Fingerprinting Automobiles with CAN Bus Data Samples

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1 Title

Hi, I'm 2d Lt David Crow. My research is about Fingerprinting Vehicles with CAN Bus Data Samples.

2 Problem Domain

Here's a picture of the controller area network **(citation)**. These are installed in most cars.

Although the CAN clearly reduces system complexity, the network's connectedness means it's a prime target for malicious intruders. If an attacker gains access to the CAN bus through *any* endpoint, they can access the rest of the devices on the network, which include the dashboard, the steering wheel, the brakes, the transmission, the engine, and so on.

To address this, modern vehicle manufacturers employ a policy of *security through obscurity* when designing the CAN bus and its components. Effectively, this means they make it difficult to interpret the meaning of CAN data without significant reverse engineering efforts. However, this security policy is insufficient for consumer protection because obfuscating a vehicle's CAN data does not adequately hide the vehicle's signature.

Why is this? Well, today's toolsets can successfully determine whether a specific vehicle generated a specific segment of CAN data, even if said data is unprocessed or limited in scope. This research presents one way to do so.

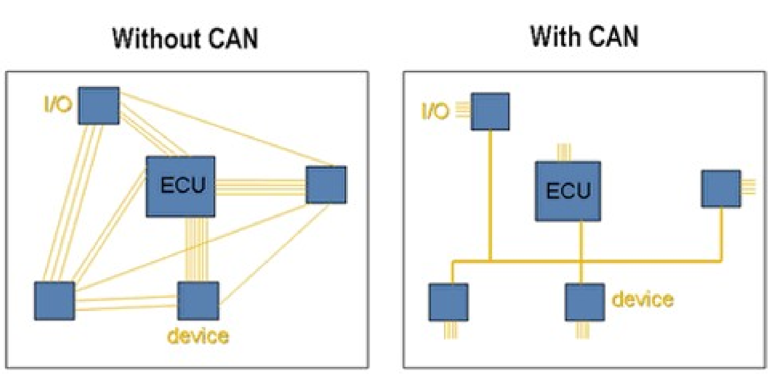
3 Objective

Specifically, we devise a system capable of identifying which distinct vehicle generated a given segment of CAN bus data. This is a multiclass classification problem which asks the following question: does a given vehicle generate data with some characteristic unique to that vehicle? In other words, does a given vehicle leave identifiable fingerprints on its data?

We hypothesize that a convolutional neural network can effectively classify vehicles, especially when compared to standard machine learning techniques.

4 Data

This research employs two datasets, one from Oak Ridge National Laboratory and one from a previous student's research **(citation)**. The lab shared nearly two and a half gigabytes of data captured on the CAN buses of nine different vehicles; Stone captured over 230 megabytes of data from 11 different vehicles.



Oak Ridge National Laboratory's Vehicles

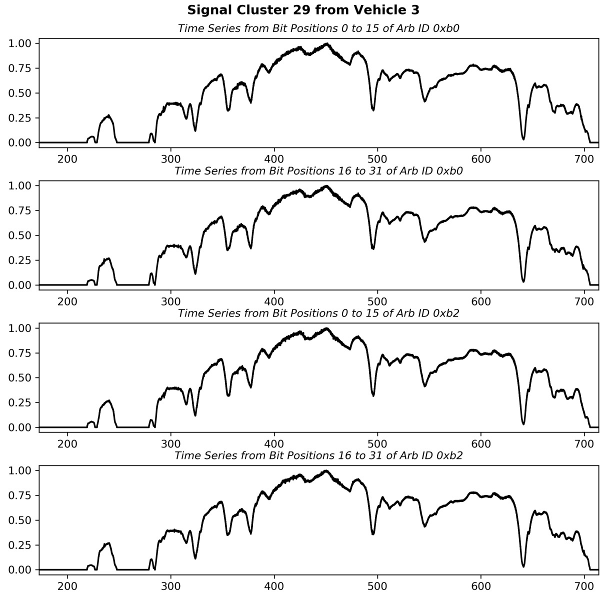
Vehicle	**Make**	**Model**	**Year**
1	Toyota	Tacoma	2008
2	Toyota	Corolla	2009
3	Nissan	Leaf	2011
4	Ford	C-Max	2013
5	Chevrolet	Volt	2015
6	Ford	F-150	2014
7	Ford	Fusion	2016
8	Subaru	WRX	2017
9	Subaru	Outback	2009

Stone's Vehicles [3]

Vehicle	**Make**	**Model**	**Year**
101	Chevrolet	Cobalt	2009
102	Chevrolet	Silverado	2011
103	Dodge	1500	2014
104	Ford	F-150	2017
105	Ford	Focus	2010
106	Honda	Accord	2012
107	Honda	Accord	2015
108	Nissan	370Z	2015
109	Nissan	XTERRA	2010
110	Saab	9-7X	2009
111	Toyota	Corolla	2009

Data Samples (Unformatted)

Vehicle	**Capture**	**ArbID**	**Data**
3	8	1532	`4A A6 6F FE FF F0 FE`
3	8	1532	`05 A2 05 A1 05 A2 05 A3`
101	101	292	`FF FF FF FF FF FE FF 00`
108	108	624	`1A 00 41 49 49 40 00 00`



Data Samples (Formatted)

Vehicle	**Capture**	**ArbID**	**Data**
3	8	1532	`074 166 111 254 255 240 254 ...`
7	24	535	`003 212 003 209 003 199 003 ...`
108	108	292	`255 248 000 128 015 254 030 ...`
111	111	624	`026 000 065 073 073 064 000 ...`

The raw CAN messages in each capture contain a bunch of information. Here's the important stuff:

Each arb ID might detail a vehicle's speed, RPM, tire pressure, brake pedal position ... but we don't actually *know* what it describes. For example, one reverse engineering pipeline might pull these signals from one arb ID. Maybe these are wheel speeds. I don't know. It's impossible to be sure without possessing insider knowledge.

