Toward Seamless Human-Mobility Interaction with Ubiquitous Sensing and Applied Machine Learning

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Oct. 21, 2019

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EECS 571

COMPUTER SCIENCE AND ENGINEERING
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@ UNIVERSITY OF MICHIGAN, ANN ARBOR

The Rapid Evolving Transportation Ecosystem

Usage based insurance


Monitor heart beat

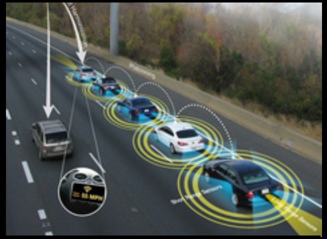

Driver monitoring system

Drowsiness alert

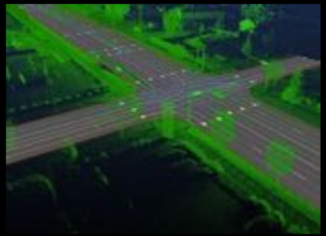

Onboard diagnostics device

Advanced driving assistance system


Self-driving cars


Platooning

HD Map


Sensing road-side infrastructures


Road survey car


V2X communication

Usage based insurance

Monitor heart beat

Driver monitoring system

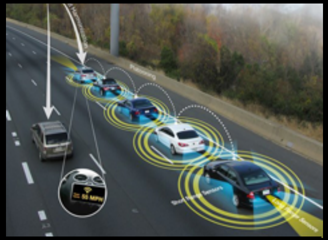
Drowsiness alert

Driver

Onboard diagnostics device

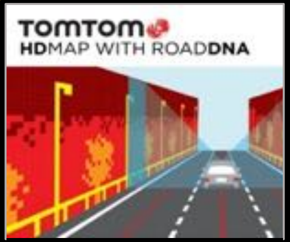
Advanced driving assistance system

Self-driving cars

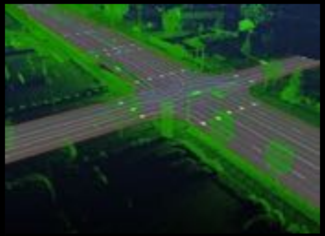


Platooning

Vehicle



HD Map



Sensing road-side infrastructures

Road survey car

V2X communication

Environment

Problem: Isolated Innovations

- Special-purpose: requires dedicated sensing module(s)
- Limited-accessibility: limited coverage, low update rate

Special-purpose:

Limited-accessibility:

Usage based insurance

Monitor heart beat

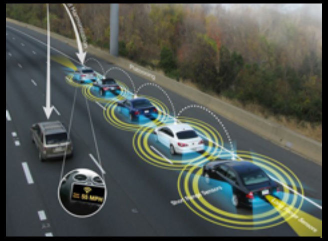

Driver monitoring system

Drowsiness alert


Onboard diagnostics device

Advanced driving assistance system


Self-driving cars


Platooning

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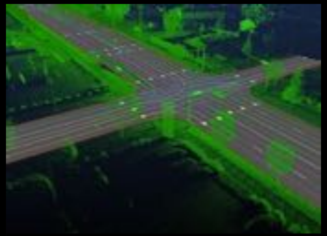
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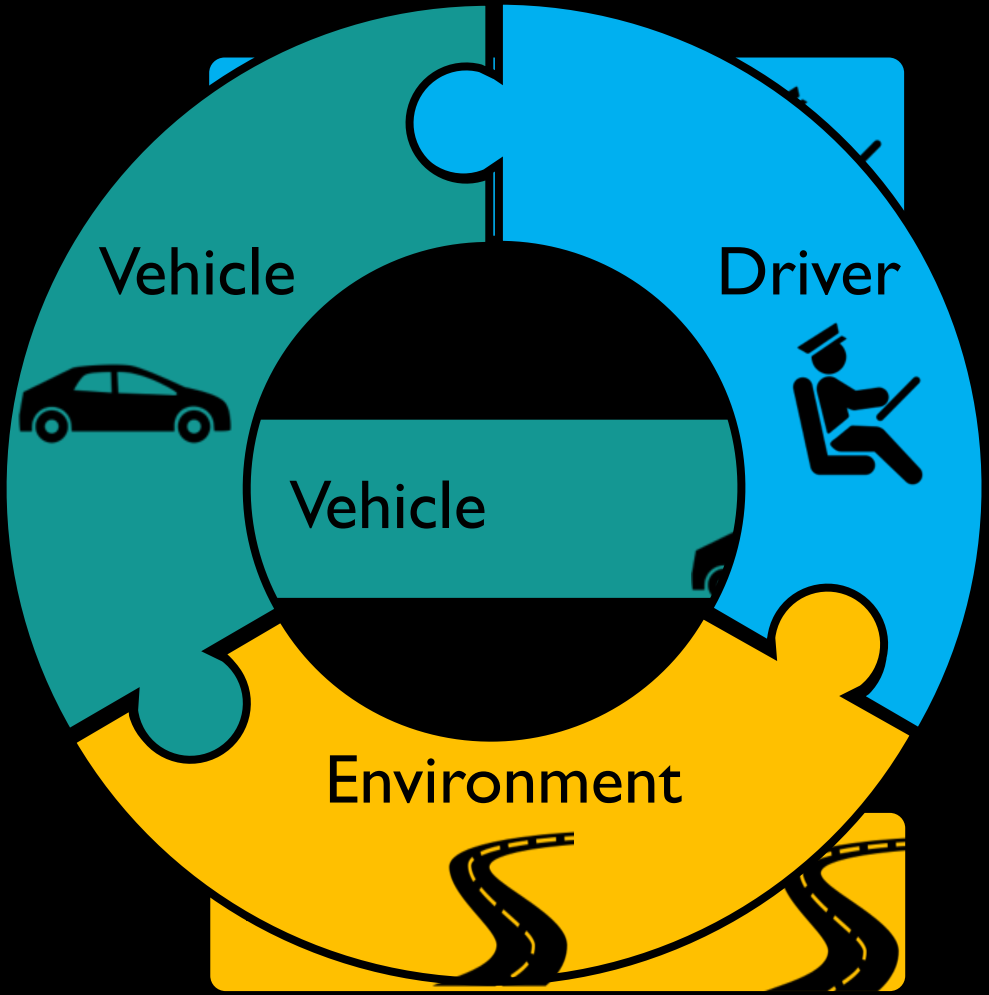
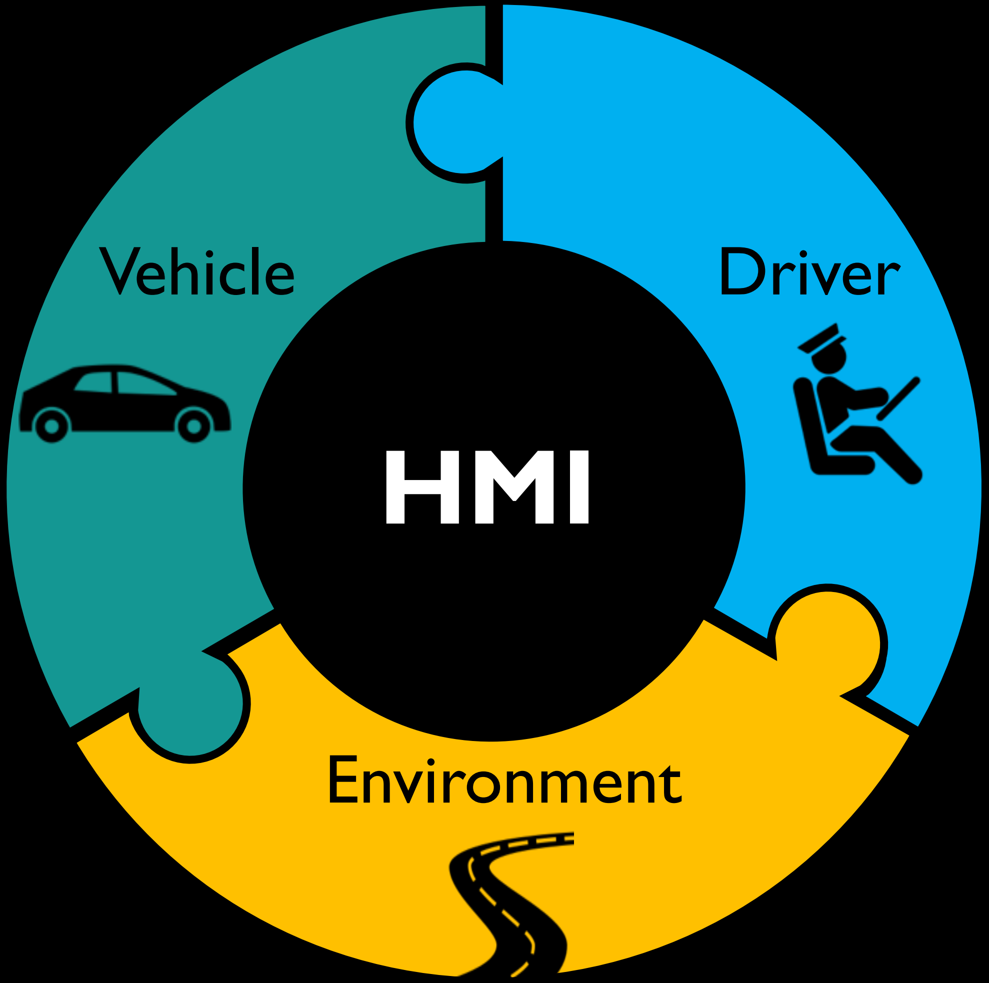


Human-Mobility Interaction (HMI)

- Accessible and reliable computing technologies for facilitating safer and more efficient transportation



With HMI, we can

- Democratize smart cars, make roads safer

Disproportionate ratio of sensing-capable cars to legacy "dummy" cars

Deploy smart transportation apps at large-scale

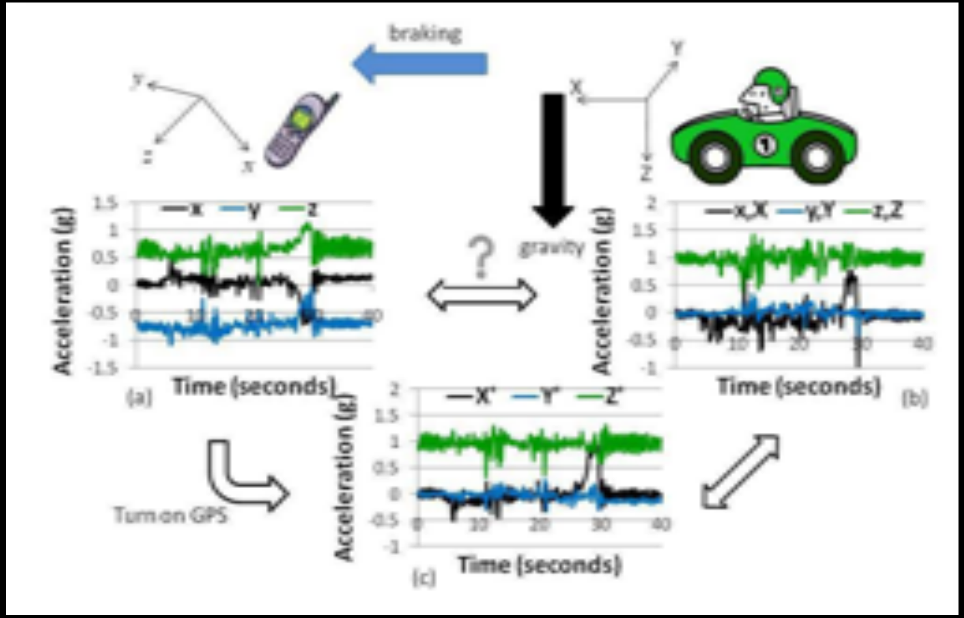
Existing Works

- Distributed sensor computing system for cars

  - Delay-tolerant networking system for streaming sequential data (e.g., GPS data) [Hull et al. 2006]
  - Extendible hardware ports for different applications

