RECURRENT NEURAL NETWORKS

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<tr><td colspan="2">Unsupervised</td><td></td><td></td><td></td><td></td><td></td><td>*</td></tr>
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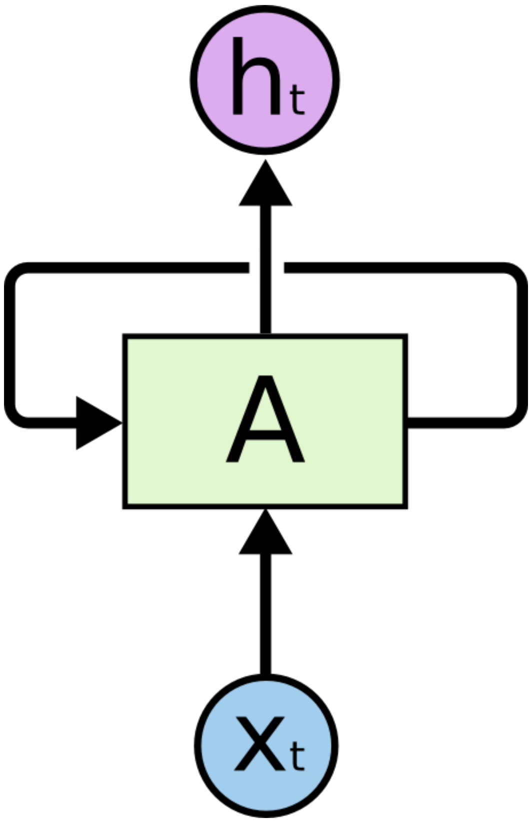
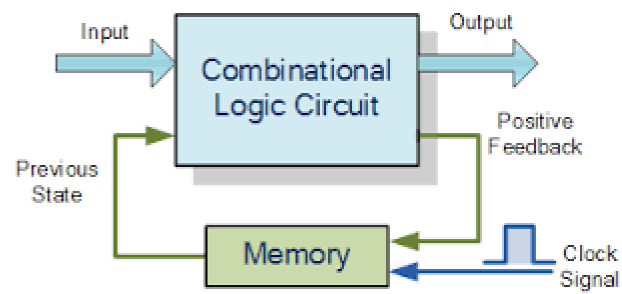
RNN INTRODUCTION

Recurrent Neural Network

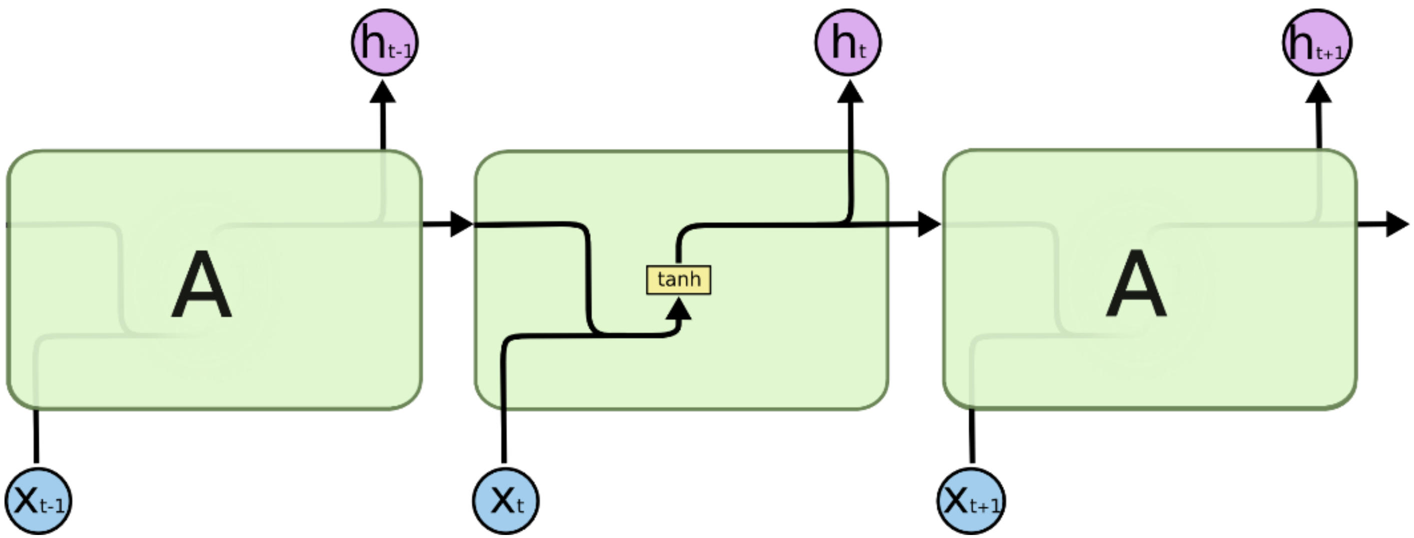


(참고)



