#### MASS 2021

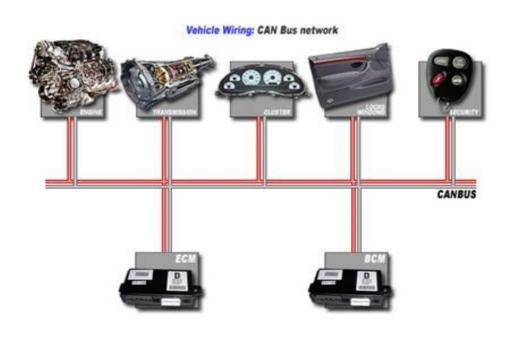
# A Transfer Learning based Abnormal CAN Bus Message Detection System

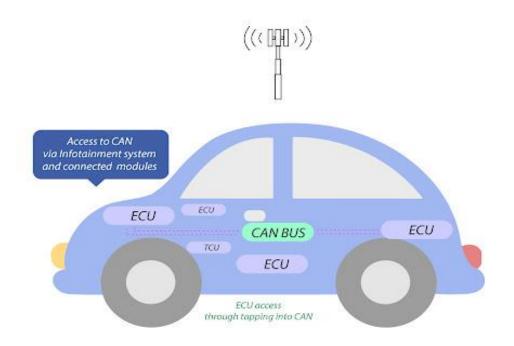
Liuwang Kang and **Haiying Shen**Department of Computer Science, University of Virginia



# Background

- Hundreds of electronic control units (ECUs) and devices communicate messages in a control area network (CAN) bus
- Modern vehicles become vulnerable to attacks when communicating with outside-vehicle environments





### Background

- Vehicle under a CAN bus attack may fail to work and affect vehicle driving safety
- CAN bus message transmission behavior (time interval) is not the same for different vehicle types



Arbitration field				Data field					
SOF	ID	RTR	IDE	r0	DLC	Data	CRC	ACK	EOF
1 bit	11 bit	1 bit	1 bit	1 bit	4 bit	0 to 64 bit	16 bit	2 bit	7 bit

Accurately detecting abnormal CAN bus messages for different vehicle types become important

#### Related Work

- Some methods [PST'17, CISR'17, ICOIN'16] try to detect abnormal CAN bus messages by statistically analyzing message transmission behaviors
- ➤ Vehicle driving conditions (e.g., KEY on and KEY start) affect message transmission behaviors greatly
- Some methods [PST'18, PLOS'16] utilize Machine Learning (ML) technologies to detect abnormal CAN bus messages by capturing message features like data field values
- > Detection performance highly depends on the training data size

### Challenges

Propose a neural network based abnormal message detection system (NaDS), to detect abnormal messages in a CAN bus

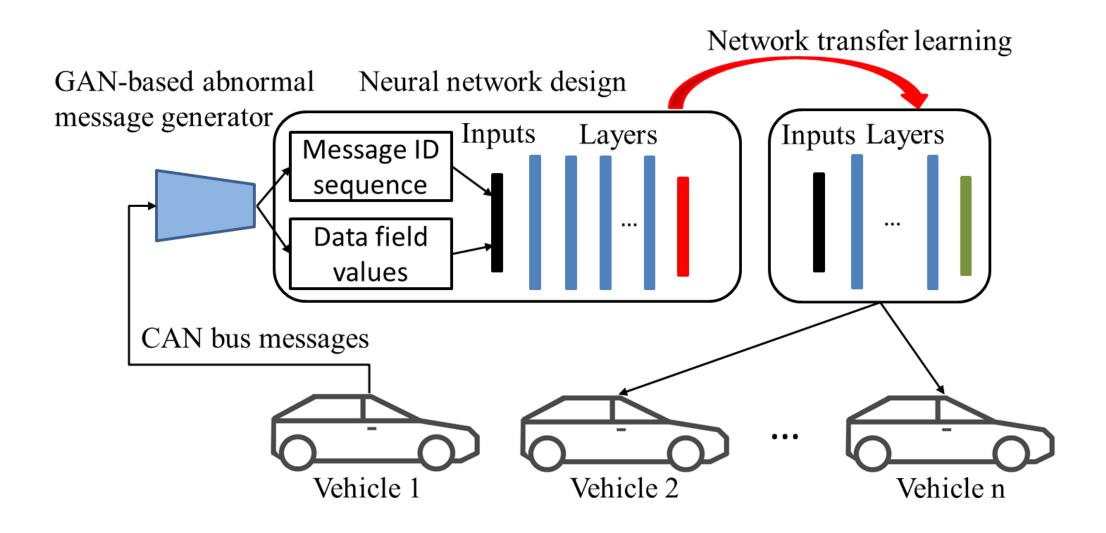
Challenge 1: How to increase accuracy for detecting both known and unknown abnormal messages?