Existing Works

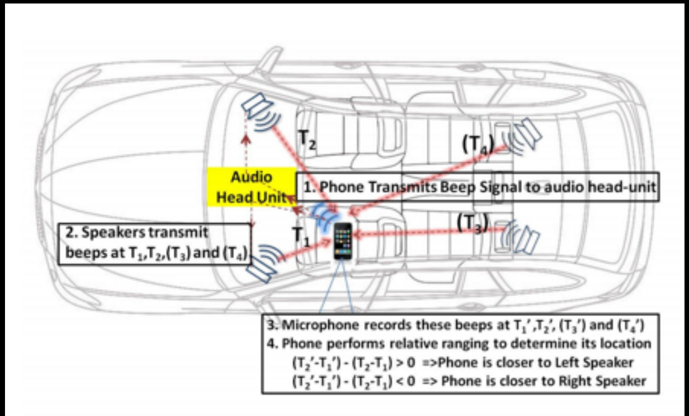
- Sensing anomalies of the environment

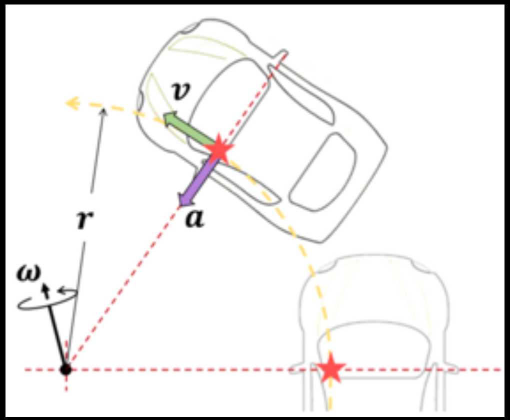


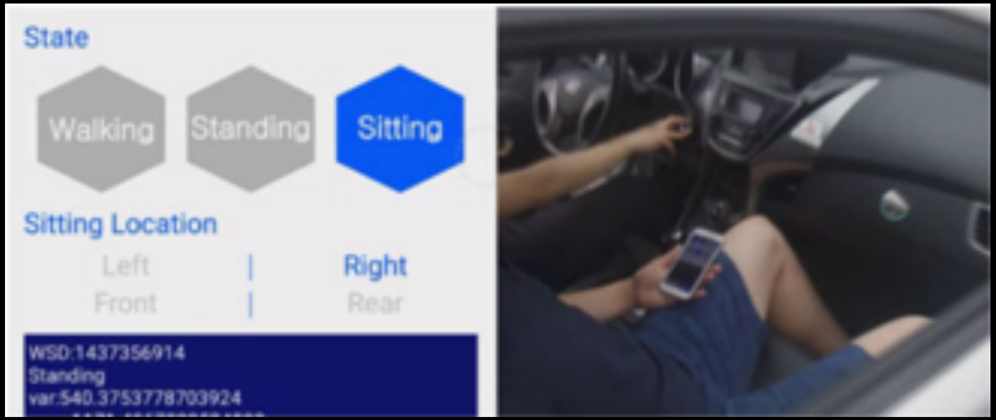
- Monitoring braking and road potholes [Mohan et al. 2008]

Existing Works

- Monitoring and regulating smartphone usage







  - Detecting in-car smartphone usage [Yang et al. 2011], [Wang et al. 2013], [Park et al. 2017]
  - Help preventing distracted driving

Existing Works

- Crowdsourced sensory (esp. GPS traces) data
  - Estimating traveling time with GPS traces with data mining [Yu et al. 2009]
  - Traffic prediction with crowdsourced location data [Pan et al. 2019]

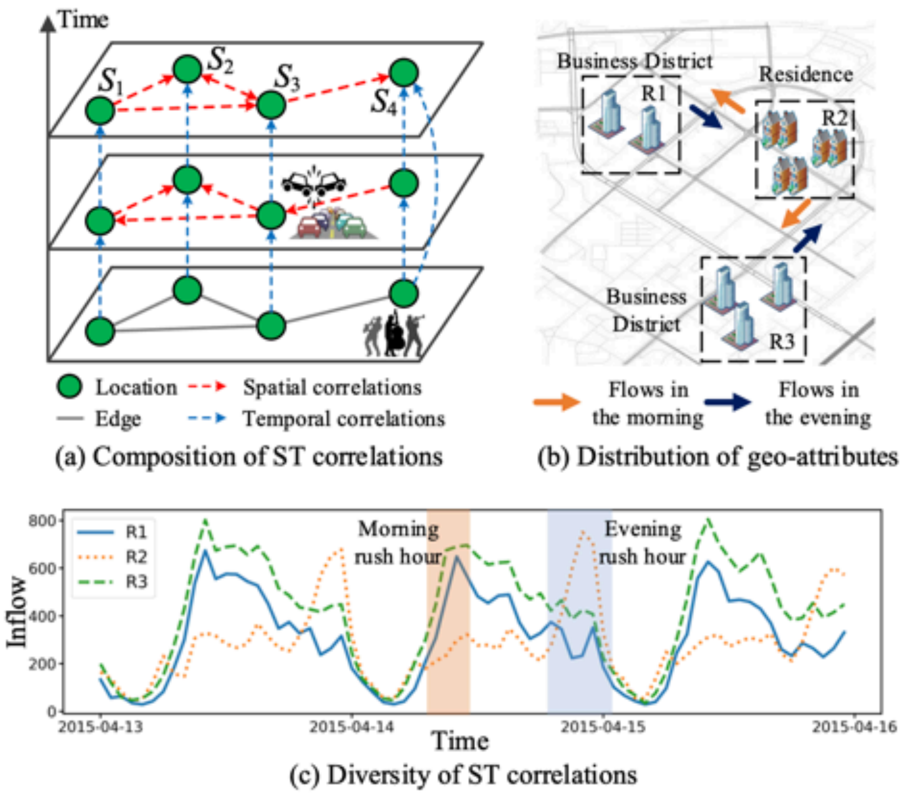


Figure 1: Challenges of urban traffic prediction.

Existing Works

- Driving behavior modeling
  - Anomaly detection of driver's condition, e.g., distracted, intoxicated [Miyajima et al. 2007]
  - Driver identification [Enev et al. 2016, Chen et al. 2017, Hallac et al. 2017]

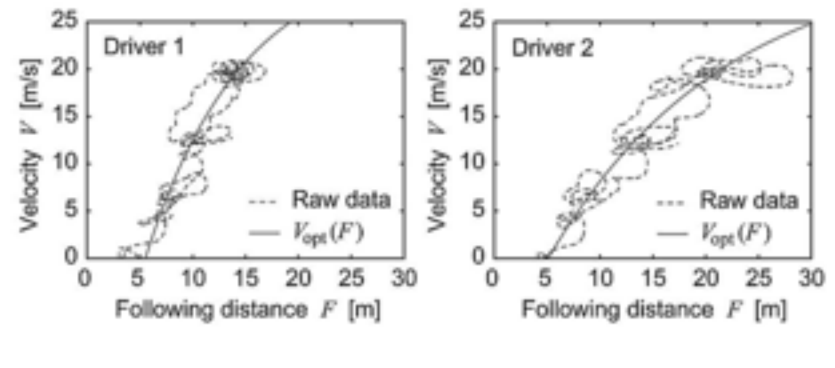


Fig. 5. *Examples of estimated OV curves for two drivers approximating two-dimensional distribution of following distance and velocity.*

(a) Initial turn after picking up car. (b) Merge onto busy road. (c) Turn in rural area. (d) Highway on-ramp.

Ubiquitous Sensing

- Exploit the sensing and communication capabilities of the most pervasive computing platform

Advantages of Ubiquitous Sensing

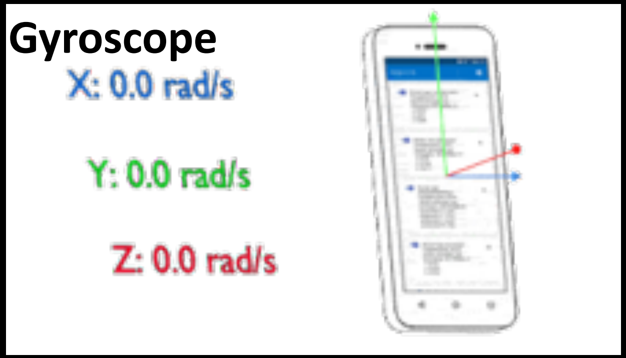
- > **2,500,000,000** smartphones in 2018[2]

Off-the-self devices

Smartphones

Wearables

- Motion sensors + camera + microphone

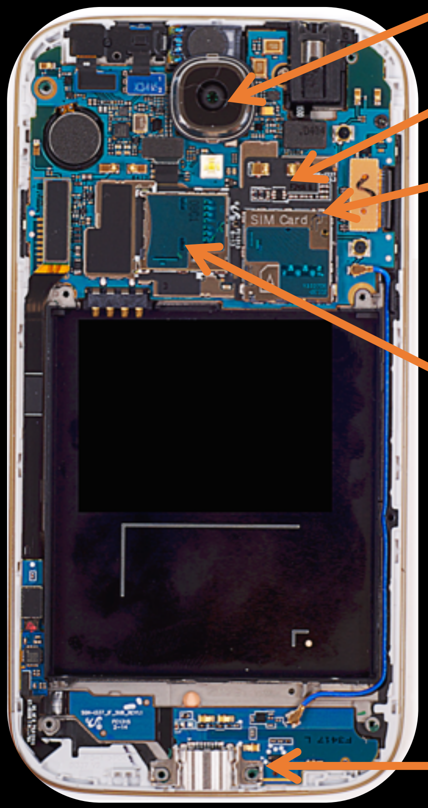


- Real-time communication and data collection

Weather data

Large-scale data collection

Limitations of Ubiquitous Sensing



Camera

GPS

IMU (accelerometer, gyroscope)

CPU

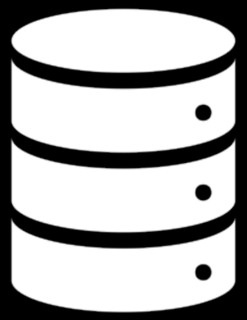
Microphone

Varying **posture** (mounted, in cupholder, etc.)

Limited type of sensors

Poor sensor quality

Key Elements of Human-Transportation Interaction

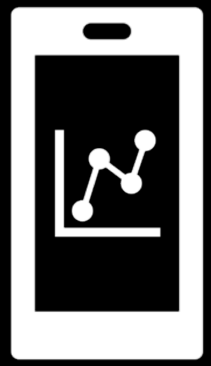


Data acquisition

- Mobile computing
- Multi-modal sensing
- Software and/or hardware prototyping

Analysis

- Machine learning
- Data mining
- Data preprocessing
- Feature engineering

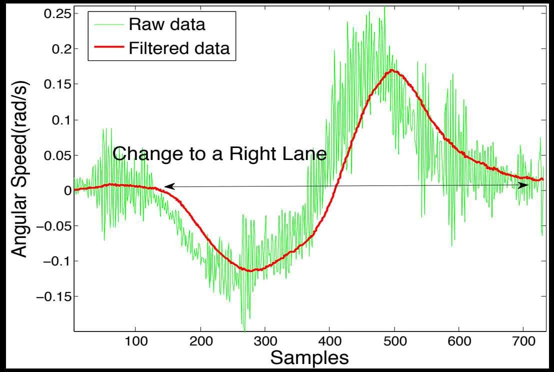


Contextualization

- Human-computer (sensor) interaction
- Incentive design for motivating usage

V-Sense: overcoming the limitation of camera and image data

[In Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services (**MobiSys 2015**), Florence, Italy]



V-Sense Outline

1. Motivation
2. Technical Design
3. Evaluation
4. Final Remarks

Detecting Steering Maneuvers

- Detecting steering maneuvers (e.g., left/right turn, lane change)
  - Lane departure warning system
  - Powertrain control (e.g., speed and steering angle)

On Legacy Vehicle

- Uses embedded front-facing camera to detect both road lanes.

These applications require **dedicated camera** for **image** data collection

Are Cameras Reliable?

- Performance may degrade due to **real-world** conditions

Are Cameras Reliable?

- A common problem

Visibility can be easily distorted!

