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Towards Data Driven Traffic Modelling: Safe Driving Based on Reinforcement Learning

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Introduction

Car-following models are based on machine learning algorithms.

The use of real traffic data leads to more precise and reliable models.

Reinforcement learning can be used in autonomous driving models.

Reinforcement learning can be used in conjunction with neural networks.

Literature Review

Research Gaps:

- Studies fail to take into consideration side vehicles.
- Algorithms are usually trained using simulations and not real-world data.

Scope of Work

Create a reinforcement learning algorithm:

- Chooses the best action in each timestep, based on the traffic conditions around the vehicle.
- Can be used inside cars as a drivers' assistance system.
- Will contribute in collision avoidance and increase of road safety levels

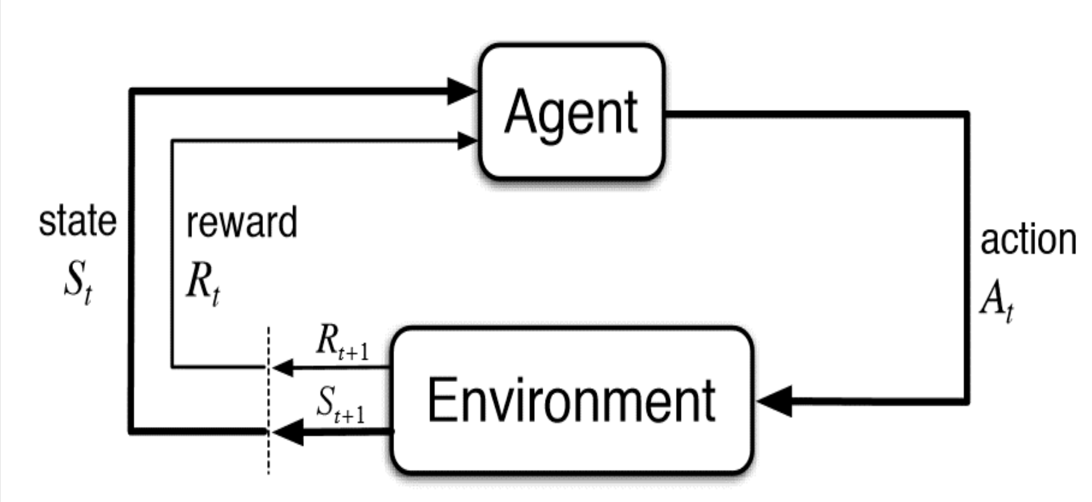
Machine Learning

- Supervised machine learning algorithms use labeled datasets in order to train algorithms.
- Unsupervised machine learning uses algorithms to analyze and cluster unlabeled datasets.
- Reinforcement learning is the science of optimizing consecutive decision making.

Reinforcement Learning

- An agent interacts with its environment by choosing the most appropriate action and receiving a reward signal.

- Markov property: “The future is independent of the past given the present”.



Q- Learning

Q-value function:

- $Q(s,a) = (1 - lr)Q(s,a) + lr[r_t + \gamma Q^*(s',a')]$

Parameters:

- Exploration rate ε
- Learning rate lr
- Discount factor γ

Data Collection

- Experiment in central Athens using 10 unmanned aerial vehicles.
- Traffic recording in 30 min phases during the morning peak period 8:00-10:30
- Data collected:
  - Coordinates WGS84
  - Speed
  - Tangent and lateral accelerations
- Vehicle types:
  - Motorcycle
  - Passenger Cars
  - Taxis
  - Van
  - Trucks
  - Buses

