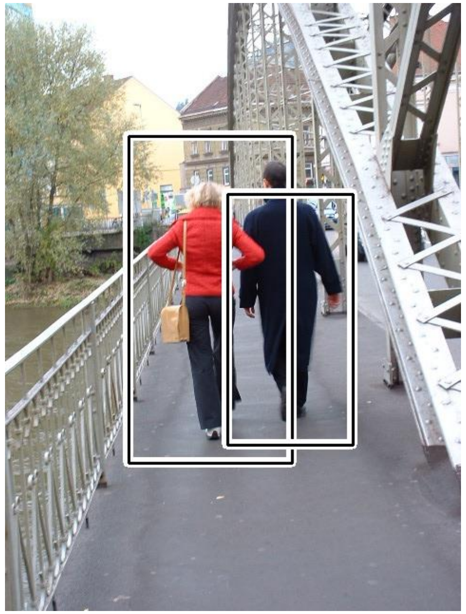
YOUTH AND SPORTS

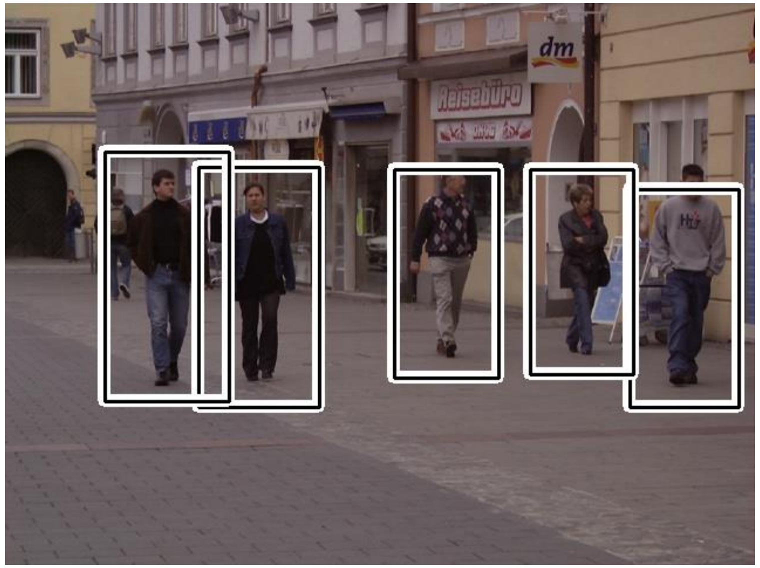
VSB TECHNICAL UNIVERSITY OF OSTRAVA | FACULTY OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE | DEPARTMENT OF COMPUTER SCIENCE

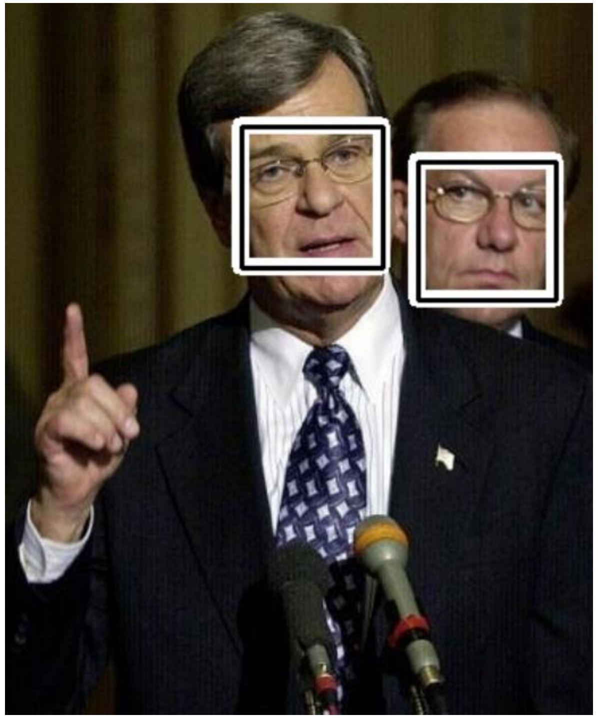


What is Object Detection?

- Output?
  - position of the objects
  - scale of the objects





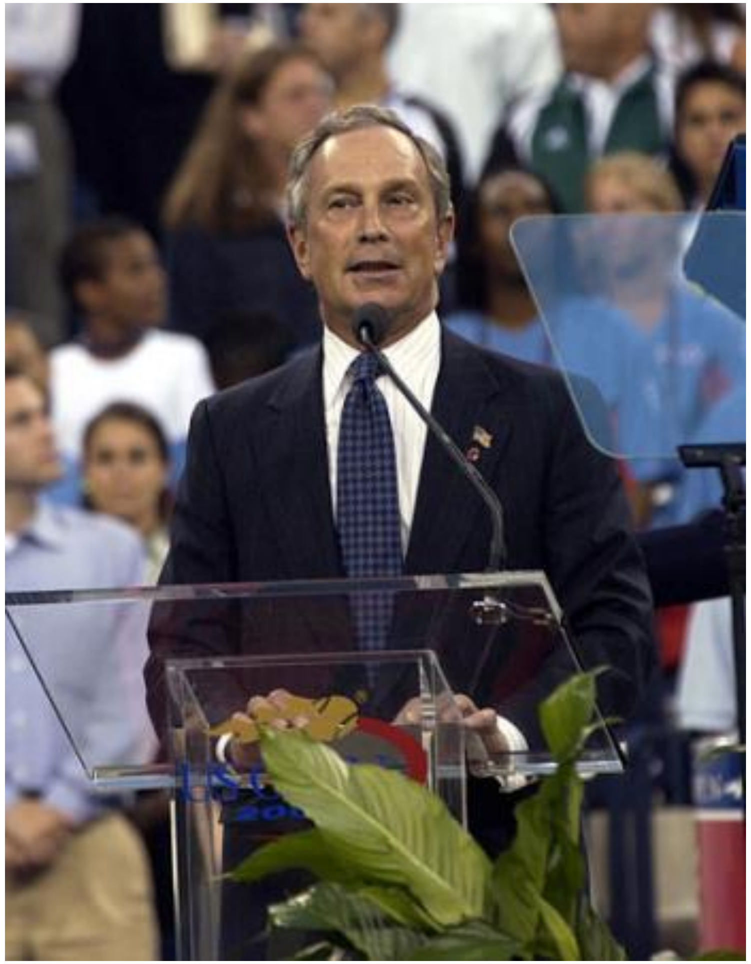


Problems (Challenges)

- different views
- Illumination challenges
- occlusion
- different backgrounds
- shadows
- …
- …

Problems (Challenges)

- low quality images



Face Detection Data Set and Benchmark Home [online]. [cit. 2020-01-25]. Dostupné z: http://vis-www.cs.umass.edu/fddb/

Problems (Challenges)

- illumination + low quality

Face Detection Data Set and Benchmark Home [online]. [cit. 2020-01-25]. Dostupné z: http://vis-www.cs.umass.edu/fddb/

Image Features

- The objects of interest can be described using various image information (e.g. shape, texture, colour). In the area of feature based detectors the image features are the carries of this information.

- Many methods for extracting the image features that are able to describe the appearance of objects were presented, especially, the detectors that are based on the histograms of oriented gradients (HOG), Haar features, or local binary patterns (LBP) are dominant and they are considered as the state-of-the-art methods.

Radovan Fusek: Descriptors for Object Detection in Image Recognition, Philosophiæ Doctor Thesis, 2016

Object Detection/Recognition

- Haar
- HOG
- LBP

Traditional Approaches

- SIFT, SURF

KeyPoints

- CNNs

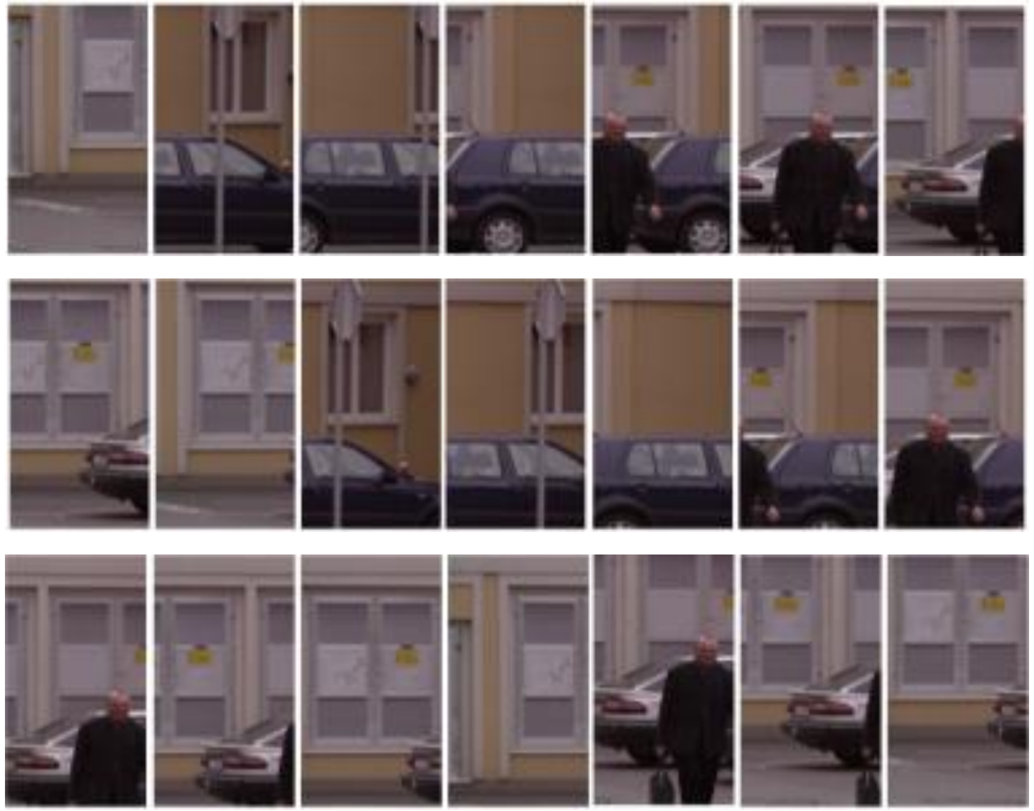
Deep Learning Approach

- Practical examples using OpenCV + Dlib (https://opencv.org/, http://dlib.net/)

Sliding Window - Main Idea

Constantine Papageorgiou and Tomaso Poggio: A Trainable System for Object Detection. *Int. J. Comput. Vision* 38, pp. 15-33. (2000)

Sliding Window - Main Idea



Constantine Papageorgiou and Tomaso Poggio: A Trainable System for Object Detection. *Int. J. Comput. Vision* 38, pp. 15-33. (2000)

Sliding Window - Main Idea

- In general, the sliding window technique represents the popular and successful approach for object detection. The main idea of this approach is that the input image is scanned by a rectangular window at multiple scales. The result of the scanning process is a large number of various sub-windows. A vector of features is extracted from each sub-window. The vector is then used as an input for the classifier (e.g. SVM classifer).

- During the classification process, some sub-windows are marked as the objects. Using the sliding window approach, the multiple positive detections may appear, especially around the objects of interest

Sliding Window - Main Idea

- These detections are merged to the final bounding box that represents the resulting detection.

- The classifer that determines each sub-window is trained over the training set that consists of positive and negative images.

- The key point is to find what values (features) should be used to effectively encode the image inside the sliding window.

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Detection Process

Feature Vector

(gradient, HOG, LBP, …)

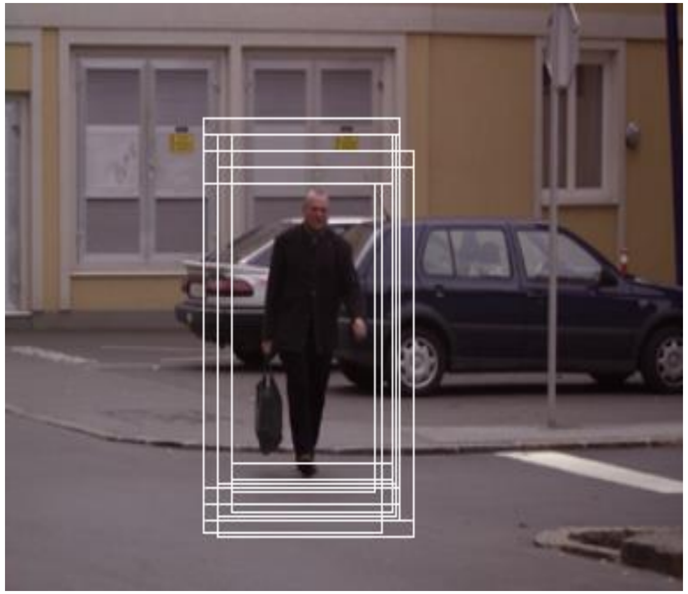
Detection Process

Feature Vector

(gradient, HOG, LBP, …)

Trainable Classifier

(SVM, ANNs, …)



Detection Process

- Typically, in the area of feature-based detectors, the detection algorithms consist of two main parts. The extraction of image features is the first part. The second part is created by the trainable classifiers that handle a final classification (object/non-object).

- The extraction of relevant features has a significant influence on the successfulness of detectors. The large number of features slows down the training and detection phases; on the other hand a very small number of features may not be able to describe the properties of object of interest. The quality of training set is also equally important.

Training Sets

- negative set - without the object of interest
- positive set
  - rotation
  - noise
  - Illumination
  - scale

Training Set – Traffic Sign

The German Traffic Sign Recognition/Detection Benchmark

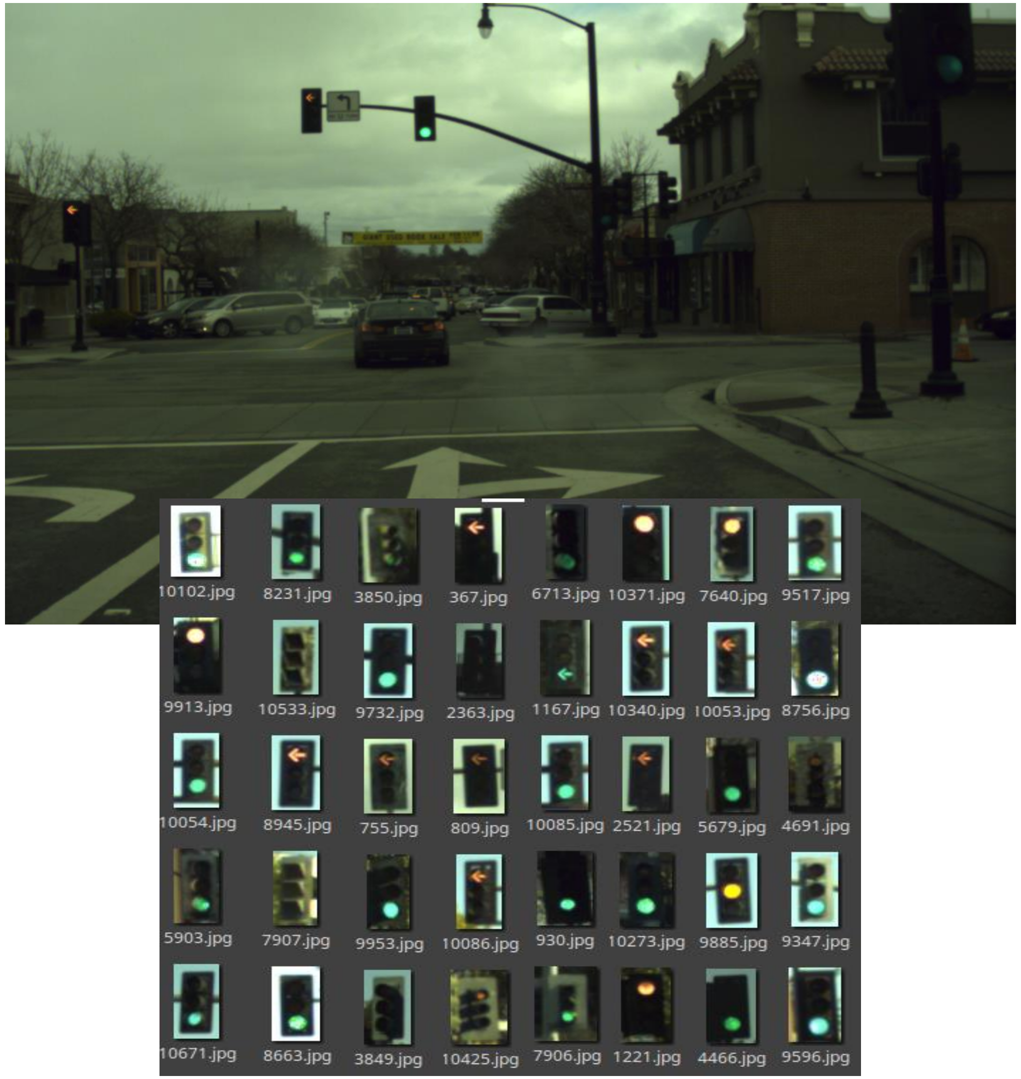
- Single-image, multi-class classification problem
- More than 40 classes
- More than 50,000 images in total
- Large, lifelike database
- Reliable ground-truth data due to semi-automatic annotation
- Physical traffic sign instances are unique within the dataset
  (i.e., each real-world traffic sign only occurs once)

The German Traffic Sign Recognition Benchmark [online]. [cit. 2020-01-25]. Dostupné z: https://benchmark.ini.rub.de/gtsrb_news.html

Training Set – Traffic Lights

Bosch Small Traffic Lights Dataset (Germany)

- Training set:
  - 5093 images
  - Annotated about every 2 seconds
  - 10756 annotated traffic lights
  - Median traffic lights width: ~8.6 pixels
  - 15 different labels
  - 170 lights are partially occluded
- Test set:
  - 8334 consecutive images
  - Annotated at about 15 fps
  - 13486 annotated traffic lights
  - Median traffic light width: 8.5 pixels
  - 4 labels (red, yellow, green, off)
  - 2088 lights are partially occluded



Bosch Small Traffic Lights Dataset [online]. [cit. 2020-01-25]. Dostupné z: https://hci.iwr.uni-heidelberg.de/content/bosch-small-traffic-lights-dataset

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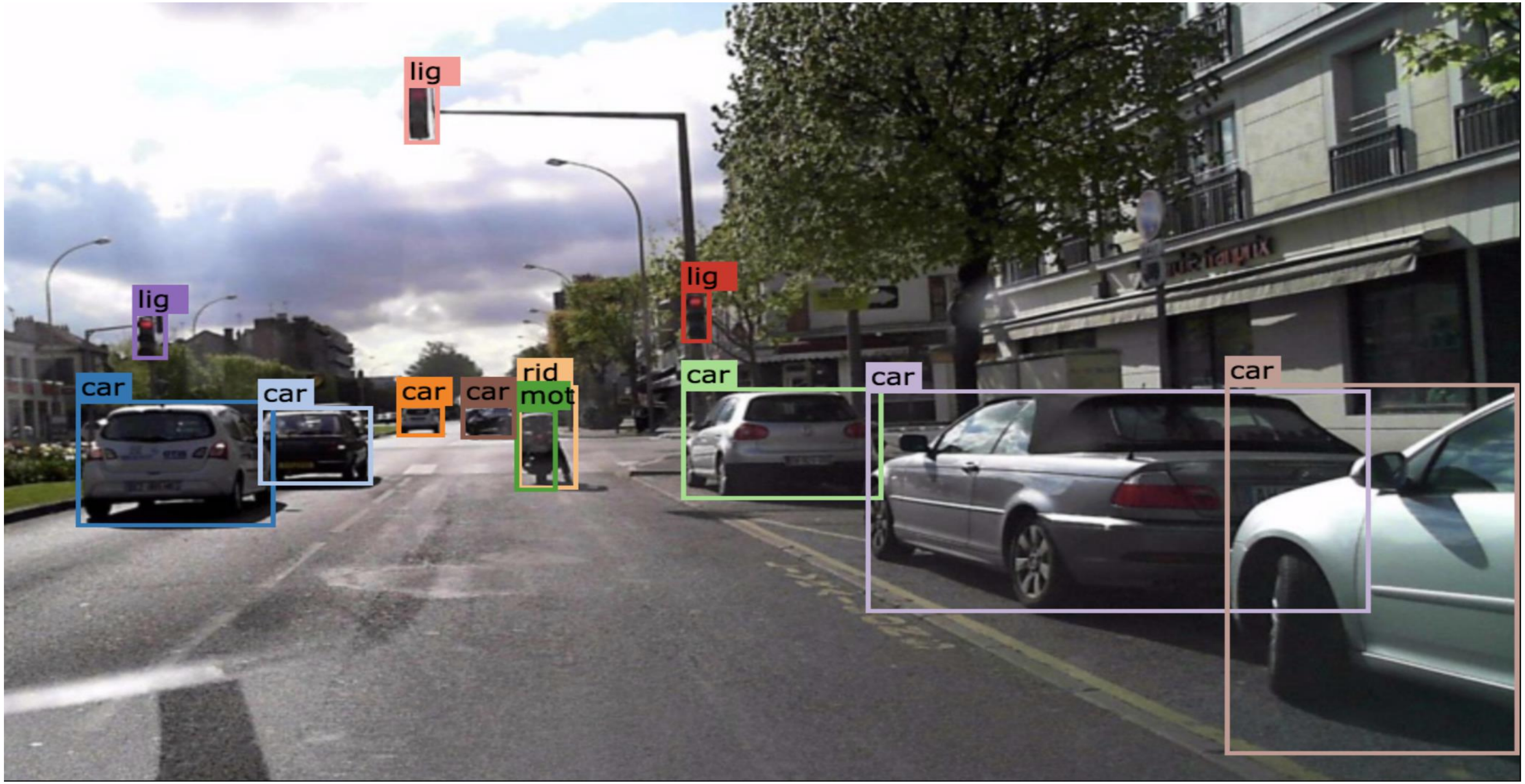
Training Set – Road Objects

