



Conducción autónoma

Sergio Paniego Blanco

@sergiopaniego

sergio.paniego@urjc.es

<https://sergiopaniego.github.io/>

<https://roboticslaburjc.github.io/>

Escuela de Ingeniería de Fuenlabrada

Teoría de la Señal y las Comunicaciones y
Sistemas Telemáticos y Computación

Outline

- ¿Qué es un coche autónomo?
 - Ejemplos reales.
 - Niveles de autonomía.
 - Niveles de seguridad.
 - Por qué usarlo?
 - Está resuelto el problema?
- ¿Cómo funciona?
 - Simuladores.
 - Deep Learning.
 - Imitation learning.
 - RL.
 - E2E vs modular.



Qué es un vehículo autónomo?

- Coche (robot) que realiza todas las tareas de conducción de forma autónoma, sin intervención humana.
 - Localization and mapping.
 - Perception.
 - Planning and decision-making.
 - Control.
- Diferentes niveles de autonomía.



Algunos ejemplos. ALVINN 1989



Algunos ejemplos. ALVINN 1989

Dean Pomerleau

@deanpomerleau

GPU? Gez, ALVINN ran on 100 MFLOP CPU, ~10x slower than iWatch;
Refrigerator-size & needed 5000 watt generator. @olivercameron

What's Hidden in the Hidden Layers?

*The contents can be easy to find with a geometrical problem,
but the hidden layers have yet to give up all their secrets*

David S. Touretzky and Dean A. Pomerleau

AUGUST 1989 • BY T B 231

tions, we fed the network road images taken under a wide variety of viewing angles and lighting conditions. It would be impractical to try to collect thousands of real road images for such a data set. Instead, we developed a synthetic road-image generator that can create as many training examples as we need.

To train the network, 1200 simulated road images are presented 40 times each, while the weights are adjusted using the back-propagation learning algorithm. This takes about 30 minutes on Carnegie Mellon's Warp systolic-array supercomputer. (This machine was designed at Carnegie Mellon and is built by General Electric. It has a peak rate of 100 million floating-point operations per second and can compute weight adjustments for back-propagation networks at a rate of 20 million connections per second.)

Once it is trained, ALVINN can accurately drive the NAVLAB vehicle at about $3\frac{1}{2}$ miles per hour along a path through a wooded area adjoining the Carnegie Mellon campus, under a variety of weather and lighting conditions. This speed is nearly twice as fast as that achieved by non-neural-network algorithms running on the same vehicle. Part of the reason for this is that the forward pass of a back-propagation network can be computed quickly. It takes about 200

milliseconds on the Sun-3/160 workstation installed on the NAVLAB.

The hidden-layer representations ALVINN develops are interesting. When trained on roads of a fixed width, the net-

work chooses a representation in which hidden units act as detectors for complete roads at various positions and orientations. When trained on roads of variable

continued

The image shows a blue van with 'NAVLAB' written on its side. Several red arrows point to different parts of the van: one to the word 'LIDAR' on the side, another to a camera mounted on the front, and a third to a '5000 Watt Generator' unit. The van is parked on a grassy area next to a paved road. In the background, there are trees and buildings, suggesting an urban or suburban setting.

Photo 1: The NAVLAB autonomous navigation test-bed vehicle and the road used for trial runs.