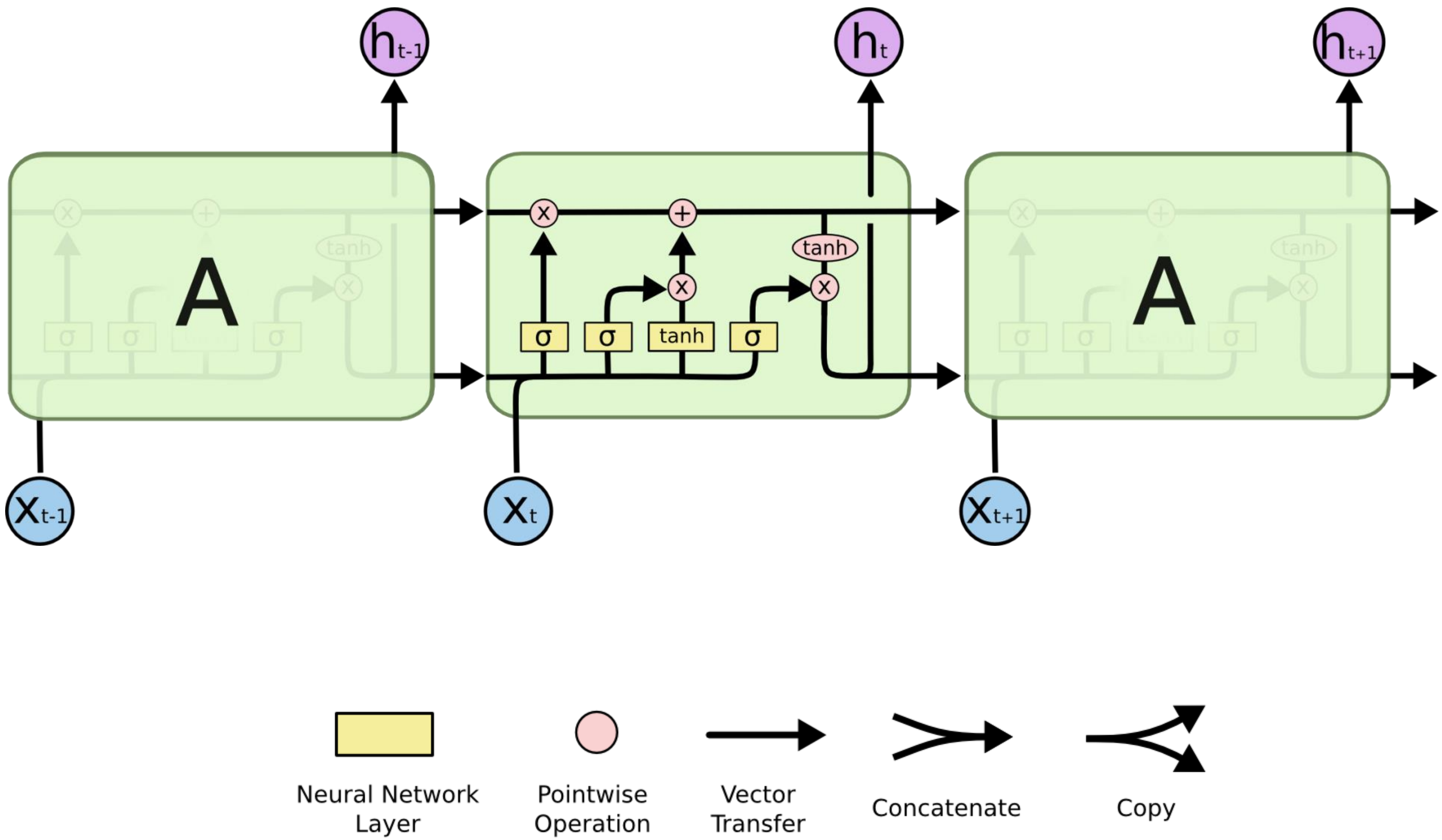
ⓘ colah.github.io/posts/2015-08-Understanding-LSTMs/

Repeating module in RNN



colah.github.io/posts/2015-08-Understanding-LSTMs/

Repeating module in LSTM



ⓘ colah.github.io/posts/2015-08-Understanding-LSTMs/

Recurrent Neural Network

We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

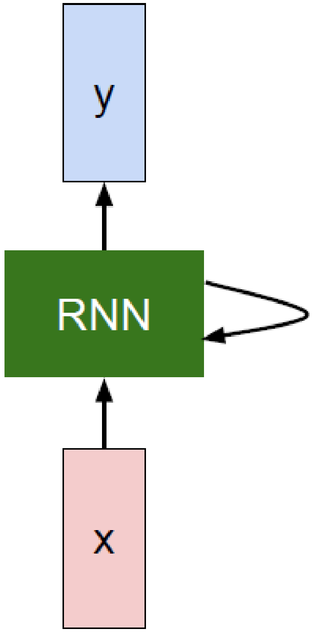
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

input vector at some time step

some function with parameters W

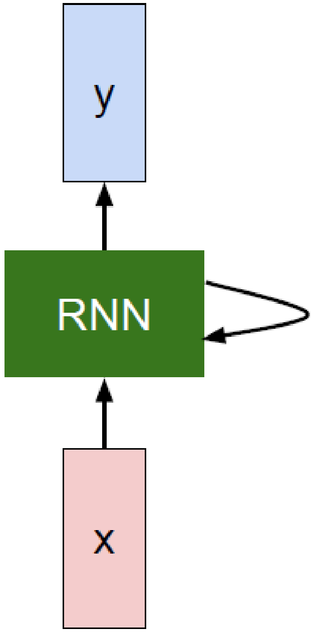


Recurrent Neural Network

We can process a sequence of vectors **x** by applying a recurrence formula at every time step:

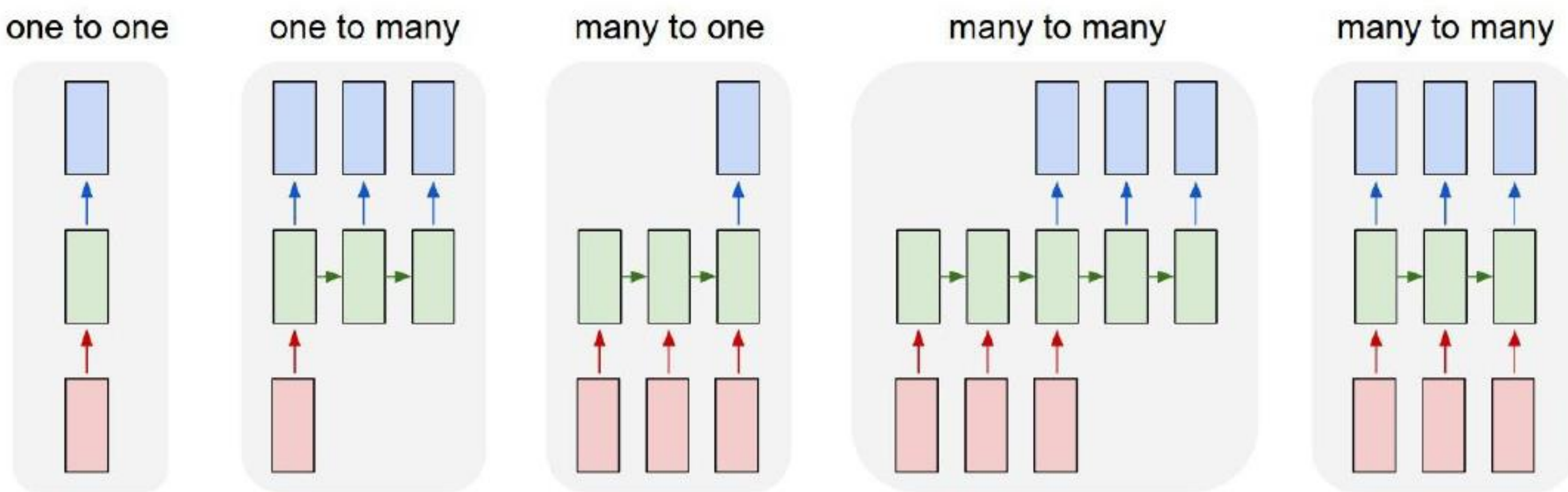
$$h_t = f_W(h_{t-1}, x_t)$$

Notice: the same function and the same set of parameters are used at every time step.



