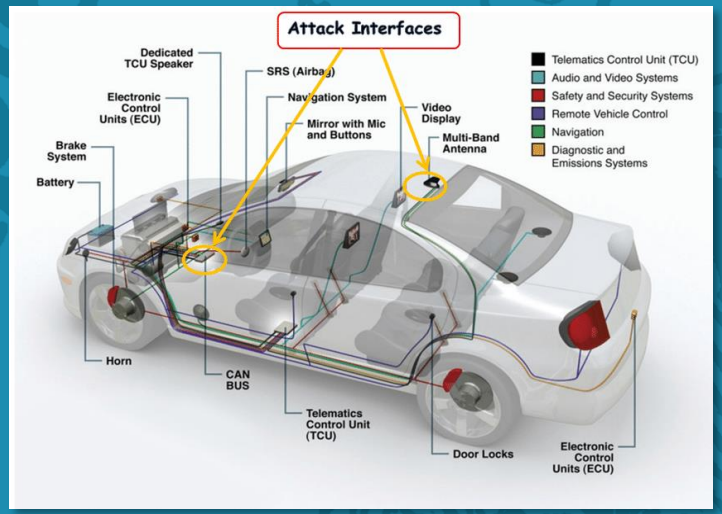
https://github.com/KULeuven-Diepenbeek/res_mol_canids

Development of a statistics-based IDS for automotive security

Wouter Hellemans, Jo Vliegen, Nele Mentens



Reviewing the questions from the preparation

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Q1: What do messages on the CAN-bus look like, and how can these be parsed with pandas in Python?

Reviewing the questions from the preparation

Q2: What kind of attacks can be performed on CAN networks?

Reviewing the questions from the preparation

Q3: Which statistical parameters can be derived from certain fields in network frames, to detect attacks on CAN?

Reviewing the questions from the preparation

Q4: How do you extract statistical parameters from a dataset?