6:19 PM · Nov 24, 2016

Algunos ejemplos. Tesla



Algunos ejemplos. Wayve



Algunos ejemplos. Taxi autónomo! *cruise*



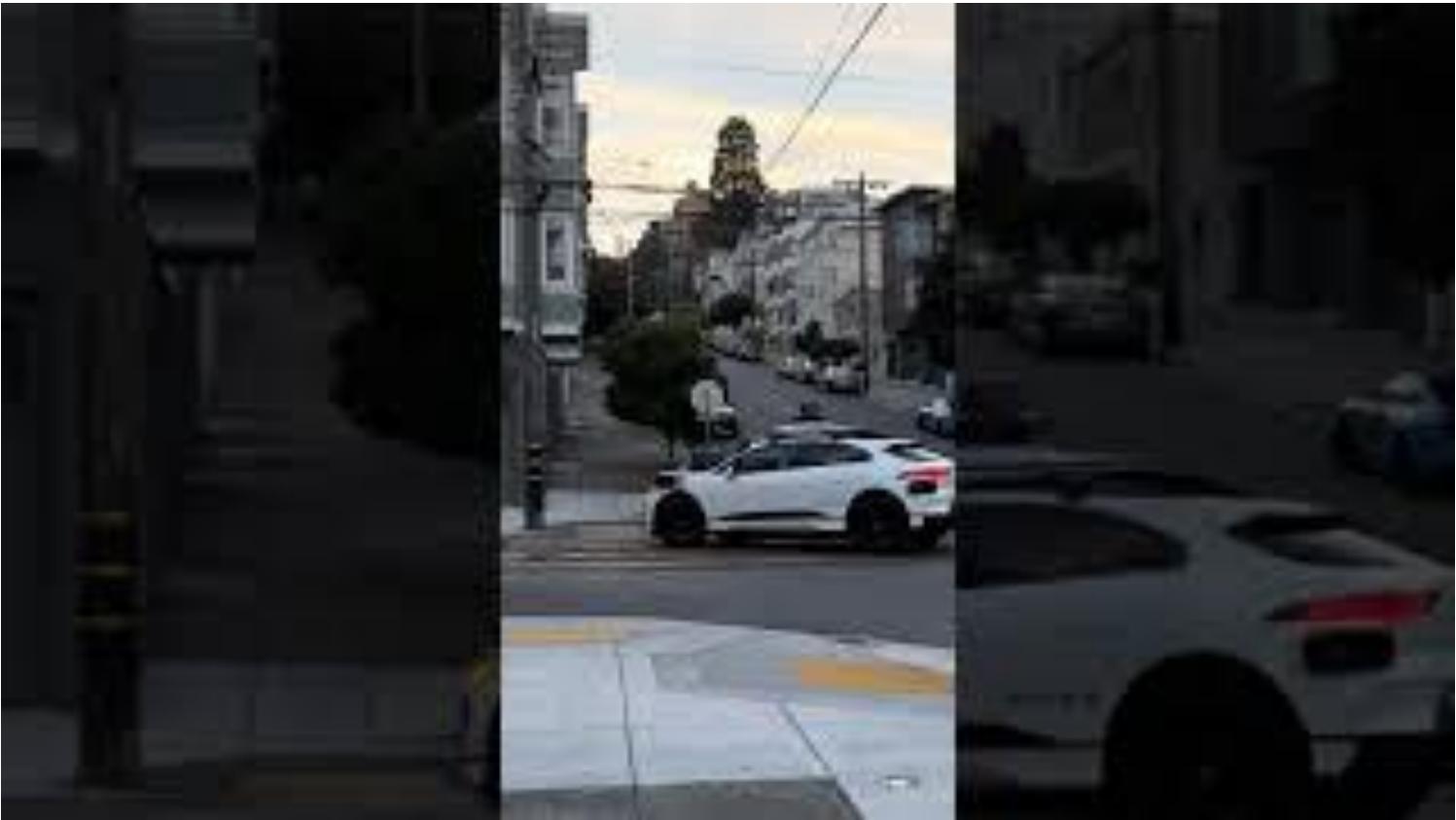
Ejemplos reales. Waymo en SF



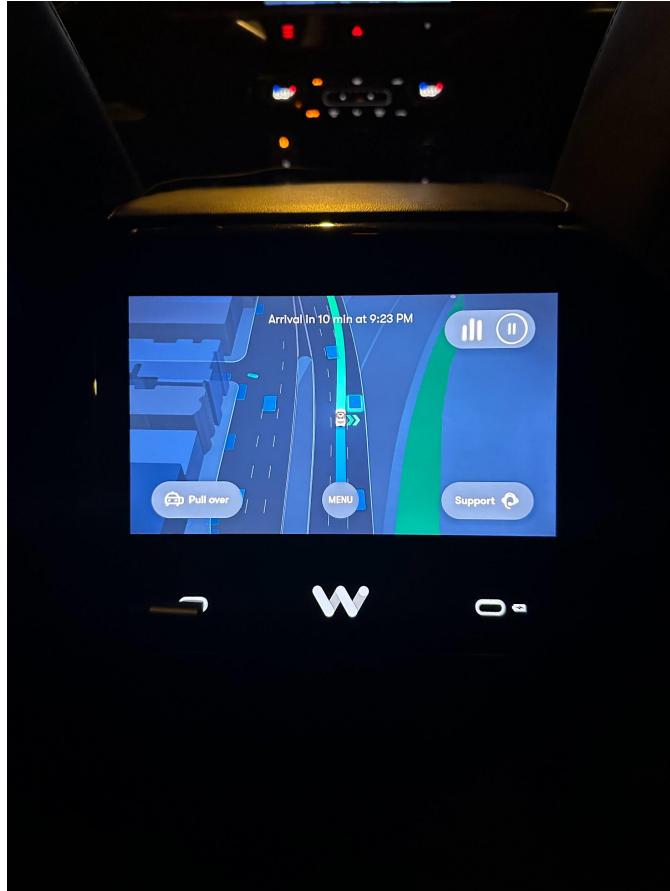
Ejemplos reales. Waymo en SF



Ejemplos reales. Waymo en SF

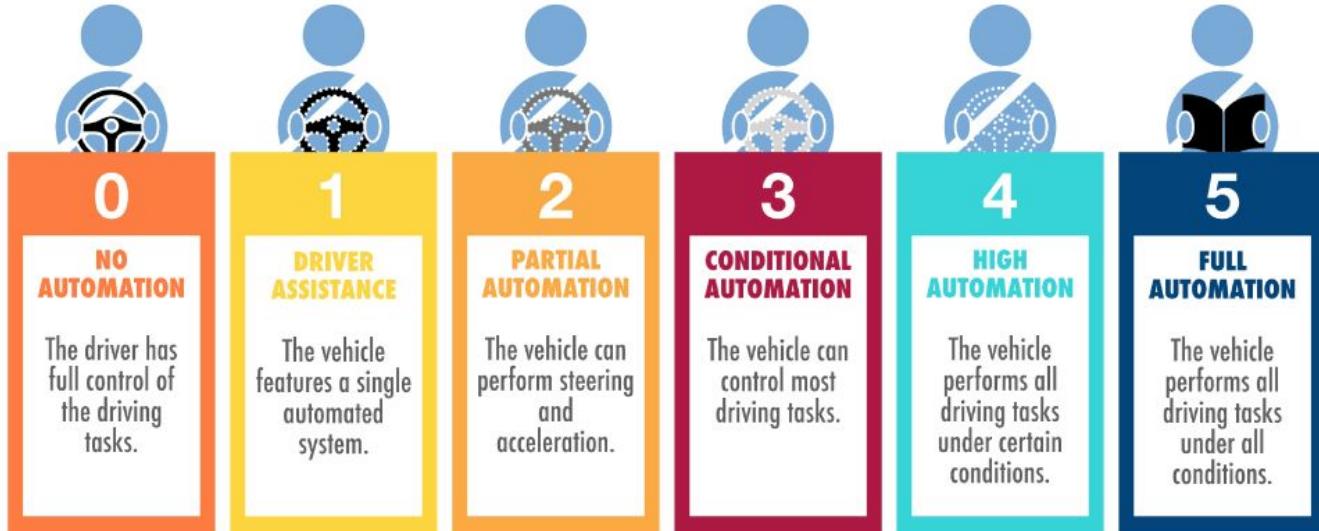


Ejemplos reales. Waymo en SF



Niveles de conducción autónoma

LEVELS OF AUTONOMOUS DRIVING





SAE J3016™ LEVELS OF DRIVING AUTOMATION™

Learn more here: sae.org/standards/content/j3016_202104

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	SAE LEVEL 0™	SAE LEVEL 1™	SAE LEVEL 2™	SAE LEVEL 3™	SAE LEVEL 4™	SAE LEVEL 5™
What does the human in the driver's seat have to do?	You are driving whenever these driver support features are engaged – even if your feet are off the pedals and you are not steering	You must constantly supervise these support features; you must steer, brake or accelerate as needed to maintain safety		You are not driving when these automated driving features are engaged – even if you are seated in “the driver’s seat”		
			When the feature requests, you must drive		These automated driving features will not require you to take over driving	

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What do these features do?	These are driver support features			These are automated driving features	
	These features are limited to providing warnings and momentary assistance	These features provide steering OR brake/acceleration support to the driver	These features provide steering AND brake/acceleration support to the driver	These features can drive the vehicle under limited conditions and will not operate unless all required conditions are met	This feature can drive the vehicle under all conditions
Example Features	<ul style="list-style-type: none"> automatic emergency braking blind spot warning lane departure warning 	<ul style="list-style-type: none"> lane centering OR adaptive cruise control 	<ul style="list-style-type: none"> lane centering AND adaptive cruise control at the same time 	<ul style="list-style-type: none"> traffic jam chauffeur 	<ul style="list-style-type: none"> local driverless taxi pedals/steering wheel may or may not be installed
					<ul style="list-style-type: none"> same as level 4, but feature can drive everywhere in all conditions



Por qué usar coches autónomos?