Lighting

Weather

Pavement

http://smartphones.wonderhowto.com/how-to/keep-your-smartphone-charged-during-power-outage-0140088/

Placement

Heavy Shadow

Sunlight Reflection

Sharp Turn

……

Detecting Vehicle Steering with Motion Sensor Data

V SENSE

1. Differentiating Steering Maneuvers
- Accurate detection of turns and lane changes in real-time

2. Reliable Performance
- Robust to lighting, weather, and pavement conditions

3. Adaptive to Different Platforms
- Achieving stable performance across different off-the-shelf device models

Example: Lane level navigation App

Use cases

V-Sense Outline

1. Motivation
2. Technical Design
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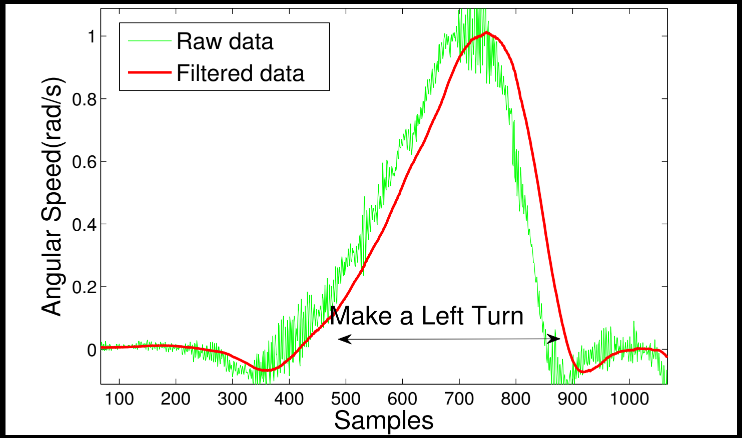
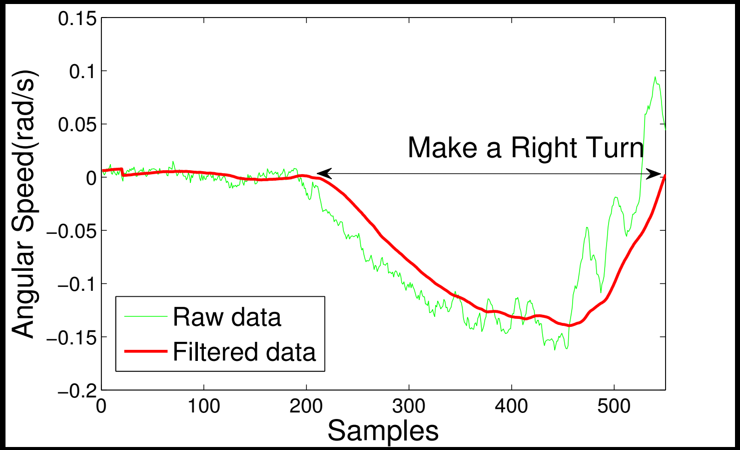
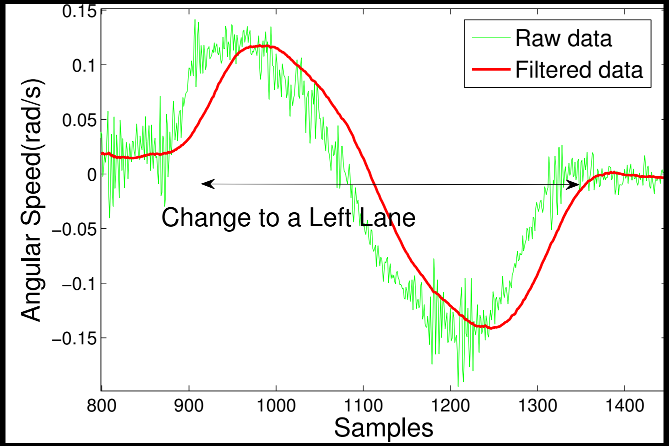
"Signatures" of Vehicle Steerings

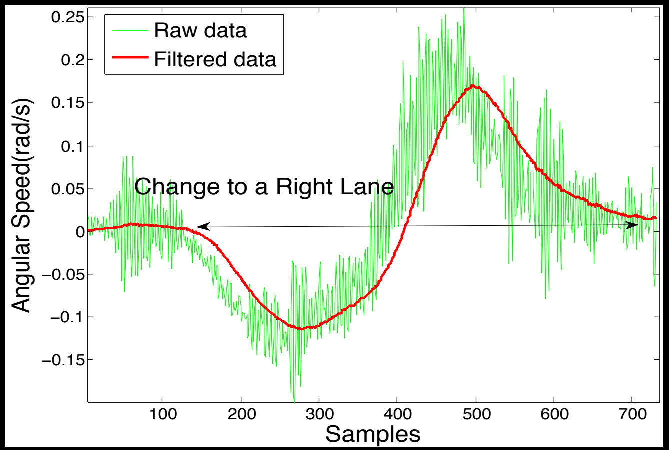
- Unique patterns in gyroscope readings when vehicle turns left/right





- Lane changes

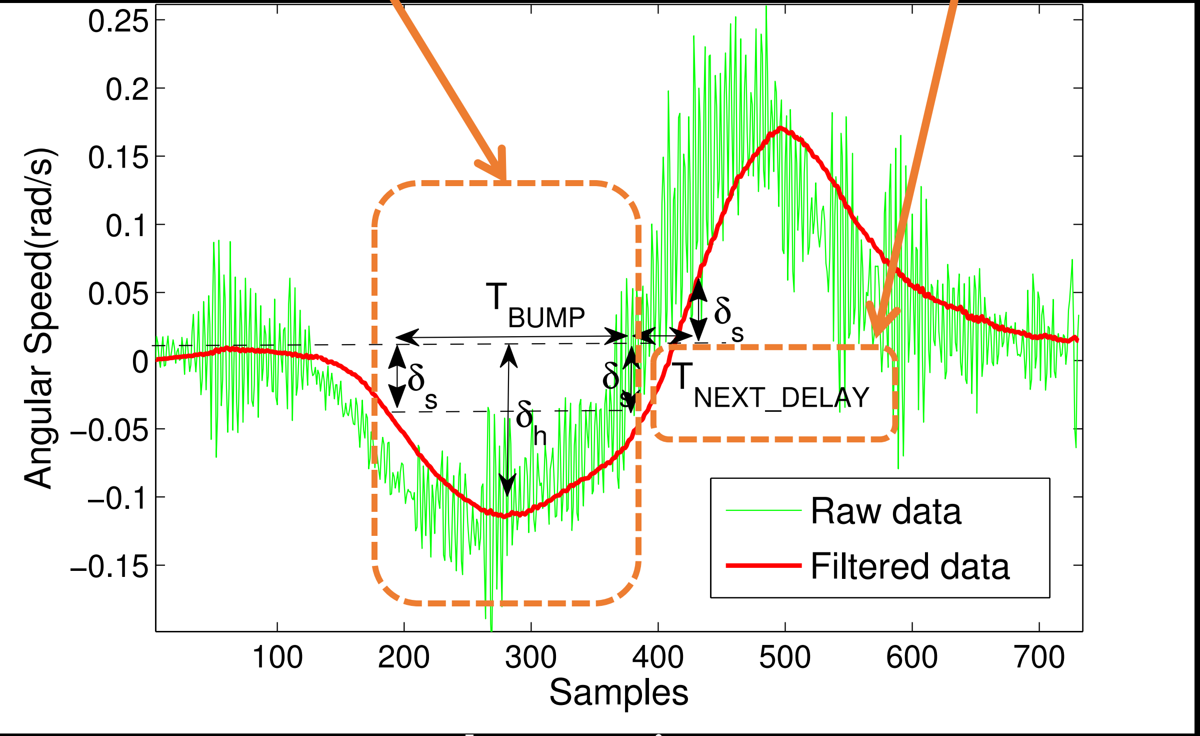




Real-time Bump Detection Algorithm

- Three-staged process

  No bump → One bump → Wait for another bump

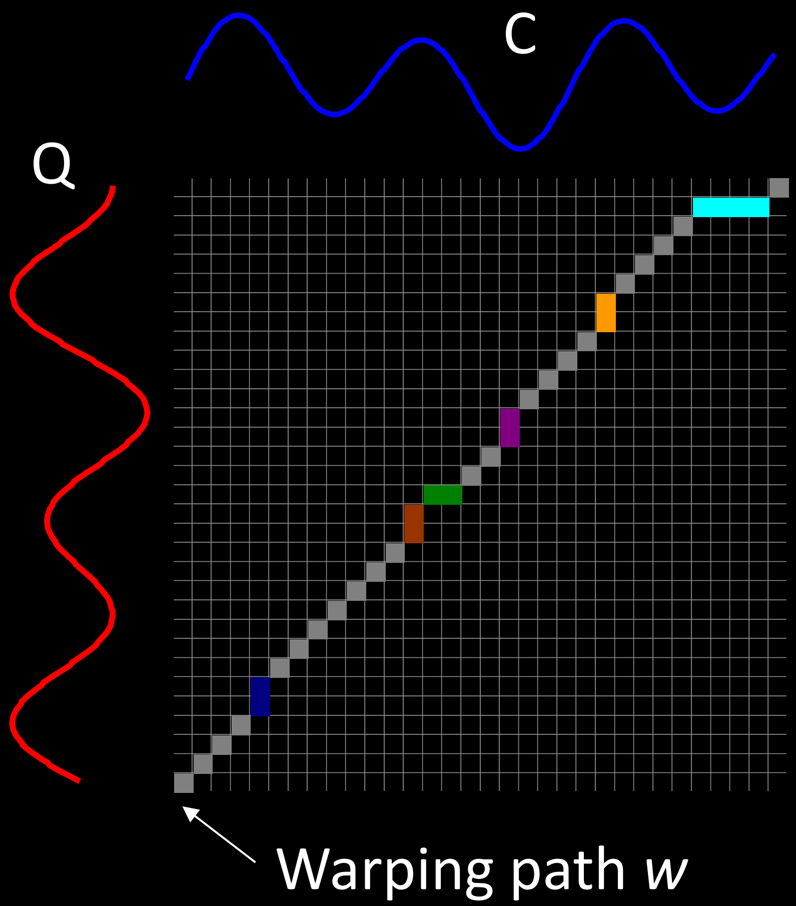


- **Linear** time complexity!

Understanding the Algorithm

- Compared with the state-of-the-art time-series pattern recognition algorithm

Dynamic time warping

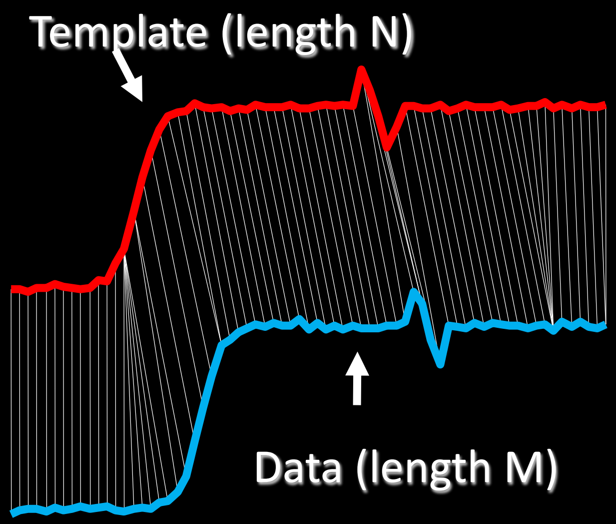


$\gamma(i,j)$ =
$d(q_i,c_j) + \min\{ \gamma(i-1,j-1), \gamma(i-1,j), \gamma(i,j-1) \}$

Understanding the Algorithm

- Compared with the state-of-the-art time-series pattern recognition algorithm

Algorithm	Statistical threshold	Training phase	Time-complexity
Dynamic time warping (DTW)	Needs pre-defined DTW distance for matching	Needs pre-defined template	O(MN)
V-Sense algorithm	Threshold derived from the natural driving pattern	Training free	O(M)