Berkeley Deep Drive



Berkeley DeepDrive [online]. [cit. 2020-01-25]. Dostupné z: https://bdd-data.berkeley.edu/

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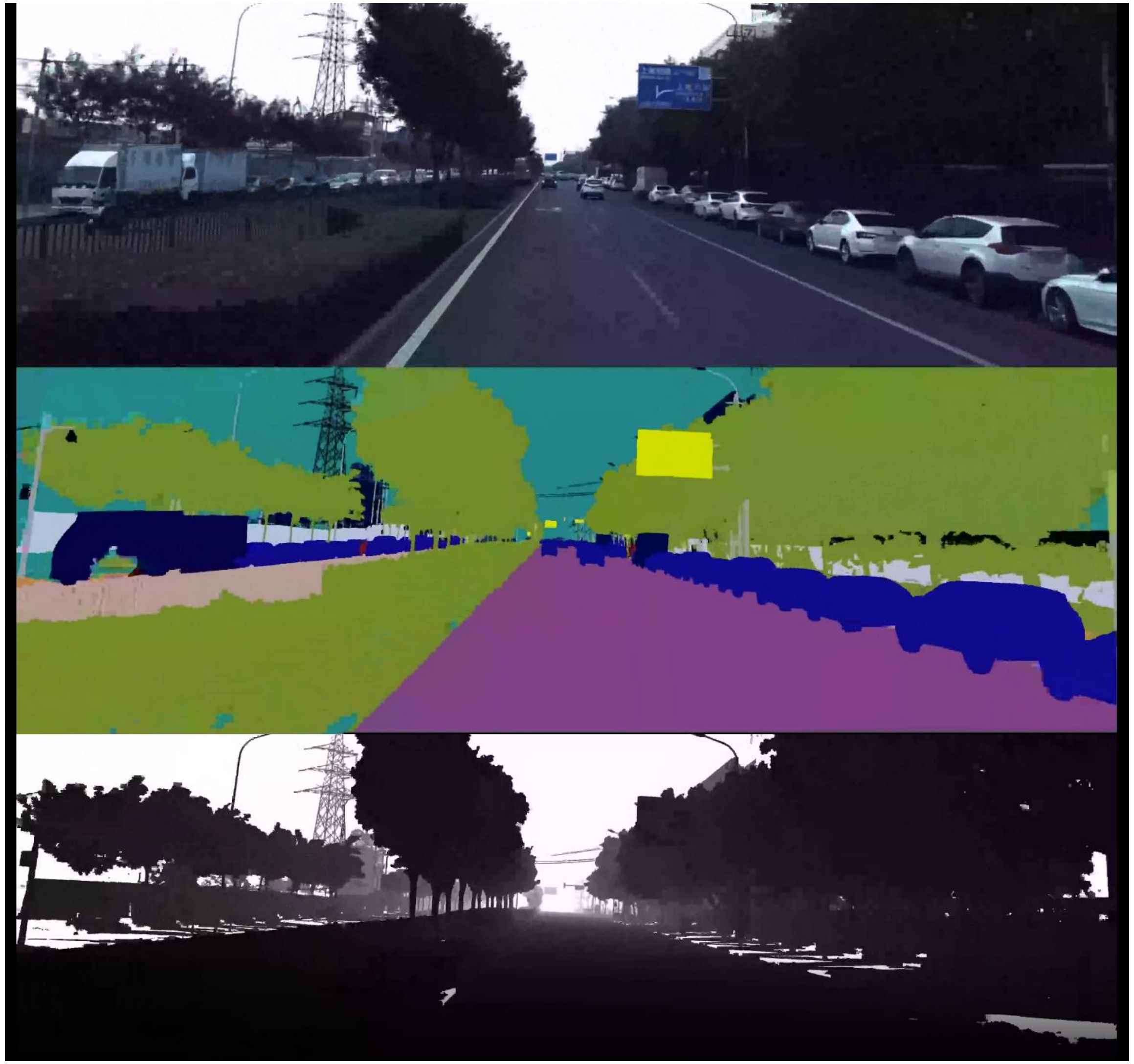
http://apolloscape.auto/

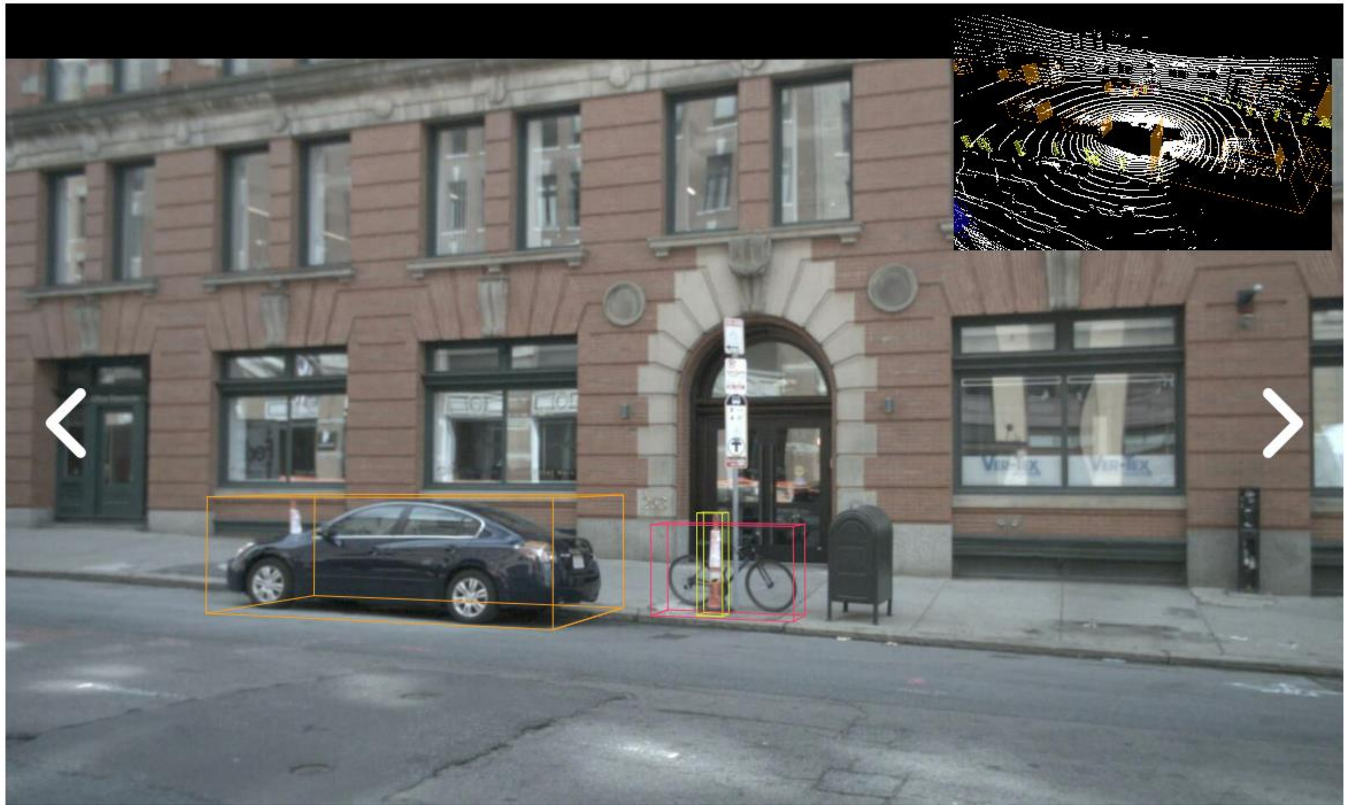
Training Set – Road Objects

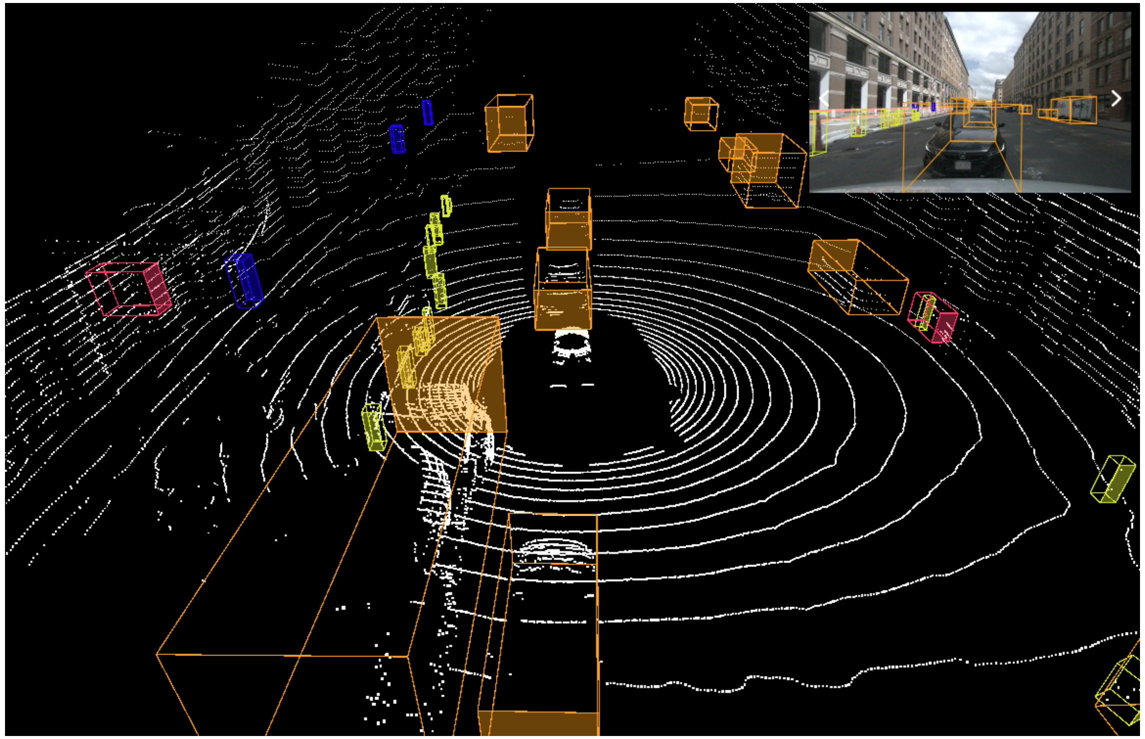


ApolloScape Dataset [online]. [cit. 2020-01-25]. Dostupné z: http://apolloscape.auto/

Training Set – Road Objects

nuScenes





NuScenes dataset [online]. [cit. 2020-01-25]. Dostupné z: https://www.nuscenes.org/nuscenes https://boxy-dataset.com/boxy/

Training Set – Road Objects

THE BOXY VEHICLES DATASET [online]. [cit. 2020-01-25]. Dostupné z: https://boxy-dataset.com/boxy/

The Boxy Vehicle Dataset and Baselines [online]. [cit. 2020-01-25]. Dostupné z: https://www.youtube.com/watch?v=8kwvPJczhd4&t=27s

- Haar
- HOG
- LBP

Traditional Approaches

- SIFT, SURF

KeyPoints

- CNNs

Deep Learning Approach

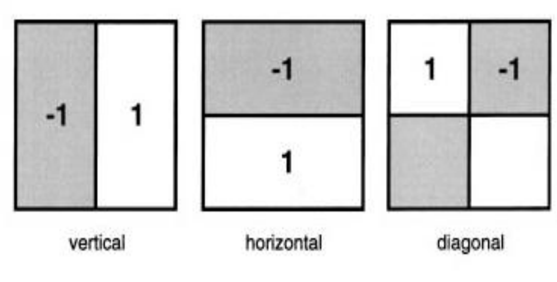
Related Works

2000

Papageorgiou (2000)

A Trainable System for Object Detection

CONSTANTINE PAPAGEORGIOU AND TOMASO POGGIO
Center for Biological and Computational Learning, Artificial Intelligence Laboratory, MIT, Cambridge, MA, USA
cpapa@ai.mit.edu
tp@ai.mit.edu

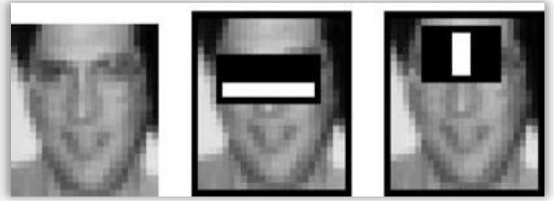


Viola, Jones (2001,2004) cit. > 6500

Robust Real-Time Face Detection

PAUL VIOLA
Microsoft Research, One Microsoft Way, Redmond, WA 98052, USA
viola@microsoft.com

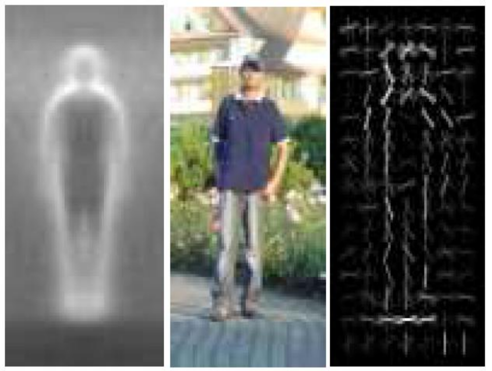
MICHAEL J. JONES
Mitsubishi Electric Research Laboratory, 201 Broadway, Cambridge, MA 02139, USA
mjones@merl.com



Dalal, Triggs (2005) cit. > 10000

Histograms of Oriented Gradients for Human Detection

Navneet Dalal and Bill Triggs
INRIA Rhône-Alps, 655 avenue de l'Europe, Montbonnot 38334, France
{Navneet.Dalal,Bill.Triggs}@inrialpes.fr, http://lear.inrialpes.fr



2005

Haar Wavelet-based Descriptors

- The main idea behind the Haar-like features is that the features can encode the differences of mean intensities between the rectangular areas. For instance, in the problem of face detection, the regions around the eyes are lighter than the areas of the eyes; the regions bellow or on top of eyes have different intensities that the eyes themselves.

- These specific characteristics can be simply encoded by one two-rectangular feature, and the value of this feature can be calculated as the difference between the sum of the intensities inside the rectangles.

Haar Wavelet-based Descriptors

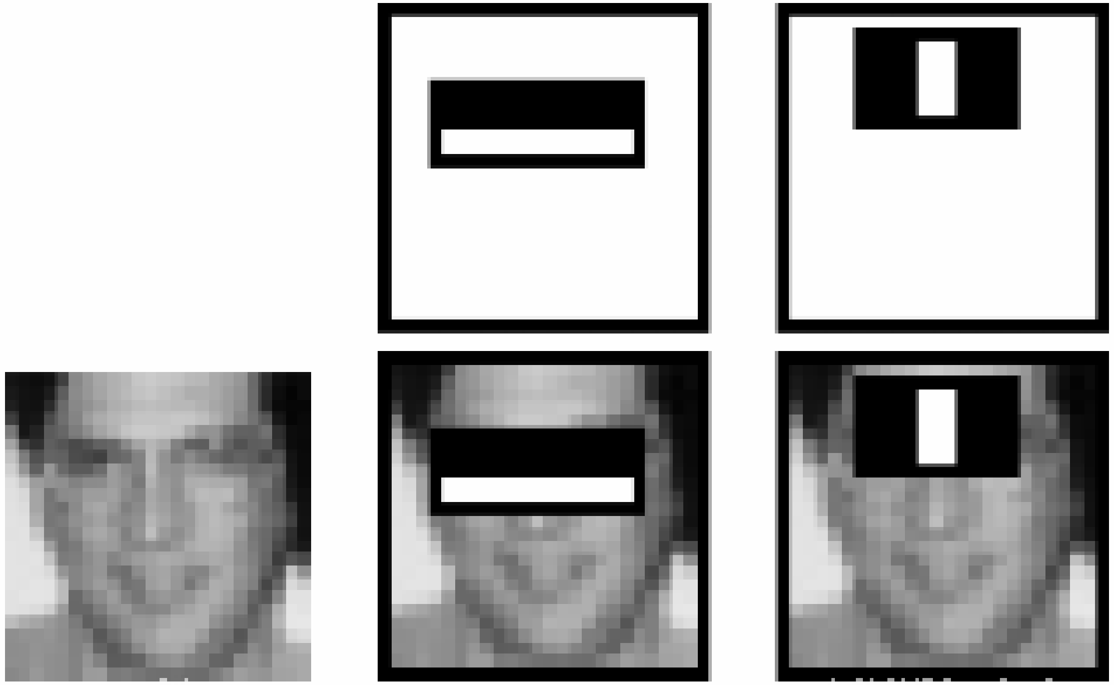
- The paper of Viola and Jones contributed to the popularity of Haar-like features. The authors proposed the object detection framework based on the image representation called the integral image combined with the rectangular features, and the AdaBoost algorithm.

- With the use of integral image, the rectangular features are computed very quickly. The AdaBoost algorithm helps to select the most important features.

- The features are used to train classifers and the cascade of classifers is used for reducing the computational time.

Haar Wavelet-based Descriptors

- faces have similar properties
  - eye regions are darker than the upper-cheeks
  - the nose bridge region is brighter than the eyes



Face Detection using Haar Cascades [online]. [cit. 2020-01-25]. Dostupné z: https://docs.opencv.org/3.4.1/d7/d8b/tutorial_py_face_detection.html

Haar Wavelet-based Descriptors

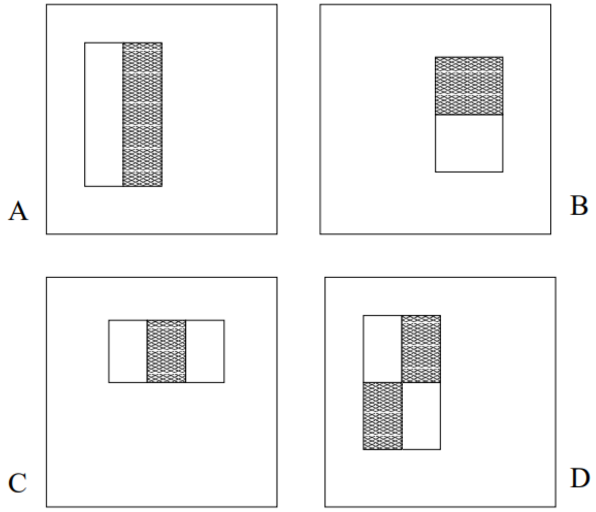


Figure 1: Example rectangle features shown relative to the enclosing detection window. The sum of the pixels which lie within the white rectangles are subtracted from the sum of pixels in the grey rectangles. Two-rectangle features are shown in (A) and (B). Figure (C) shows a three-rectangle feature, and (D) a four-rectangle feature.