- Seguridad y salud pública: 94% de los accidentes son provocados por error humano.
- Reducción del estrés del conductor, mejora de productividad y movilidad (personas que no conducen).
- Coste y propiedad: menor coste operativo y propiedad compartida.
- Costes externos: menor congestión, costes de parking, contaminación.



Por qué usar coches autónomos?

- Los coches de Waymo ya son más seguros que el humano.

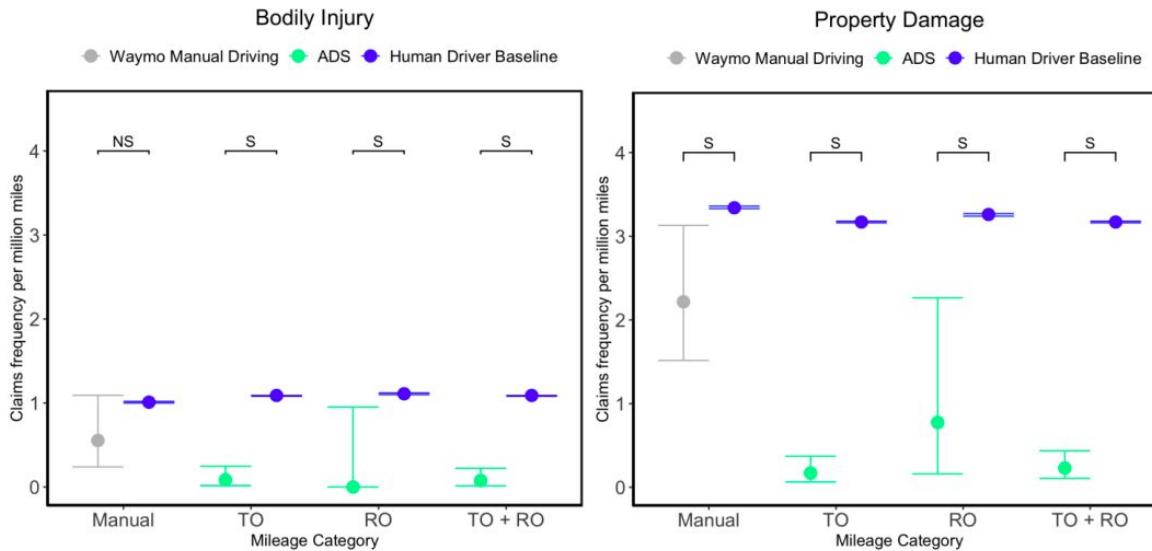
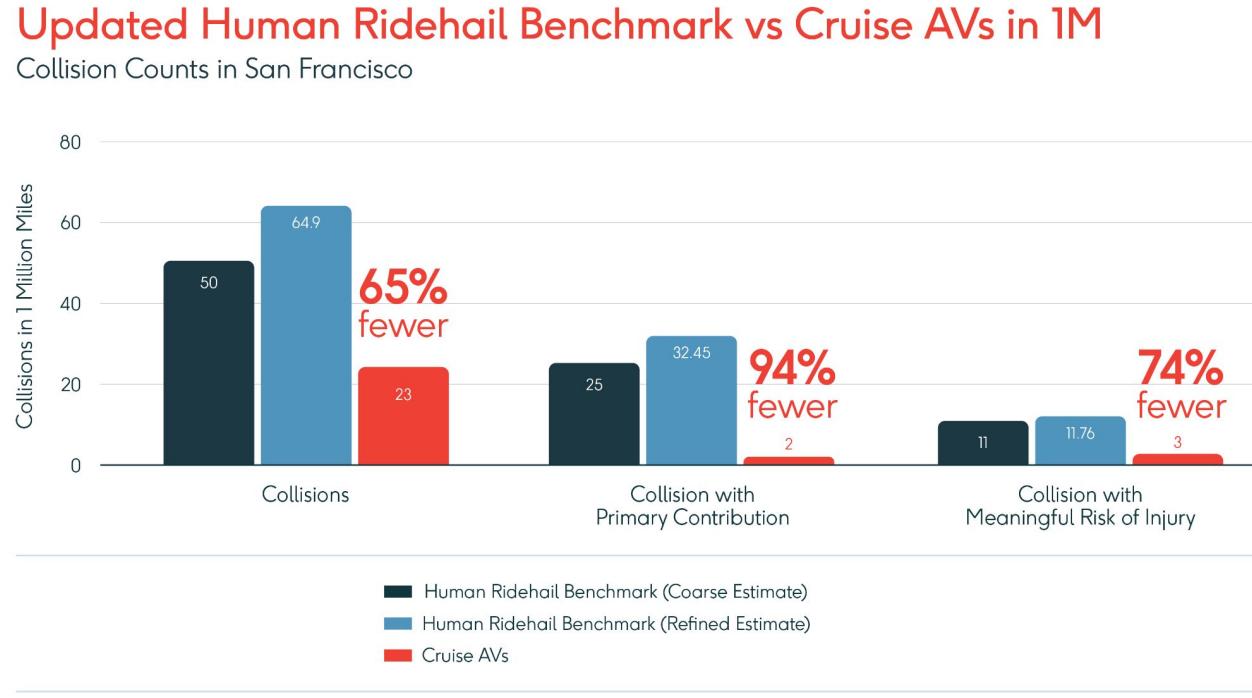


Figure 2. Comparison of Swiss Re human driver baselines with Waymo liability insurance claims for bodily injury (left) and property damage (right). S=significant (non-overlapping 95% CIs), NS=non-significant or inconclusive results (overlapping CIs). ADS=Waymo One Automated Driving System, Baseline=Swiss Re private passenger vehicle (human driver) baselines, calibrated for each mileage category. "Manual" is a mode in which the Waymo vehicle is driven manually (i.e., without the ADS engaged). Testing operations ("TO") is a phase of public road testing in which the ADS is engaged under monitoring of a trained autonomous specialist (human driver) who is seated in the driver's seat and can take over the driving task at any time. TO collisions were included even if they occurred up to 5 seconds after the autonomous specialist took over control (disengaged the ADS). Rider-only ("RO") is a mode where the ADS operates the vehicle without any human behind the steering wheel. Testing operation and Rider-only ("TO+RO") is the combination of the TO and RO datasets.



Por qué usar coches autónomos?

- Los coches de Cruise son más seguros que el humano.



No todo es tan bonito

- Seguridad y salud pública: nuevos peligros como fallos software, hacking, reducción del uso del cinturón por falsa sensación de seguridad...
- Nuevos estresores: vehículo no llega a determinadas zonas (lluvia, falta de mapa...).
- Coste y propiedad: ahora mismo son más caros (sensores, actualizaciones software...). Problemas de propiedad compartida (parecido a un autobús).
- Costes externos: realmente podrían subir.