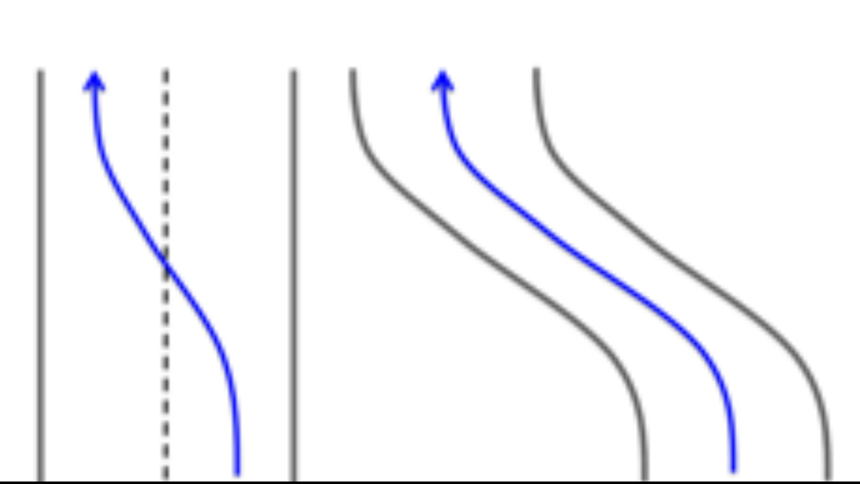


Dynamic time warping

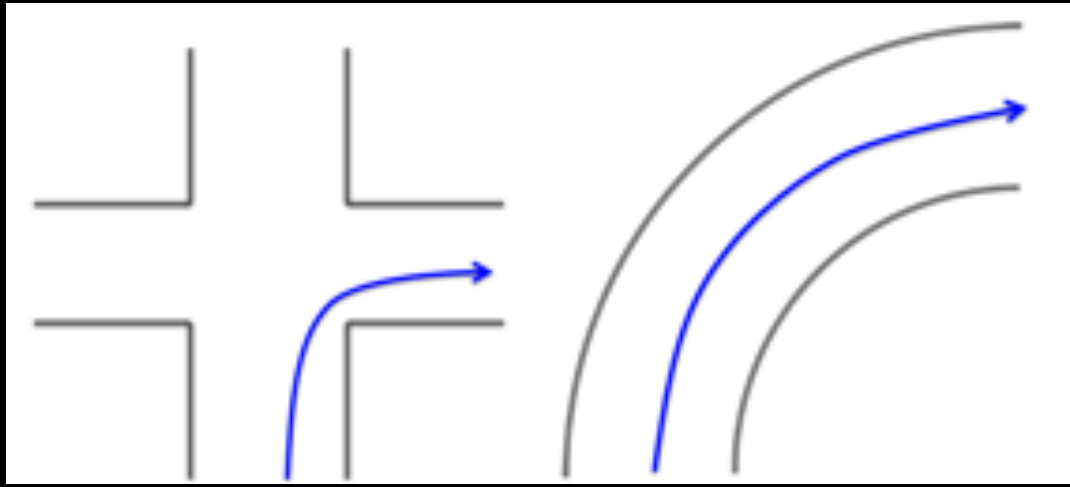
Important for real-time applications on mobile platforms

Differentiating Steering Maneuver and Curvy Roads

How to differentiate **steering maneuvers** and **driving on curved roads**?



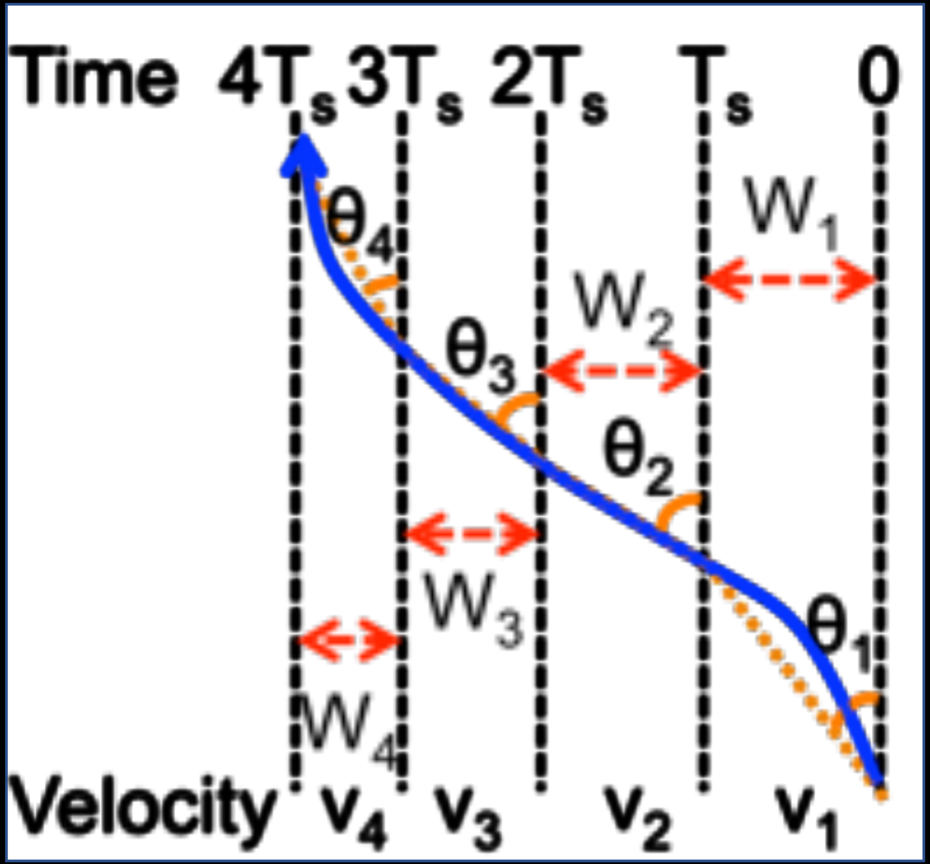
W_{lane_change} $W_{S\_curved\_road}$



W_{turn} $W_{L\_curved\_road}$

Car's horizontal displacement[4]: $W_{steer} \ll W_{curved\_road}$

Measure the Horizontal Displacement



Angular speed in yaw axis

Heading at time n

$$\theta_n = \theta_{n-1} + Y_n T_s$$

Horizontal displacement at time n

$$W_n = v_n T_s \sin(\theta_n)$$

Integrated horizontal displacement

$$W_{final} = \sum_{n=1}^{N} W_n$$

$$= \sum_{n=1}^{N} v_n T_s \sin(\theta_n)$$

$$= \sum_{n=1}^{N} v_n T_s \sin\left(\sum_{k=1}^{n} Y_k T_s\right)$$

V-Sense Outline

1. Motivation
2. Technical Design
3. Evaluation
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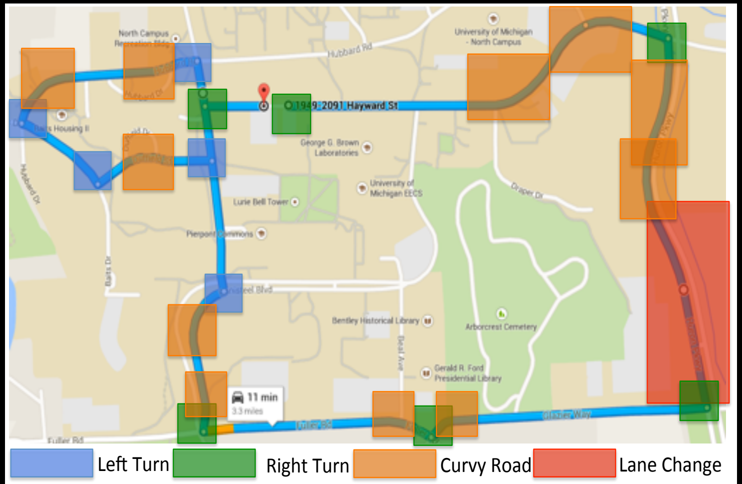
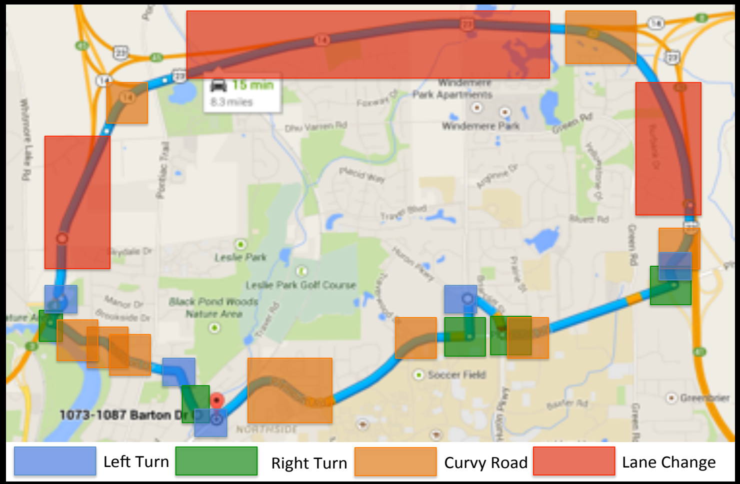
Evaluation

- Experiment settings

- Test Environments
  - On both local road and freeway
- More than 40 hours on-road test

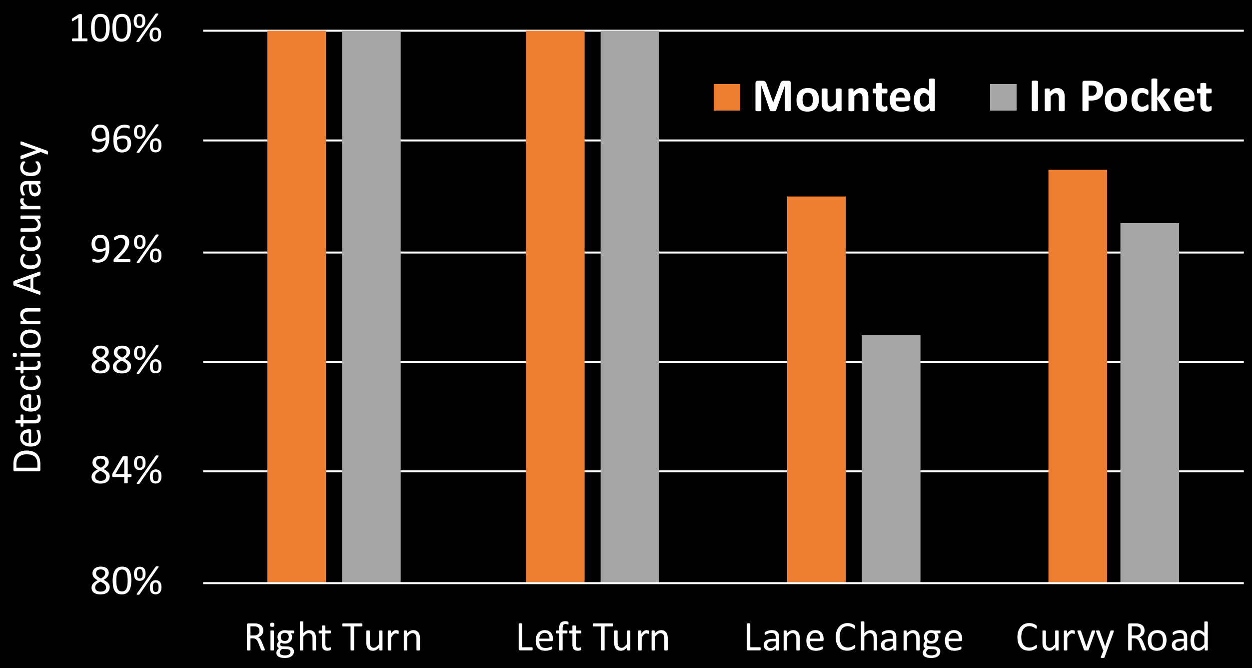
Mobile devices	Samsung Galaxy S3 & S4
# of cars	2
# of participant	Male: 9; Female: 3