FLEXIBILITY OF RNN

RNN offers a lot of flexibility



Vanilla N.N.

Image Captioning

Sentiment Classification

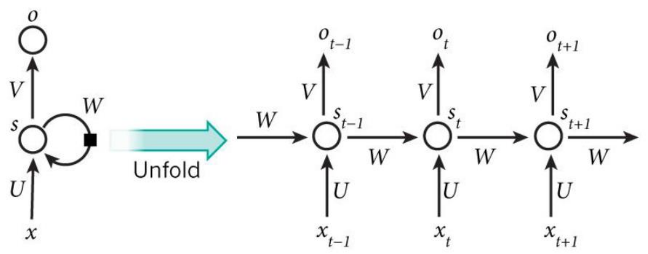
Machine Translation

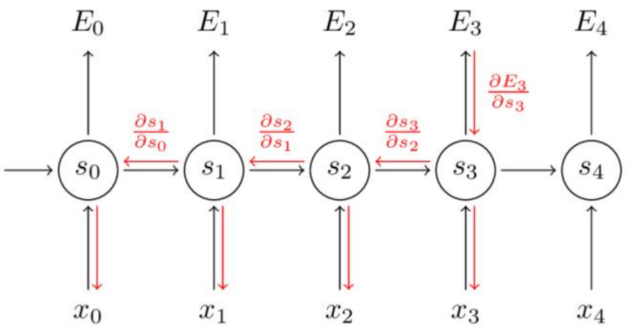
Video Classification on Frame Level

TRAINING

Training

- Backpropagation through time (BPTT)
  - Unfold and apply SGD





예시

Human Activity Recognition

예제코드

- LSTM
- Seq2Seq

APPLICATIONS

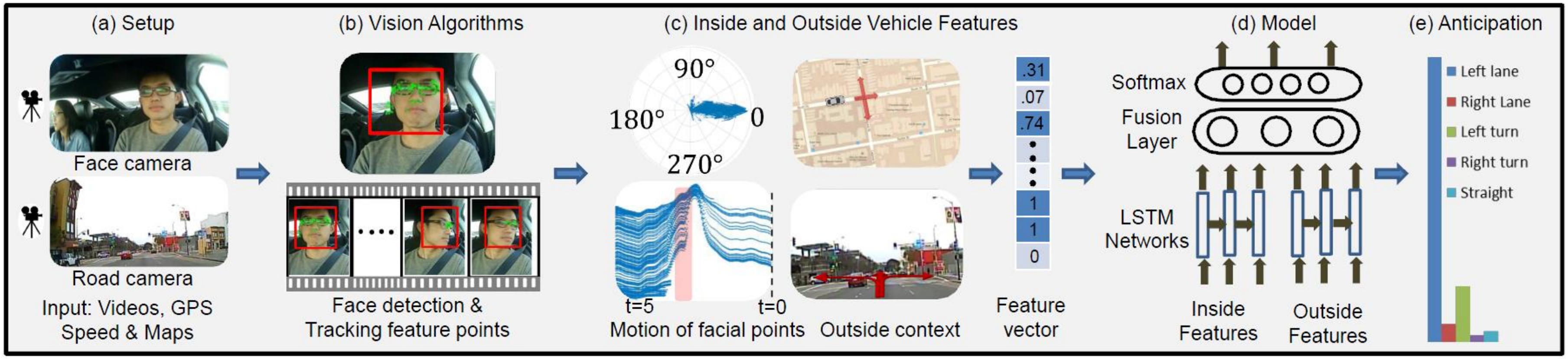
CAR THAT KNOWS BEFORE YOU DO VIA SENSORY–FUSION DEEP LEARNING ARCHITECTURE

ICCV 2015, Cornell Univ., Stanford Univ., Brain Of Things Inc

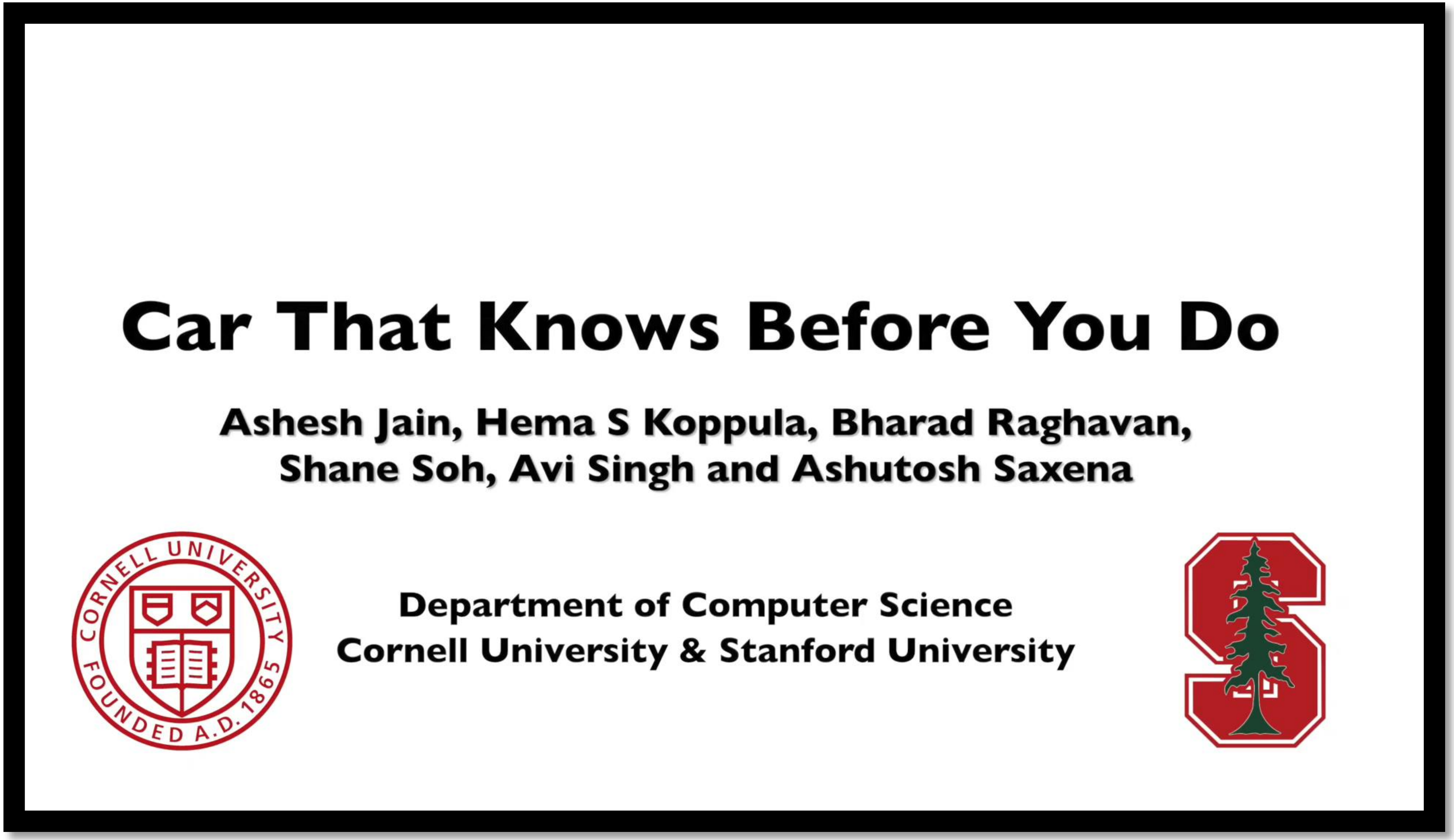
				Tasks					
				ADAS					
				Self Driving					
				Localization	Perception	Planning/ Control	Driver state	Vehicle Diagnosis	Smart factory
Methods	Traditional	Non-machine Learning		GPS, SLAM		Optimal control			
		Machine-Learning based method	Supervised: SVM MLP		Pedestrian detection (HOG+SVM)				
	Deep-Learning based		Supervised: CNN		Detection/ Segmentation/Classification	End-to-end Learning			
			Supervised: RNN (LSTM)		Dry/wet road classification	End-to-end Learning	Behavior Prediction/ Driver identification		*
			Supervised: DNN					*	*
			Reinforcement			*			
			Unsupervised						*