There are many motivations for using features rather than the pixels directly. The most common reason is that features can act to encode ad-hoc domain knowledge that is difficult to learn using a finite quantity of training data. For this system there is also a second critical motivation for features: the feature based system operates much faster than a pixel-based system.

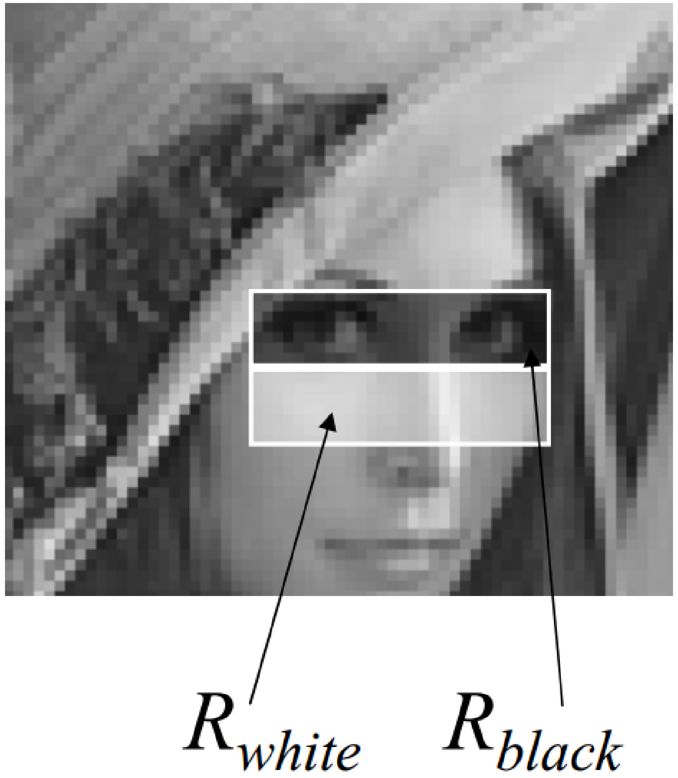
The simple features used are reminiscent of Haar basis functions which have been used by Papageorgiou et al. [10]. More specifically, we use three kinds of features. The value of a *two-rectangle feature* is the difference between the sum of the pixels within two rectangular regions. The regions have the same size and shape and are horizontally or vertically adjacent (see Figure 1). A *three-rectangle feature* computes the sum within two outside rectangles subtracted from the sum in a center rectangle. Finally a *four-rectangle feature* computes the difference between diagonal pairs of rectangles.

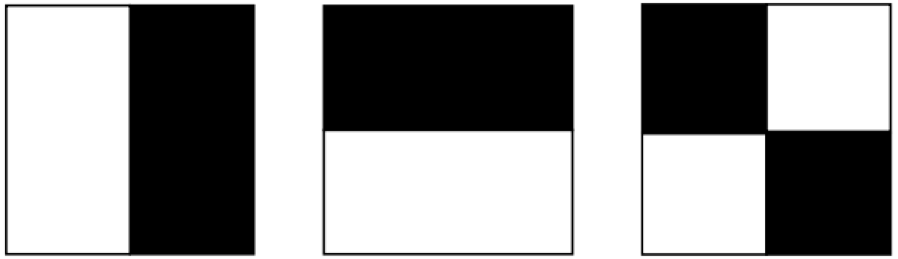
P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, Kauai, HI, USA, 2001, pp. I-I, doi: 10.1109/CVPR.2001.990517.

Face Detection using Haar Cascades [online]. [cit. 2020-01-25]. Dostupné z: https://docs.opencv.org/3.4.1/d7/d8b/tutorial_py_face_detection.html

Features

- Rectangular features



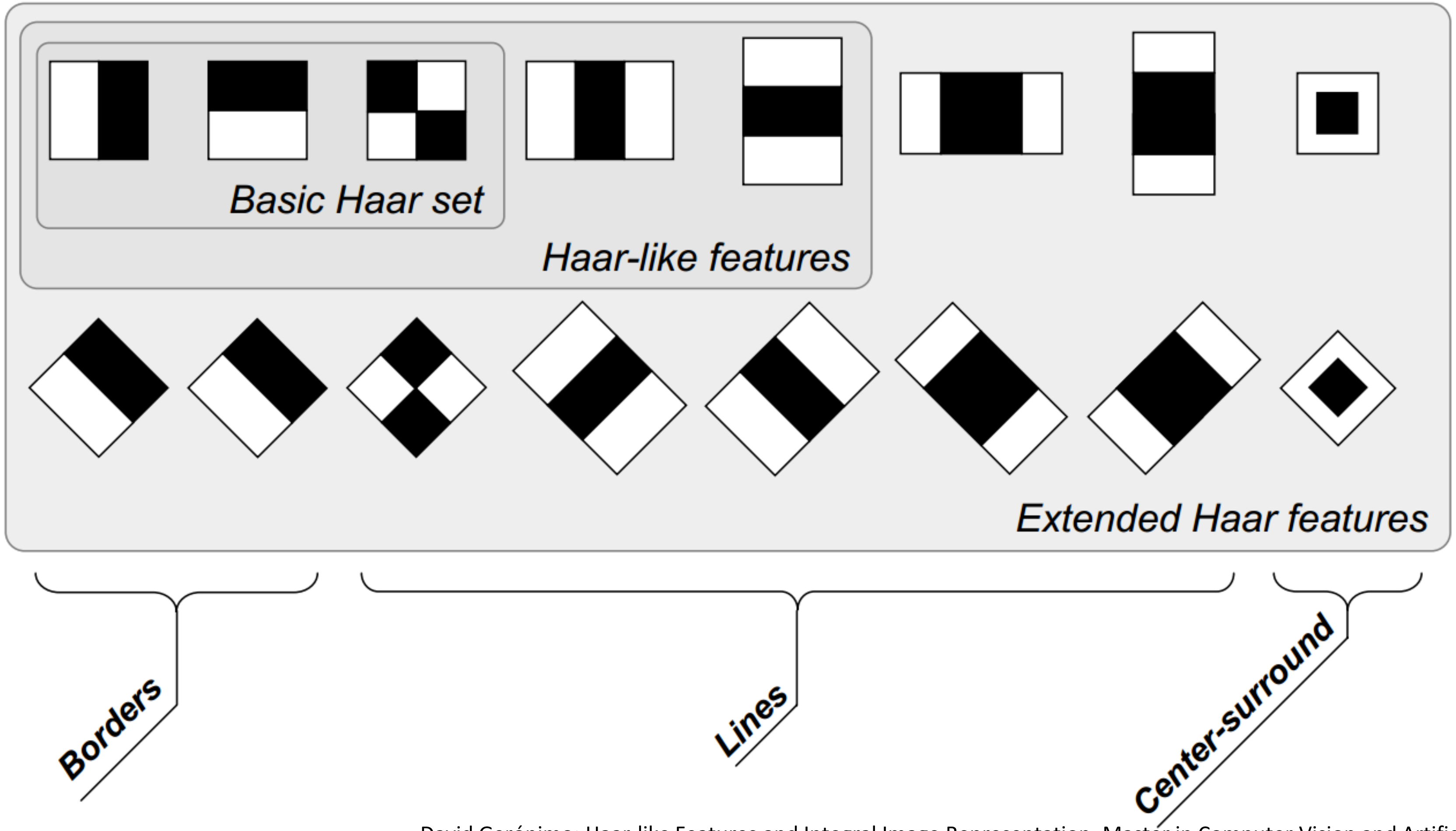


Haar-Feature = white region - black region

David Gerónimo: Haar-like Features and Integral Image Representation, Master in Computer Vision and Artificial Intelligence, 18th December 2009

Features

Different sets



David Gerónimo: Haar-like Features and Integral Image Representation, Master in Computer Vision and Artificial Intelligence, 18th December 2009

Face Detection

- 24x24 sub-window aprox. 160,000 rectangular features
- How speed the computational speed?
  - decrease memory accesses

David Gerónimo: Haar-like Features and Integral Image Representation, Master in Computer Vision and Artificial Intelligence, 18th December 2009

Integral Image

1	1	1
1	1	1
1	1	1

Original image *(i)*

1	2	3
2	4	6
3	6	9

Integral image (ii)

Integral Image

Original image (I)

7	7	7	7	4	8	4	1
7	7	7	8	4	4	1	1
7	7	8	4	8	4	4	1
7	8	4	7	**8**	4	1	1
7	8	7	7	4	8	1	1
7	8	7	7	8	8	1	1

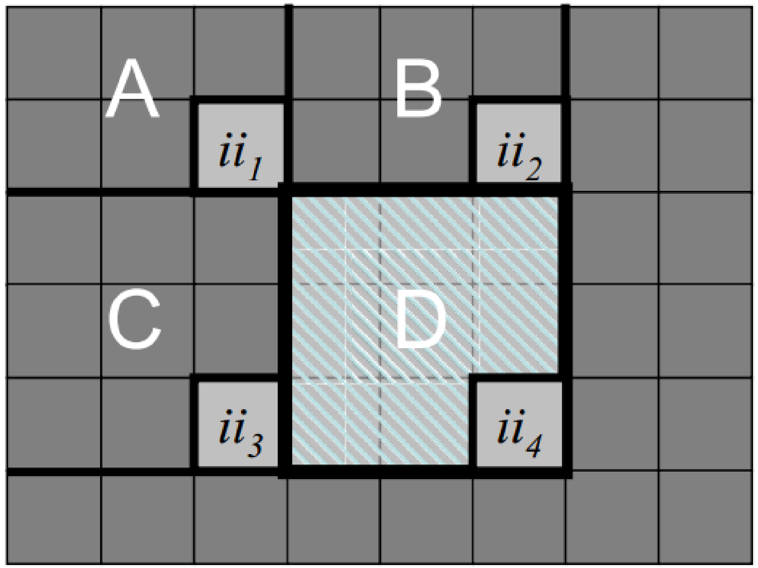
Integral image (ii)

7	14	21	28	32	40	44	45
14	28	42	57	65	77	82	84
21	42	64	83	99	119	124	127
28	57	83	109	**133**			

$$133 = 99 + 109 - 83 + 8$$

Integral Image

Integral image (ii)

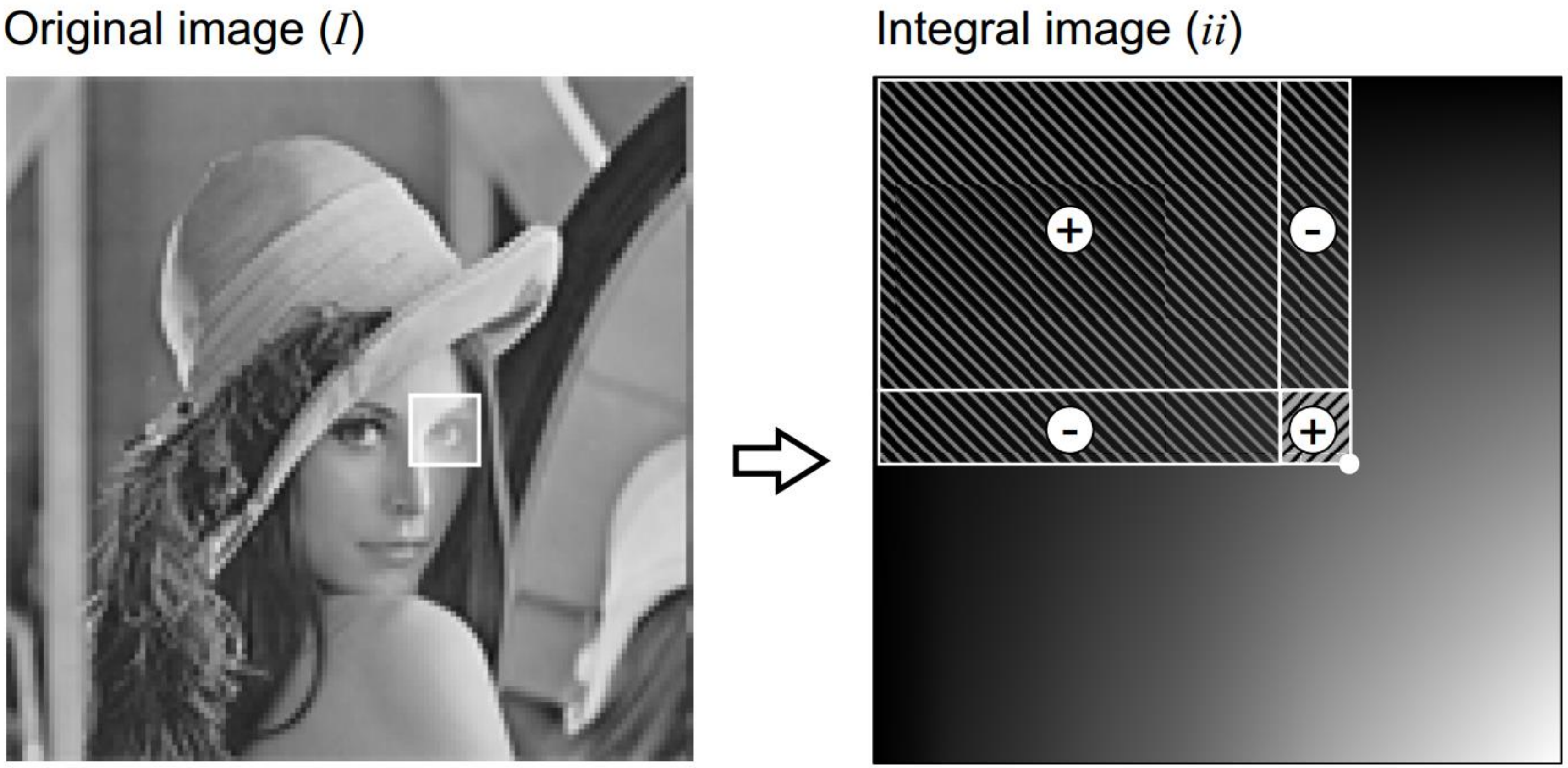


$$ii_1 = \mathrm{sum}(A)$$
$$ii_2 = \mathrm{sum}(A) + \mathrm{sum}(B)$$
$$ii_3 = \mathrm{sum}(A) + \mathrm{sum}(C)$$
$$ii_4 = \mathrm{sum}(A) + \mathrm{sum}(B) + \mathrm{sum}(C) + \mathrm{sum}(D)$$

$$\mathrm{sum}(D) = ii_4 + ii_1 - ii_2 - ii_3$$

David Gerónimo: Haar-like Features and Integral Image Representation, Master in Computer Vision and Artificial Intelligence, 18th December 2009

Integral Image



Integral Image

Integral image (ii)

7	14	21	28	32	40	44	45
14	28	42	57	65	77	82	84
21	42	64	83	99	119	124	127
28	57	83	109	133	153	159	163
35	72	105	138	166	194	201	206
42	87	127	167	203	239	247	253

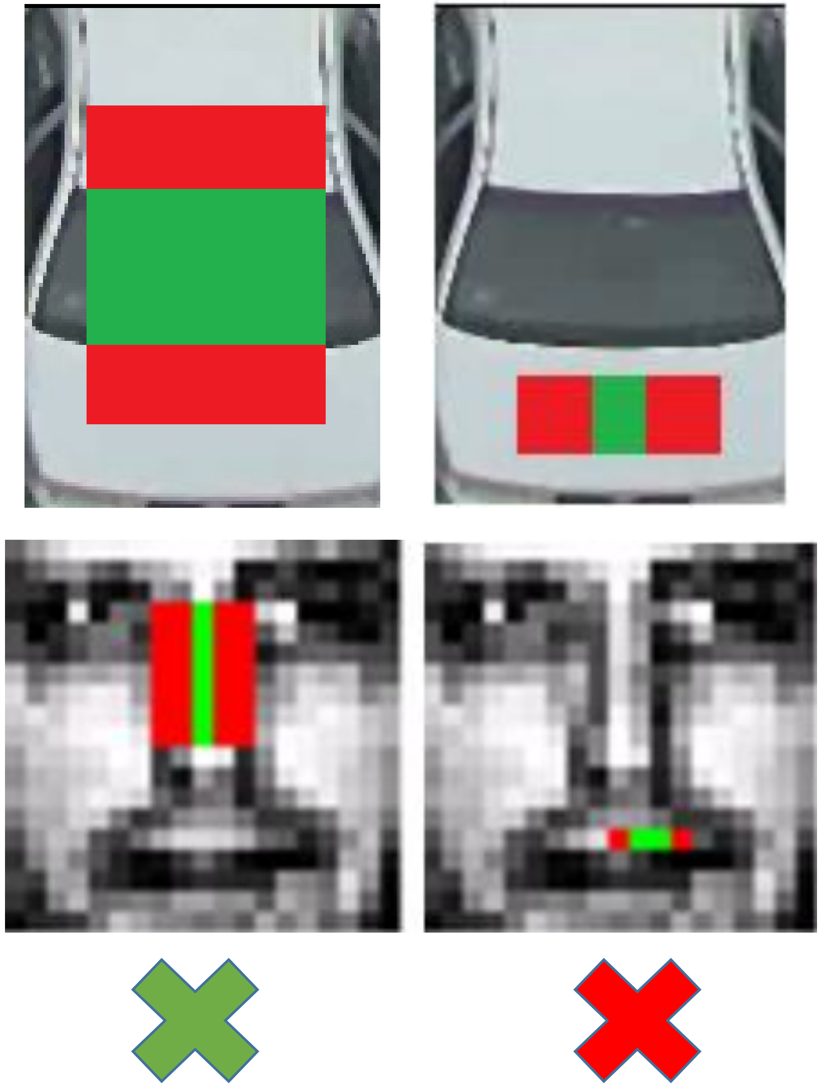
Original image (I)

7	7	7	7	4	8	4	1
7	7	7	8	4	4	1	1
7	7	8	4	8	4	4	1
7	8	4	7	8	4	1	1
7	8	7	7	4	8	1	1
7	8	7	7	8	8	1	1

$\rightarrow$ 54

$$54 = 194 + 42 - 77 - 105$$

Feature Selection



Feature Selection

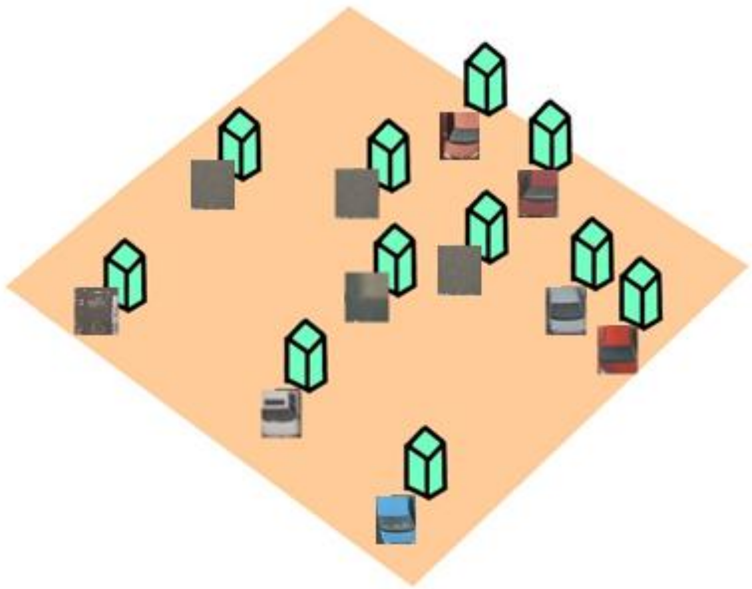
- AdaBoost (Adaptive Boost) is an iterative learning algorithm to construct a “strong” classifier as a linear combination of weighted simple “weak” classifiers

- weak classifier - each single rectangle feature (features as weak classifiers)

- during each iteration, each example/image receives a weight determining its importance

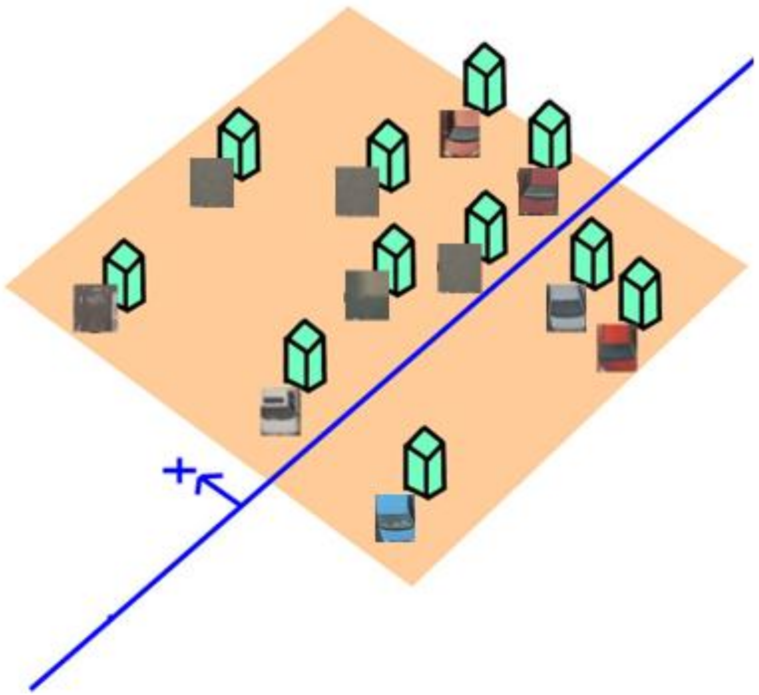
Feature Selection

- AdaBoost starts with a uniform distribution of "weights" over training examples.