Dataset Format

Track ID	Type	Traveled Dist. [m]	Avg. Speed [km/h]	Trajectory(lat [deg]	lon [deg]	Speed [km/h]	Tan. Accel. [ms-2]	Lat. Accel. [ms-2]	Time [ms]
1	Medium Vehicle	375.28	23.2130	37.9914	23.7323	11.1338	-0.0779	0.0523	12000
2	Car	518.37	9.5308	37.9885	23.7291	32.9903	0.3480	-0.0038	12200
3	Car	157.22	36.7533	37.9902	23.7293	31.0879	-0.1004	0.0188	12200
4	Heavy Vehicle	350.69	31.8811	37.9886	23.7291	29.2202	-0.1182	-0.1445	12200
5	Car	497.14	23.4255	37.9910	23.7364	55.6260	0.1025	0.0104	12400
6	Car	427.66	8.2330	37.9902	23.7293	31.3172	-0.0307	0.0133	14000
7	Car	850.43	12.5886	37.9885	23.7291	34.9722	0.3087	-0.0703	14200
8	Car	831.82	19.2699	37.9910	23.7364	61.1052	0.0092	-0.0262	14400
9	Car	329.05	13.1328	37.9886	23.7291	28.3907	-0.2543	-0.0576	14600
10	Car	847.80	12.8347	37.9886	23.7291	40.6251	0.3589	-0.0250	14600
11	Motorcycle	236.79	27.6768	37.9886	23.7291	45.5406	0.0332	0.0230	14800
12	Car	636.95	24.5505	37.9910	23.7363	54.8595	0.1071	0.0134	15600
13	Car	241.80	6.6857	37.9885	23.7291	35.2763	0.1398	0.0001	16200
14	Car	249.04	7.4587	37.9886	23.7291	36.8343	0.1524	-0.0402	16200
15	Car	43.74	8.9461	37.9923	23.7301	21.7403	0.1399	0.0861	17000
16	Car	483.95	26.3971	37.9886	23.7291	37.7706	-0.4250	-0.1424	17800
17	Car	637.47	23.3220	37.9910	23.7364	56.2176	0.1164	0.0139	18400
18	Motorcycle	41.59	8.3183	37.9923	23.7301	14.4228	-0.3637	0.1845	18400
19	Car	239.47	23.5542	37.9885	23.7291	36.5177	0.6641	-0.0284	18600
20	Heavy Vehicle	495.71	23.6052	37.9911	23.7363	56.2237	0.1540	0.0115	18800
21	Car	415.15	31.6640	37.9910	23.7363	56.2337	0.1321	0.0025	20600
22	Car	830.54	21.6349	37.9910	23.7363	63.9345	0.2450	0.0010	21800
23	Bus	634.09	17.5324	37.9910	23.7363	51.2941	0.1534	-0.0093	22000
24	Motorcycle	244.34	8.1297	37.9885	23.7291	33.4819	0.2645	0.0277	22200
25	Heavy Vehicle	344.33	20.8684	37.9886	23.7291	29.5654	-0.2496	-0.2222	22200
26	Motorcycle	472.76	32.8562	37.9926	23.7314	34.0226	-0.0690	-2.0088	22400
27	Motorcycle	541.73	38.2398	37.9926	23.7315	33.1216	0.1999	0.0081	22600
28	Car	494.06	19.9843	37.9910	23.7363	52.6961	0.0428	0.0281	24600
29	Motorcycle	541.61	39.1523	37.9925	23.7315	38.4969	0.5359	-0.0065	24800
30	Medium Vehicle	242.92	4.4940	37.9885	23.7291	29.0284	0.4372	-0.0079	25000

Data Processing

- Data recorded every 0.8s
- Coordinate conversion to UTM
- Separation of traffic directions
- Rotation of the axes to agree with the road.
- Calculation of distances between the vehicle under inspection and the ones on the right, left, in the front and the back.
- Deviation of distances between vehicles:

Vehicle Types	Dx (m)	Dy (m)
Car - Motorcycle	0.8	3.0
Car - Car	1.0	4.0
Car - Van	1.2	4.0
Car – Truck	1.5	5.0
Car - Bus	1.5	5.0