• Difficult to collect sufficient training data including all kinds of attacks

Challenge 2: How to form a well-trained ML model for one vehicle type in spite of a small amount of training data?

• The training data size affects ML model' performance greatly

# Neural Network based Abnormal Message Detection System



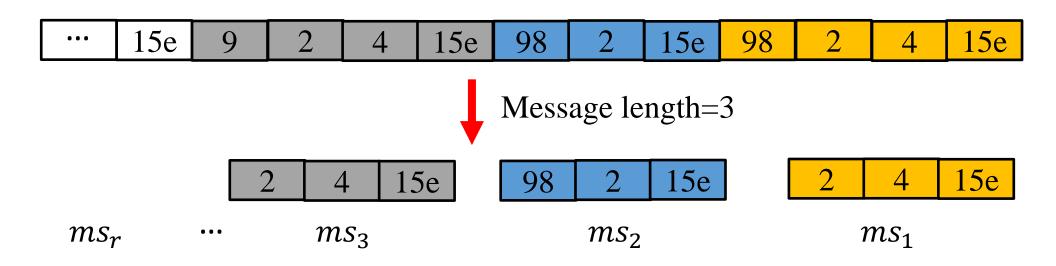
### Challenge 1

How to increase accuracy for detecting both known and unknown abnormal messages?

Observations from message ID sequence dissimilarity analysis results

Message ID sequence: A series of message IDs from itself to the previous message with the same message ID type

• Step 1: Determine message sequence  $ms_1$  and previous message sequences  $(ms_2, ms_3, ..., ms_r)$  for a message

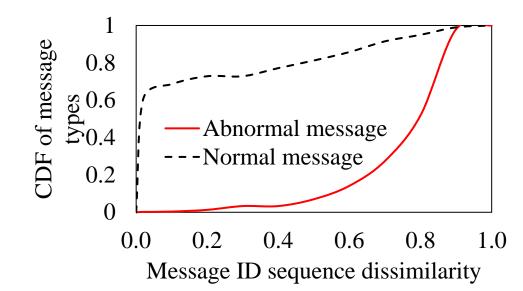


Observations from message ID sequence dissimilarity analysis results

• Step 2: Calculate Hamming distances between  $ms_1$  and  $(ms_2, ms_3, ..., ms_r)$ 

$$H(ms_1, ms_i) = \frac{N_{min}(ms_1, ms_i)}{N_{total}(ms_1, ms_i)}$$

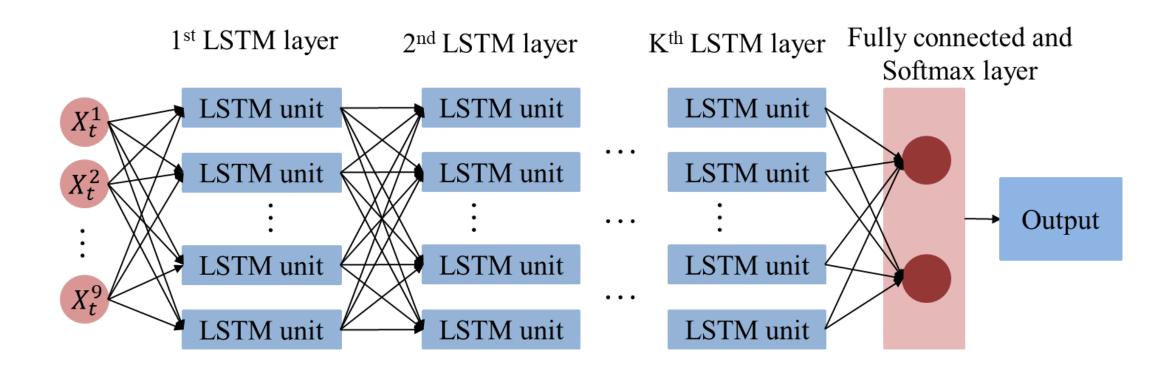
 $N_{min}(ms_1, ms_i)$  – the minimum number of changed messages to ensure  $ms_1 = ms_i$  $N_{total}(ms_1, ms_i)$  – the total number of messages in  $ms_1$ 