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Short overview of CAN-bus

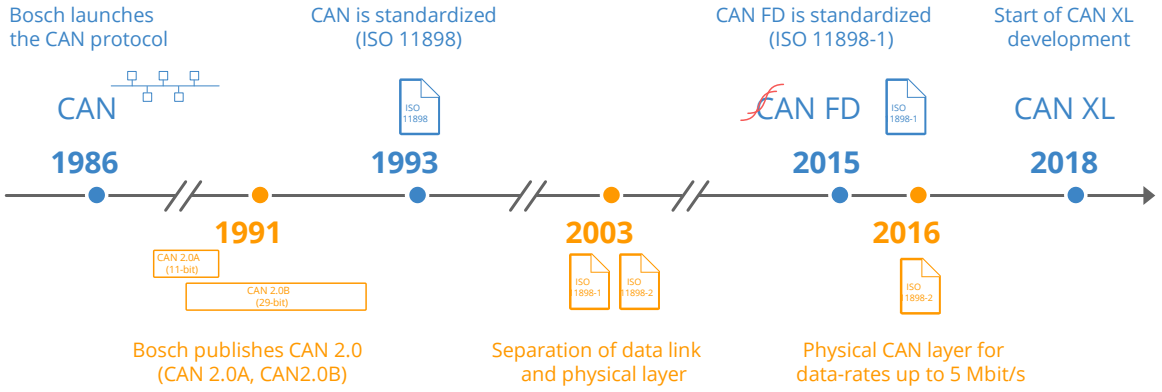
… and the frames that use it

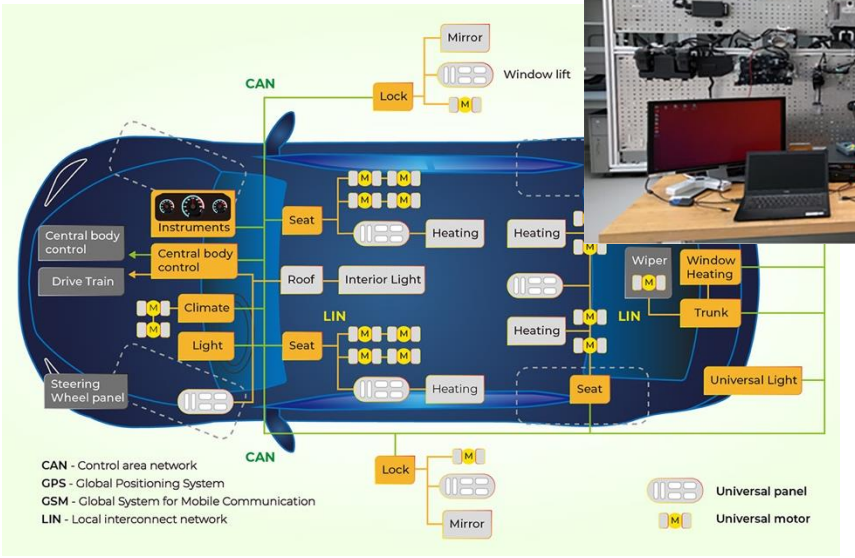
Short overview of CAN-bus

Modern cars can contain up to 150 **Electronic Control Units (ECUs)**

Controller Area Network (CAN): protocol for ECU-to-ECU communication

- 3 generations: CAN CC, CAN FD, and CAN XL
- IP of Robert Bosch GmbH





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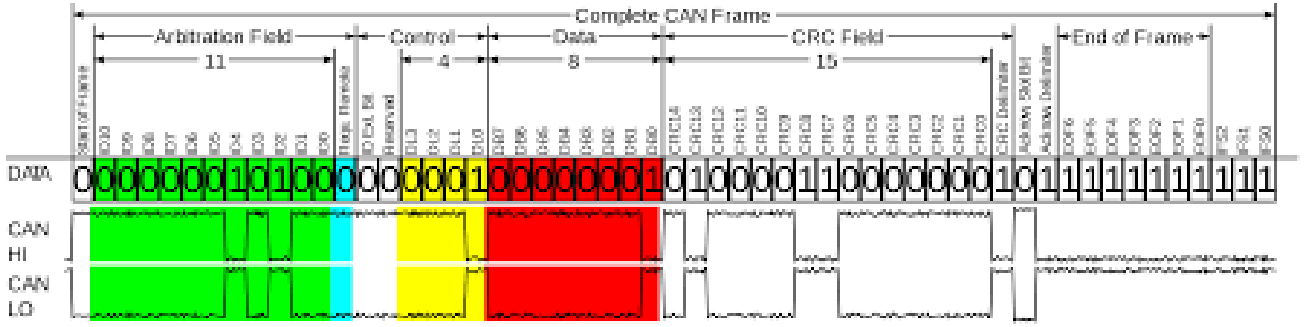
… and the frames that use it

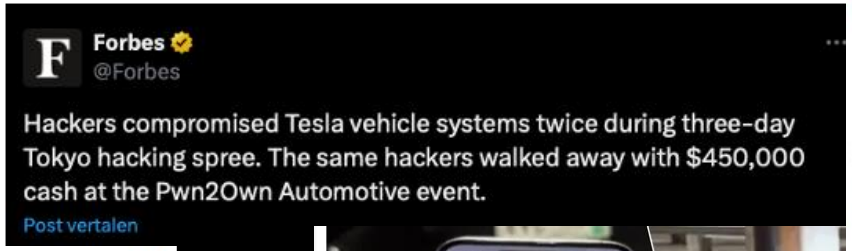
A message on the CAN bus is called a **frame**

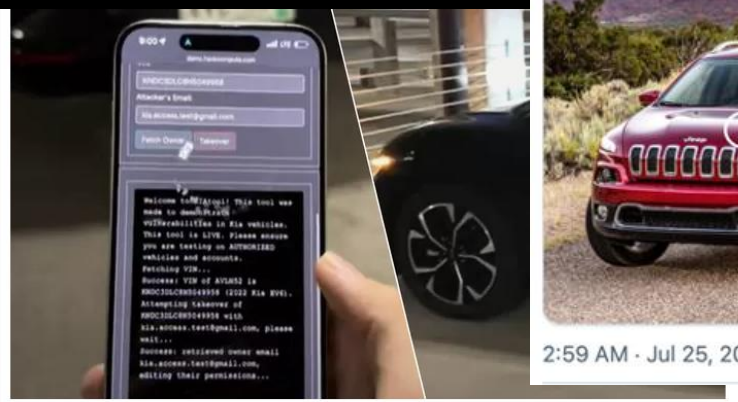


A frame consists (mainly) of 3 fields

- The identifier (Identifier)
- Metadata concerning the length of the message (DLC)
- The actual data (Data)

Attacks on CAN





De onderzoekers tonen hoe ze een speciale app maakten om miljoenen voertuigen te hacken. © HLN

Miljoenen auto's waren te hacken met eenvoudige truc: "Traceren, ontgrendelen en starten"

wielen", zegt HLN-techexpert Kenneth Dée.