Feature Selection

- AdaBoost starts with a uniform distribution of “weights” over training examples.
- Select the classifier with the lowest weighted error (i.e. a “weak” classifier)



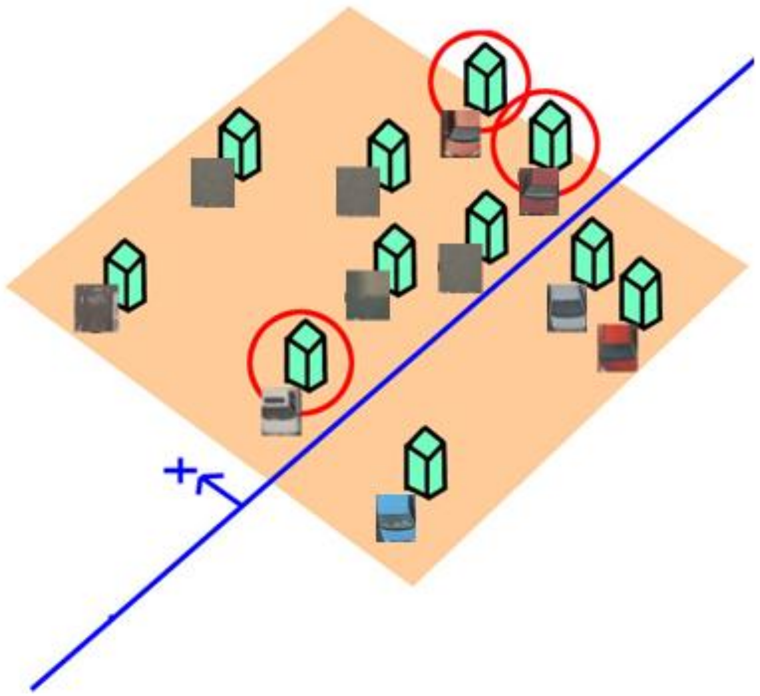
Slide taken from a presentation by Qing Chen, Discover Lab, University of Ottawa

Feature Selection

- AdaBoost starts with a uniform distribution of “weights” over training examples.

- Select the classifier with the lowest weighted error (i.e. a “weak” classifier)

- Increase the weights on the training examples that were misclassified.



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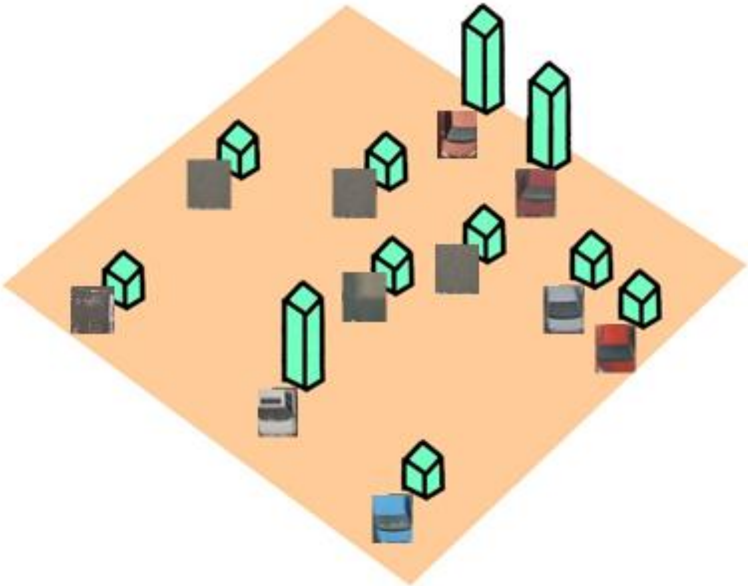

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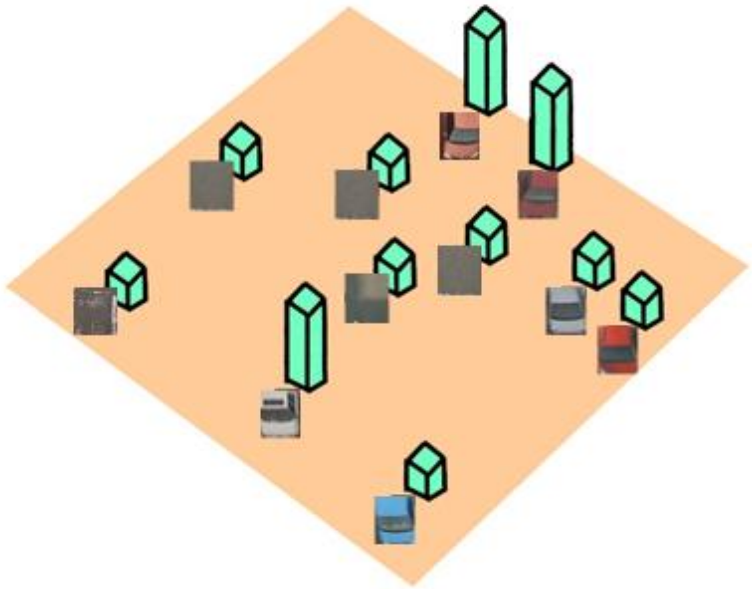
Feature Selection

- AdaBoost starts with a uniform distribution of “weights” over training examples.
- Select the classifier with the lowest weighted error (i.e. a “weak” classifier)
- Increase the weights on the training examples that were misclassified.
- (Repeat)



Slide taken from a presentation by Qing Chen, Discover Lab, University of Ottawa

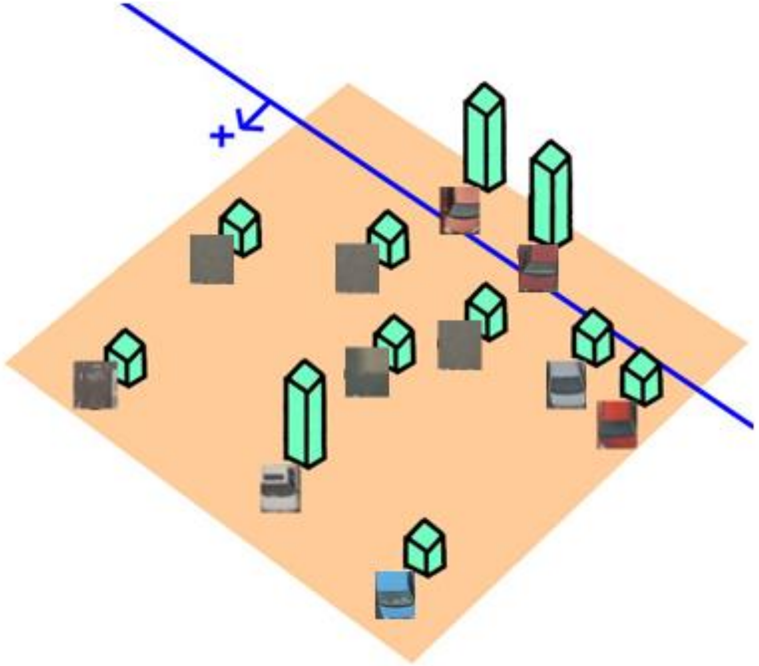
Feature Selection

- AdaBoost starts with a uniform distribution of "weights" over training examples.

- **Select the classifier with the lowest weighted error (i.e. a "weak" classifier)**

- Increase the weights on the training examples that were misclassified.

- (Repeat)



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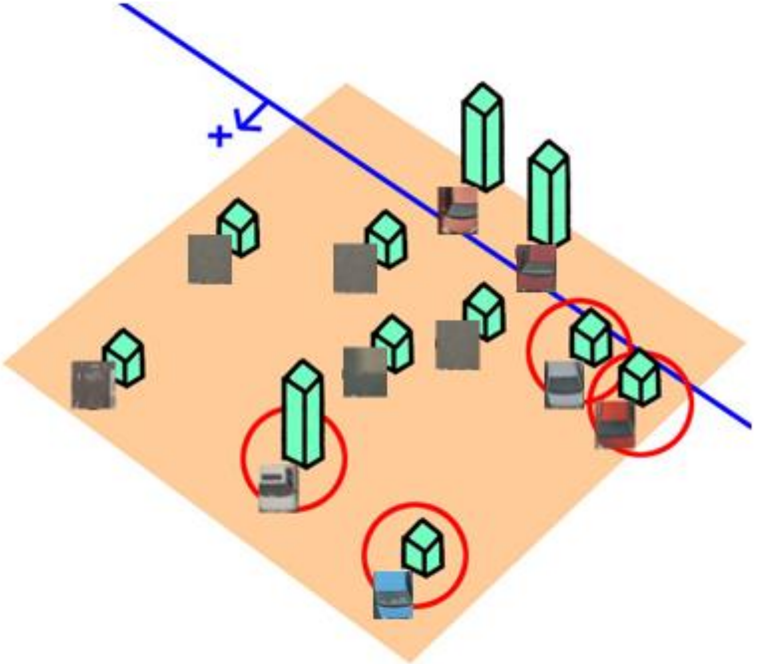

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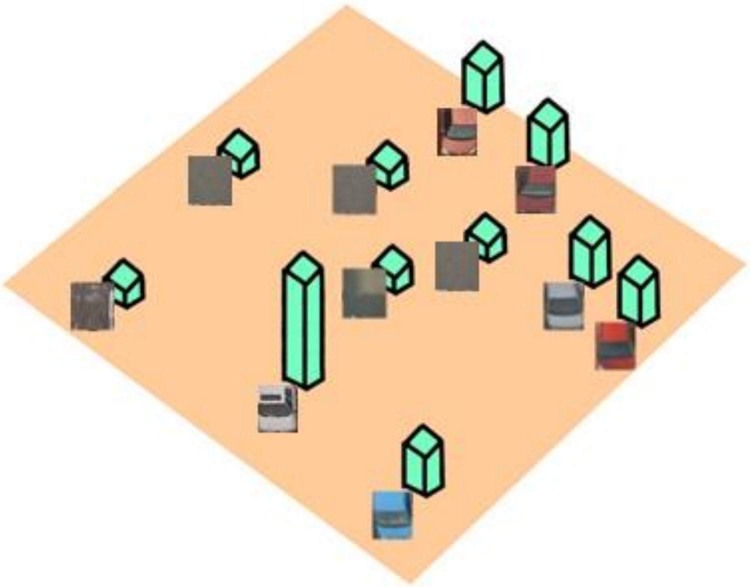

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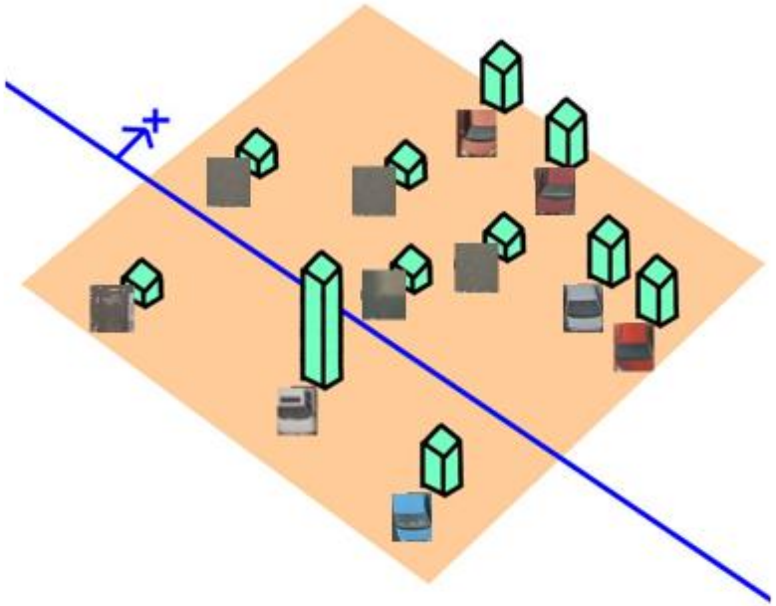

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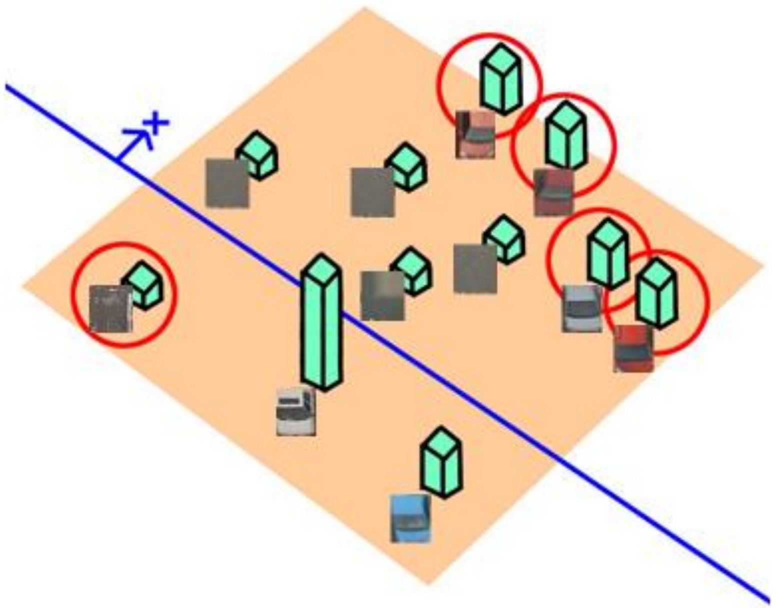

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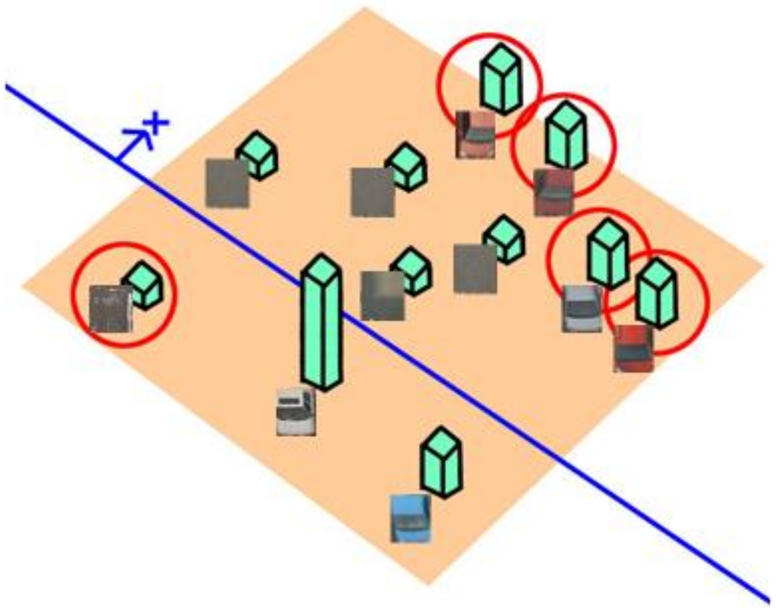
Feature Selection



- At the end, carefully make a linear combination of the weak classifiers obtained at all iterations.

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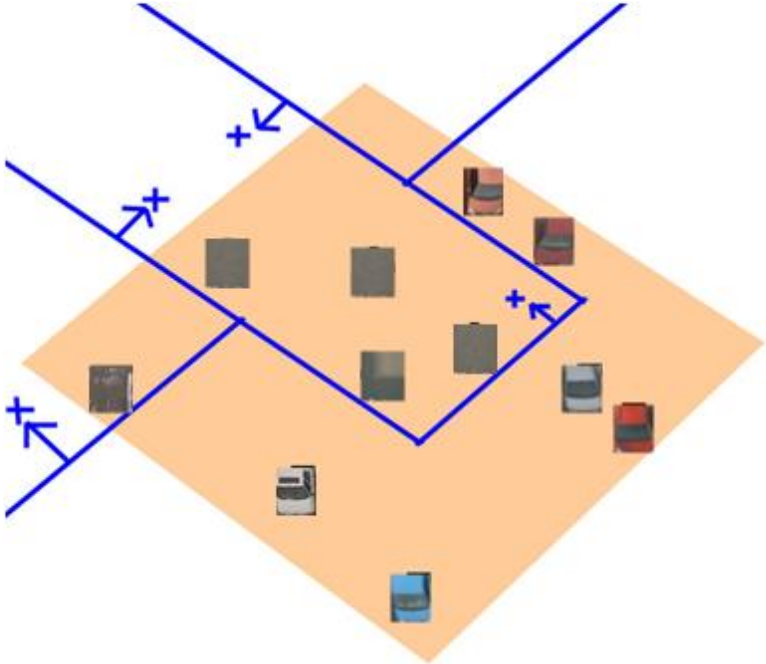
Feature Selection



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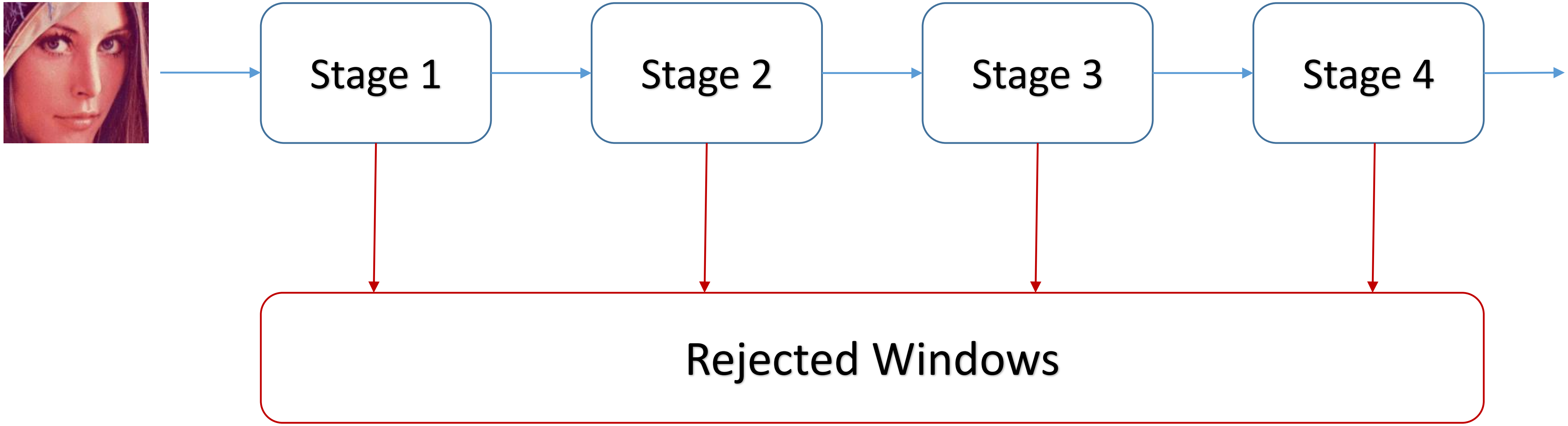
Slide taken from a presentation by Qing Chen, Discover Lab, University of Ottawa