Overview

- An approach for anticipating driving maneuvers, several seconds in advance: lane change, keeping straight, turn, ...
- Generic sensory-fusion RNN-LSTM architecture for anticipation in robotics applications

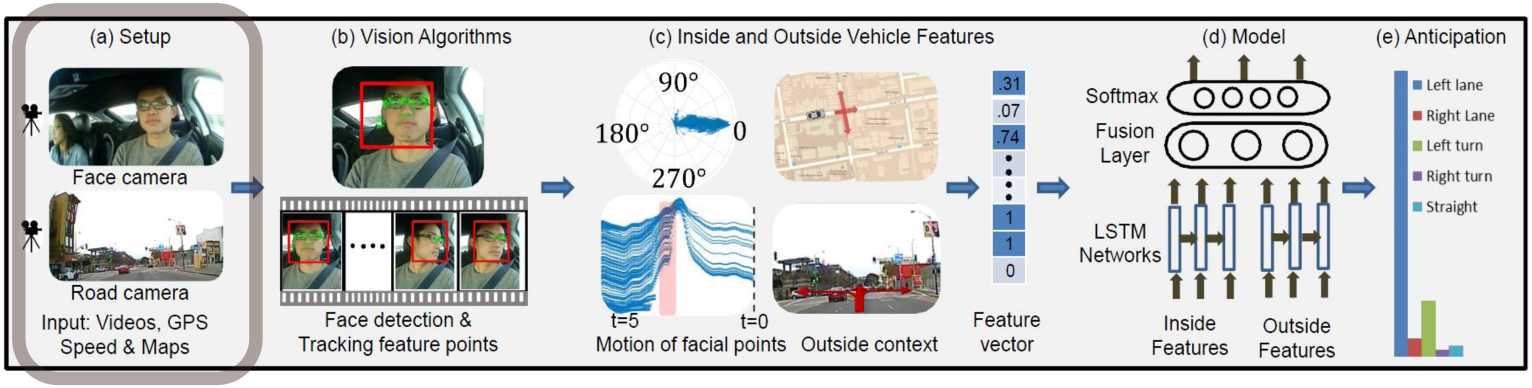


Demo Video



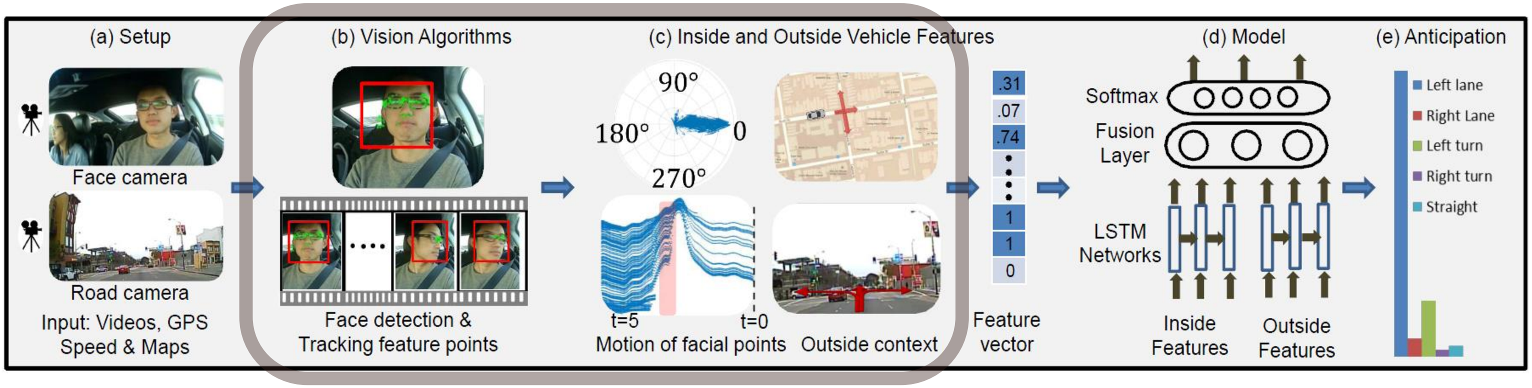
https://youtu.be/O5I1hBwkwJc

Setup



- Driver-facing camera inside the vehicle
- Camera facing the road
- Speed logger of the car
- Global Positioning System (GPS)

Features



1. Face detection and tracking:

   - Driver's face: Viola Jones face detector

   - Point extract: Shi-Tomasi corner detector

   - Facial points tracker: KLT(Kanade-Lucas-Tomasi)