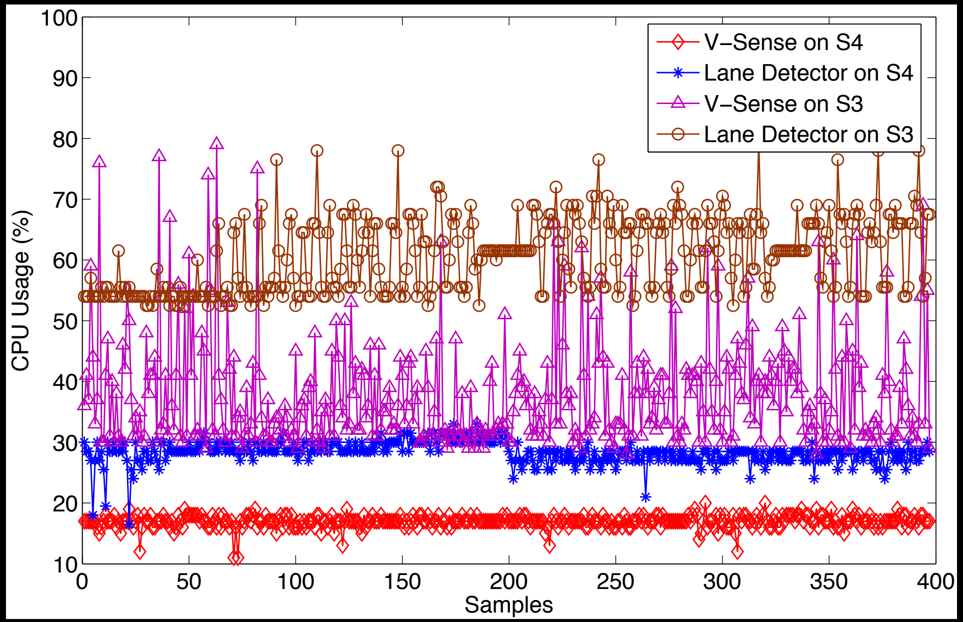




Performance

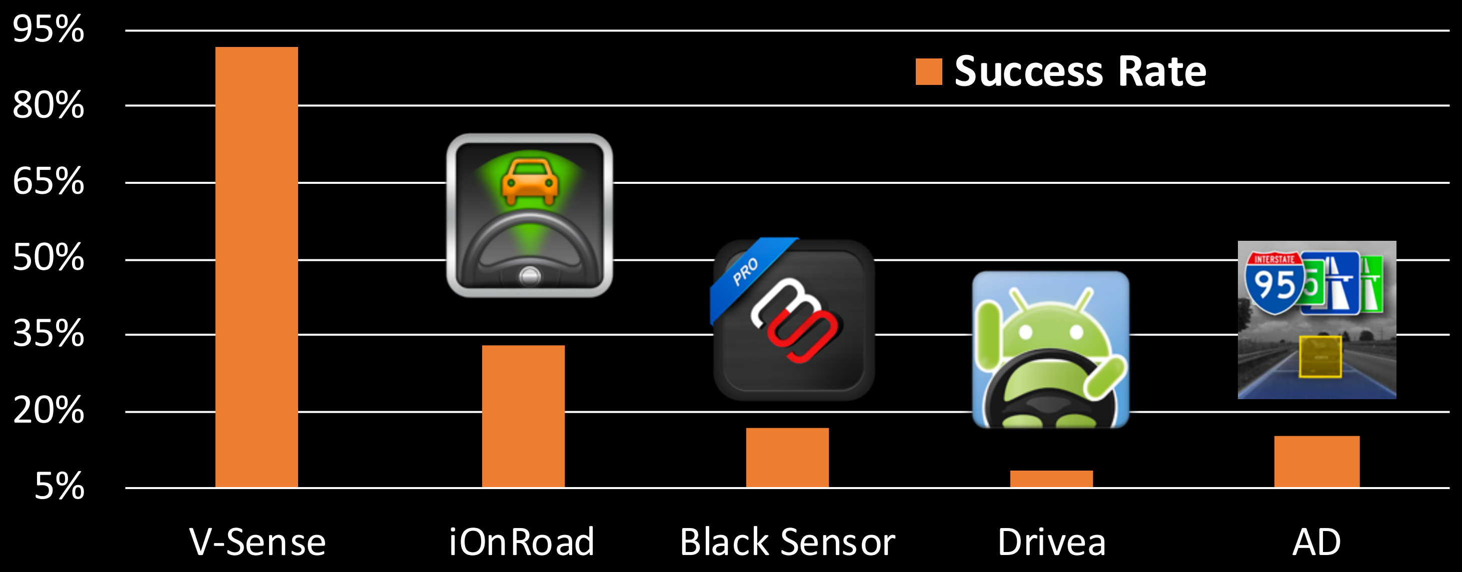
- Detection accuracy
- Overhead (CPU usage)
  - Compare with existing camera-based steering detection[5] method





Compare with Existing Works

- Success rate of detection of lane change in urban area



~1,000,000 installs

~50,000 installs

~50,000 installs

110 ratings

V-Sense: Demo


WLAN networks available
vsenselane
V-Sense II, 2015, RTCL, UM
magnetic X
System Log
18.8
mph
Waiting For
Action
Turned angle: -2.9305122
Turned distance: 0.41673502

V-Sense Outline

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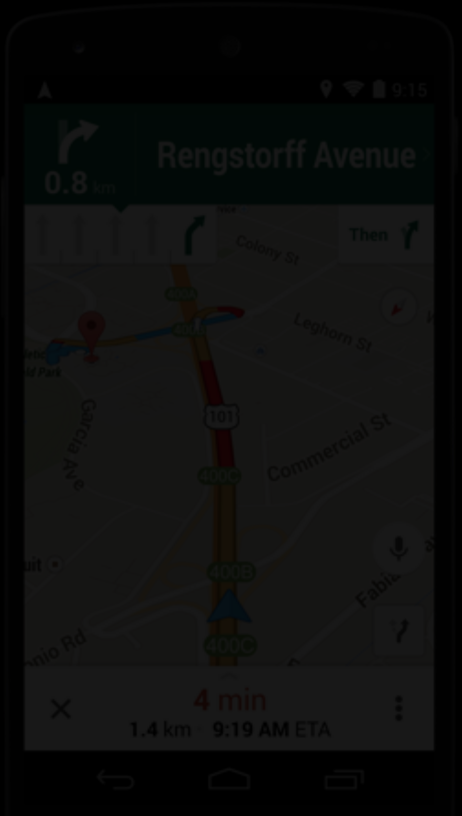
Application: Lane-level Navigation on Smartphones

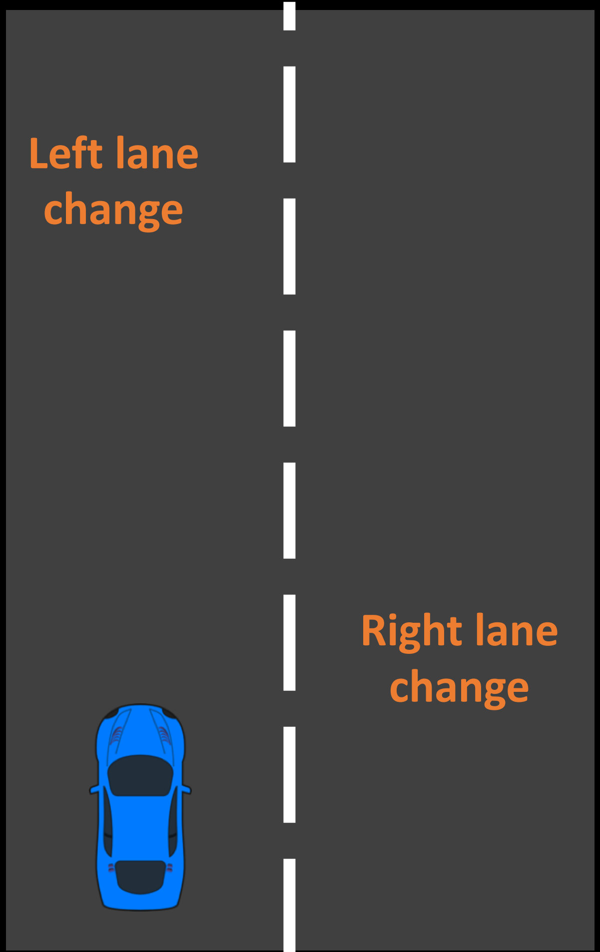


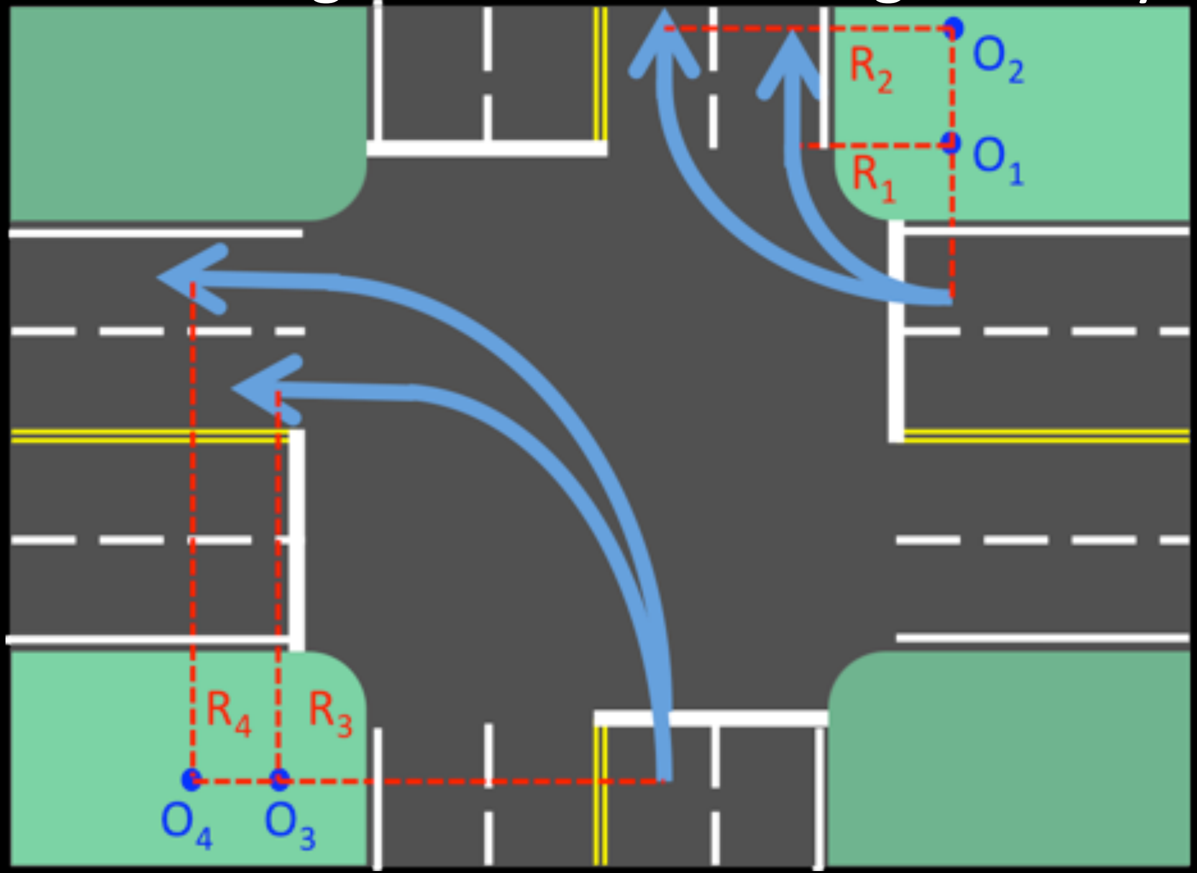
GPS Accuracy

GPS modules are **unstable** and **inaccurate** for lane level navigation

Application: Fine-grained Lane Guidance

- On road: track lane change maneuvers
- Intersection: compare the turning radius with road geometry





TurnsMap: Enhancing Driving Safety at Left Turns with Mobile Crowdsensing

[In Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing (**UbiComp 2019**), London, UK]

Risky left turns

Make Road Safer, Together

- Every moment, millions of cars are driving on the road

Key question:

Can we exploit crowd for transportation safety?