Cascade of Classifier

The idea of cascade classifier is reject the non-face region as soon as possible



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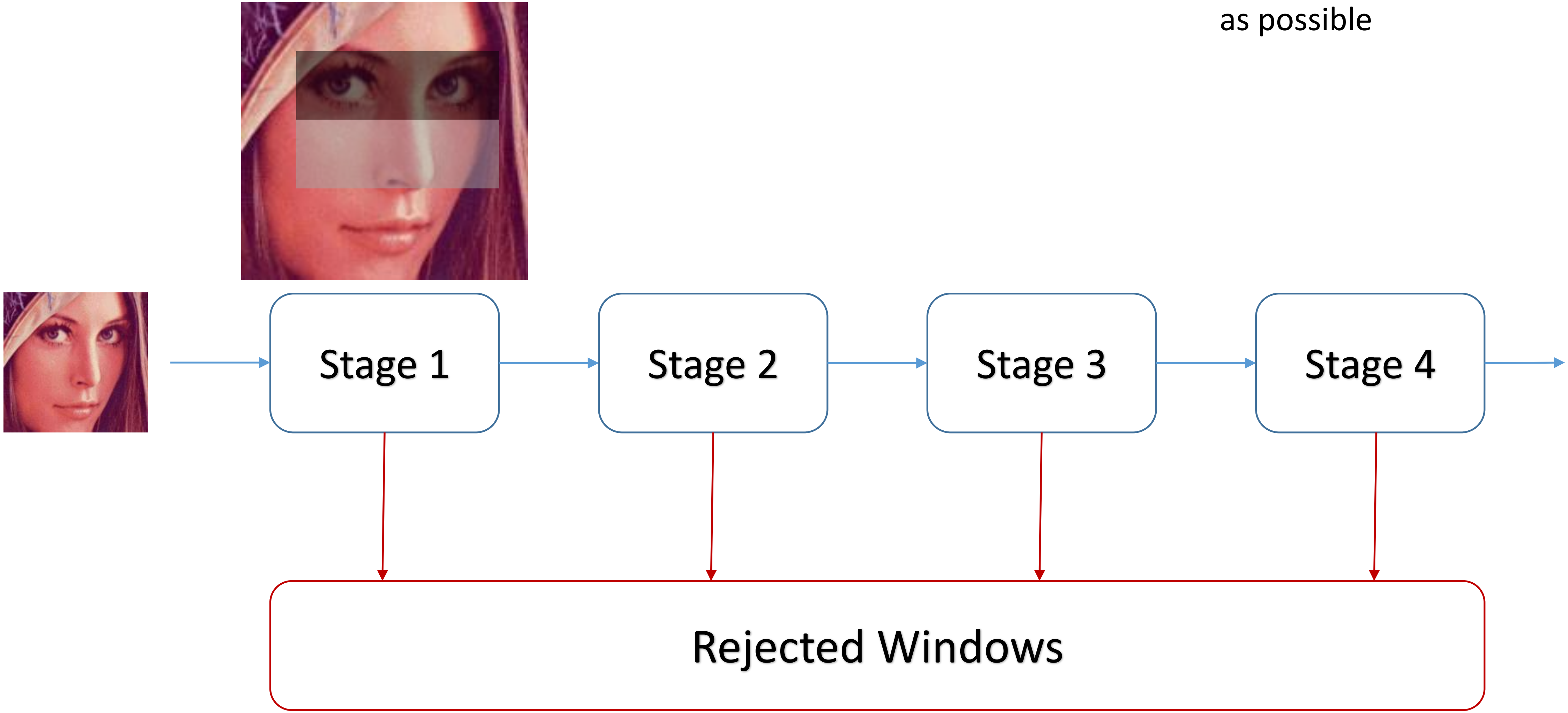

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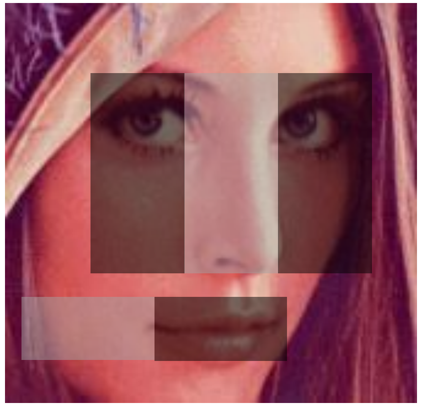

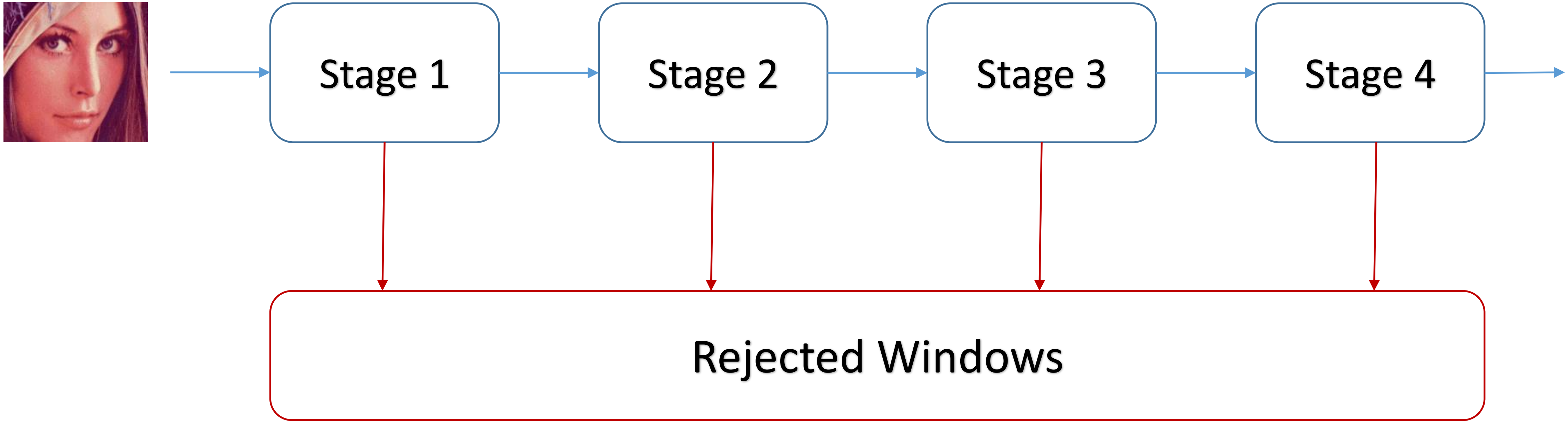

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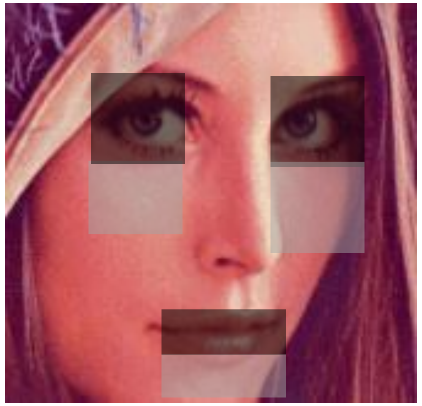

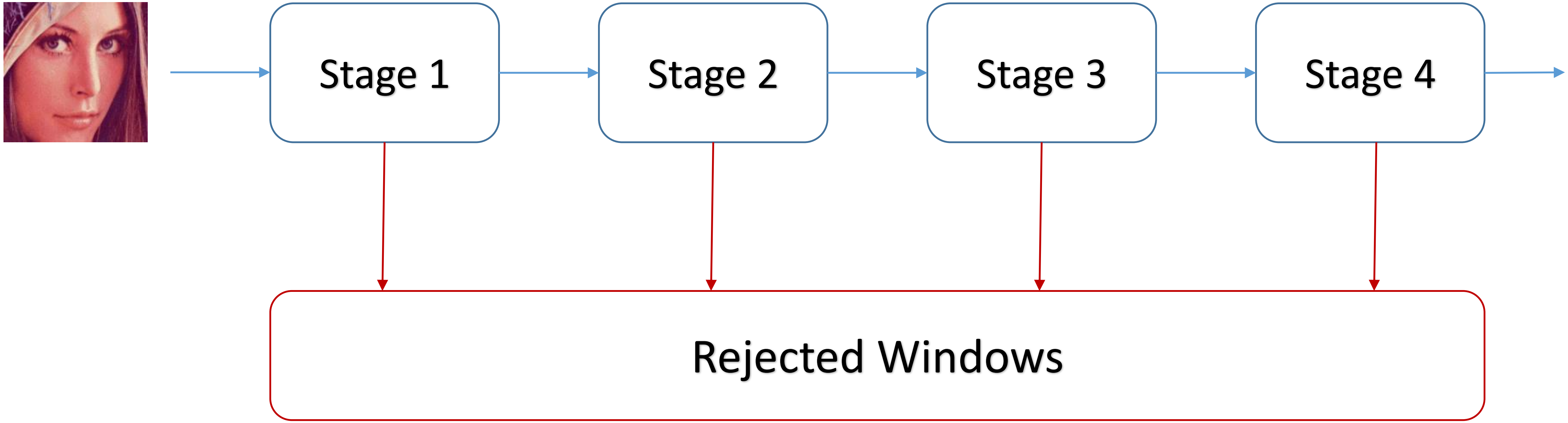

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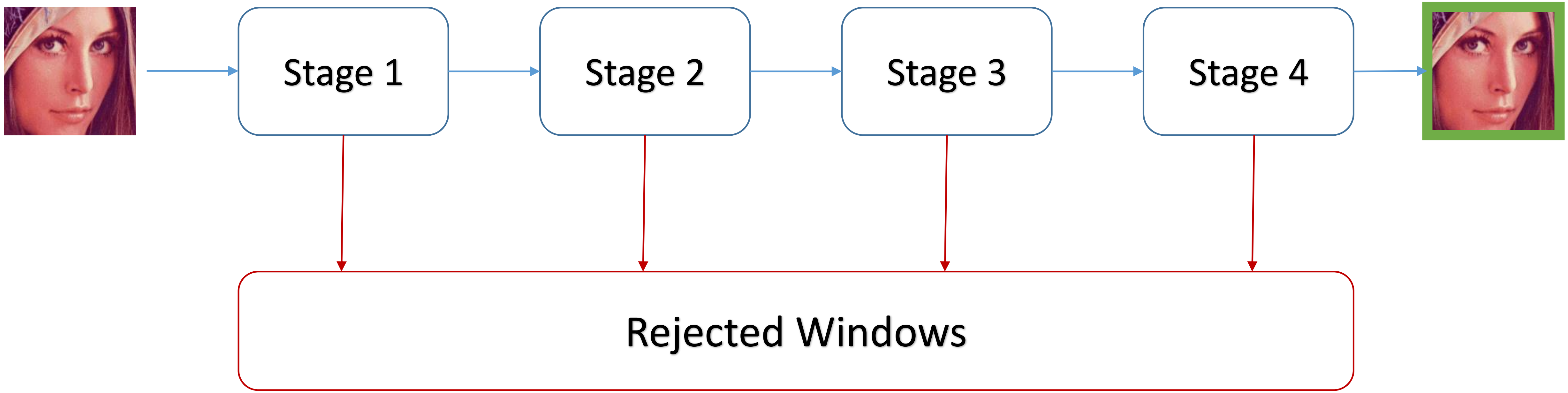


Cascade of Classifier

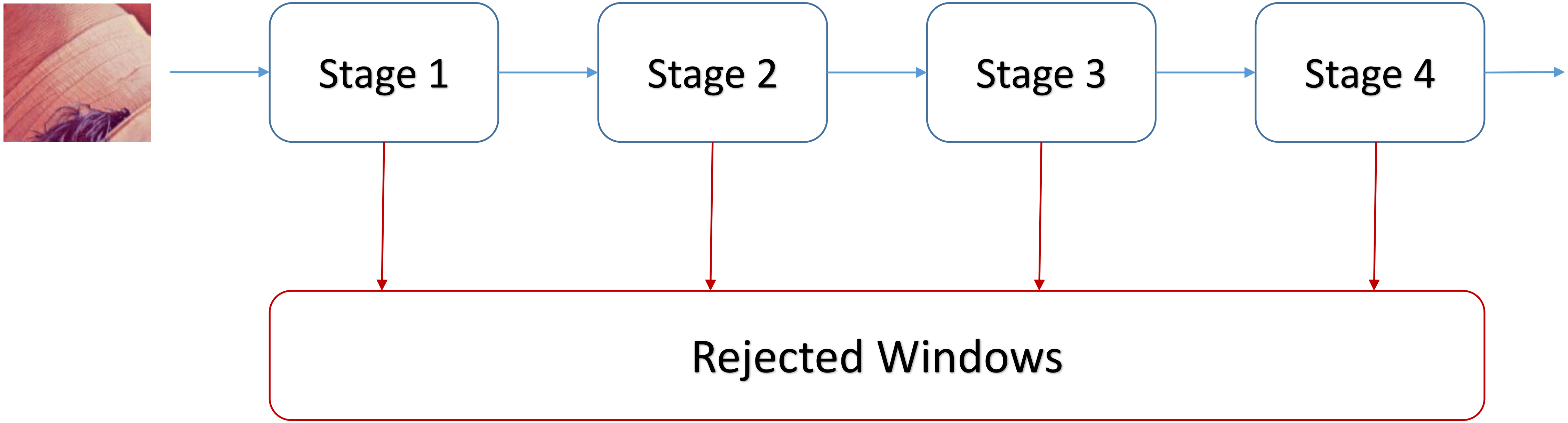
The idea of cascade classifier is reject the non-face region as soon as possible

Stage 1 → Stage 2 → Stage 3 → Stage 4 →

Rejected Windows

Cascade of Classifier

The idea of cascade classifier is reject the non-face region as soon as possible



Cascade of Classifier

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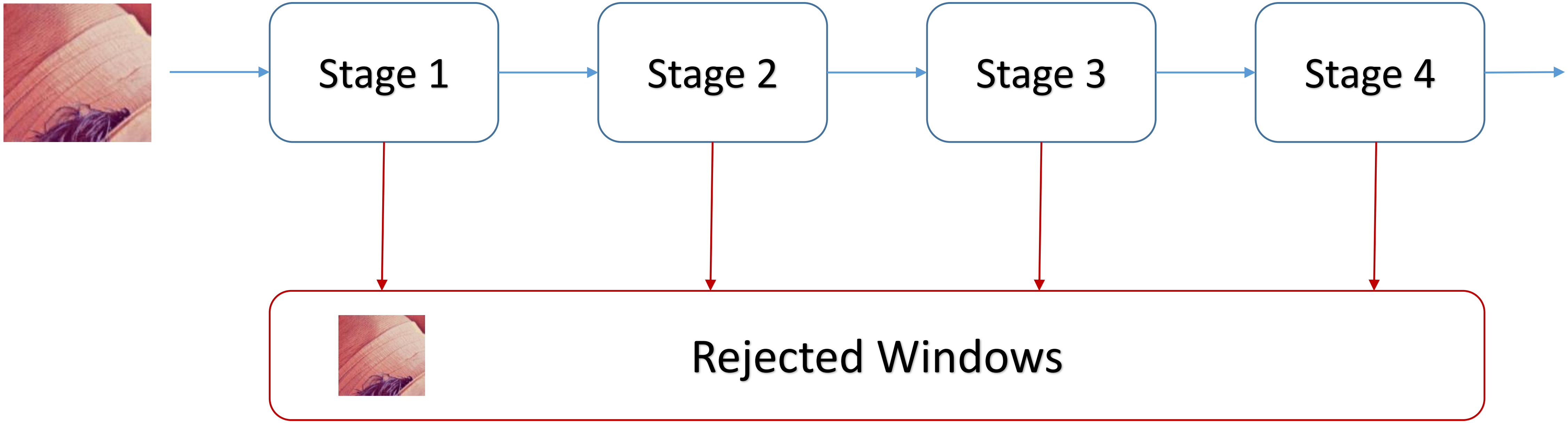


Haar Features

OpenCV Face Detection: Visualized [online]. [cit. 2020-01-25]. Dostupné z: https://vimeo.com/12774628

Face Detection - Evaluation

Face Detection Data Set and Benchmark Home [online]. [cit. 2020-01-25]. Dostupné z: http://vis-www.cs.umass.edu/fddb/

Face Detection - Evaluation

TP = number of true positives
FP = number of false positives
FN = number of false negatives
TN = number of true negatives

precision = TP/(TP+FP)
sensitivity = TP/(TP+FN)
F1 score (harmonic mean of precision and sensitivity) = 2 × precision × sensitivity/(precision + sensitivity)

Face Detection - Evaluation

Figure 8. *Matching detections and annotations*. In this image, the ellipses specify the face annotations and the five rectangles denote a face detector's output. Note that the second face from left has two detections overlapping with it. We require a valid matching to accept only one of these detections as the true match, and to consider the other detection as a false positive. Also, note that the third face from the left has no detection overlapping with it, so no detection should be matched with this face. The blue rectangles denote the true positives and yellow rectangles denote the false positives in the desired matching.

Face Detection Data Set and Benchmark Home [online]. [cit. 2020-01-25]. Dostupné z: http://vis-www.cs.umass.edu/fddb/

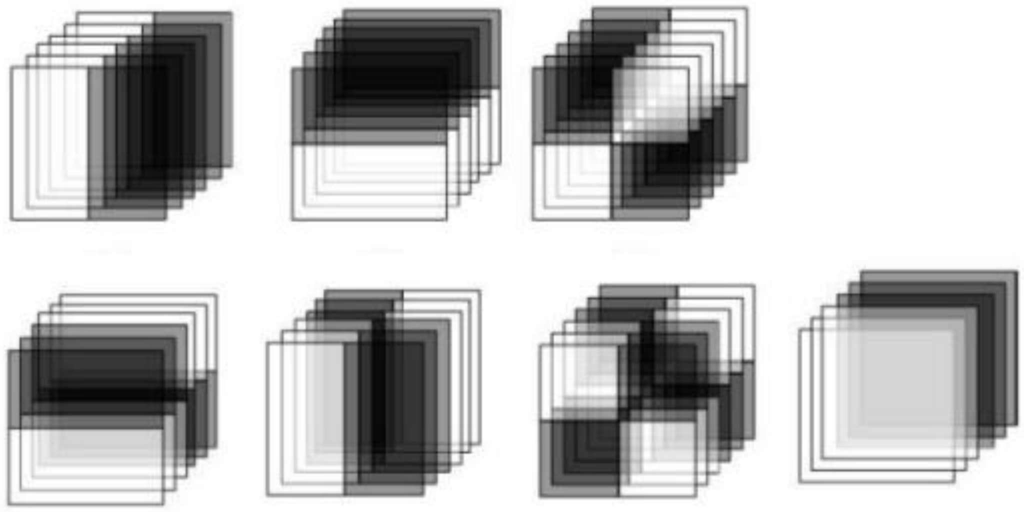
Haar Features

- Since Viola and Jones popularized the Haar-like features for face detection, the Haarlike features and their modifcations were used in many detection tasks (e.g. pedestrian, eye, vehicle).

- In the area of pedestrian detection, in [1], the authors presented the component-based person detector that is able to detect the occluded people in clustered scenes in static images. The detector uses the Haar-like features to describe the components of people (heads, legs, arms) combined with the SVM classifer. The Viola and Jones detection framework was successfully extended for moving-human detection in [2]. In [3], the authors proposed the method for estimating the walking direction of pedestrian.

Haar Features

- The 3D Haar-like features for pedestrian detection were presented in [4]. The authors extend the classical Haar-like features using the volume flters in 3D space (instead of using rectangle flters in 2D space) to capture motion information. The 3D features are then combined with the SVM classifer. To compute the 3D Haar-like features using the integral image like the classical 2D features, the authors introduced Integral Volume that extends 2D integral image to the three dimensions.