2. Head motion features ($\phi_{face} \in \mathbb{R}^9$):

   - histogram features are used

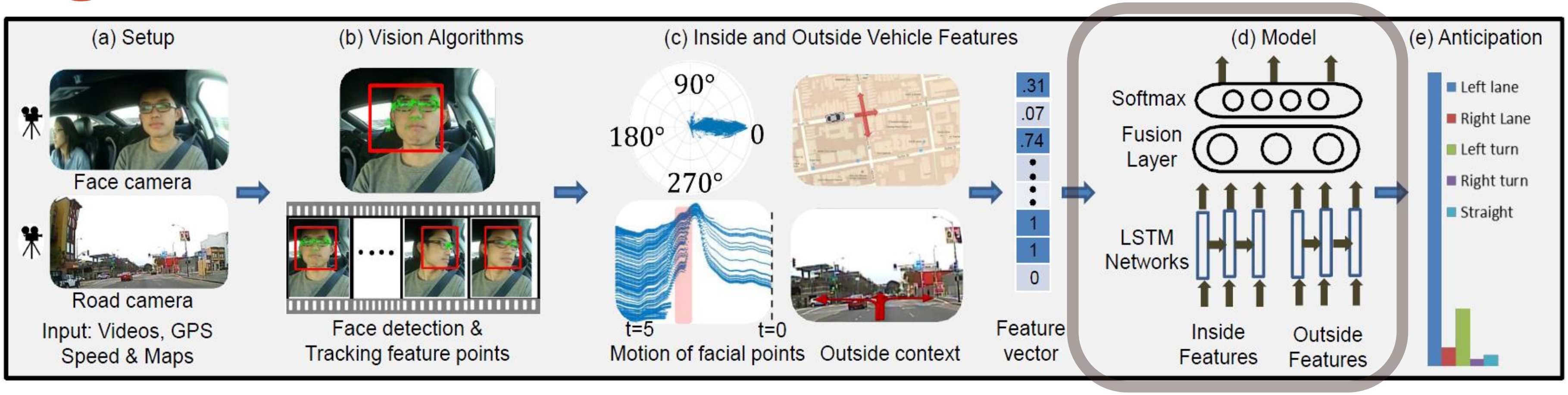
   - matches facial points and

     create histograms of corresponding horizontal motions

3. 3D head pose and facial landmark features($\phi_{face} \in \mathbb{R}^{12}$): CLNF tracker model

- Aggregate ϕ_{face} for every 20 frames

Network Architecture – at a glance



LSTM units is used for training

- \- consider accumulated information from the past:

  noted as event $\{(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T), \mathbf{y}\}$ $\left(\begin{array}{c} \mathbf{x}_t\text{: } \textit{observation at time } t \\ \mathbf{y}\text{:}\textit{representation of the event} \end{array} \right)$

  \- y_t is updated as $\mathbf{y}_t = \mathrm{softmax}\big(\mathbf{W}_y \mathbf{h}_t + \mathbf{b}_y\big)$,

  with the representation $\mathbf{h}_t = f(\mathbf{W}\mathbf{x}_t + \mathbf{H}\mathbf{h}_{t-1} + \mathbf{b})$

Data set

- Fully natural driving
- 1180 miles of natural freeway, city driving
- Collected across two states
- Ten drivers, different kinds of driving maneuvers
- 2 months to take
- About 17GB
- 700 events of annotation
  - 274 lane change
  - 131 turns
  - 295 straight

Result

- With sensory fusion:
  - Precision of 84.5%
  - Recall of 77.1%
  - Anticipates maneuvers 3.5 seconds on average
- With incorporating the driver's 3D head-pose:
  - Precision of 90.5%
  - Recall of 87.4%
  - Anticipates maneuvers 3.16 seconds on average

Method	Pr (%)	Re (%)	Time-to-maneuver (s)
F-RNN-EL	84.5 $\pm$ 1.0	77.1 $\pm$ 1.3	3.58
F-RNN-EL w/ 3D head-pose	**90.5** $\pm$ 1.0	**87.4** $\pm$ 0.5	3.16

CHARACTERIZING DRIVING STYLES WITH DEEP LEARNING

W. Dong et al.

ArXiv 2016

IBM Research China, Nanjing Univ., Univ. of Waterloo

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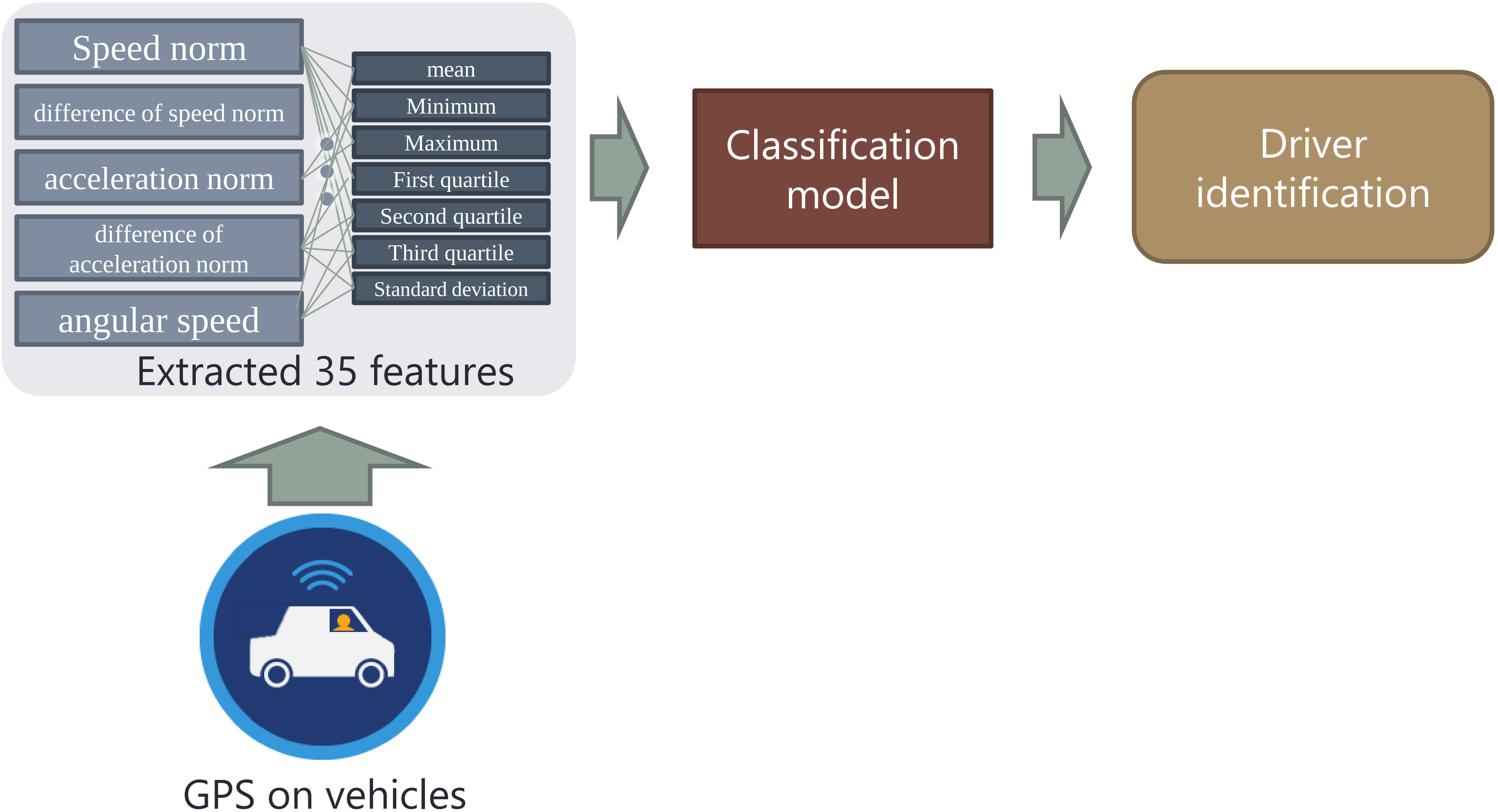
Speed norm
difference of speed norm
acceleration norm
difference of acceleration norm
angular speed
mean
Minimum
Maximum
First quartile
Second quartile
Third quartile
Standard deviation
Extracted 35 features
Classification model
Driver identification
GPS on vehicles