TurnsMap Outline

1. Motivation
2. Overview of TurnsMap
3. Technical Design
4. Evaluation
5. Final Remarks

Unprotected Left Turns are Risky

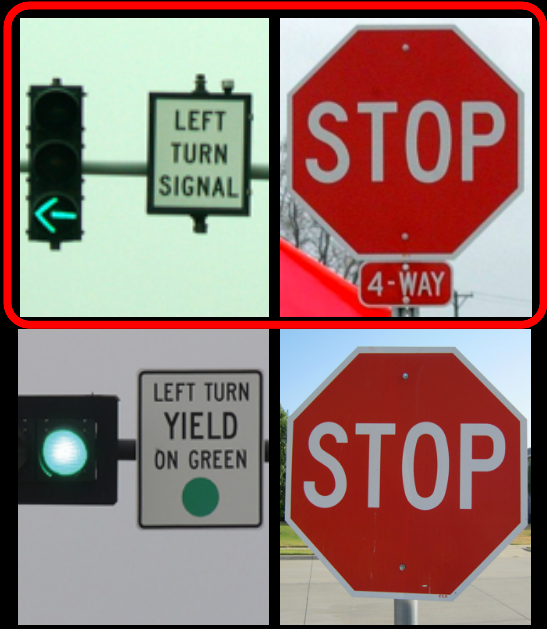
- Left turns are risky
- Protected left turns are reported to be the safest

53% of all intersection-related crashes are related to left turns [7]

--- U. S. Department of Transportation

Intersection with left-turn protection can reduce the accident rate by 87% [8]

--- NHTSA Report



Unprotected Left Turns are Risky

- Left turns are risky
- Protected left turns are reported to be the safest

Lack of Publicized Intersection Data

- Left turns are risky
- Protected left turns are reported to be the safest

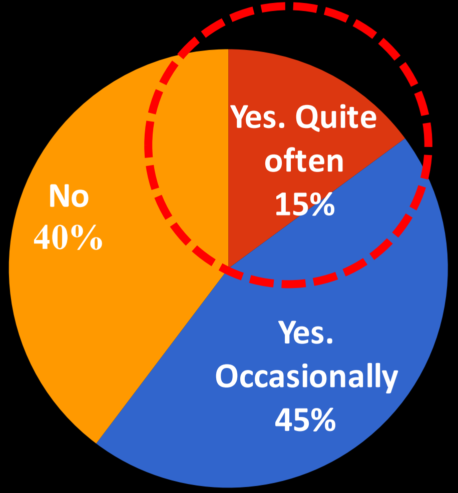
Mapping cars on average take 2 years to update an area

Google StreetView misclassifies stop sign as car plate and blurs it

- Lack of publicized data
  1. Government database: Scattered, incomplete (e.g., data.gov, Open Data Portal);
  2. Community-based database: Slowly growing (e.g., OpenStreetMap);
  3. Road survey services: High cost, low-update rate (e.g., Google StreetView, TomTom, Here)

Demand for this Information

- For human drivers
- For self-driving cars



Survey result from **567** participants

- Have you experienced risky unprotected left turns when you are using navigation apps?
- **60%** said yes!

Handling unprotected left turns is one of the most challenging tasks for self-driving cars.

> *The Waymo vans have trouble with many **unprotected left turns** and with merging heavy traffic in the Phoenix area*
>
> *--- The Information, Aug 28, 2018* [9]

TurnsMap Outline

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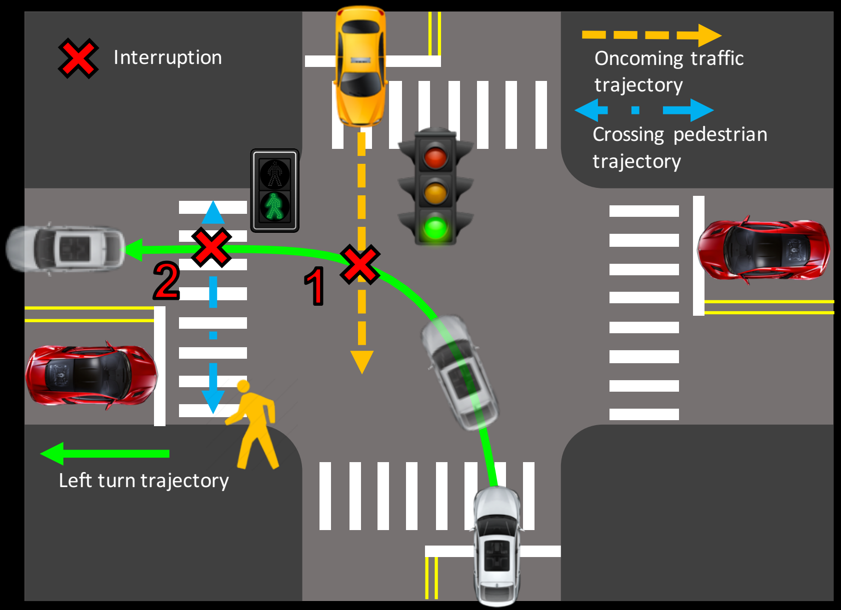
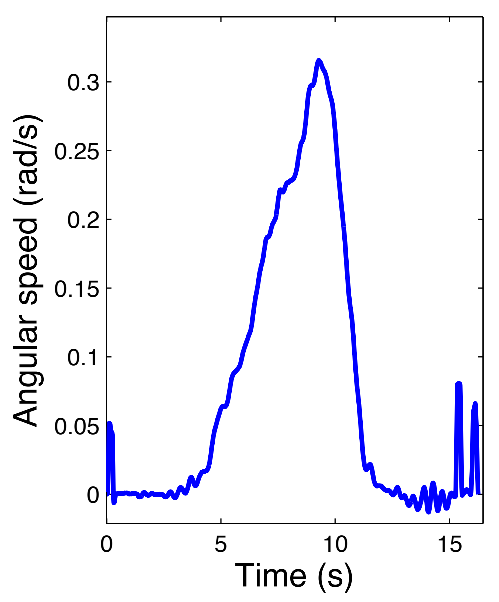
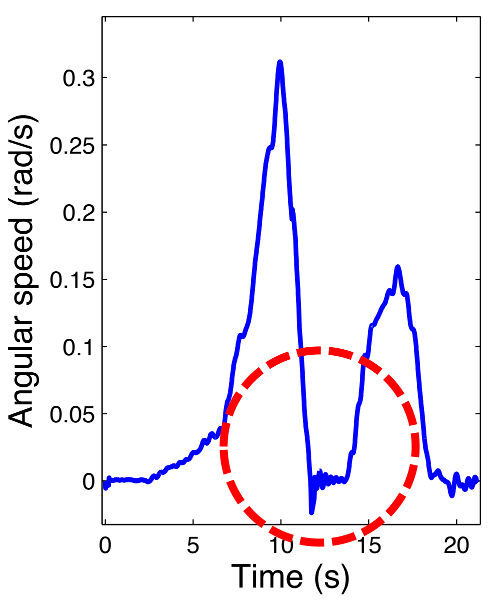
Infer Left-turn Protection via Sensor Data



- Interruptions due to the oncoming traffic and/or crossing pedestrians

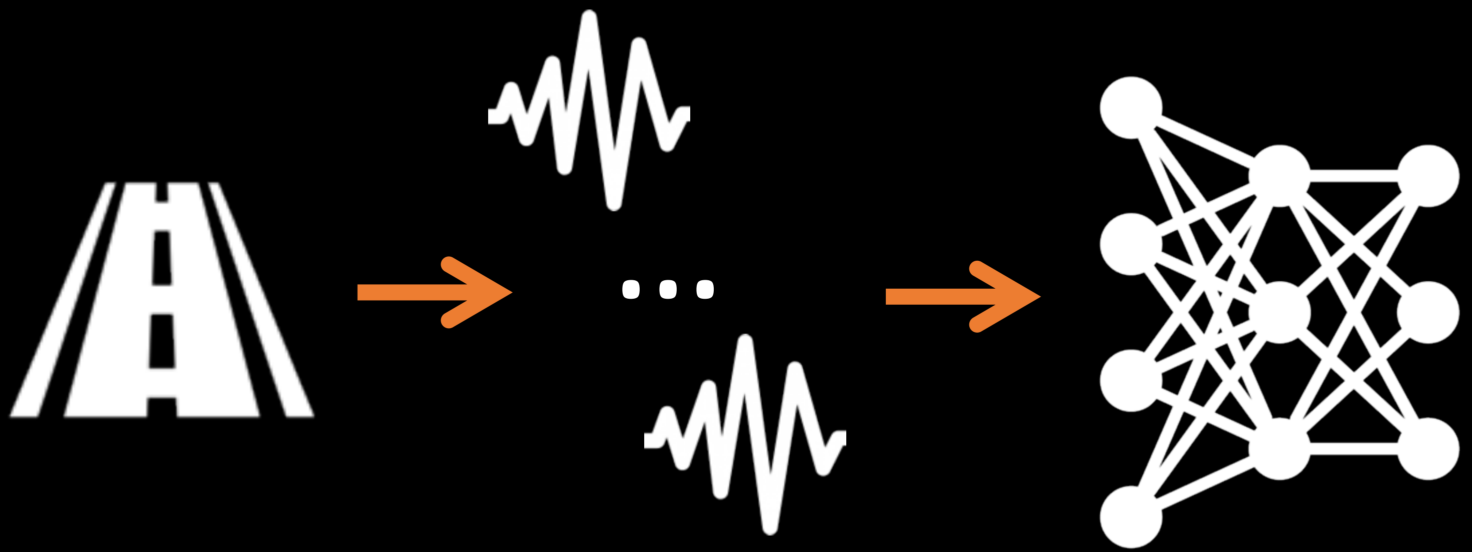




- Understanding the root cause of the risk at left turns
- Key idea

Infer Left-turn Protection via Sensor Data

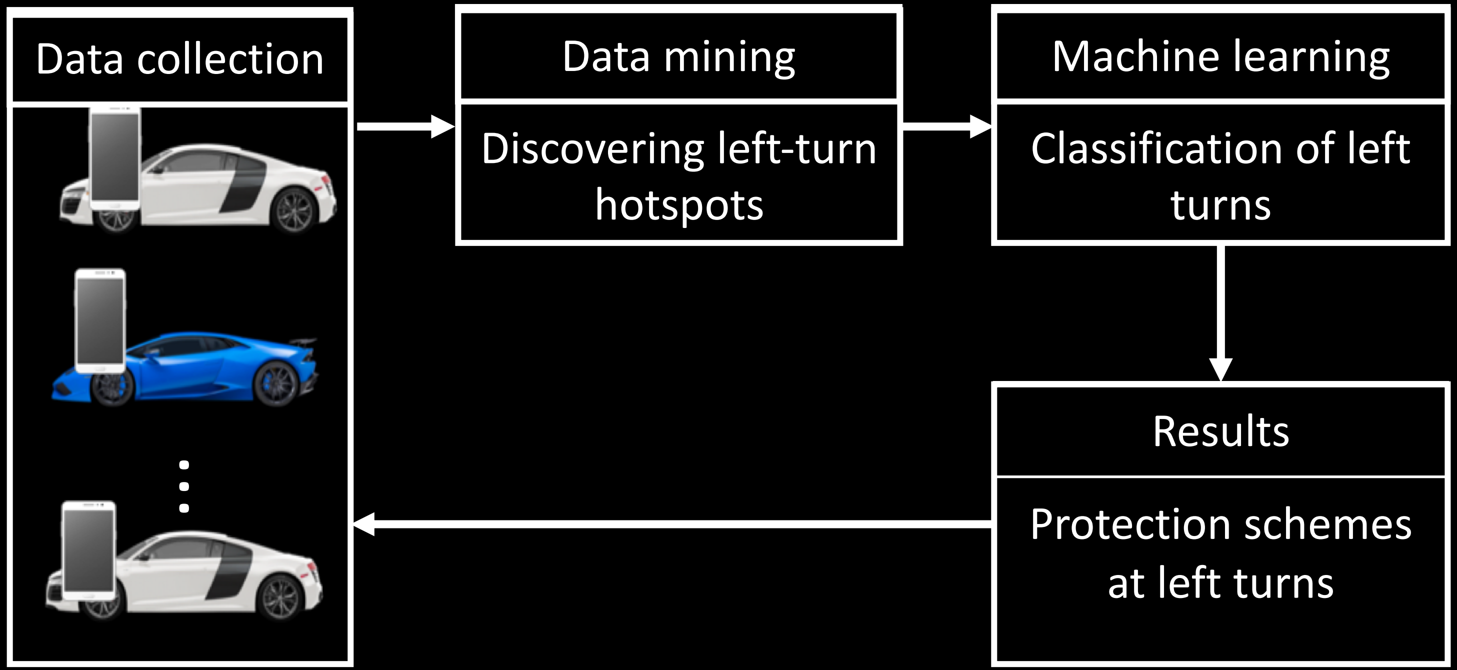
- Understanding the root cause of the risk at left turns
- Key idea



- Key idea: Use crowdsensed motion sensor readings to infer intersection settings