Haar Features

[1] Mohan, A., Papageorgiou, C., Poggio, T.: Example-based object detection in images by components. IEEE Trans. Pattern Anal. Mach. Intell. 23(4), 349–361 (Apr 2001), http://dx.doi.org/10.1109/34.917571

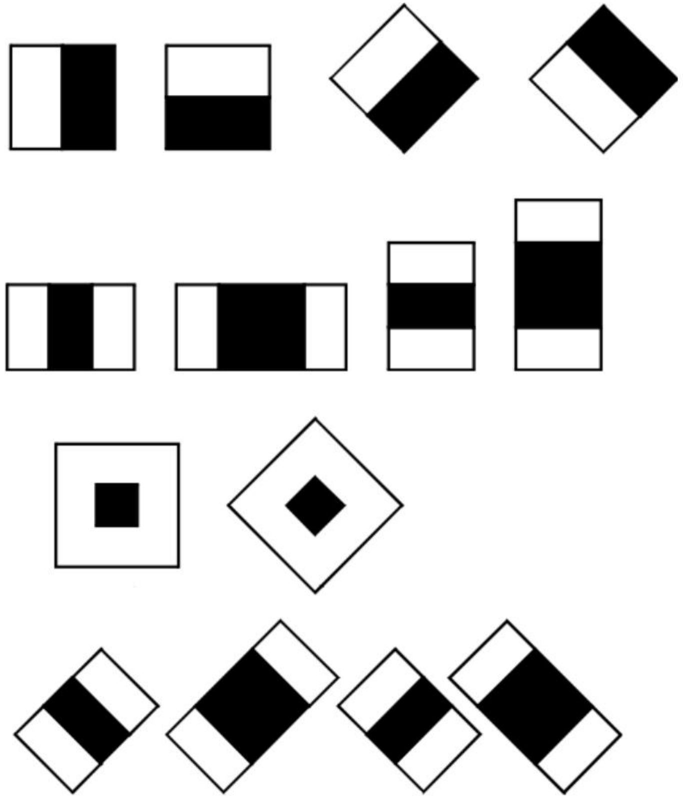
[2] Viola, P., Jones, M., Snow, D.: Detecting pedestrians using patterns of motion and appearance. In: Computer Vision, 2003. Proceedings. Ninth IEEE International Conference on. pp. 734 –741 vol.2 (oct 2003)

[3] Shimizu, H., Poggio, T.: Direction estimation of pedestrian from multiple still images. In: Intelligent Vehicles Symposium, 2004 IEEE. pp. 596–600 (2004)

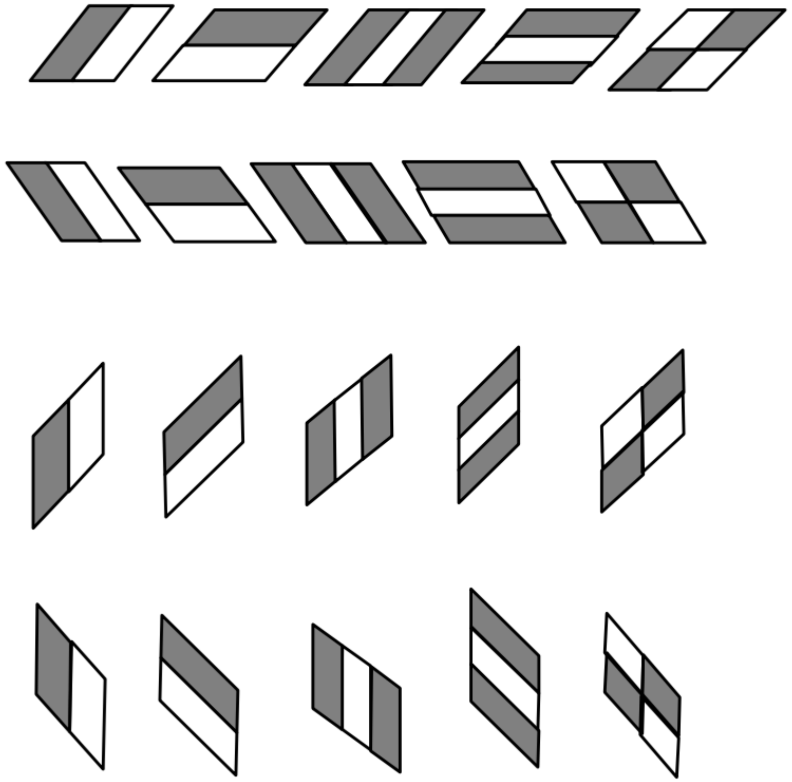
[4] Cui, X., Liu, Y., Shan, S., Chen, X., Gao, W.: 3d haar-like features for pedestrian detection. In: Multimedia and Expo, 2007 IEEE International Conference on. pp. 1263–1266 (July 2007)

Haar Features

The modified version of Haar-like features that more properly reflect the shape of the pedestrians than the classical Haar-like features.



Lienhart, R., Maydt, J.: An extended set of haar-like features for rapid object detection. In: Image Processing. 2002. Proceedings. 2002 International Conference on. vol. 1, pp. I–900–I–903 vol.1 (2002)



Hoang, V.D., Vavilin, A., Jo, K.H.: Pedestrian detection approach based on modified haar-like features and adaboost. In: Control, Automation and Systems (ICCAS), 2012 12th International Conference on. pp. 614-618 (Oct 2012)

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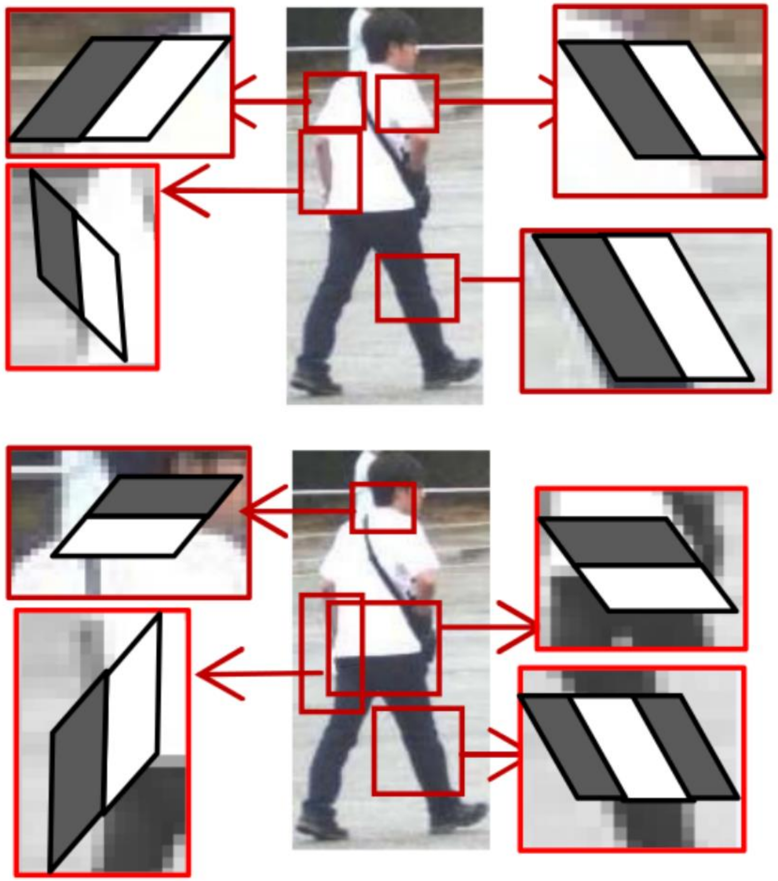

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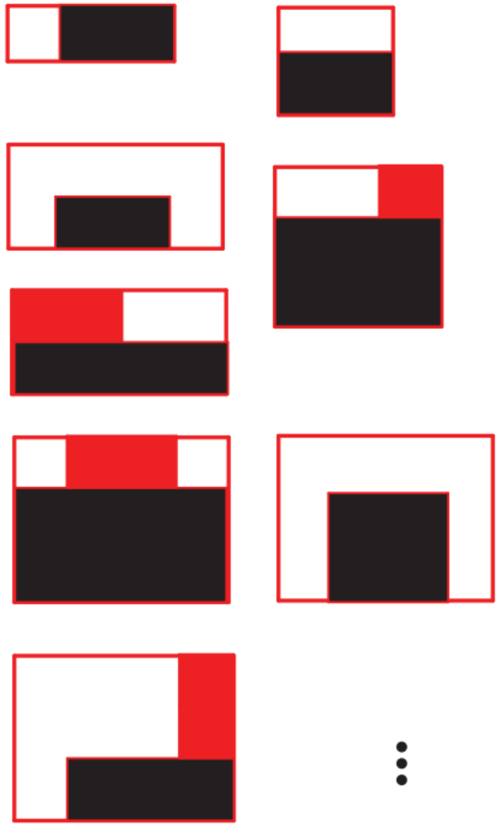

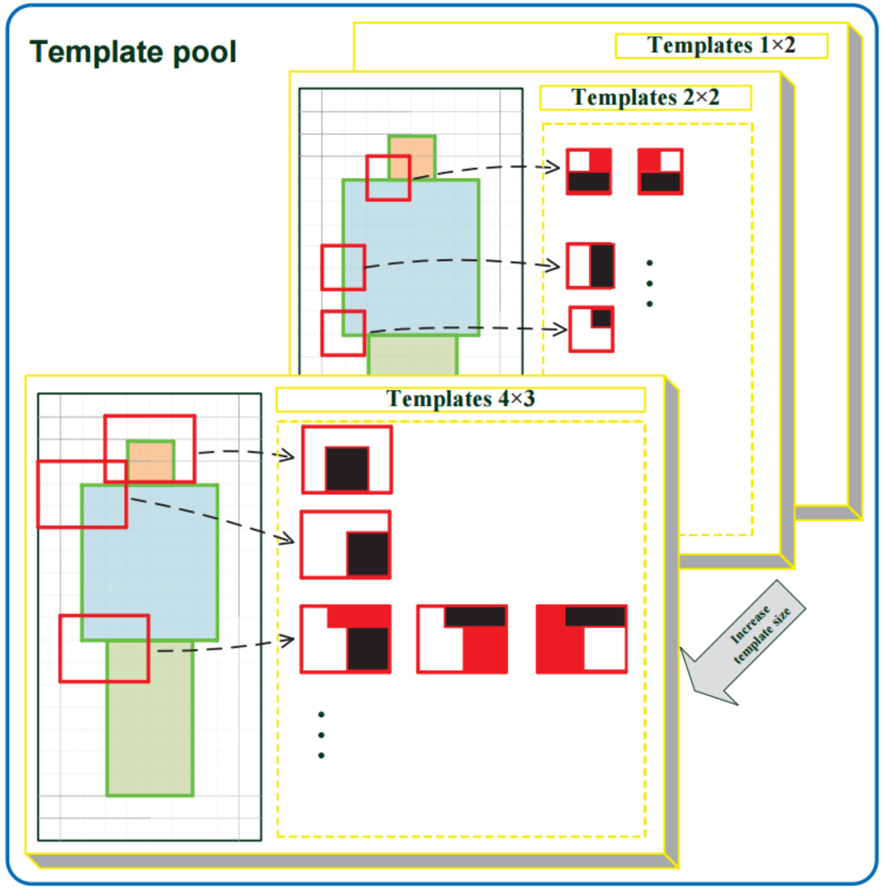

S. Zhang, C. Bauckhage, and A. B. Cremers. Informed haar-like features improve pedestrian detection. In CVPR, 2014.

Haar Features

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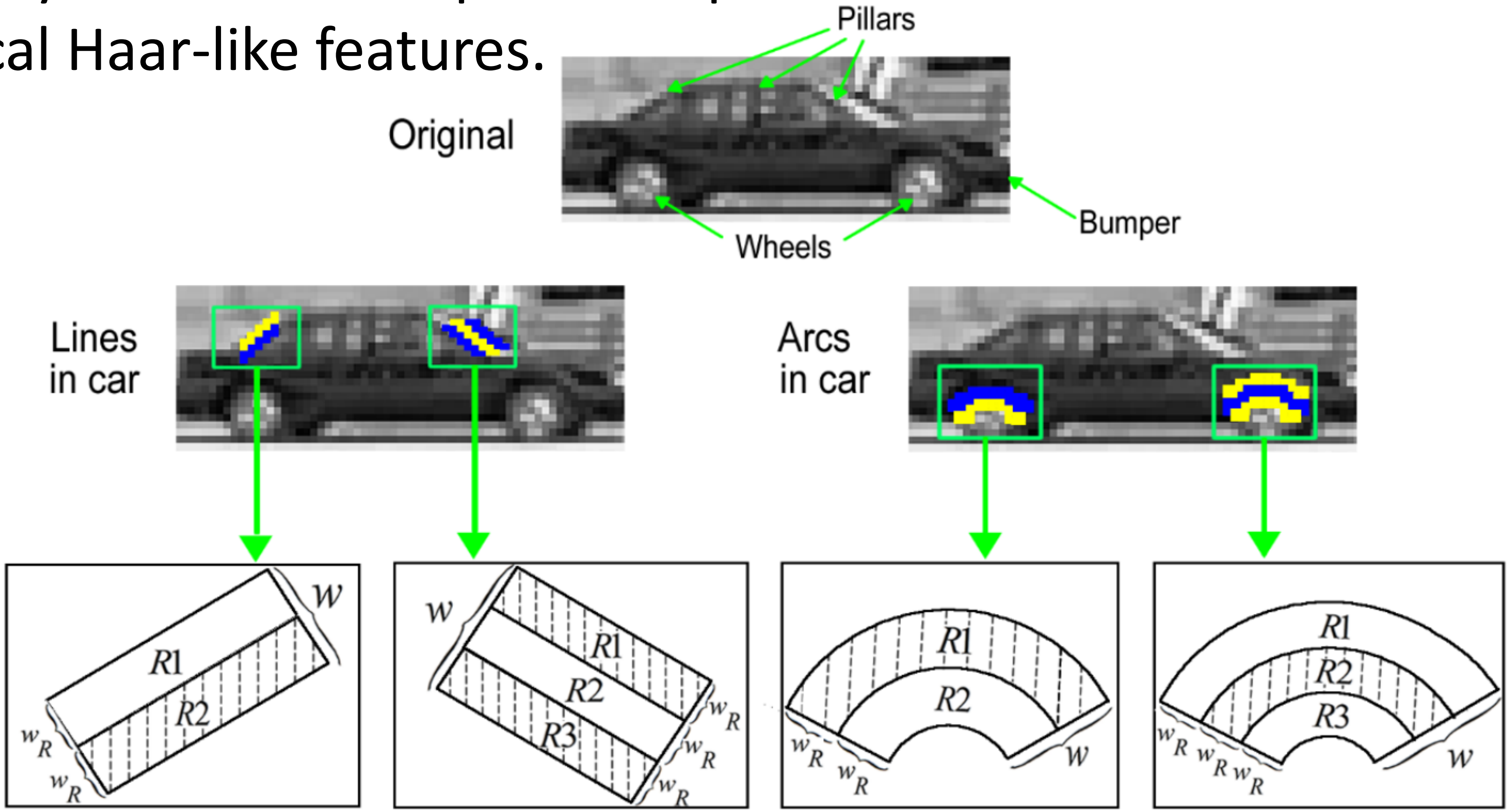


Zheng, W., Liang, L.: Fast car detection using image strip features. In: Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. pp. 2703–2710 (2009)

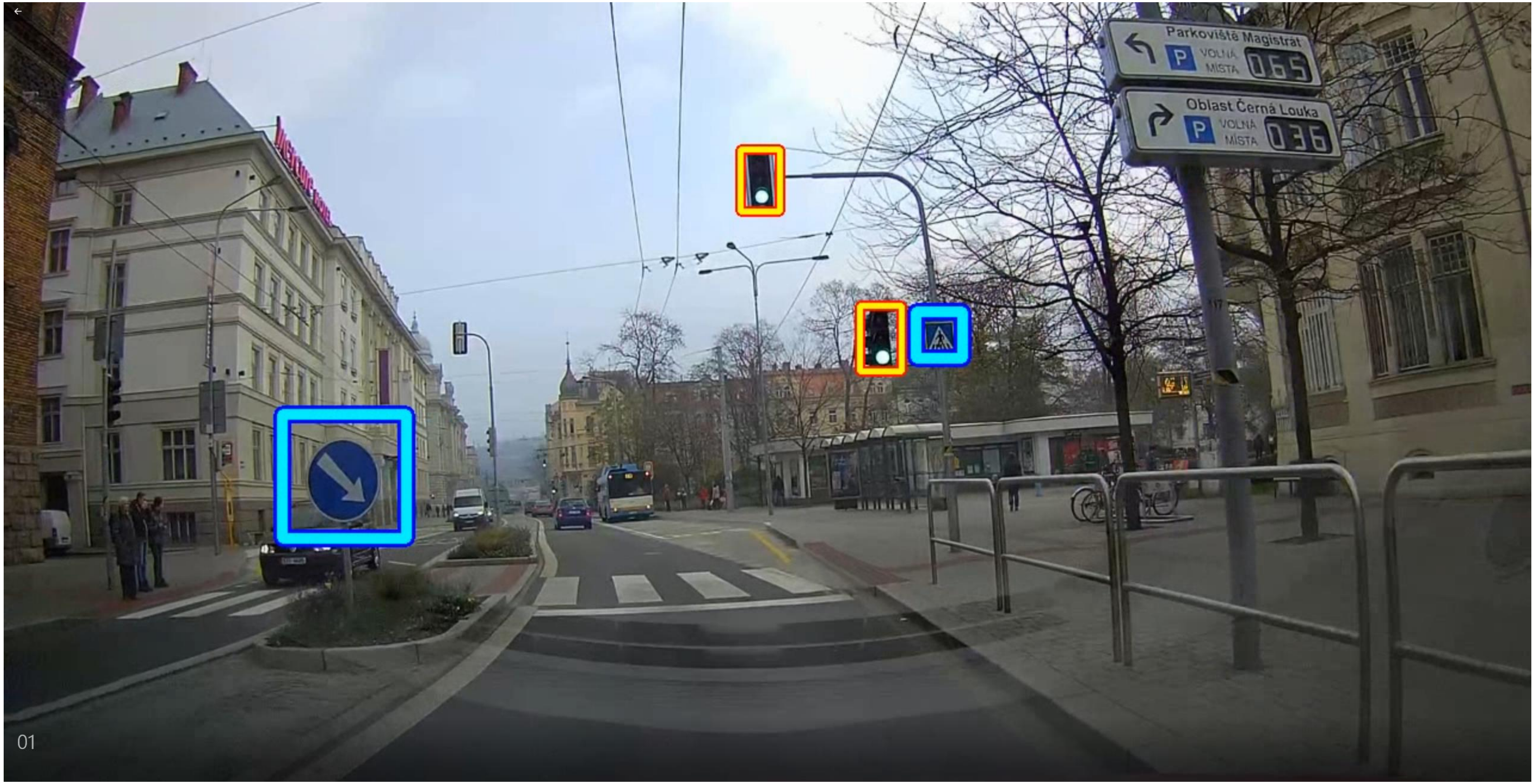
Haar Features

Five most significant Haar features selected for the first stage of each of the 3 trained detectors

https://ieeexplore.ieee.org/abstract/document/8050341

A. Suleiman, Y. Chen, J. Emer and V. Sze, "Towards closing the energy gap between HOG and CNN features for embedded vision," *2017 IEEE International Symposium on Circuits and Systems (ISCAS)*, Baltimore, MD, 2017, pp. 1-4.
doi: 10.1109/ISCAS.2017.8050341