Data

- **목표**: GPS**데이터를 이용하여 사용자** ID **분류 수행**
- Input sensor
  - GPS trajectory as a sequence (x, y, t)
- Dataset and feature map
  - Training/Test data
    - Data from 50/1,000 drivers (original data: Kaggle 2015 competition on Driver Telematics Analysis)
  - Data transformation
    - Feature map (35=5 x 7)
      - Basic features (5)
        :Speed norm; difference of speed norm; acceleration norm; difference of acceleration norm; angular speed
      - Statistical features (7)
        : mean; min; max; ¼; ½; ¾; standard deviation of each basic feature

Machine Learning

- Machine Learning Models
  - CNN
    - Six layers model (3 conv. + 3 FC)
  - RNN
    - RNN model
  - Gradient boosting decision tree (GBDT)
    - For reference

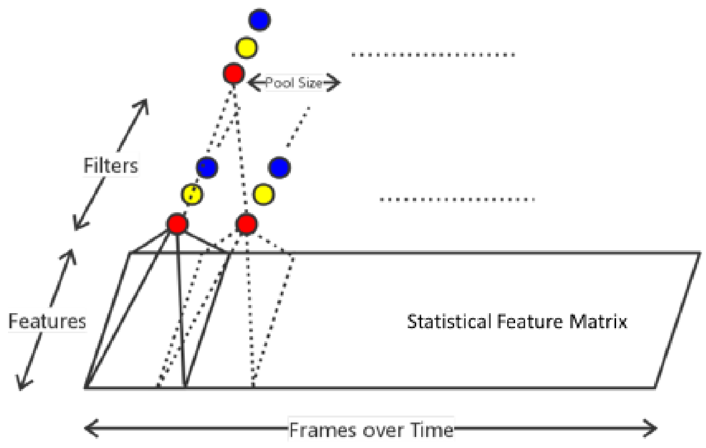

Figure 3: 1-D convolution and pooling in CNN

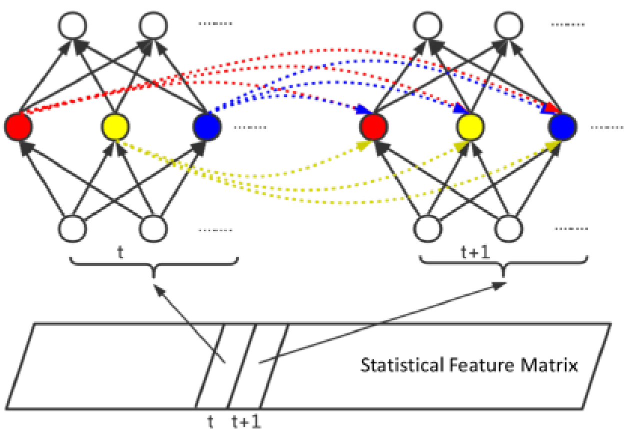

Figure 4: RNN training on the input statistical feature matrix

Experimental Results

- Experiments
  - 80% for training, 20% for testing
  - Small scale test for 50 drivers data
    - Include 35,000 segments from 8,000 trips
  - large scale test for 1,000 drivers data

Table 1: Results on 50 drivers' data

Method	Seg (%)	Trip (%)	Trip Top-5 (%)
NoPoolCNN	16.9	28.3	56.7
CNN	21.6	34.9	63.7
PretrainIRNN	28.2	44.6	70.4
IRNN	34.7	49.7	76.9
StackedIRNN	**34.8**	**52.3**	**77.4**
GBDT	18.3	29.1	55.9
TripGBDT	-	51.2	74.3

Table 2: Results on 1000 drivers' data

Method	Seg (%)	Trip (%)	Trip Top-5 (%)
CNN	23.4	26.7	46.7
StackedIRNN	**27.5**	**40.5**	**60.4**
TripGBDT	-	9.2	15.8