No todo es tan bonito

A screenshot of a Twitter post from the account @WholeMarsBlog. The post contains a quote about Cruise's driverless vehicle operations. The quote is enclosed in a white rounded rectangle with a thin black border. The rest of the tweet is in dark mode.

Whole Mars Catalog [Subscribe](#) ...
Every Cruise vehicle was supposedly supported by 1.5 workers per vehicle — more than a manually driven car.

The workers remotely intervened to assist the vehicles every 2.5 - 5 miles on average, according to two people familiar with operations \$GM

Half of Cruise's 400 cars were in San Francisco when the driverless operations were stopped. Those vehicles were supported by a vast operations staff, with 1.5 workers per vehicle. The workers intervened to assist the company's vehicles every 2.5 to 5 miles, according to two people familiar with its operations. In other words, they frequently had to do something to remotely control a car after receiving a cellular signal that it was having problems.

6:40 PM · Nov 3, 2023 · 510.5K Views

<https://twitter.com/WholeMarsBlog/status/1720496170219532628>

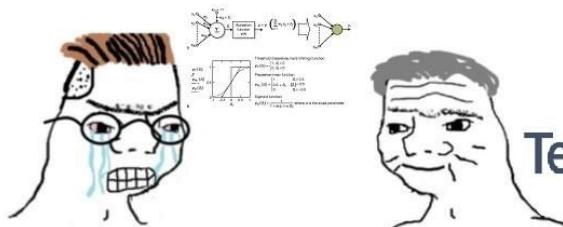
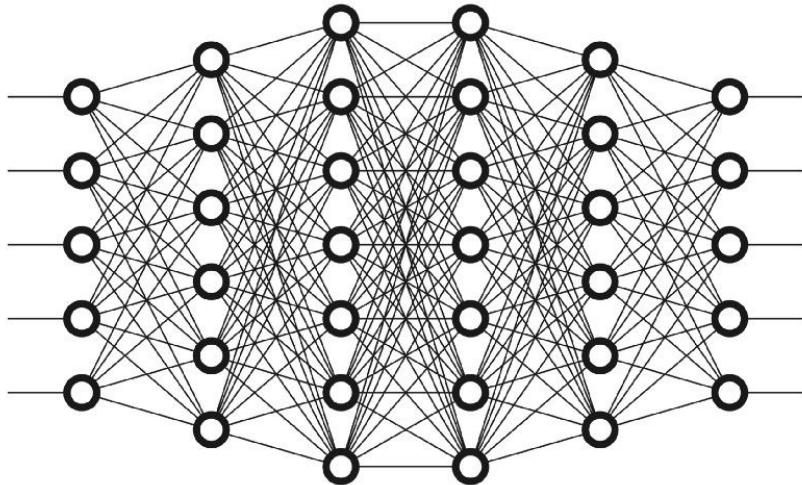
Propiedad de los coches autónomos

- Coches privados conducidos por humanos.
- Coches autónomos privados
- Coches autónomos compartidos.
- Coches autónomos con carreras (rides) compartidas.



Por qué ha crecido este campo últimamente?

- Deep learning.
- GPUs.
- Sensores potentes.
- Datasets.
- Simuladores.



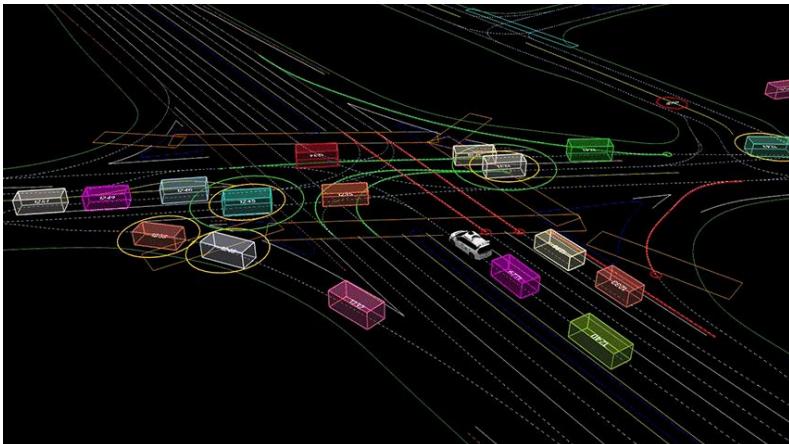
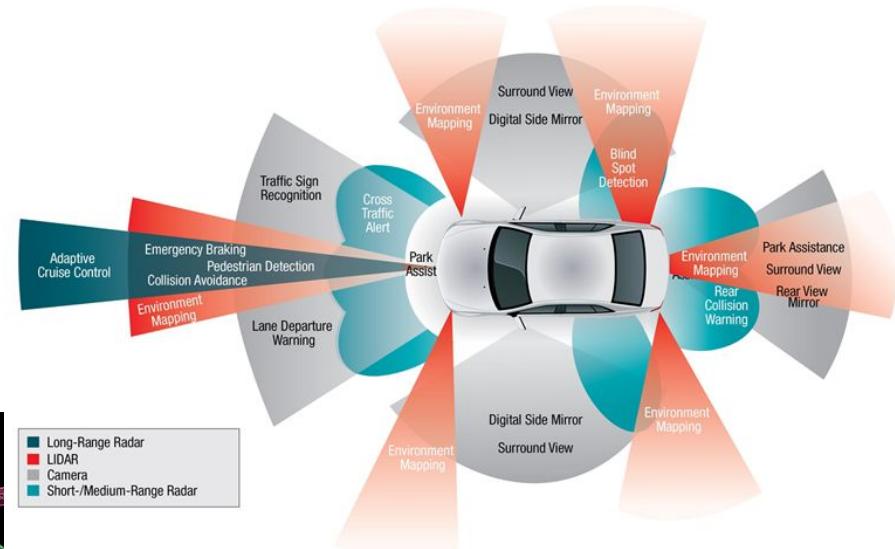
No you can't just use python to
create ml models you have to know
statistics and probability.



TensorFlow

Por qué ha crecido este campo últimamente?

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Por qué ha crecido este campo últimamente?

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- Simuladores.



Si ya hay ejemplos reales, está el problema resuelto?

- Generalización:
 - Diferentes vehículos.
 - Diferentes ciudades (o entornos no urbanos).
 - Diferentes tiempos atmosféricos.
 - Situaciones nunca vistas en los datos.
 - ...



Si ya hay ejemplos reales, está el problema resuelto?

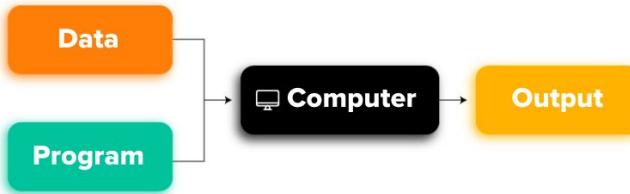


Si ya hay ejemplos reales, está el problema resuelto?