Luckily for us, deep learning doesn't particularly care about the meaning of each arb ID. Thus, for every arb ID in every capture, the formatting process entails the following **(make a nice graphic)**:

1. Concatenate all data chunks into one string
2. Split string into list of hex bytes
3. Convert list of hex bytes to list of int bytes
4. Split list of int bytes into list of 1,024-byte samples
5. Label each sample with generating vehicle (if it's not clear, the task is fully supervised)

Formatting the datasets in this way gives nearly three hundred thousand samples.

5 Methodology

We then train a simple model on 90% of the data. This simple model is the best version identified in an iterative model-tuning process **(show model)**. Although it's passable, we can do better ...

... So, we also feed these samples into a convolutional neural network. By again looping over model configurations, we identify the best convnet for this task **(model diagram; parameters; other details)**. This model has about **(number)** parameters.

Number of Samples Per Vehicle (Imbalanced)

Vehicle	**Samples**	**Proportion**
1	4440	1.49 %
2	6895	2.32 %
3	141847	47.72 %
4	14633	4.92 %
5	43377	14.59 %
6	9511	3.20 %
7	35142	11.82 %
8	5018	1.69 %
9	8211	2.76 %
101	4102	1.38 %
102	1824	0.61 %
103	1757	0.59 %
104	2182	0.73 %
105	3791	1.28 %
106	1695	0.57 %
107	2198	0.74 %
108	3020	1.02 %
109	2553	0.86 %
110	2974	1.00 %
111	2083	0.70 %

6 Analysis

The full dataset is severely imbalanced—Vehicles 3, 5, and 7 are significantly overrepresented, and the remaining vehicles are underrepresented.

The red rows indicate those classes which are either significantly over- or underrepresented.

To address this imbalance, we train on the full dataset and compute balanced accuracy, which accounts for the imbalance. We do the same with a balanced dataset, which we balance by randomly sampling from each of the classes.

7 Results

Results indicate that the simple model can adequately classify vehicles, but it's clear that the convnet is a bit better.

8 Impacts & Limitations

9 Future Work

Devising a siamese neural network capable of learning the difference between CAN segments is the logical next step for this research. As a reminder, an SNN can generalize to new classes because it learns why two observations come from the same class or from different classes. A standard CNN, on the other hand, must learn every class. For this reason, an SNN is extensible: one can train an SNN on a set of vehicles and, because it knows why samples from two vehicles are different, one can introduce new vehicles and still maintain solid performance.

10 References

Here are some references . . .

11 Thank You

. . . And thanks for watching. Let me know if you have any questions!

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111	2083	0.70 %

Number of Samples Per Vehicle (Balanced)

Vehicle	Samples	Proportion
1	1695	5.00 %
2	1695	5.00 %
3	1695	5.00 %
4	1695	5.00 %
5	1695	5.00 %
6	1695	5.00 %
7	1695	5.00 %
8	1695	5.00 %
9	1695	5.00 %
101	1695	5.00 %
102	1695	5.00 %
103	1695	5.00 %
104	1695	5.00 %
105	1695	5.00 %
106	1695	5.00 %
107	1695	5.00 %
108	1695	5.00 %
109	1695	5.00 %
110	1695	5.00 %
111	1695	5.00 %

Balanced Accuracy for Each Model

Model	Dataset	Accuracy
Multi-layer perceptron	Imbalanced	81.71 %
Multi-layer perceptron	Balanced	76.95 %
Convolutional neural network	Imbalanced	83.18 %
Convolutional neural network	Balanced	80.94 %

Best and Worst Vehicles for Each Model

Model	Dataset	Best Vehicle	Worst Vehicle
MLP	Imbalanced	1	111
MLP	Balanced	6	105
CNN	Imbalanced	9	102
CNN	Balanced	105	7

Class Accuracy for Each Vehicle

Vehicle	MLP Imbalanced	MLP Balanced	CNN Imbalanced	CNN Balanced	Median
1	98.31 %	83.29 %	92.58 %	88.20 %	90.39
2	86.89 %	76.61 %	88.69 %	80.88 %	83.88
3	93.59 %	81.82 %	93.60 %	74.21 %	87.70
4	94.40 %	76.52 %	94.55 %	77.87 %	86.13
5	96.85 %	70.72 %	97.56 %	81.57 %	89.21
6	96.20 %	94.72 %	94.72 %	83.63 %	94.72
7	89.50 %	70.47 %	92.71 %	48.27 %	79.98
8	94.99 %	92.49 %	96.85 %	89.34 %	93.74
9	96.03 %	86.26 %	98.34 %	92.64 %	94.33
101	87.54 %	60.22 %	89.00 %	83.38 %	85.46
102	97.63 %	84.31 %	82.51 %	75.56 %	83.41
103	85.67 %	89.51 %	93.57 %	81.59 %	87.59
104	83.18 %	89.55 %	89.29 %	87.83 %	88.56
105	91.80 %	50.83 %	93.94 %	94.83 %	92.87
106	89.38 %	89.70 %	85.59 %	85.17 %	87.48
107	82.52 %	69.44 %	87.41 %	79.26 %	80.89
108	94.42 %	73.61 %	95.12 %	89.64 %	92.03
109	90.79 %	85.71 %	93.60 %	82.67 %	88.25
110	82.18 %	84.50 %	83.78 %	87.81 %	84.14
111	74.01 %	70.98 %	88.07 %	78.80 %	76.40
N/A	81.71 %	76.95 %	83.18 %	80.94 %	N/A