Abnormal messages have much larger message ID sequence dissimilarity value than normal messages

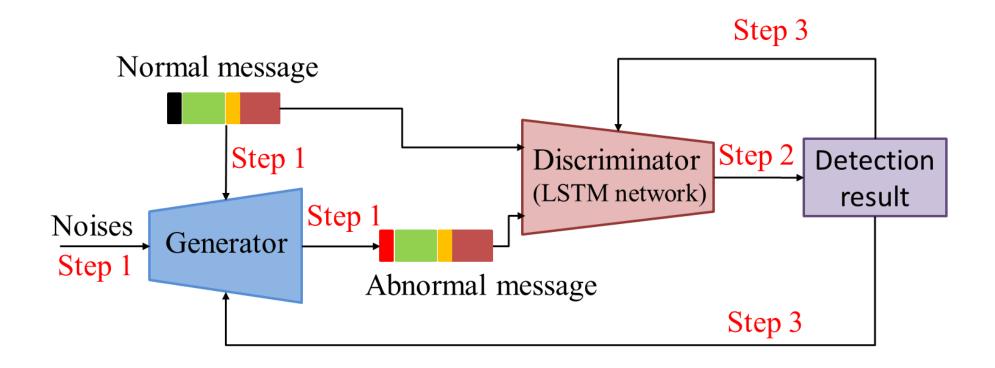
LSTM-NN based abnormal message detection method

Utilize a LSTM neural network to detect abnormal messages by inputting message ID sequence and values in the data filed



GAN-based abnormal message generator

Utilize a GAN to generate all possible abnormal messages for training the LSTM network



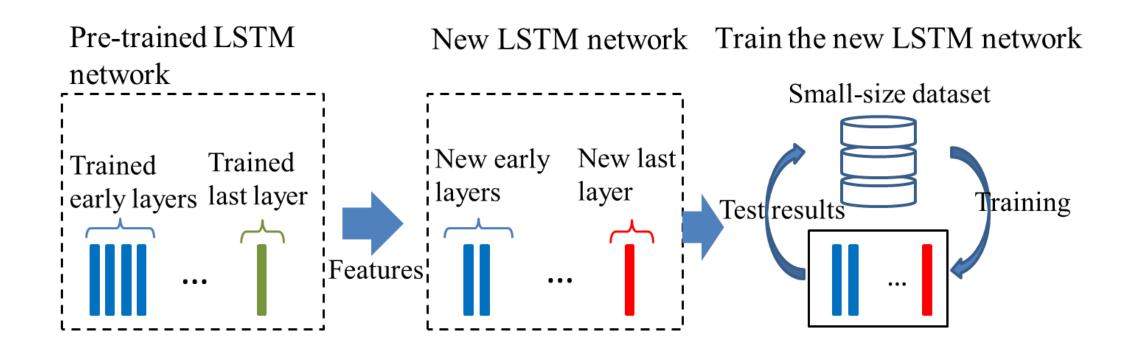
### Challenge 2

How to create a well-trained ML model for one vehicle type in spite of a small amount of training data

## Transferring a Pre-Trained Detection Model

Transfer learning for LSTM network

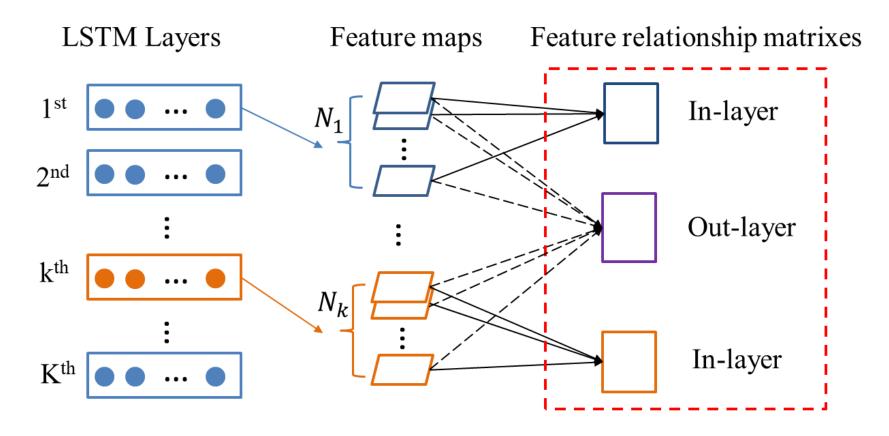
Transfers the pre-trained LSTM network of a vehicle into another LSTM network for detecting abnormal messages for a new vehicle type