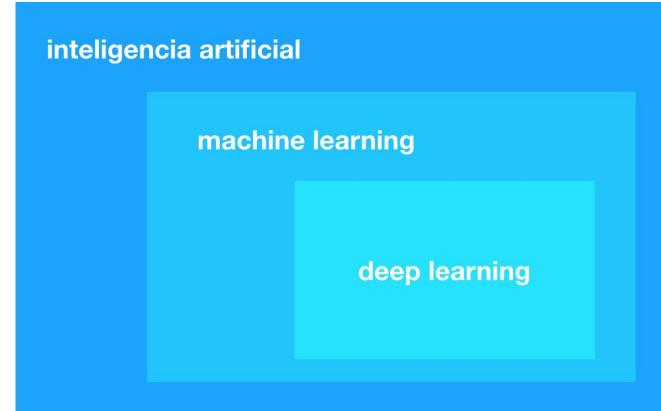
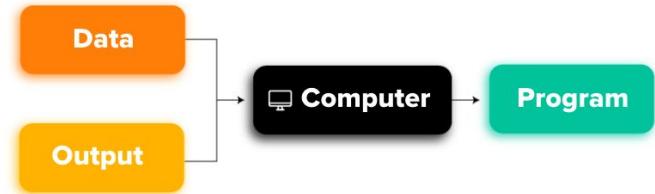