DETECTING ROAD SURFACE WETNESS

			Tasks					
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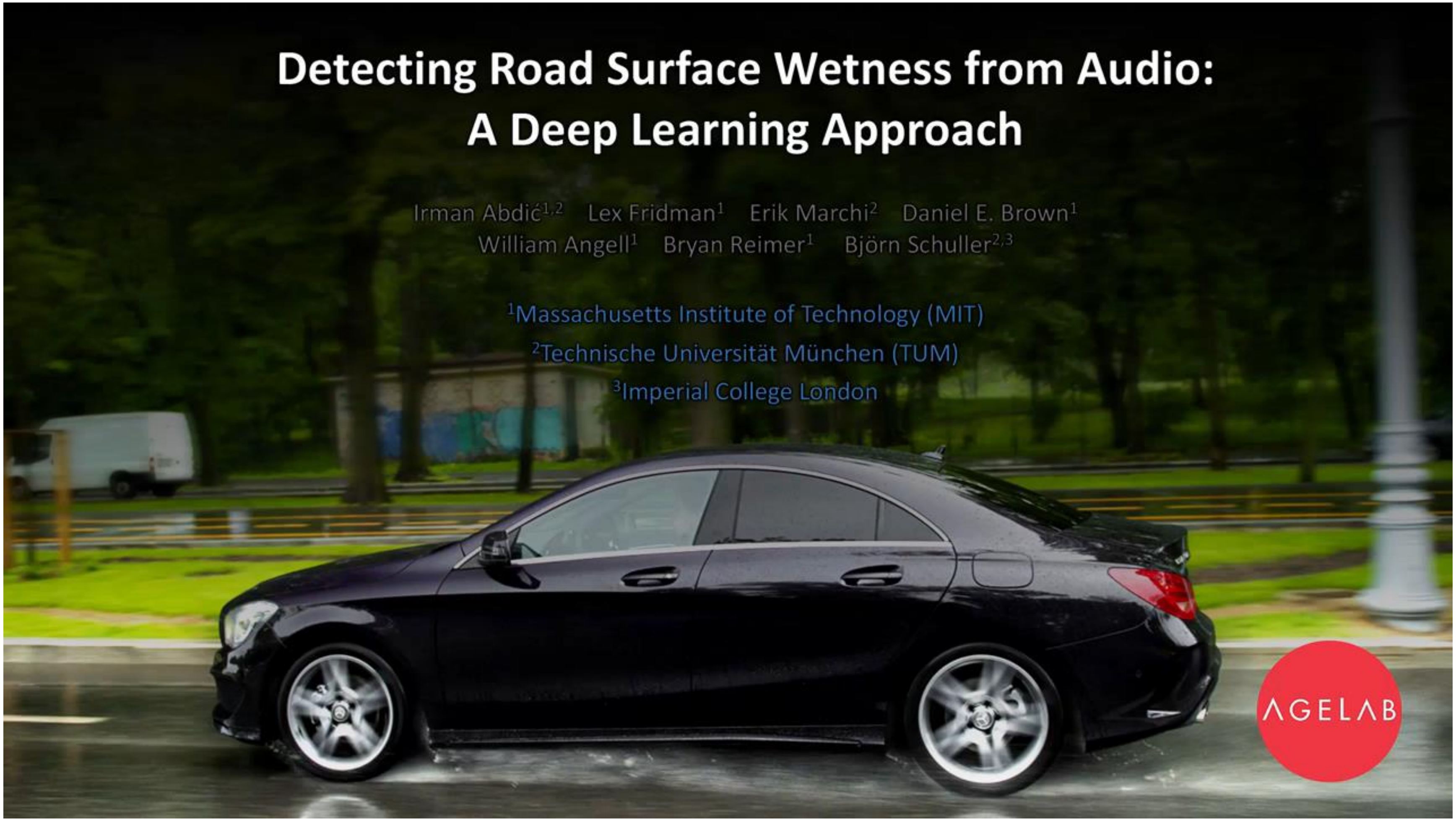
Dataset/Machine Learning

- Shotgun microphone behind the rear tire
- Spectogram + LSTM

- **관련 기사**
  - http://www.ibtimes.co.uk/heres-how-self-driving-cars-can-detect-dangerous-roads-using-sound-ai-1532407

Detecting Road Surface wetness



END-TO-END DRIVING WITH RNNS

					Tasks					
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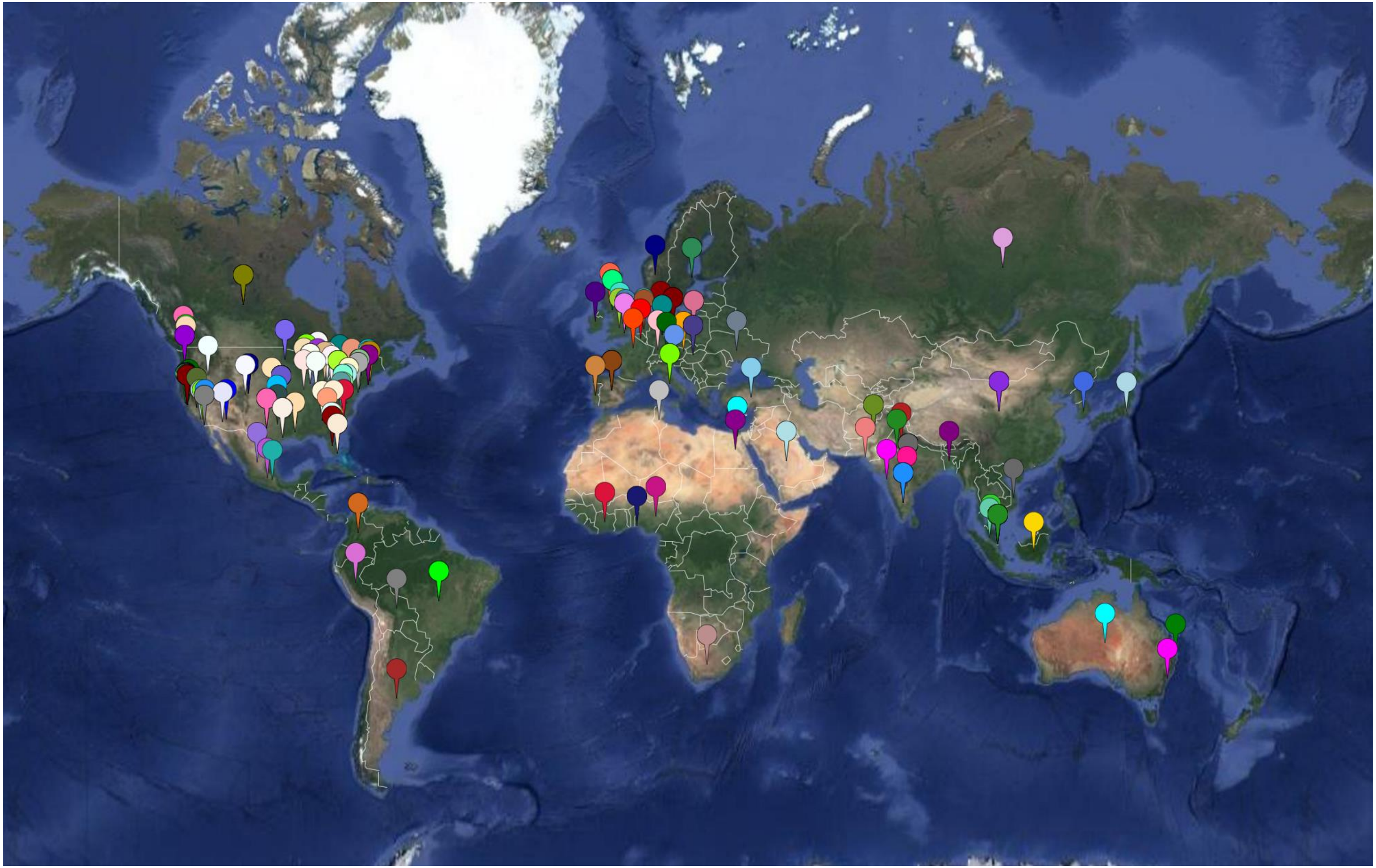
End-to-end Driving with RNNs