### Transferring a Pre-Trained Detection Model

Extracting features in LSTM neural network

Uses a feature map to indicate features of units in each LSTM layer and feature relationship matrixes to describe relationships between feature maps in two layers or the same layer



# Transferring a Pre-Trained Detection Model

Training the transferred LSTM neural network

Add a fully connected and softmax layer into the transferred LSTM network and train it as follows by minimizing the cross-entropy loss *L* 

$$L = \frac{1}{CS} \sum_{i=1}^{S} \sum_{c=1}^{C} y(o(s_i) \to c) \log(p_c)$$

 $y(o(s_i) \rightarrow c)$  – indicates a binary indicator and equals to 1 if detection result  $o(s_i)$  on sample  $s_i$  is the same as classification status c

 $p_c$  - the probability that c is the correct classification status of  $s_i$ 

#### Performance Evaluation

#### Experiment settings

- Implement NaDS by running MATLAB on one laptop (Intel i5 CPU and 16 gigabyte memory)
- Contain 961,723 abnormal messages and 2,747,421 normal messages from three different vehicle types (KIA, SONATA, and SPARK)

#### Comparison methods

• Message time interval-based detection system (TIDS)[CISR'17], GAN based intrusion detection system (GIDS) [PST'18] and ML based detection system (RLD) [PLOS'16]

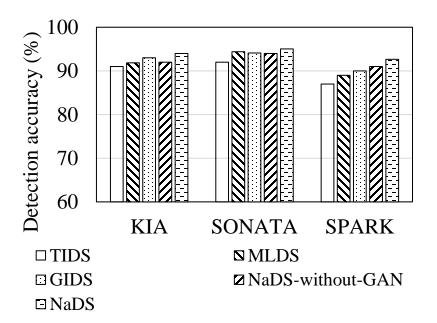
#### **Evaluation metrics**

• Abnormal message detection accuracy

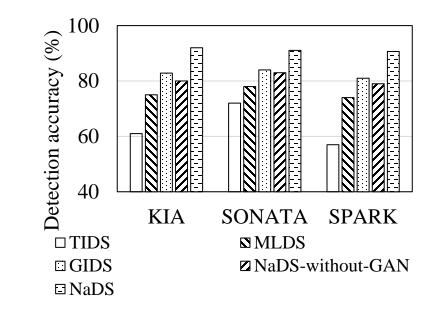
#### Performance Evaluation

#### Abnormal message detection accuracy comparisons

- NaDS has the highest detection accuracy on known abnormal messages
- Detection accuracy decreases for unknown abnormal messages and NaDS keeps the maximum detection accuracy value



Accuracies for known abnormal messages

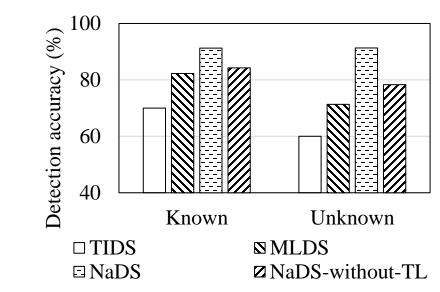


Accuracies for unknown abnormal messages

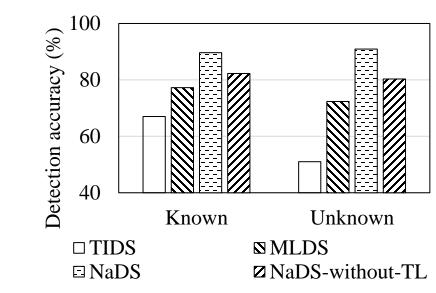
#### Performance Evaluation

#### Detection accuracy comparisons on new vehicle types

- Abnormal message detection accuracy of NaDS keeps stable because of transfer learning
- Abnormal message detection accuracy of other methods decrease greatly



Accuracies when LSTM network transfers from KIA to SONATA



Accuracies when LSTM network transfers from KIA to SPARK

#### Summary

Propose NaDS to detect abnormal messages in CAN bus on different vehicle types

- Built a LSTM-NN based abnormal message detection method
- Developed a network transfer method to transfer a pre-trained LSTM network
- Used real CAN bus message data to verify NaDS

#### Future work

Consider more message related information



Thank you!