Kenneth Dee 27-09-24, 15:00 Laatste update: 28-09-24, 08:26

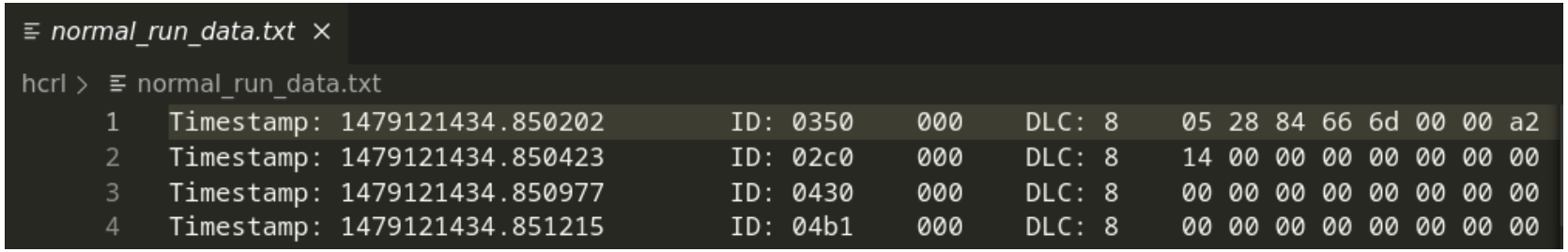
CAN is vulnerable to cyberattacks such as: DoS, Fuzzing, Spoofing, Replay...

Datasets & analysis

Datasets

We'll be doing experiments on a **dataset** from HCRL (Hacking and Countermeasure Research Lab):

A "normal_data_set" is available in .txt format.



Also "attacked" datasets can be found:

1. DoS Attack : Injecting messages of '0000' CAN ID every 0.3 milliseconds. '0000' is the most dominant.
2. Fuzzy Attack : Injecting messages of totally random CAN ID and DATA values every 0.5 milliseconds.
3. Spoofing Attack (RPM/gear) : Injecting messages of certain CAN ID related to RPM/gear information every 1 millisecond.

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Datasets

We'll be doing experiments on a **dataset** from HCRL (Hacking and Countermeasure Research Lab).

The dataset can be downloaded from this URL:

https://drive.google.com/drive/folders/1ed2PlvcSu9ONt-8KK3sgG4Qw1Bp0ccOr?usp=sharing

Example – How to detect malicious frames?

Maybe the Hamming distance between 2 subsequent frames might be an indicator?

Hamming distance = number of positions in which two (equally sized) inputs differ. For example:

- `Hello Jim`
  `Hello Tim`
  Hamming distance: 1
- `31 = 0b01 1111`
  `32 = 0b10 0000`
  Hamming distance: 6

Example – How to detect malicious frames?

Maybe the Hamming distance between 2 subsequent frames might be an indicator?

The two messages:

0350_8_052884666d0000a2
02c0_8_1400000000000000

The two messages, in binary:

0000001101010000_1000_00000101001010001000010001100110011011010000000000000000010100010
0000001011000000_1000_00010100000000000000000000000000000000000000000000000000000000