System Overview

1. Data collection
2. Finding left turn hotspots
3. Classification based on machine learning



TurnsMap Outline

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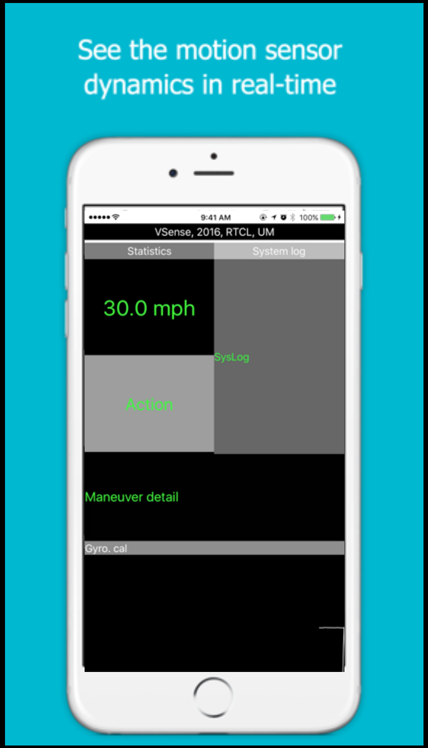
Collection and Discovery of Left Turn Hotspots

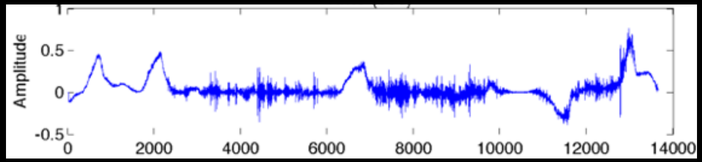


Available on the App Store

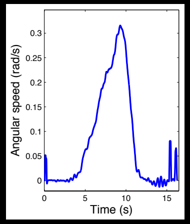
Get it on Google play

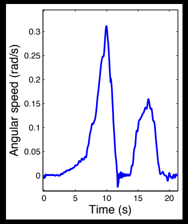
Collection and Discovery of Left Turn Hotspots

Gyroscope, accelerometer, and GPS

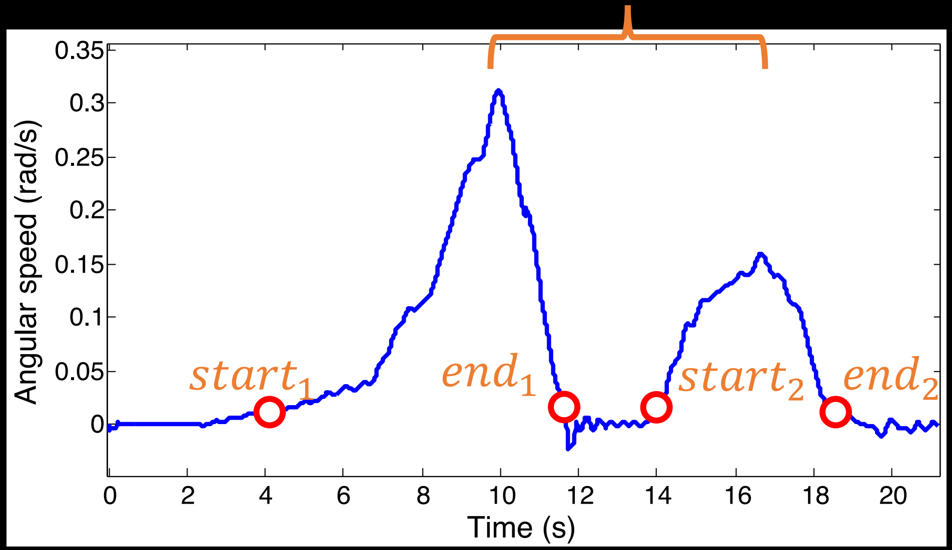


Framing data snippets that contain left turns



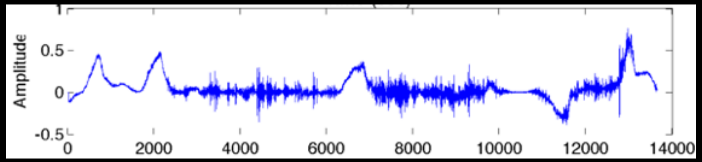


Do they belong to the same left turn maneuver?

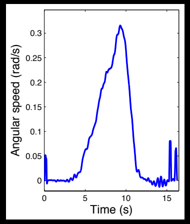


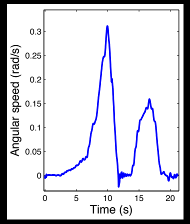
Collection and Discovery of Left Turn Hotspots

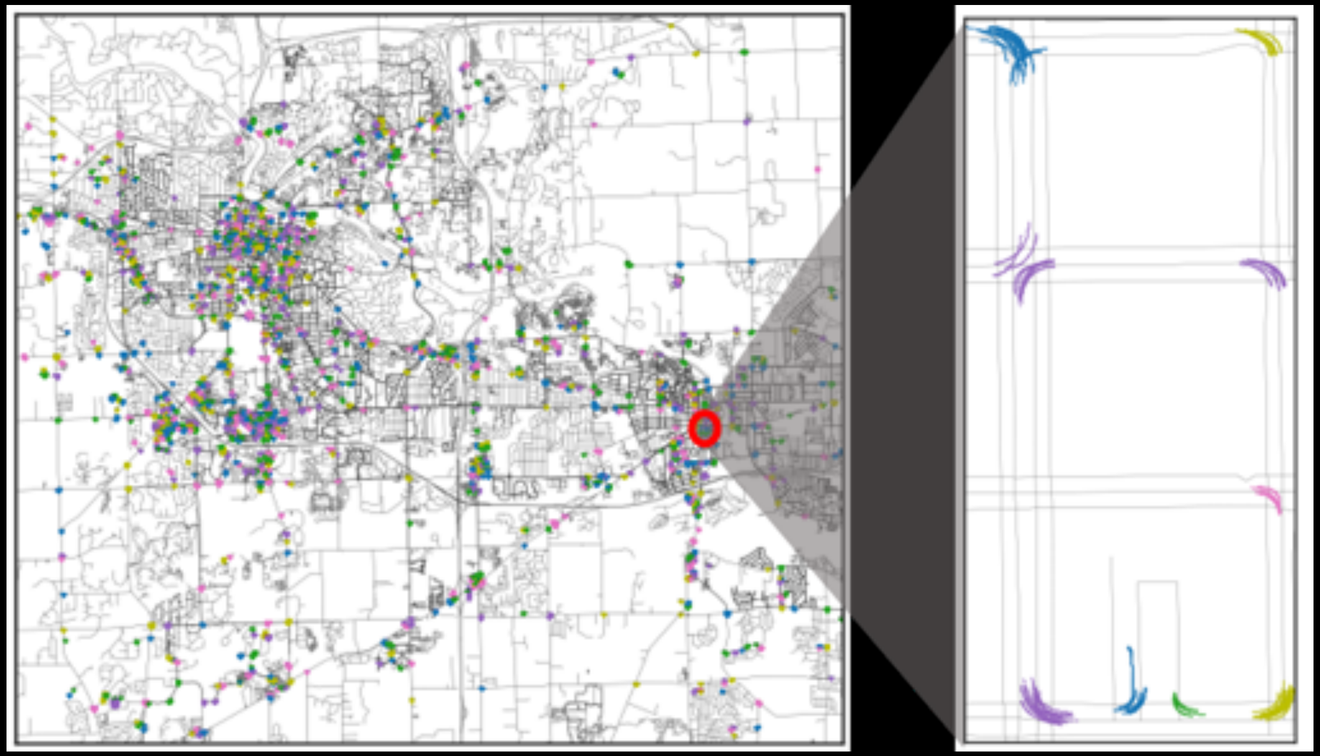
Gyroscope, accelerometer, and GPS



Framing data snippets that contain left turns

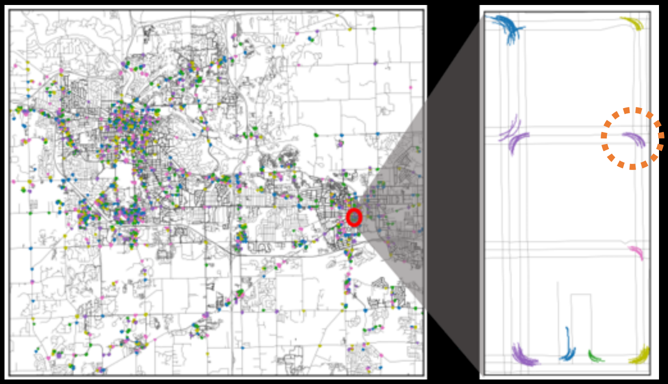


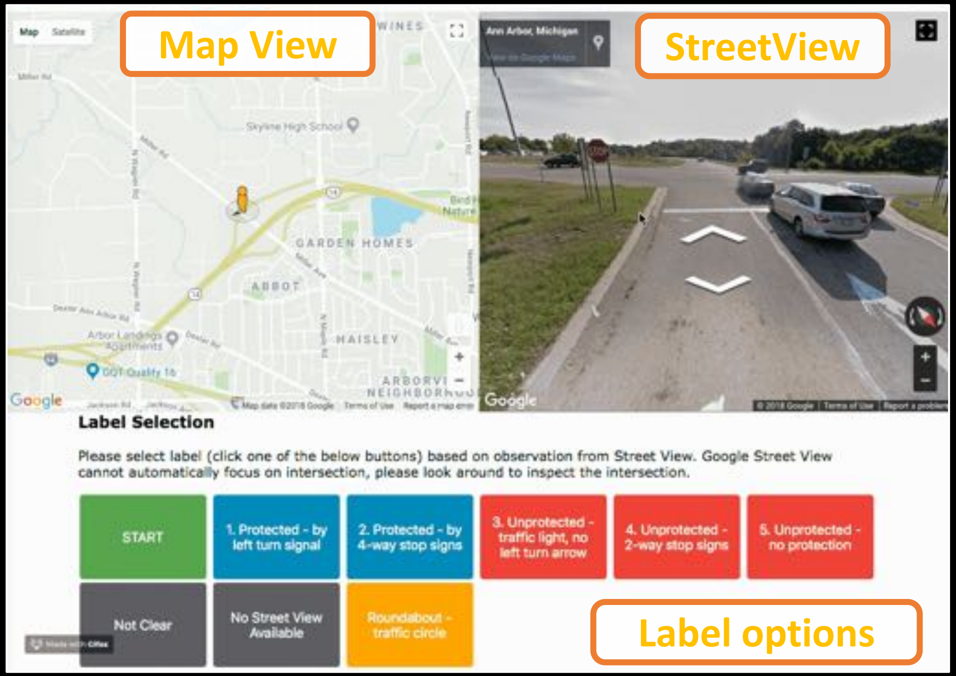




Finding Ground Truth

- Outsourcing labeling tasks via Amazon Mechanical Turk
  - Recruited **231** workers
  - Labeled **1,100** hotspots
  - Collected **6016** labels => **5.47** labels / hotspot

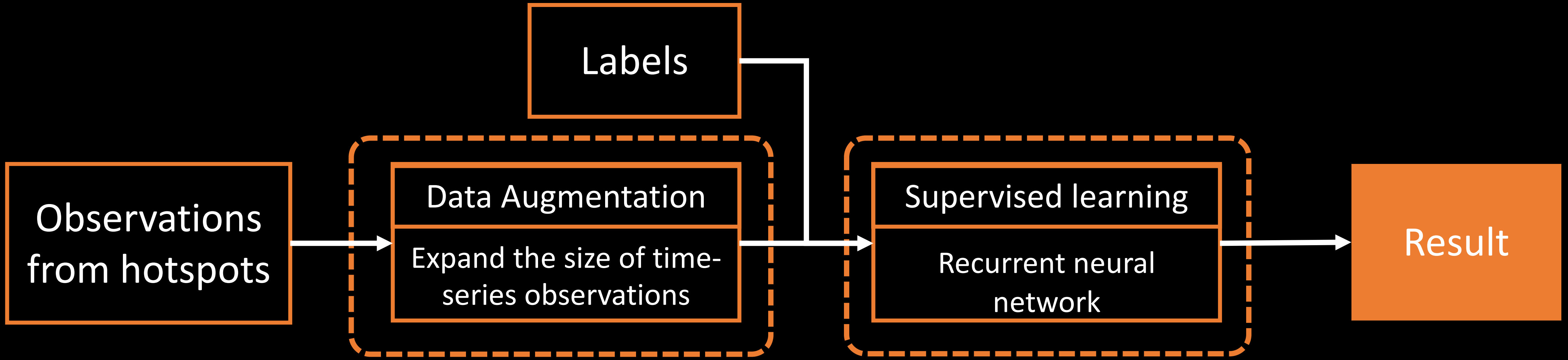




Interactive labeling system design

Opt.	Description
1	Traffic light - protected
2	Stop sign – all-way
3	Traffic light - regular
4	Stop sign – two-way
5	Unprotected
6	None of the above