- 1st and 3rd place winner of the Udacity end-to-end steering competition used RNNs:
  - Sequence-to-sequence mapping from images to steering angles

- **관련 링크**
  - https://medium.com/udacity/challenge-2-using-deep-learning-to-predict-steering-angles-f42004a36ff3
  - https://medium.com/udacity/teaching-a-machine-to-steer-a-car-d73217f2492c

UDACITY

Self-Driving Car Engineer Nanodegree



1^{st} Place Winner

- LSTM inputs: 3D convolution of image sequence
- Outputs: predicted steering angle, speed, torque
- Sequence length = 10

3rd Place Winner

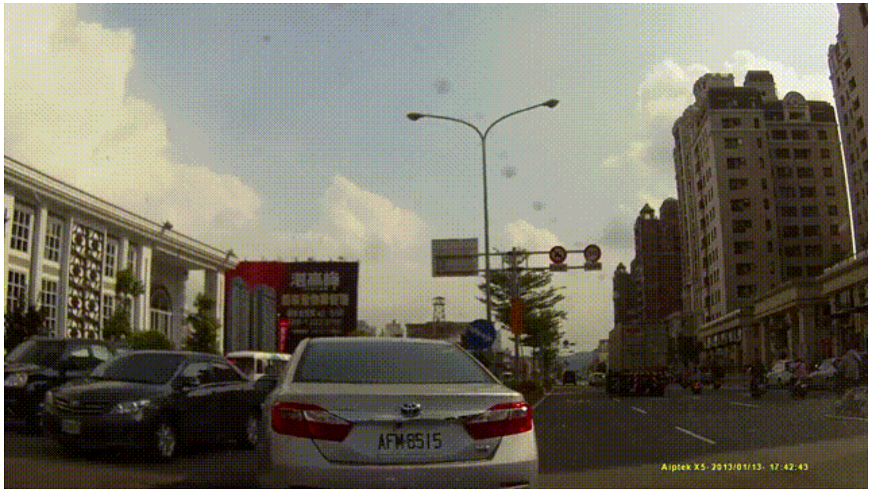
- LSTM inputs: 3000 features extracted with CNN
- Outputs: predicted steering angle
- Sequence length = 10

ANTICIPATING ACCIDENTS IN DASHCAM VIDEOS

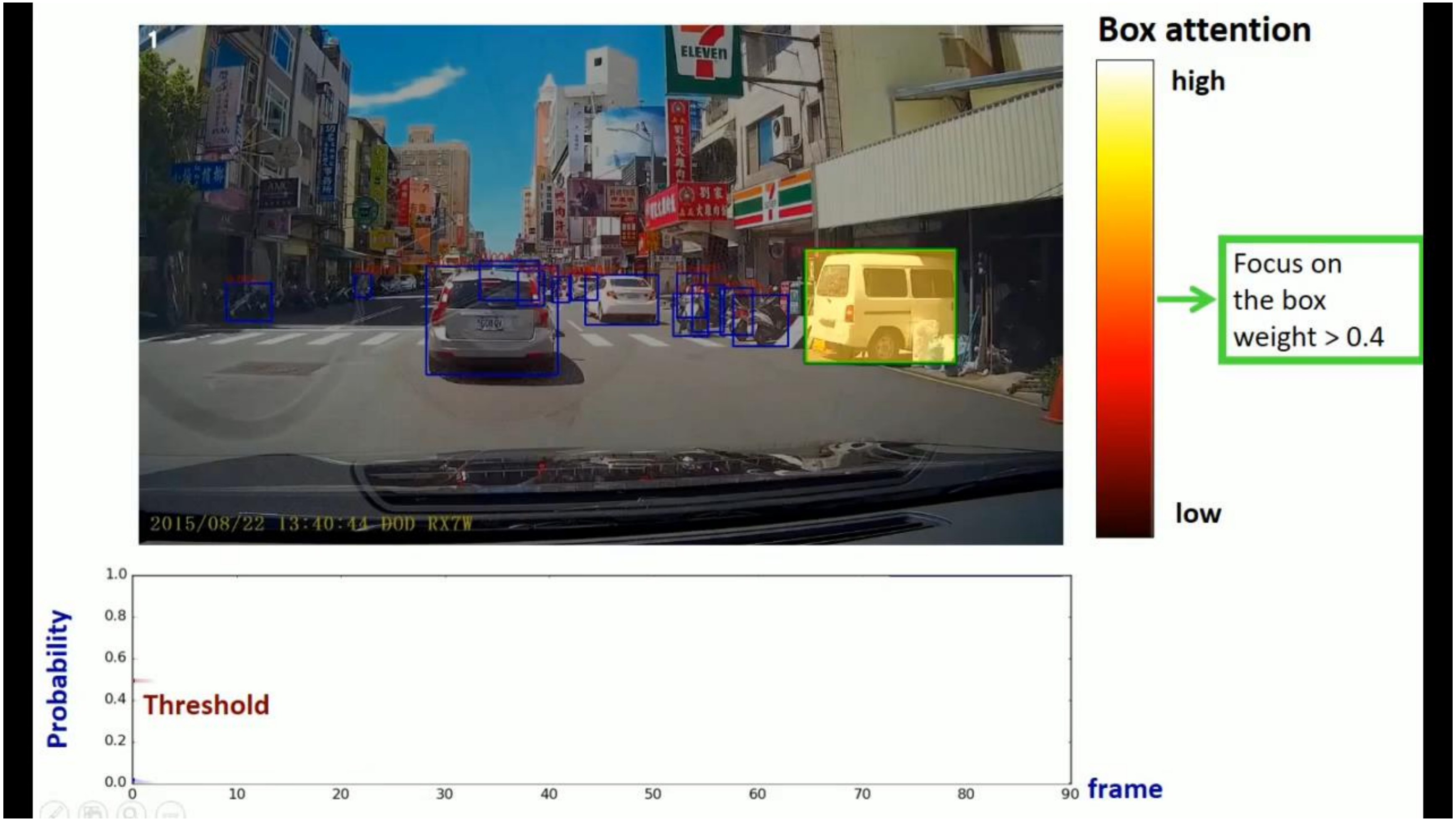
Dataset

	Positive examples	Negative examples	Total
Training set	455	829	1284
Testing set	165	301	466
Total	620	1130	1730

Positive example



Negative example


1
2015/08/22 13:40:44 DOD RX7W
Box attention
high
low
Focus on
the box
weight > 0.4
Probability
1.0
0.8
0.6
0.4
0.2
0.0
Threshold
0
10
20
30
40
50
60
70
80
90
frame