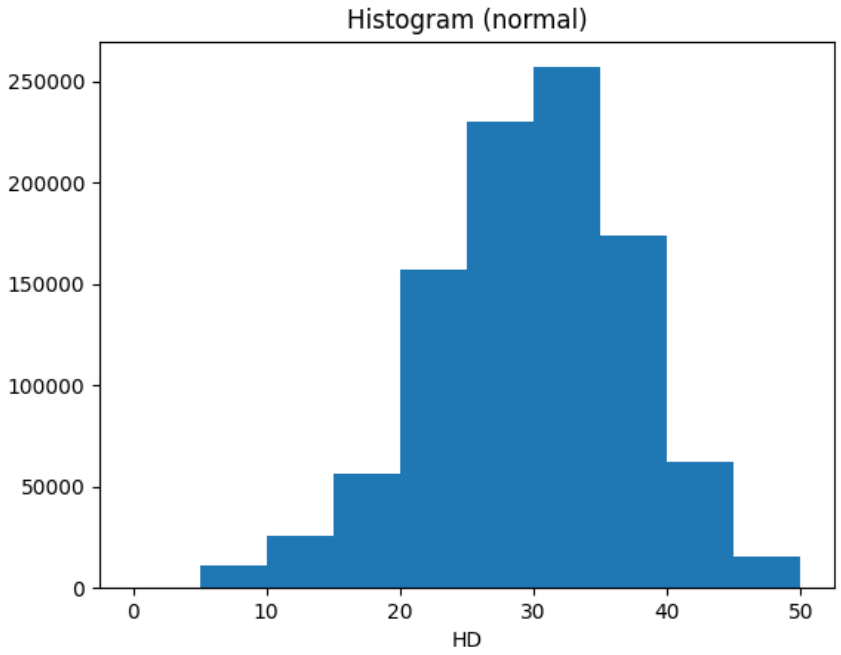
… and exored …

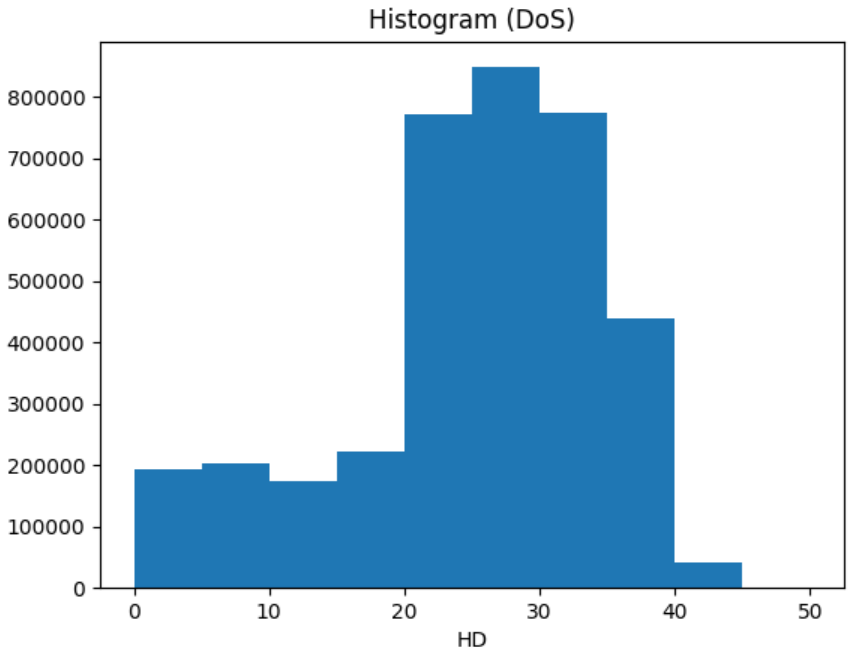
0000000110010000_0000_00010001001010001000010001100110011011010000000000000000010100010

… shows 21 bits of value '1', so the Hamming distance is **21**

Example – How to detect malicious frames?

Maybe the Hamming distance between 2 subsequent frames might be an indicator?





… now you try

Can you find a statistical feature that *MIGHT* be an indication?

Example

Our "*hypothesis"* is that if the HD with the previous frame is < 10, the message is classified as "malicious"

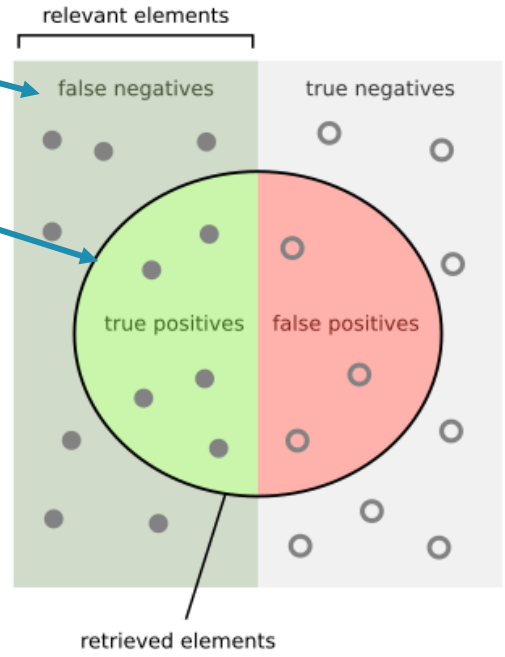
When applied to the first 100 frames of the DoS dataset, two frames are marked as "malicious".

How to evaluate the performance of our IDS?