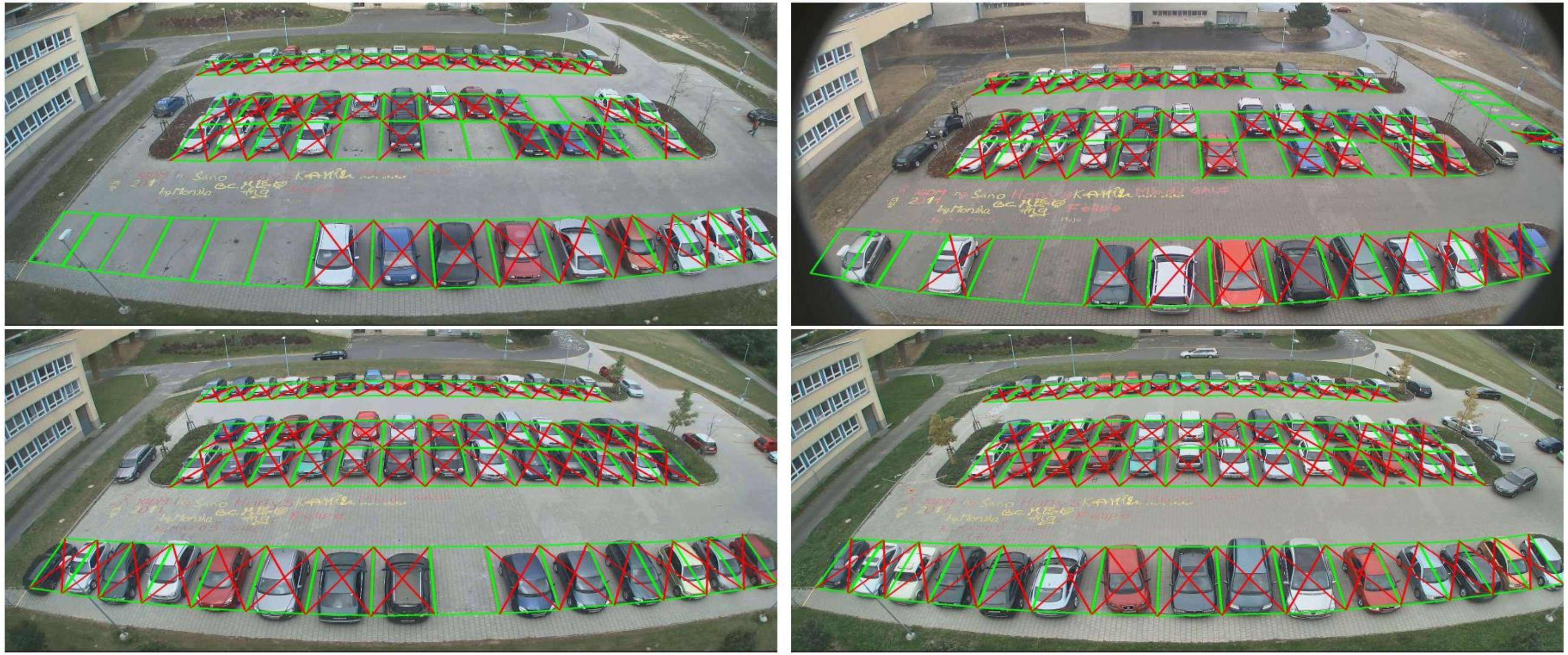
Haar Features



Haar Features

- Fusek, R., Mozdřeň, K., Šurkala, M., Sojka, E.: **AdaBoost for Parking Lot Occupation Detection**. Advances in Intelligent Systems and Computing, vol. 226, pp. 681-690 (2013)

http://mrl.cs.vsb.cz/



Parking Lot Occupation

- Haar
- HOG
- LBP

Traditional Approaches

- SIFT, SURF

KeyPoints

- CNNs

Deep Learning Approach

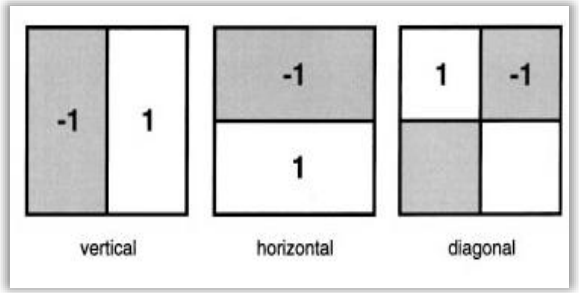
Related Works

2000

Papageorgiou (2000)

A Trainable System for Object Detection

CONSTANTINE PAPAGEORGIOU AND TOMASO POGGIO
Center for Biological and Computational Learning, Artificial Intelligence Laboratory, MIT, Cambridge, MA, USA
cpapa@ai.mit.edu
tp@ai.mit.edu

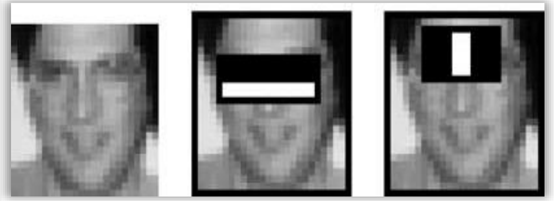


Viola, Jones (2001,2004)

Robust Real-Time Face Detection

PAUL VIOLA
Microsoft Research, One Microsoft Way, Redmond, WA 98052, USA
viola@microsoft.com

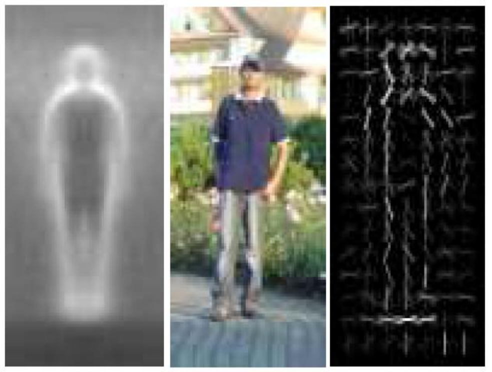
MICHAEL J. JONES
Mitsubishi Electric Research Laboratory, 201 Broadway, Cambridge, MA 02139, USA
mjones@merl.com



Dalal, Triggs (2005)
cit. 10947

Histograms of Oriented Gradients for Human Detection

Navneet Dalal and Bill Triggs
INRIA Rhône-Alps, 655 avenue de l'Europe, Montbonnot 38334, France
{Navneet.Dalal,Bill.Triggs}@inrialpes.fr, http://lear.inrialpes.fr



2005

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Object Detection (Analysis)
HOG

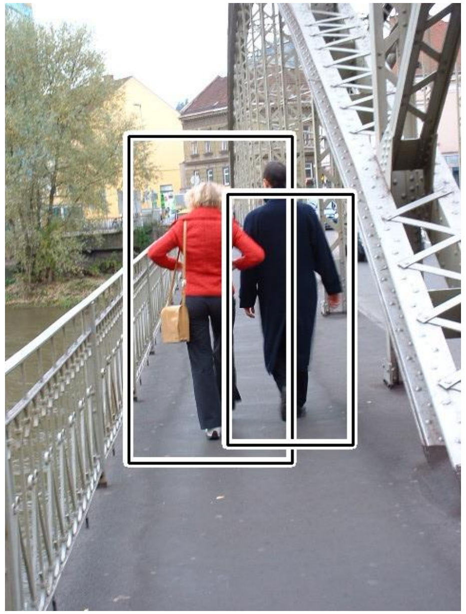
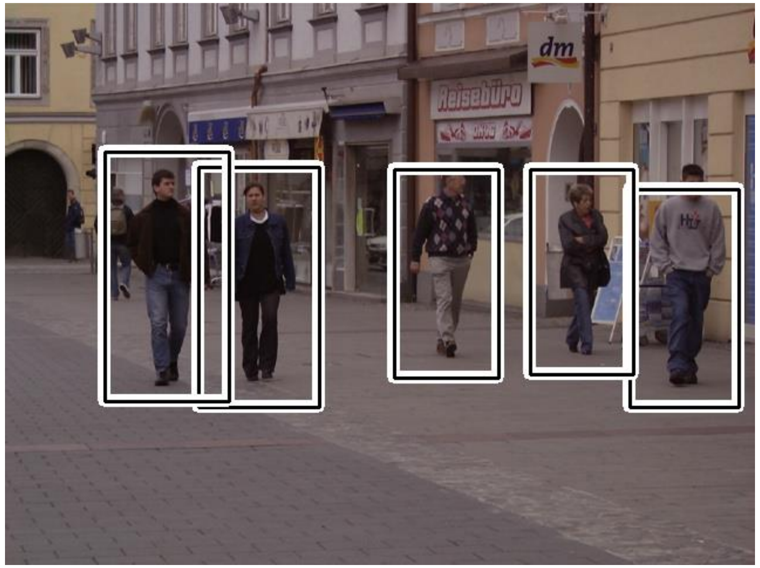
What is Object Detection?

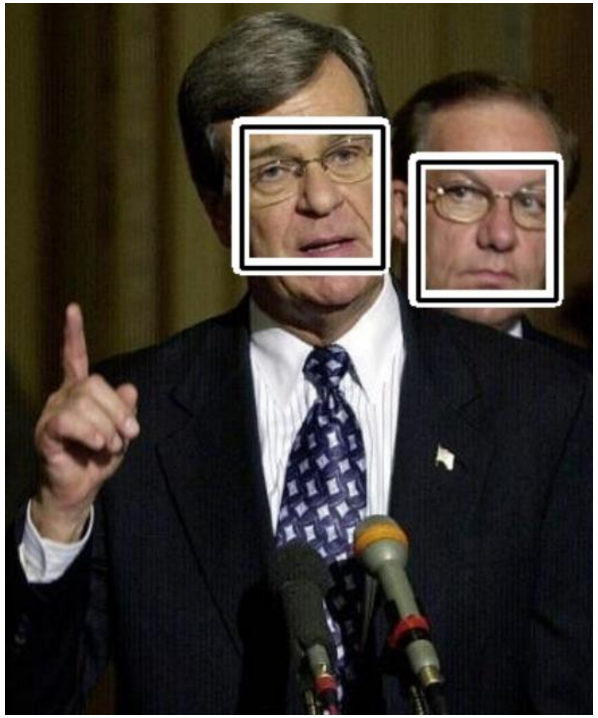
- It is clear that the images contain many objects of interest. The goal of the object detection
  systems is to find the location of these objects in the images (e.g. cars, faces, pedestrians).

- For example, the vehicle detection systems are crucial for traffic analysis or intelligent scheduling, the people detection systems can be useful for automotive safety, and the face detection systems are a key part of face recognition systems.

What is Object Detection?

- Output?
  - position of the objects
  - scale of the objects



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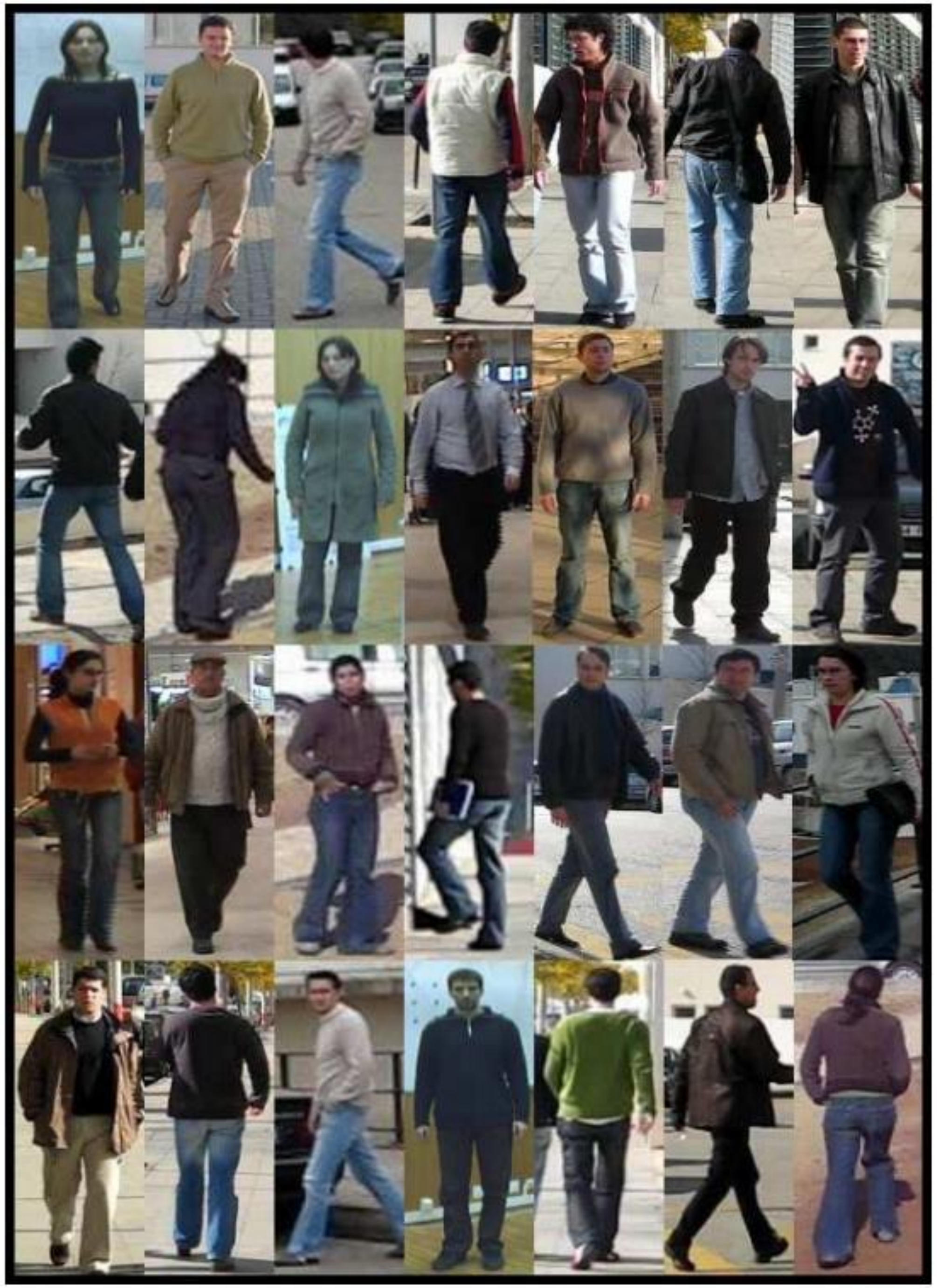
Pedestrian Detection - Challenges?



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Related Works

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Papageorgiou (2000)

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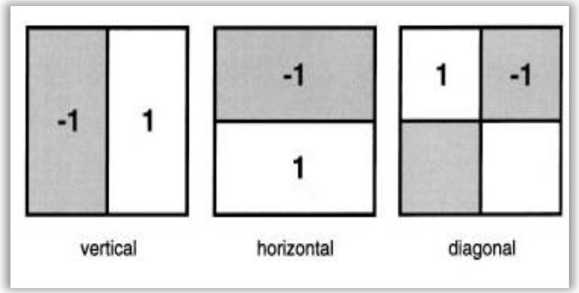

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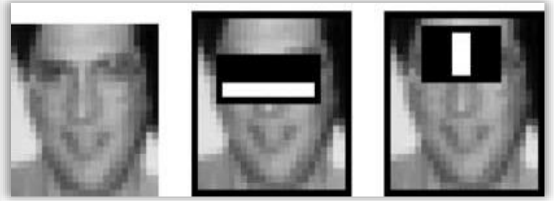

Dalal, Triggs (2005)

Histograms of Oriented Gradients for Human Detection

Navneet Dalal and Bill Triggs
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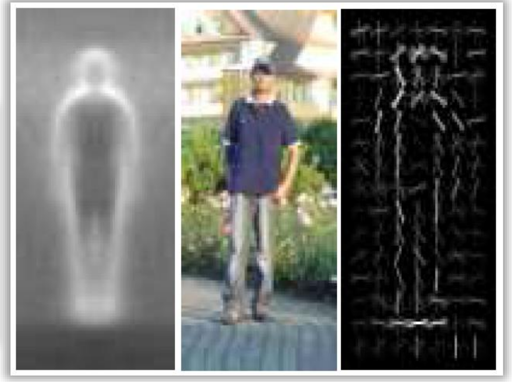
{Navneet.Dalal,Bill.Triggs}@inrialpes.fr, http://lear.inrialpes.fr



2005

Histograms of Oriented Gradients (HOG)

- In recent years, the object detectors that are based on edge analysis that provides valuable information about the objects of interest were used in many detection tasks. In this area, the histograms of oriented gradients (HOG) [1] are considered as the state-of-theart method.

- In HOG, a sliding window is used for detection. The window is divided into small connected cells in the process of obtaining HOG descriptors. The histograms of gradient orientations are calculated in each cell. It is desirable to normalize the histograms across a large block of image. As a result, a vector of values is computed for each position of window. This vector is then used for recognition, e.g. by the Support Vector Machine classifier.

Radovan Fusek: Descriptors for Object Detection in Image Recognition, Philosophiæ Doctor Thesis, 2016

Histograms of Oriented Gradients (HOG)

- Dalal and Trigs experimented with the size of detection window and they suggested the rectangular window with the size 64 × 128 pixels. They also tried to reduce the size of the window to 48 × 112 pixels. Nevertheless, they obtained the best detection result with the size 64 × 128 pixels.

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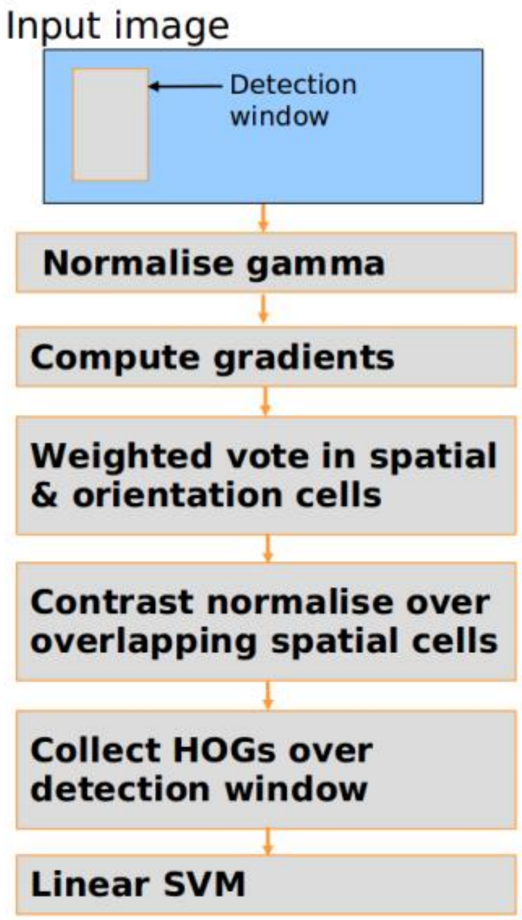
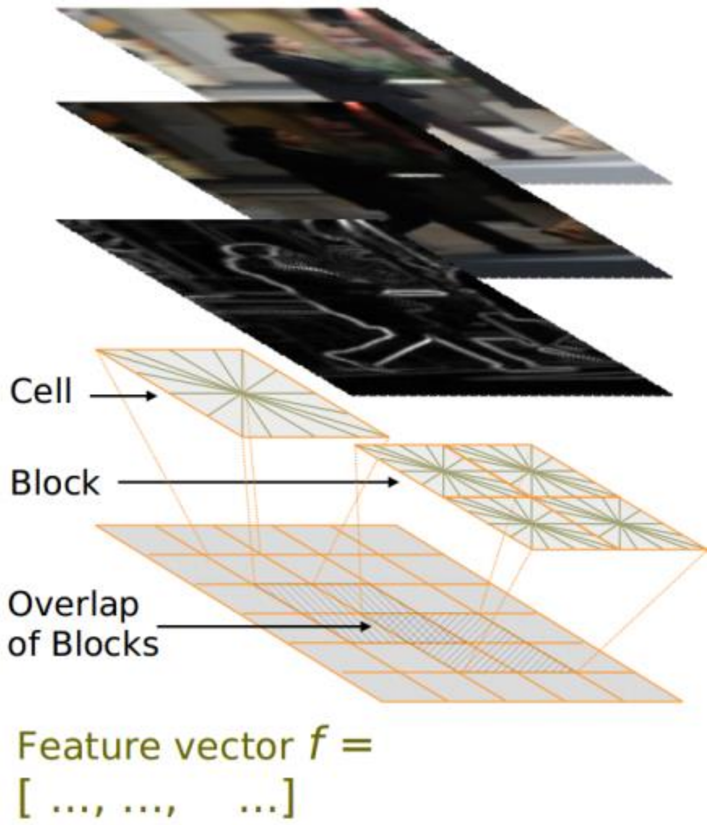
Histograms of Oriented Gradients (HOG)

Basic Steps:

- In HOG, a sliding window is used for detection.
- The window is divided into small connected cells.
- The histograms of gradient orientations are calculated in each cell.
- Support Vector Machine (SVM) classifier.