Methodology Implementation

State recognition in 2 stages

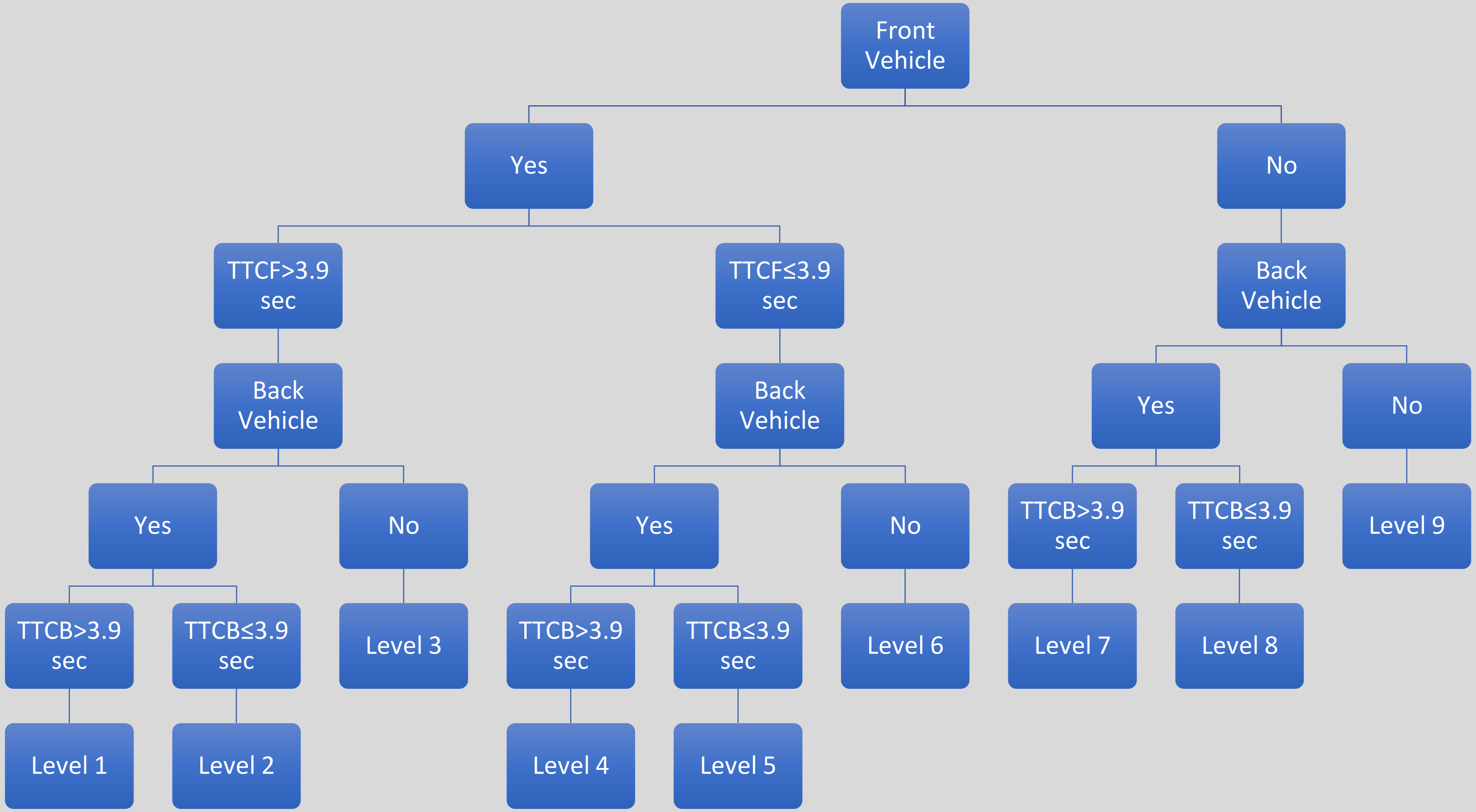
- 1st based on the vehicles front-back (9 states):
  - Critical time to collision 2.4s
  - Reaction time 1.5s
- 2nd based on lateral vehicles (8 states):
  - Critical distances: smaller than 84.14% of the distribution

Critical distances:

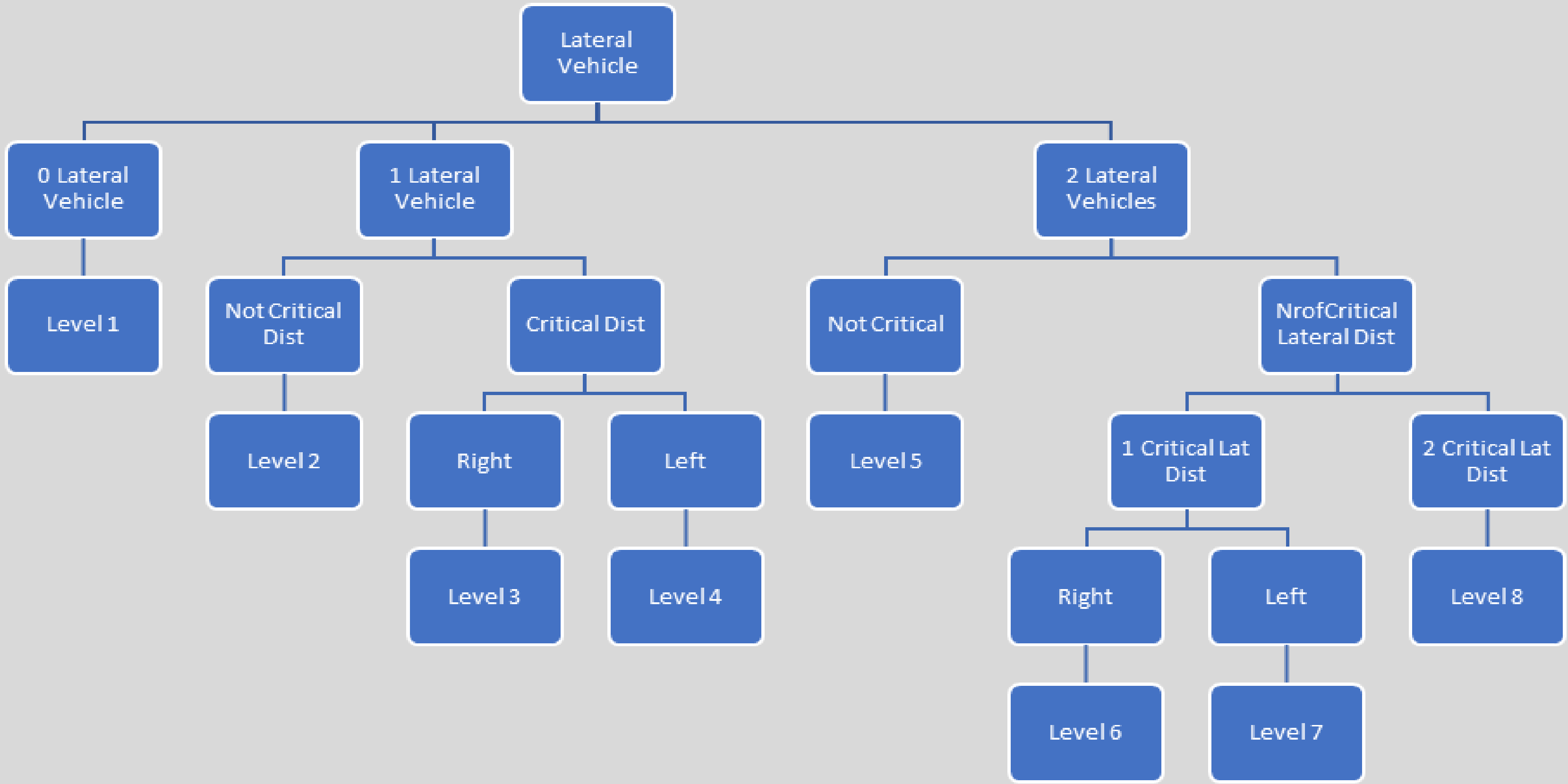
- Car – Motorcycle: 1.350 m
- Car – Car: 1.925 m
- Car – Van: 2.382 m
- Car – Truck: 2.556 m
- Car – Bus: 2.466 m

- 72 combinations of states from stage 1 and 2 → **72 states**

1^{st} Stage


Front Vehicle
Yes
No
TTCF>3.9 sec
TTCF≤3.9 sec
Back Vehicle
Back Vehicle
Back Vehicle
Yes
No
Yes
No
Yes
No
TTCB>3.9 sec
TTCB≤3.9 sec
Level 3
TTCB>3.9 sec
TTCB≤3.9 sec
Level 6
TTCB>3.9 sec
TTCB≤3.9 sec
Level 9
Level 1
Level 2
Level 4
Level 5
Level 7
Level 8

2nd Stage


Lateral Vehicle
0 Lateral Vehicle
1 Lateral Vehicle
2 Lateral Vehicles
Level 1
Not Critical Dist
Critical Dist
Not Critical
NrofCritical Lateral Dist
Level 2
Right
Left
Level 5
1 Critical Lat Dist
2 Critical Lat Dist
Level 3
Level 4
Right
Left
Level 8
Level 6
Level 7

Available Actions

2 levels – 2 axes of movement

Longitudinal axis

- Accelerate
- Do nothing
- Decelerate

Transverse axis

- Accelerate
- Do nothing
- Decelerate

9 combinations – **9 actions**

Reward Function

- Appropriate action – (1) unit
- Partly appropriate action (correct action relating to only one axis) – (-0.5) unit (negative since it does not contribute to safe driving)
- Wrong action towards both axes – (-2) units

Assumptions

- The ideal actions arise logically
- In extreme conditions the driver should remain inactive

Results

- 6 Scenarios were tested
- Different combinations of the Q-learning parameters

Scenarios	Parameters’ values
I	γ=0.9 lr=0.2 e=0.4
II	γ=0.9 lr=0.5 e=0.4
III	γ=0.9 lr=0.2 e=0.2
IV	γ=0.9 lr=0.2 e=0.5
V	γ=0.9 lr=0.2 e=0.7
VI	γ=0.7 lr=0.2 e=0.2