Deep Learning

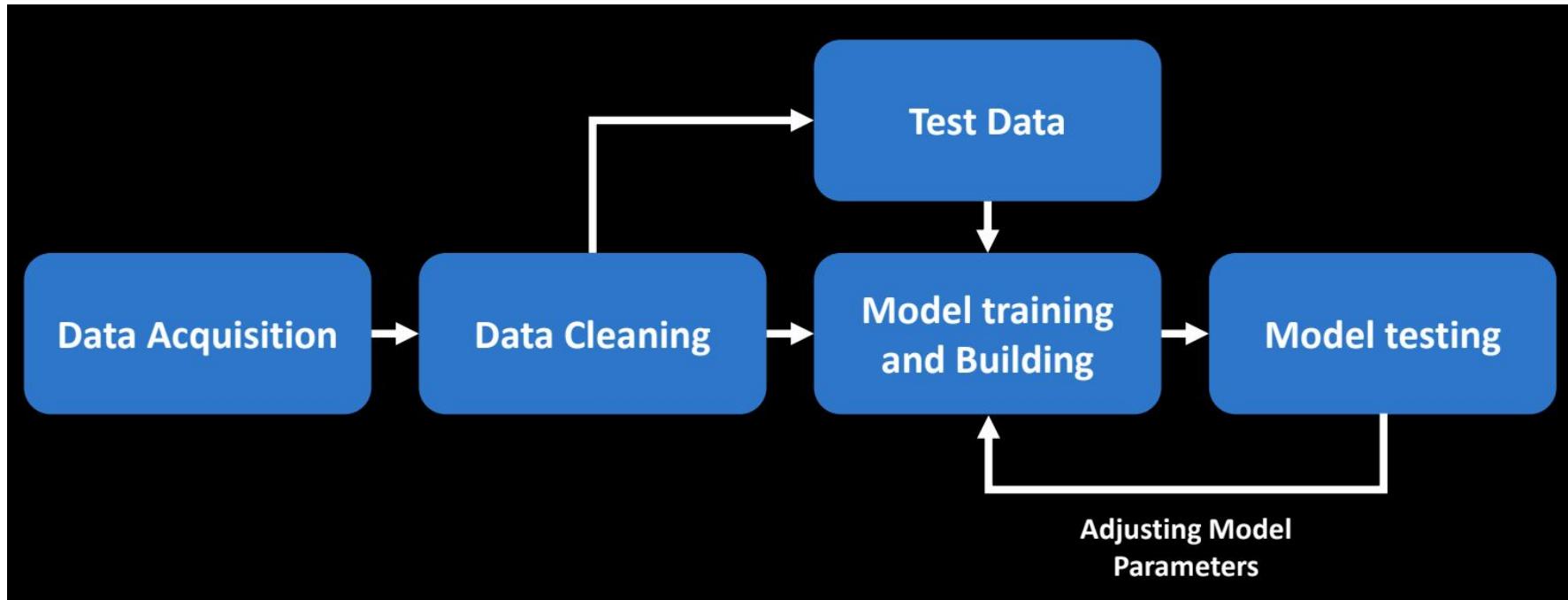
TRADITIONAL PROGRAMMING



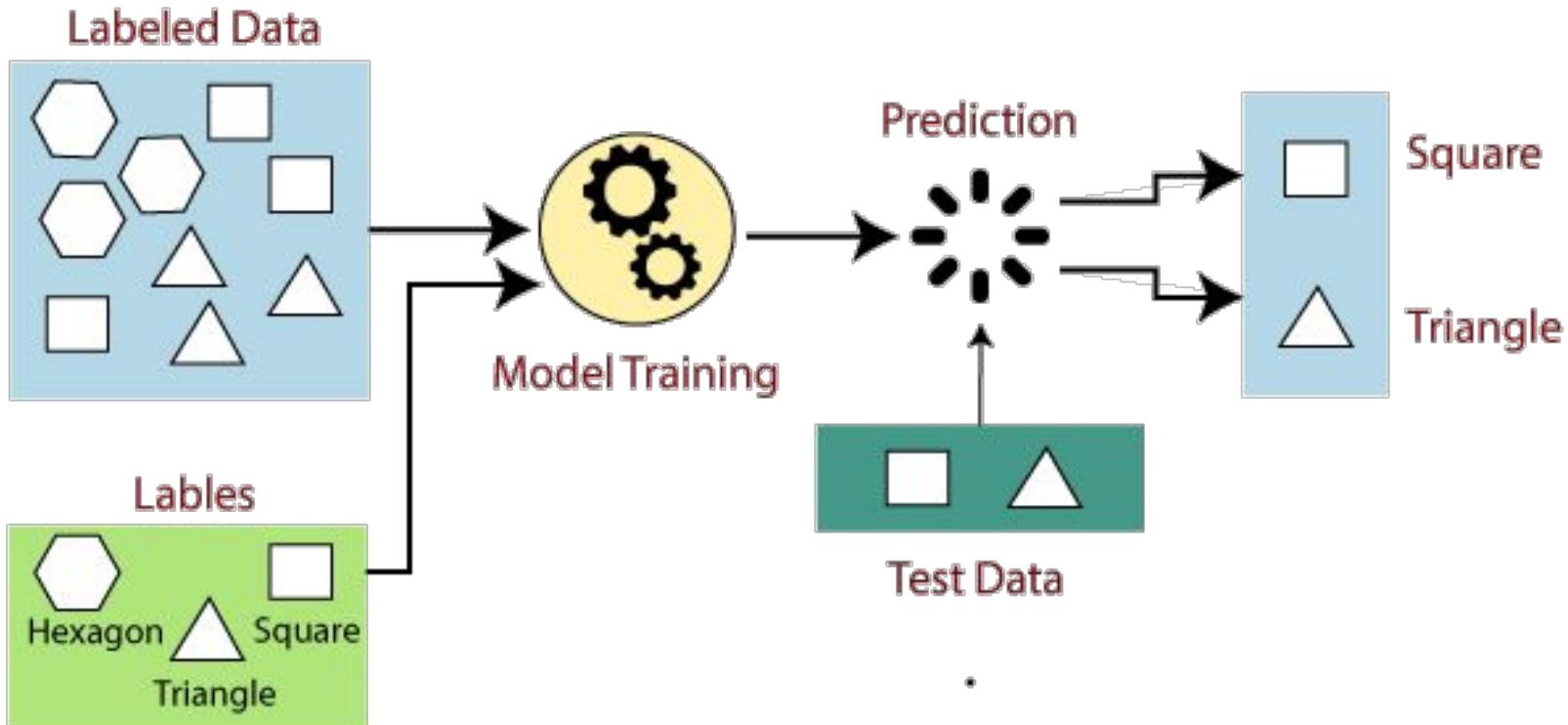
MACHINE LEARNING



Deep Learning



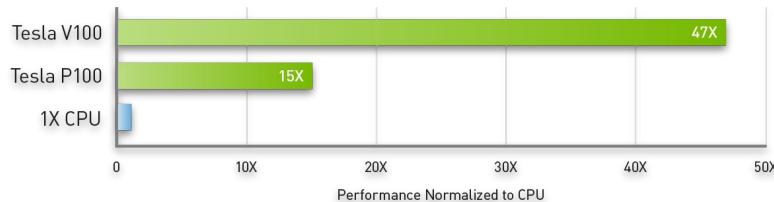
Deep Learning



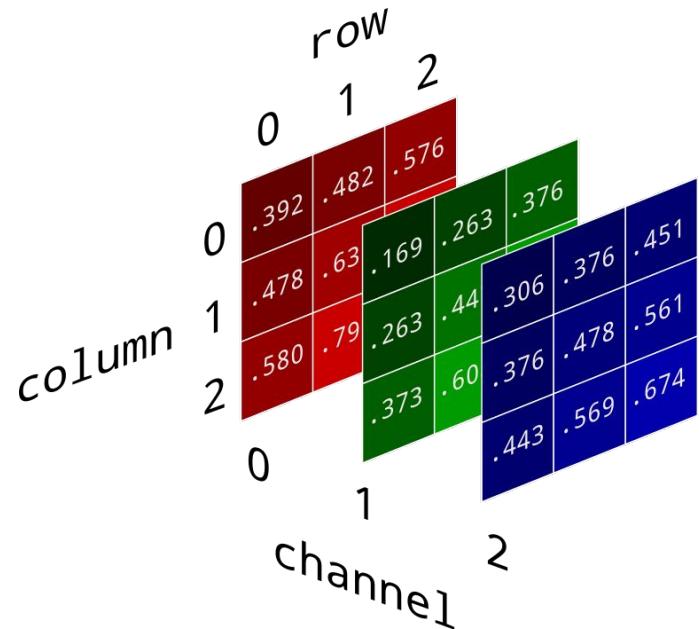
GPUs

- Unidad de procesamiento gráfico.
- Gran capacidad de procesamiento en paralelo para cálculos matriciales y operaciones vectoriales.

47X Higher Throughput Than CPU Server on Deep Learning Inference



Workload: ResNet-50 | CPU: 1X Xeon E5-2690v4 @ 2.6 GHz | GPU: Add 1X Tesla P100 or V100



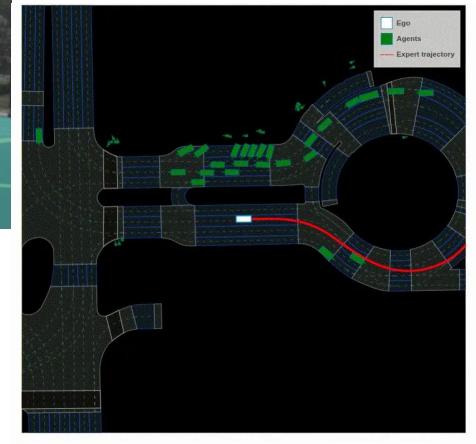
Sensores

- Cámaras monoculares.
- Cámaras omnidireccionales (360º).
- Cámaras de evento.
- Lidar.
- Radar.
- Sensores propioceptivos (velocidad, aceleración, gps...).



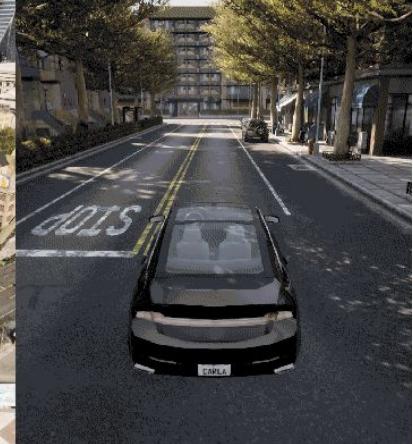
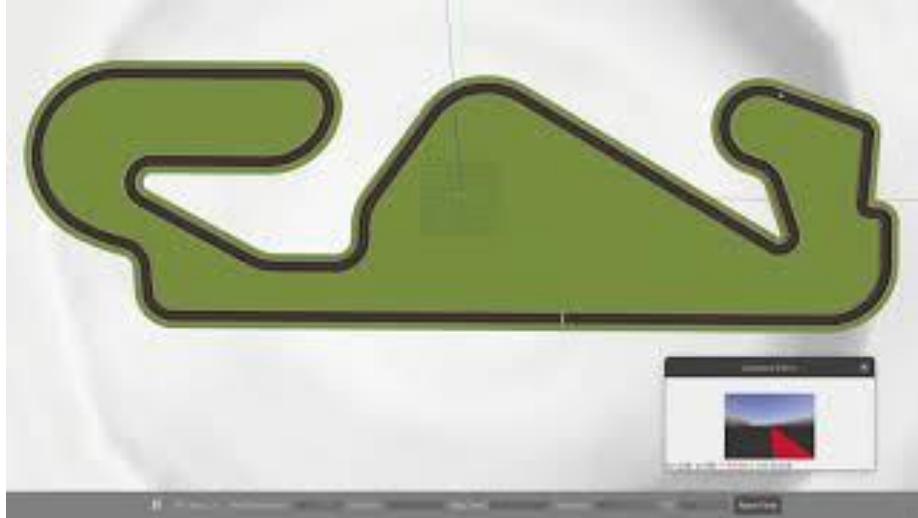
Datasets

- Disponibilidad de grandes datasets para tareas variadas:
 - Lane-following:
 - CommaAI.
 - Udacity.
 - Perception:
 - nuScenes.
 - BDD100K.
 - Planning:
 - nuPlan.