Navneet Dalal, Bill Triggs : Object Detection using Histograms of Oriented Gradients [online]. [cit. 2020-01-25]. Dostupné z: http://host.robots.ox.ac.uk/pascal/VOC/voc2006/slides/dalal.ppt

- For gradient computation, the image without Gaussian smoothing is filtered with the [1, 0, -1] kernel to compute the horizontal and vertical derivatives.
- Then the derivatives are used to compute the magnitude of the gradient and orientation .

$$D_X = [-1 \quad 0 \quad 1] \text{ and } D_Y = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \qquad I_X = I * D_X \text{ and } I_Y = I * D_Y$$

magnitude of the gradient is $|G| = \sqrt{I_X^2 + I_Y^2}$

orientation of the gradient is given by: $\theta = \arctan \dfrac{I_Y}{I_X}$

- In the next step, the image is divided into the cells and the cell histograms are constructed. The histogram bins are spread over 0 to 180 degrees or 0 to 360 degrees. The corresponding histogram bin is found for each pixel inside the cell. Each pixel contributes a weighted vote for its corresponding bin. The pixel contribution can be the gradient magnitude.

- Next step represents contrast normalization. For this purpose, the cells are grouped into the large blocks (i.e. 2×2 cells are considered as blocks). The histograms are normalized within the blocks (e.g. using L2-norm). In the paper, the two main block geometries are presented; rectangular and circular.

- The final HOG descriptor is represented by histogram vectors of all blocks within the detection window

Radovan Fusek: Descriptors for Object Detection in Image Recognition, Philosophiæ Doctor Thesis, 2016

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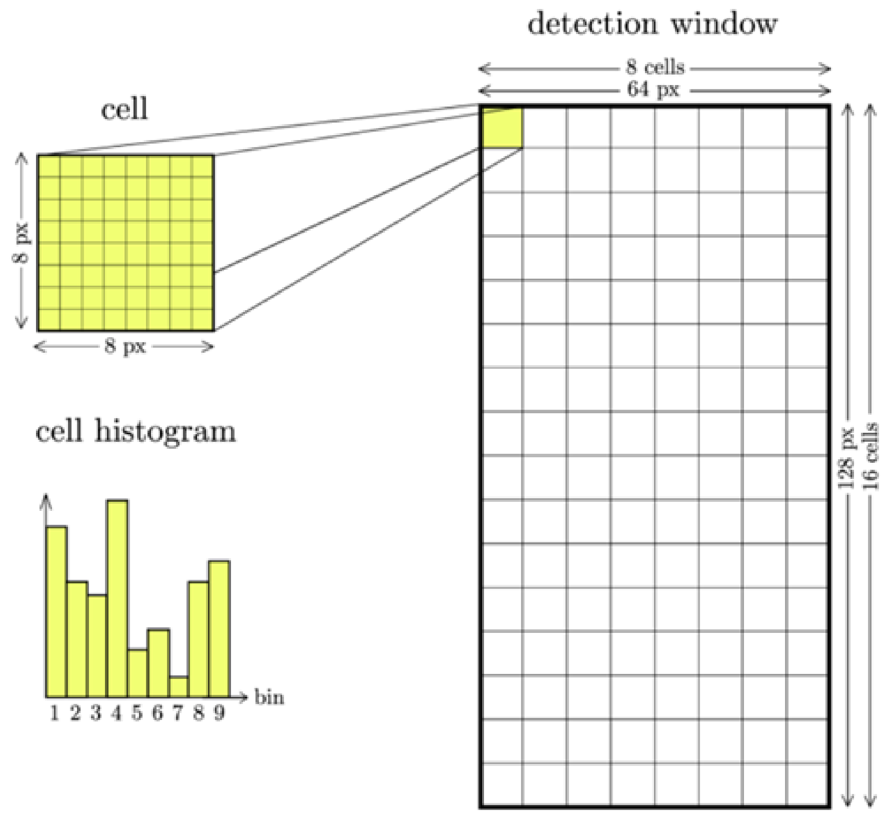
They also tried to reduce the size of the window to 48 × 112 pixels. Nevertheless, they obtained the best detection result with the size 64 × 128 pixels.



Blocks, Cells:

- 8 x 8 cell
- 16 x 16 block – overlap
- normalization within the blocks

- **<u>Final Vector</u>: Collect HOG blocks into vector**

Bauer,S., Brunsmann, U., FPGA Implementation of a HOG-based Pedestrian Recognition System, Stefan Schlotterbeck-Macht Faculty of Engineering Aschaffenburg University of Applied Sciences, Aschaffenburg, Germany

- The classical HOG descriptors suffer from the large number of features, which causes that the training and detection phases can be time consuming. The sufficient amount of training data is also needed to find a separating hyperplane by the SVM classifier.

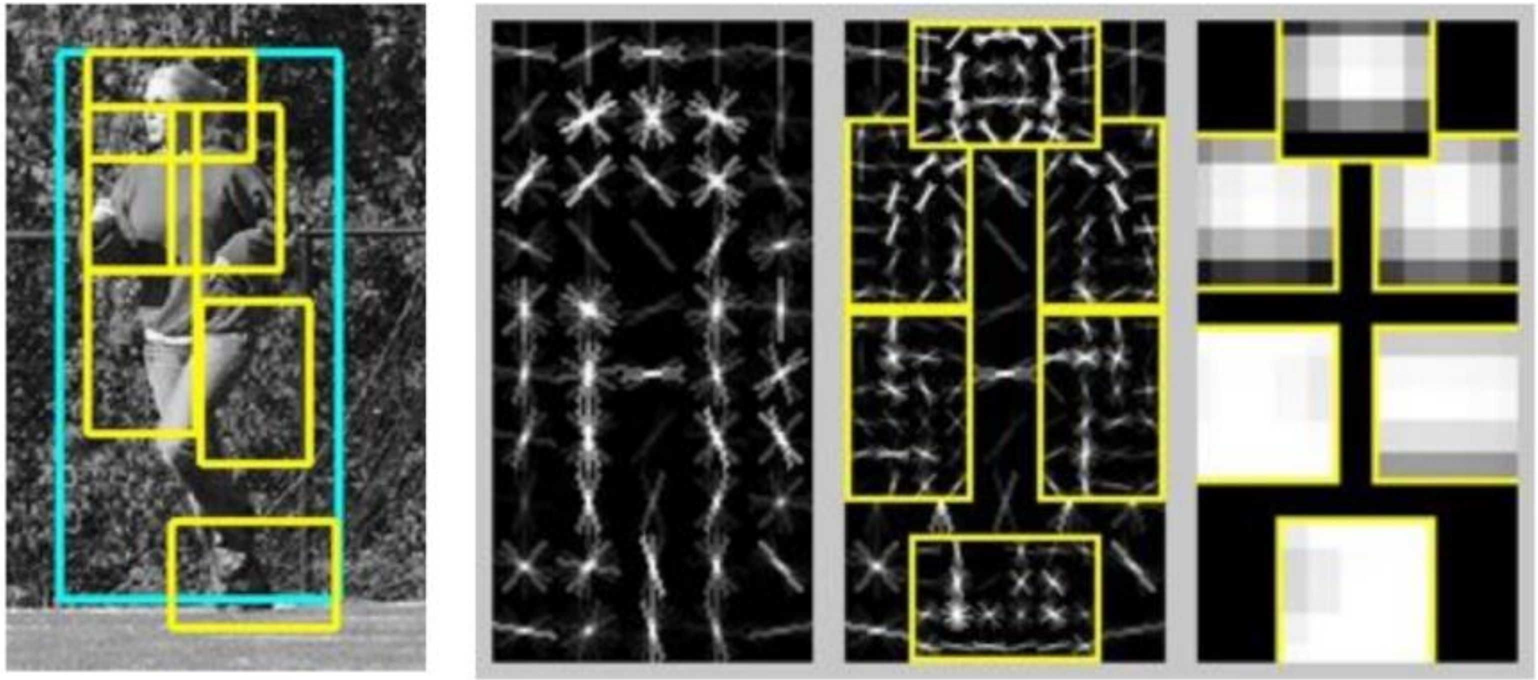
- Sometimes, it is desirable to use the methods for the dimensionality reduction of feature vector. In addition the that, the classical HOG descriptors are not rotation invariant.

- These shortcomings became the motivation for creating many variations of HOG-based detectors. Many methods and applications based on HOG were presented in recent years.

In [1], the authors applied the principal component analysis (PCA) to the HOG feature vector to obtain the PCA-HOG vector. This vector contains the subset of HOG features and the vector is used as an input for the SVM classifier. Their method was used for pedestrian detection with the satisfactory results.

Felzenszwalb et al. proposed the part-based detector that is based on HOG. In this method, the objects are represented using the mixtures of deformable HOG part models and these models are trained using a discriminative method (see following image). This method obtained excellent performance for object detection tasks [2, 3].

[1] Kobayashi, T., Hidaka, A., Kurita, T.: Neural information processing. chap. Selection of Histograms of Oriented Gradients Features for Pedestrian Detection, pp. 598–607. Springer-Verlag, Berlin, Heidelberg (2008)
[2] Felzenszwalb, P.F., McAllester, D.A., Ramanan, D.: A discriminatively trained, multiscale, deformable part model. In: CVPR (2008)
[3] Felzenszwalb, P., Girshick, R., McAllester, D., Ramanan, D.: Object detection with discriminatively trained part-based models. Pattern Analysis and Machine Intelligence, IEEE Transactions on 32(9), 1627–1645 (2010)

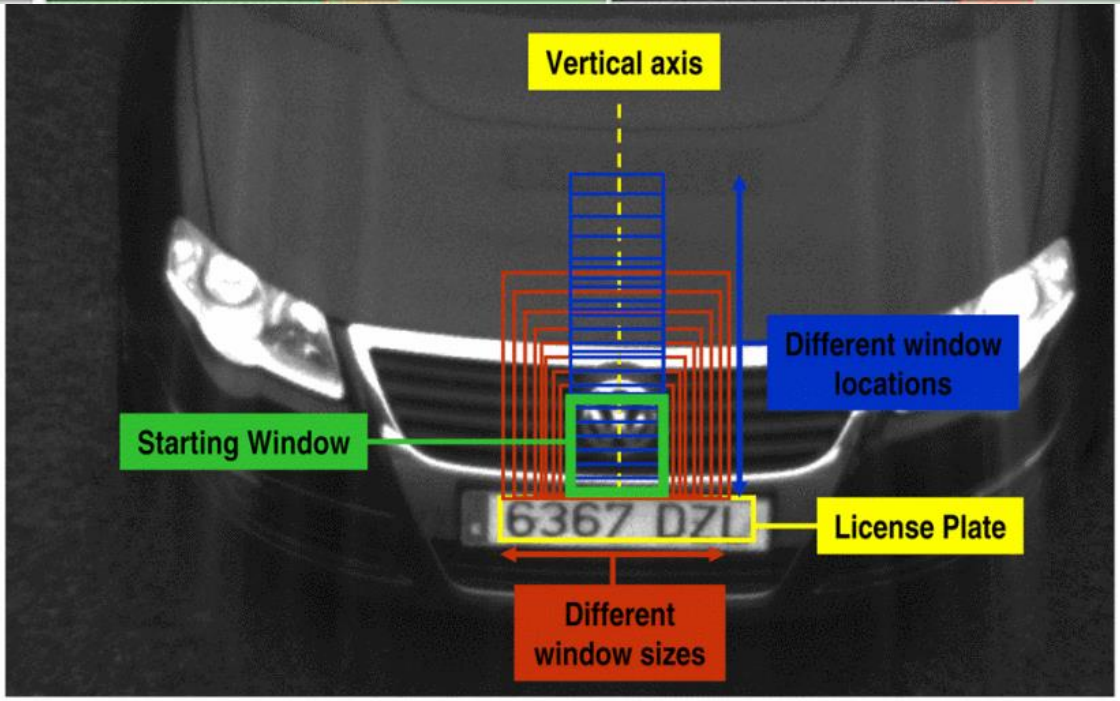


An example of person detection using a part model. The model is defined by the coarse global template that covers the entire object and higher resolution part templates. The templates represent the histogram of oriented gradient [2].

[1] Kobayashi, T., Hidaka, A., Kurita, T.: Neural information processing. chap. Selection of Histograms of Oriented Gradients Features for Pedestrian Detection, pp. 598–607. Springer-Verlag, Berlin, Heidelberg (2008)
[2] Felzenszwalb, P.F., McAllester, D.A., Ramanan, D.: A discriminatively trained, multiscale, deformable part model. In: CVPR (2008)
[3] Felzenszwalb, P., Girshick, R., McAllester, D., Ramanan, D.: Object detection with discriminatively trained part-based models. Pattern Analysis and Machine Intelligence, IEEE Transactions on 32(9), 1627–1645 (2010)

Vehicle Logo, License Plate Localization/Recognition

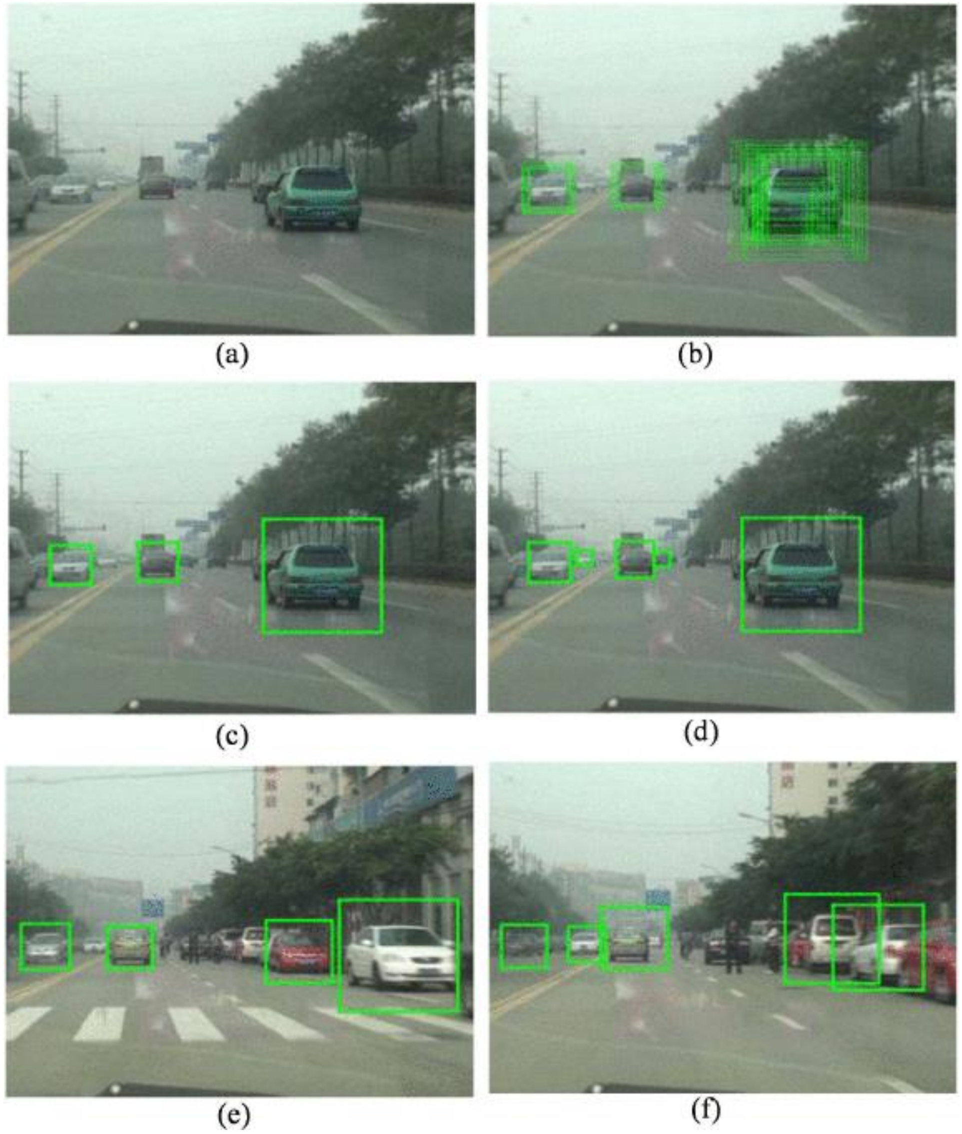
Histograms of Oriented Gradients (HOG

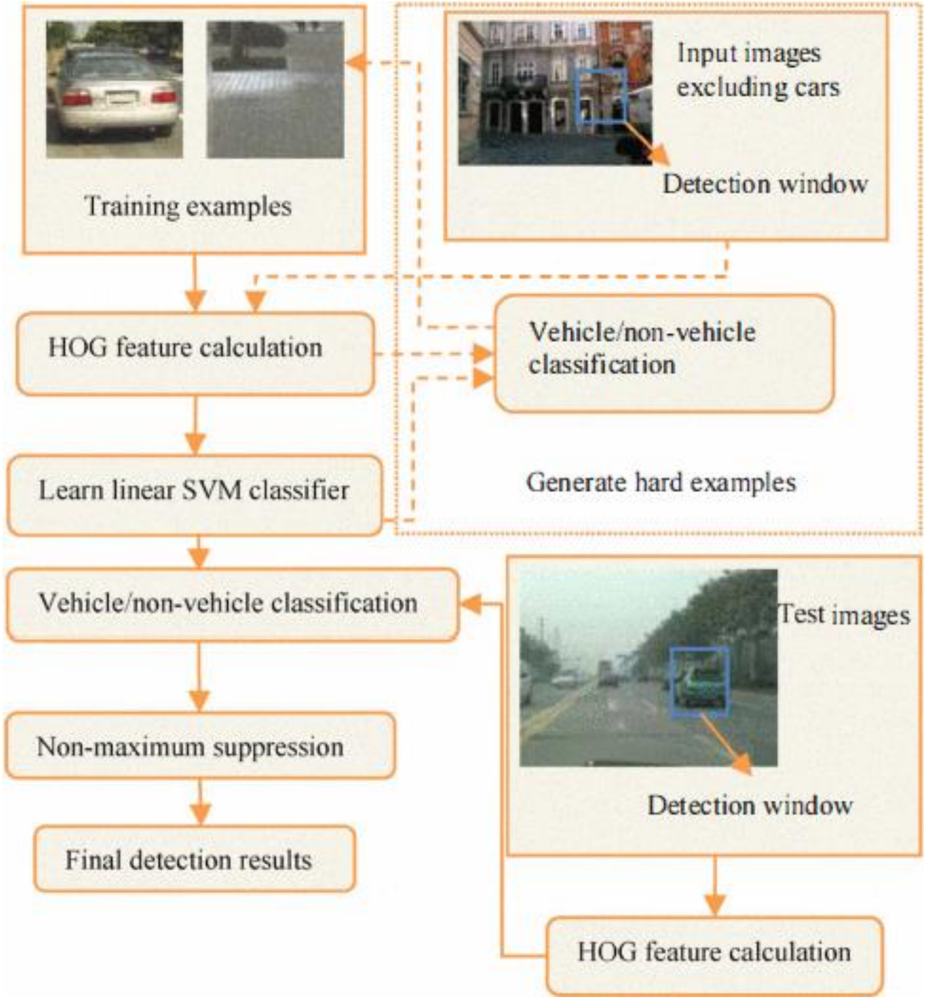


https://ieeexplore.ieee.org/abstract/document/6728559

D. F. Llorca, R. Arroyo and M. A. Sotelo, "Vehicle logo recognition in traffic images using HOG features and SVM," *16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013)*, The Hague, 2013, pp. 2229-2234.
doi: 10.1109/ITSC.2013.6728559

Histograms of Oriented Gradients (HOG) and Automotive





https://ieeexplore.ieee.org/abstract/document/5581983

L. Mao, M. Xie, Y. Huang and Y. Zhang, "Preceding vehicle detection using Histograms of Oriented Gradients," *2010 International Conference on Communications, Circuits and Systems (ICCCAS)*, Chengdu, 2010, pp. 354-358. doi: 10.1109/ICCCAS.2010.5581983