Evaluation

malicious

classified as malicious



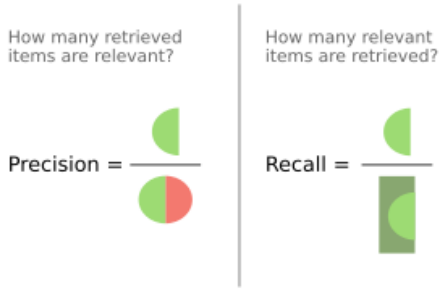
The dataset comes with the "correct" answer, per frame

T: injected message

R: normal message

For every frame, the datasets also provides: ok / not ok

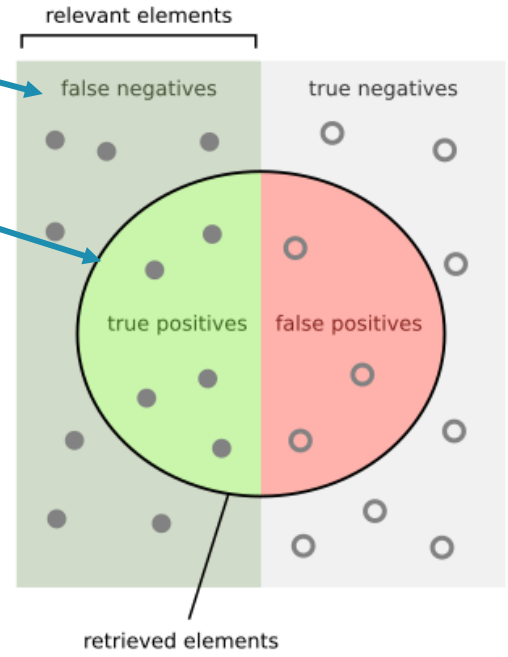
	T	R
Ok	False negative	True negative
Not ok	True positive	False positive



Evaluation

malicious

classified as malicious



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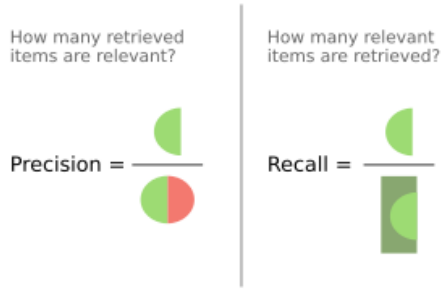


Precision: how good are your positives ? Tp / (Tp + Fp)

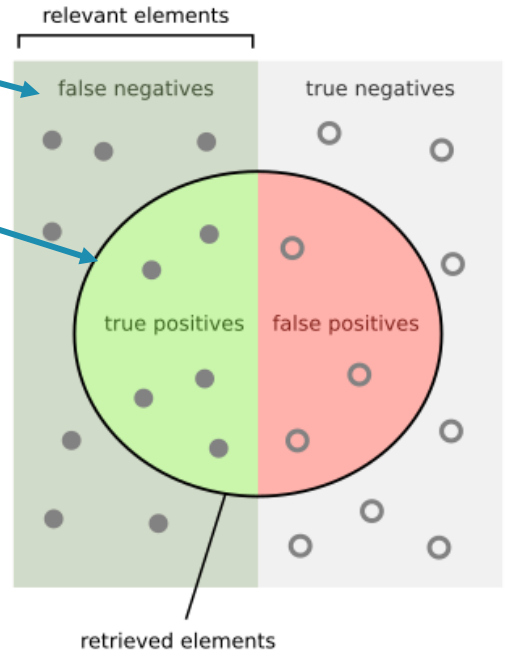
Accuracy: how good are your decisions, overall? (Tp + Tn) / (Tp + Tf + Fp + Fn)

Recall: how good did you cover all positives? Tp / (Tp + Fn)

Evaluation

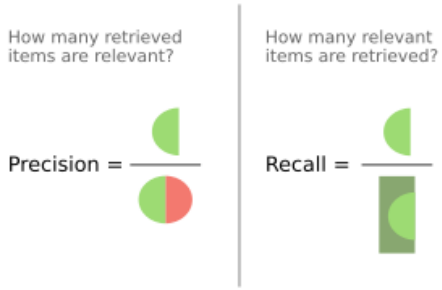
malicious

classified as malicious



If we experiment with different parameters:

HD	Accuracy	Precision	Recall
5	0.884785	0.882467	0.995365
10	0.873942	0.900210	0.955839
15	0.848938	0.907834	0.912773



… now you try

How do your hypotheses score?

Combined decision making

How would make a decision when multiple models are at work ?

- Classify as malicious when **1 out of n** models classifies as malicious
- Classify as malicious when **all n** models classify as malicious
- Classify as malicious when **≥ n/2 out of n** models classify as malicious

Q&A

That's it

We hope you had fun (and have learned something :))