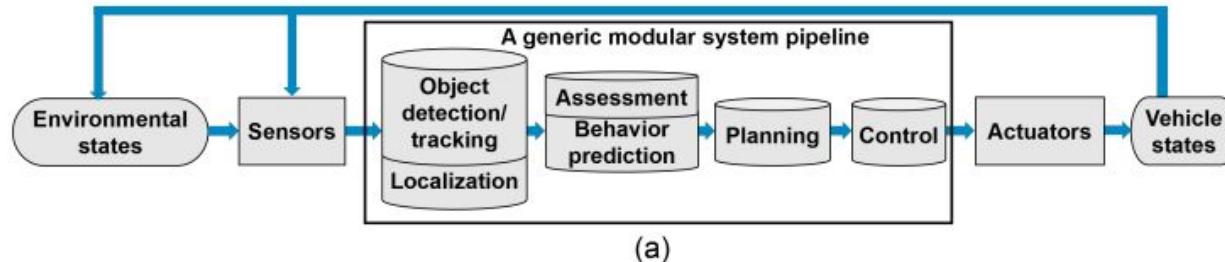
Simuladores

- CARLA.
- Gazebo.

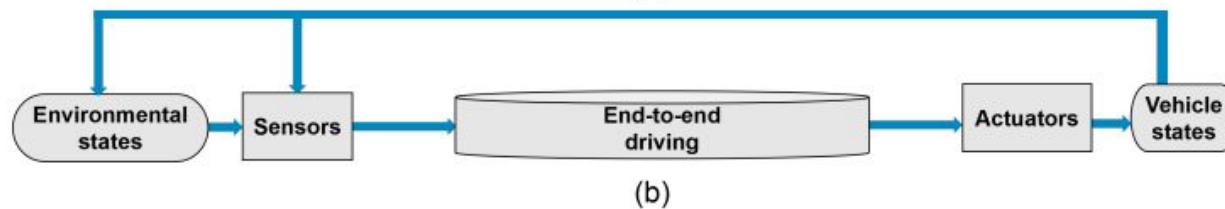


Cómo funcionan de verdad?

- Dos paradigmas:
 - Conducción modular: resolvemos cada tarea por separado.
 - Aprendizaje extremo a extremo: todo se resuelve en una sola pasada hacia delante.



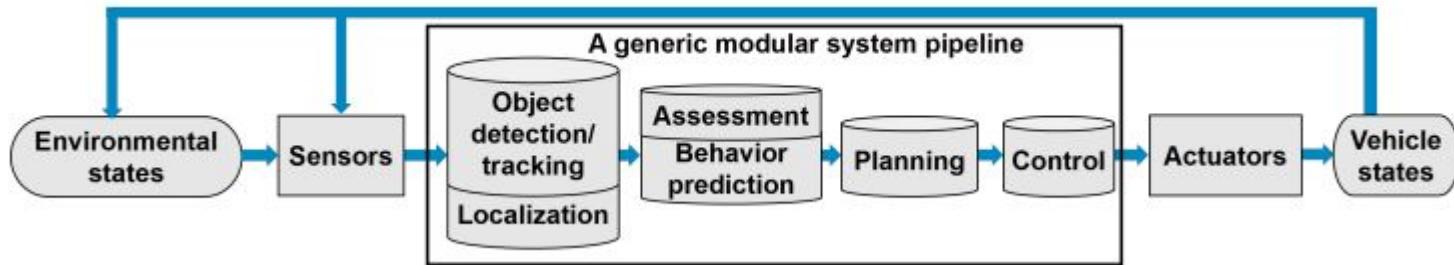
(a)



(b)

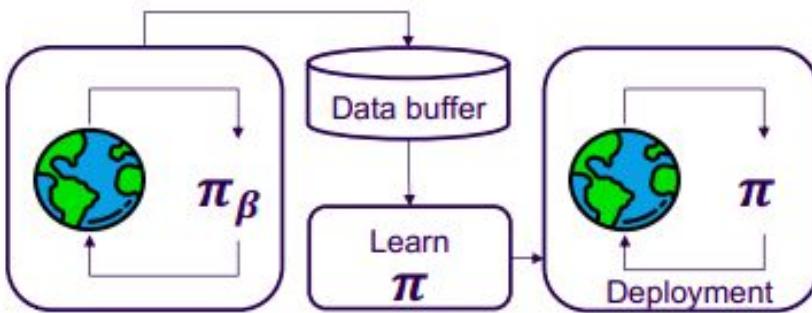
Aproximación modular

- Conducción modular:
 - Varios componentes se comunican.
 - Cada componente resuelve una tarea.
 - Se divide la tarea compleja en mini tareas.
 - Propagación de errores y demasiada complejidad.



Aprendizaje extremo a extremo. Imitation learning

- Se genera un dataset a partir de la conducción de expertos.
 - Se guardan los pares sensores-salidas de control.
- Se entrena con ese dataset que aprende a partir de los datos crudos.
- Diferencia entre la evaluación open-loop (dataset) vs closed-loop (Carla Leaderboard, Behavior Metrics).



Aprendizaje extremo a extremo. Imitation learning

Driving Input, 10^8 dimensions



Cameras (6 @ 25 Hz)



GNSS

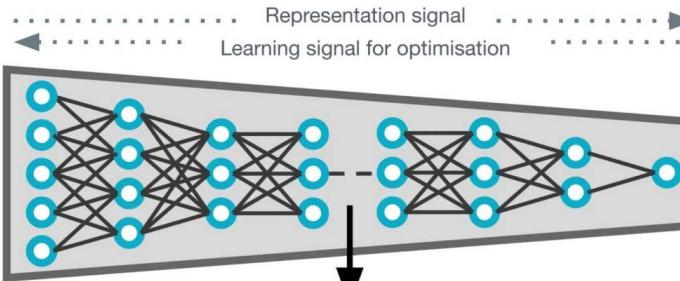


Basic Sat-nav Map



Vehicle State

+ other sensing modalities
where required, e.g. RADAR



Driving Output, 10^1 dimensions



Motion Plan

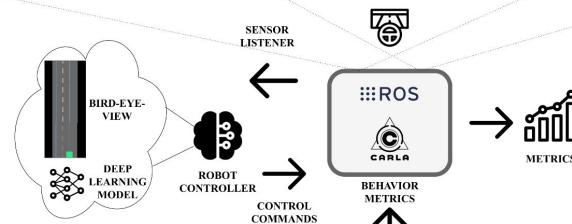


Vehicle Controls



Semantics, geometry, motion prediction.