- Best scenario based on
  - Convergence
  - Cumulative Reward
  - Regret
  - Accuracy (Number of Errors)*

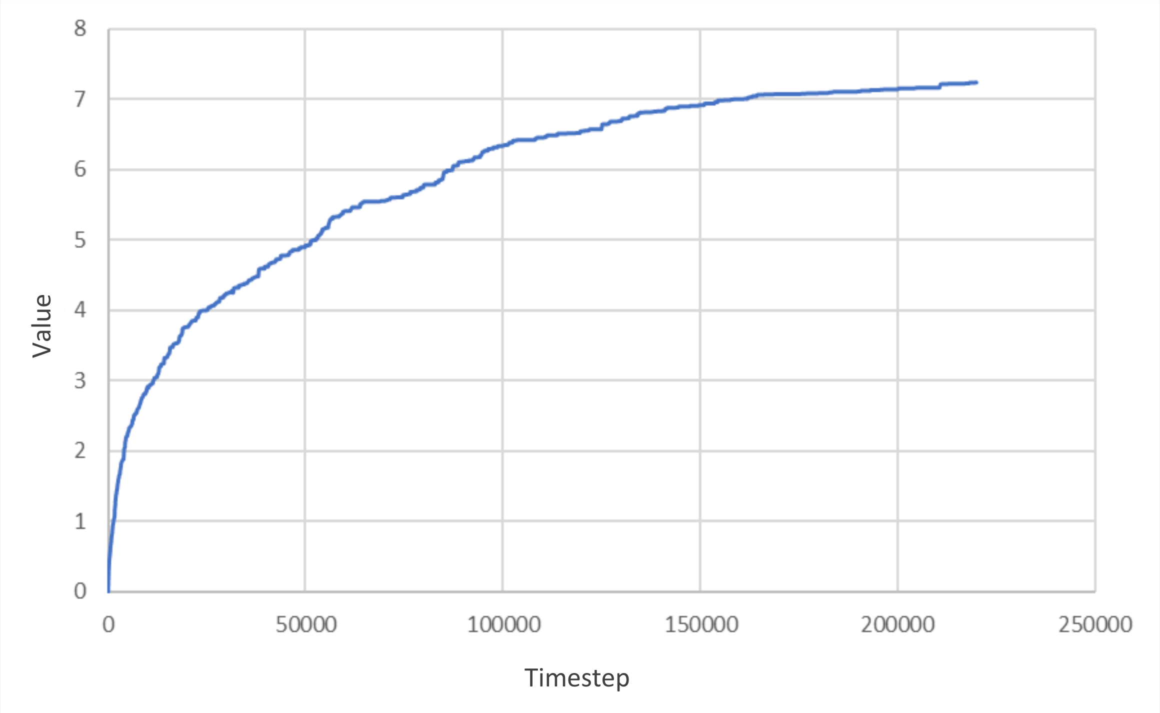
Scenario	Cumulative reward	Regret	Errors
I	43233.5	156766.5	10
II	43175	156825	13
III	131490.5	68509.5	4
IV	-425.5	200425.5	6
V	-87961	287961	10
VI	131507	68493	9

**The scenarios were tested using 54976 instances. When the agent failed to chose the correct, logical action towards safer driving, an error was recorded.*

Optimal Solution

- 220,000 timesteps used for training
- Best Scenario: Scenario III (γ=0.9 ε=0.2 lr=0.2)
  - Converges fast
  - Least errors
  - Small regret
- Optimal Q- table is obtained (72x9)
  - Values for all combination of states and actions
  - Selection of the optimal action based on the current state of the environment

Value of the mean optimal action



- Converges
- Large slope initially

Conclusions

- The algorithm learns fast and converges quickly.
- The algorithm can be further training using more data.
- This is one of the first research studies conducted that take into consideration lateral vehicles.
- The algorithm developed can contribute in driving behavior improvement.
- Reinforcement learning is an appropriate method for creating driver’s assistance systems and enhance safety levels.
- Some zero values in the Q-table – need for the algorithm to be exposed to more critical states.

Next Research Steps

- Use of deep reinforcement learning.
- Categorize drivers of surrounding traffic based on their behavior.
- Take into consideration behavior and characteristics of the examined vehicle's driver.
- Training using more critical states.
- Incorporate more variables in the model:
  - ✓ Weather
  - ✓ Visibility
  - ✓ Traffic Conditions

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