Aprendizaje extremo a extremo. Imitation learning



Aprendizaje extremo a extremo. Imitation learning

CARLA Leaderboard 1.0 – SENSORS Track (0.9.10.1)

Copy CSV Search:

Team	Submission	Driving score	Route completion	Infraction penalty	Collisions pedestrians	Collisions vehicles	Collisions layout	Red light infractions	Stop sign infractions	Off-road infractions	Route deviation
Units	%	%	[0, 1]		Infractions/Km	Infractions/Km	Infractions/Km	Infractions/Km	Infractions/Km	Infractions/Km	Infractions/Km
+	Interfuser	ReasonNet	79.95	89.89	0.89	0.02	0.13	0.01	0.08	0.00	0.04
+	Interfuser	InterFuser	76.18	88.23	0.84	0.04	0.37	0.14	0.22	0.00	0.13
+	PPX	TCP	75.14	85.63	0.87	0.00	0.32	0.00	0.09	0.00	0.04
+	DP	TF++ WP Ensemble	66.32	78.57	0.84	0.00	0.50	0.00	0.01	0.00	0.12
+	WOR	Learning from All Vehicles (LAV)	61.85	94.46	0.64	0.04	0.70	0.02	0.17	0.00	0.25
+	Attention Fields	TF++ WP	61.57	77.66	0.81	0.02	0.41	0.00	0.03	0.00	0.08
+	DP	TransFuser	61.18	86.69	0.71	0.04	0.81	0.01	0.05	0.00	0.23
+	DP	TransFuser (reproduced)	55.04	89.65	0.63	0.05	0.56	0.00	0.23	0.00	0.16
+	Anonymous	TF++	52.82	71.40	0.76	0.02	0.53	0.09	0.01	0.00	0.15
+	GBT_AI_TEAM	GBT-AI-Autonomous driving	49.38	75.19	0.68	0.12	0.36	0.38	0.15	0.00	0.31

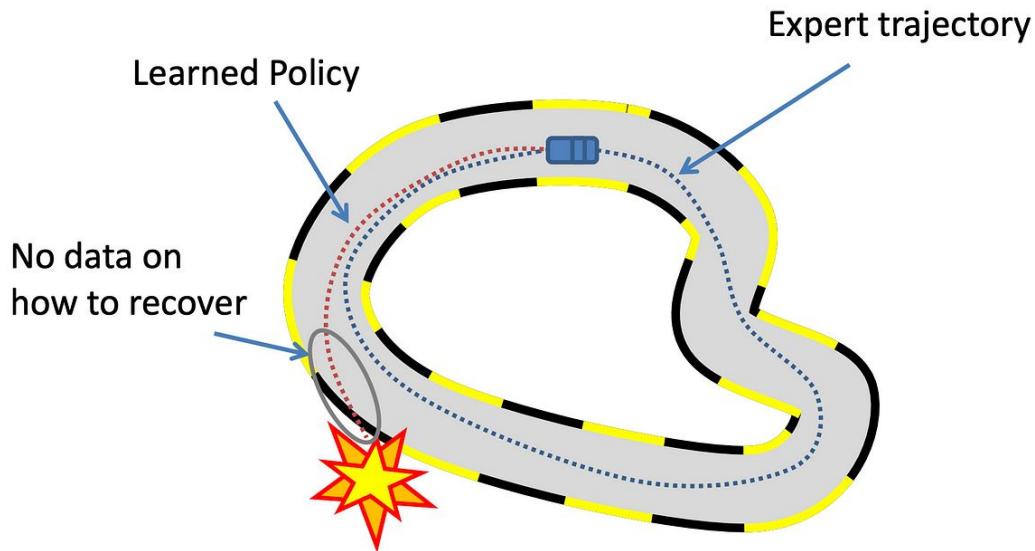
Showing 1 to 10 of 31 entries

Previous 1 2 3 4 Next



Aprendizaje extremo a extremo. Imitation learning

- Problemas:
 - Qué pasa en situaciones que no están en el dataset?
 - Gran necesidad de datos.
 - Datos desbalanceados.



Lo que hacemos nosotros!

- Estudio de las implicaciones de la memoria.
- Estudio de las implicaciones de técnicas de optimización en las redes.
- Desarrollo de sistema para conducción con tráfico (TFM).
- Desarrollo de sistema para navegación mediante comandos (GSoC).



Lo que hacemos nosotros!



Lo que hacemos nosotros!



End-to-End Autonomous Driving Model for Route
Navigation Task in Behavior Metrics

Meiqi Zhao

Mentors: Sergio Paniego, Nikhil Paliwal



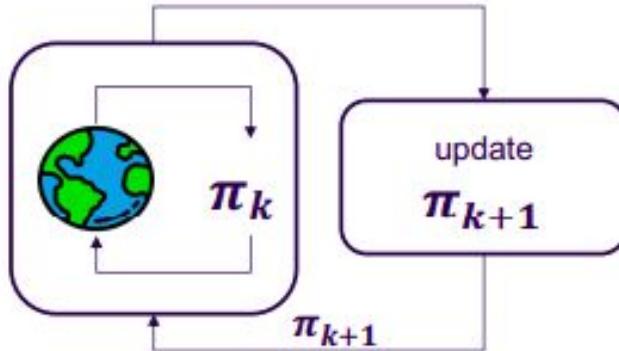
Google Summer of Code



Aprendizaje extremo a extremo.

Aprendizaje por refuerzo (RL)

- Aprendizaje por ensayo-error.
- Necesitamos primero aprender la política en simulación por seguridad!
- Muchísimo consumo de datos → paralelización del entrenamiento.



Lo que hacemos nosotros!

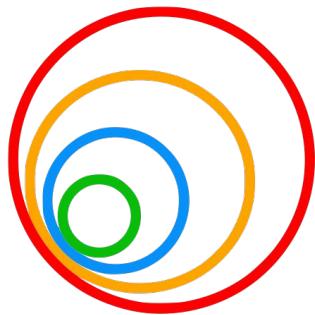


Estado de la cuestión y open problems

- Soluciones muy potentes en entornos controlados:
 - En industria.
 - En investigación.
- Falta generalización.
- Movimiento hacia soluciones E2E.
- Cuándo tendremos coches autónomos?
 - Predicciones no muy claras: 2020s-2060s



Cuña publicitaria



Google Summer of Code

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- BehaviorMetrics, <https://github.com/JdeRobot/BehaviorMetrics>





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Sergio Paniego Blanco

@sergiopaniego

sergio.paniego@urjc.es

<https://sergiopaniego.github.io/>

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