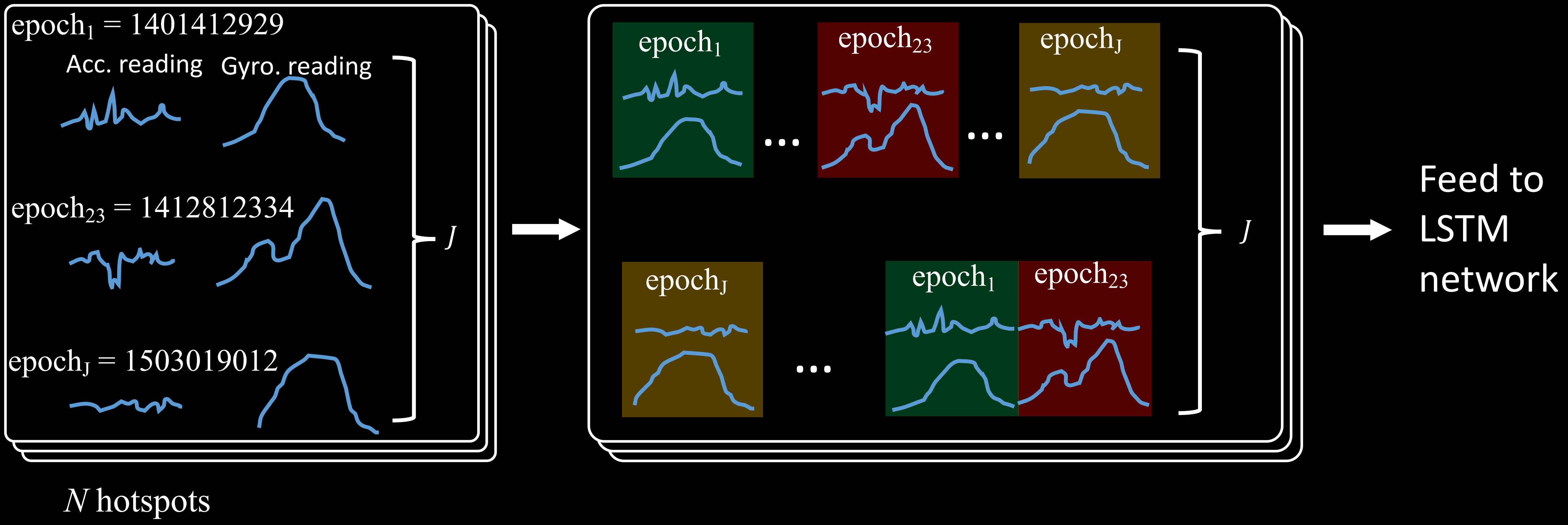
Understanding Statistical Features with Machine Learning



- Data augmentation
  - Generate larger training data set
- Long-and short-term memory (LSTM) algorithm captures the dependency through time

Data Augmentation: Random Permutation + Concatenation (RPCat)

Data augmentation for extending the observation set



Data Augmentation: Random Permutation + Concatenation (RPCat)

Data augmentation for extending the observation set

Generate **10x** larger observations for training!

$epoch_1$ = 1401412929

Acc. reading Gyro. readi

$epoch_{23}$ = 1412812334

$epoch_J$ = 1503019012

N hotspots

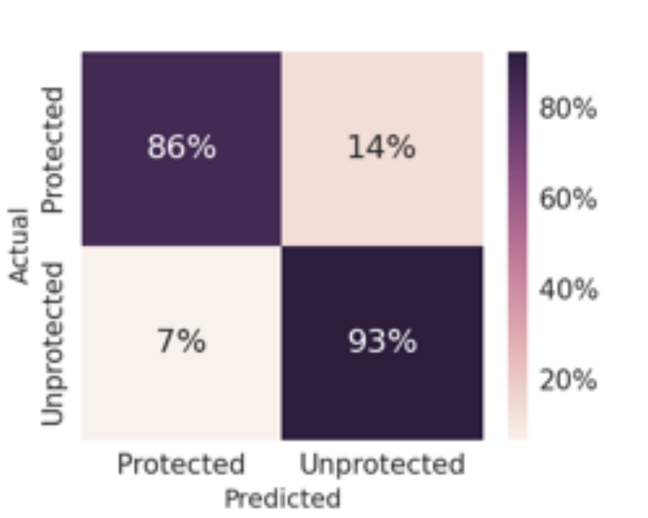
J

Feed to LSTM network

TurnsMap Outline

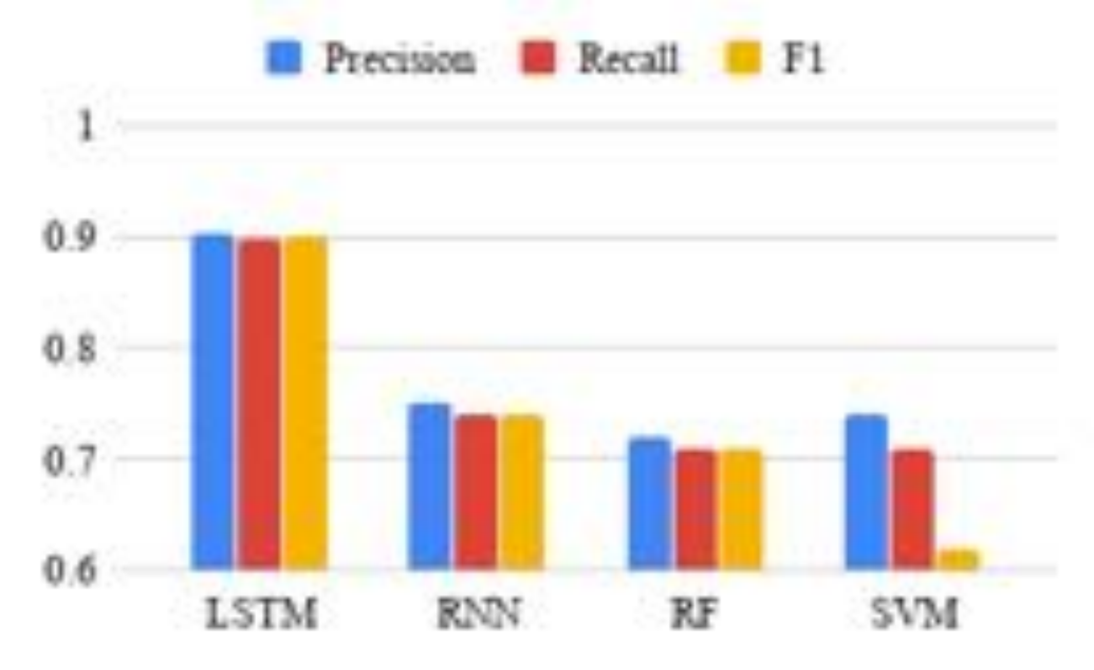
1. Motivation
2. Overview of TurnsMap
3. Technical Design
4. Evaluation
5. Final Remarks

Classification Accuracy

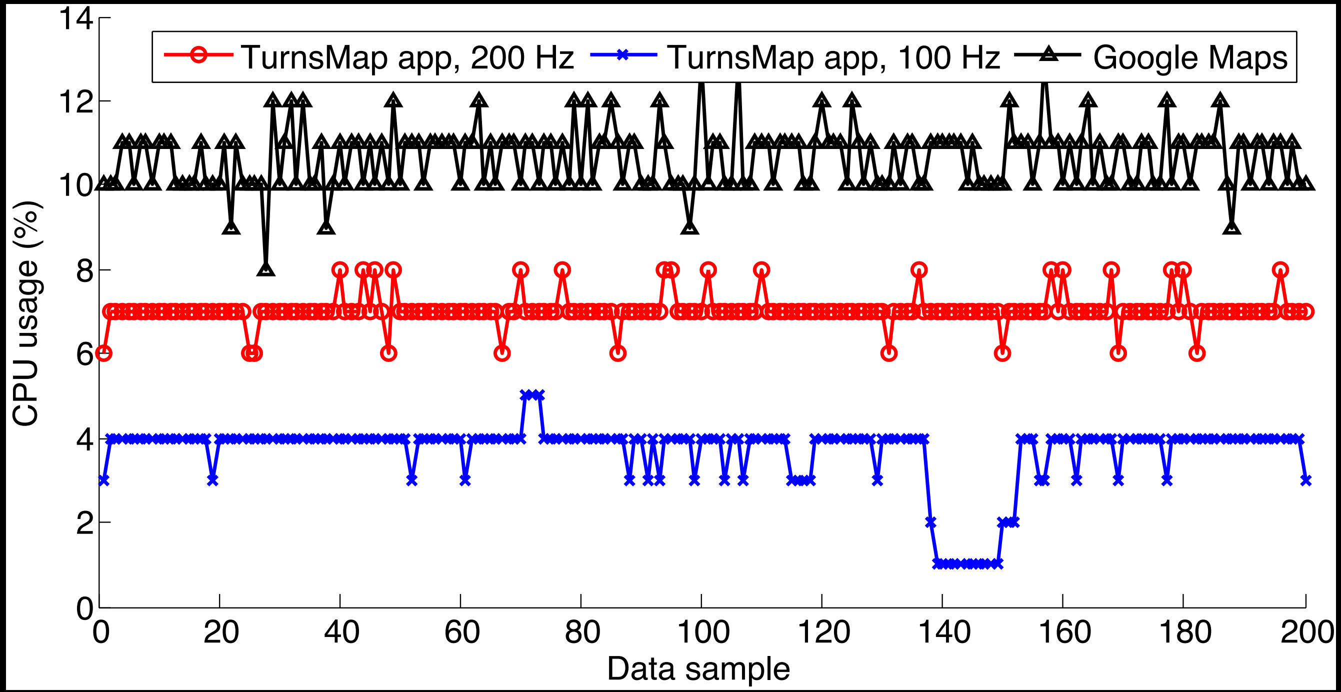


Category	Precision	Recall	F-1
Protected	0.90	0.86	0.88
Unprotected	0.91	0.93	0.92

- Evaluation metrics
- Compare LSTM with other machine learning algorithms



Overhead of the Data Collection App

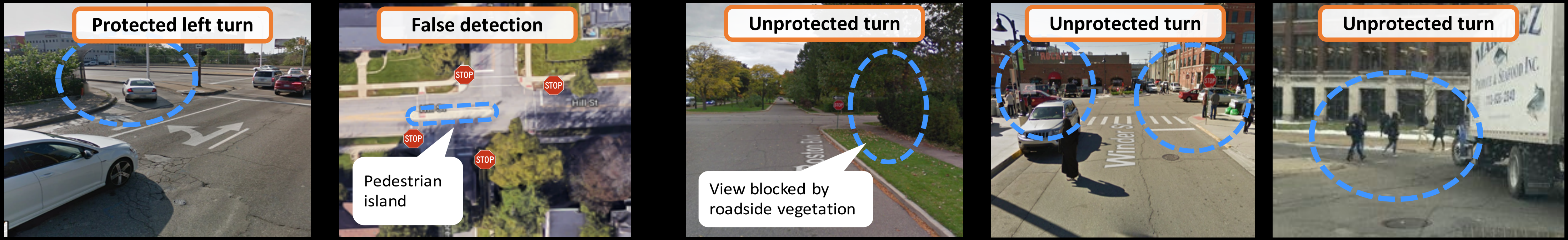


- CPU usage
- Battery usage

- TurnsMap on average uses **45** mA --- only **6%** of Google Maps' power consumption

Apply TurnsMap

Findings



TurnsMap Outline

1. Motivation
2. Overview of TurnsMap
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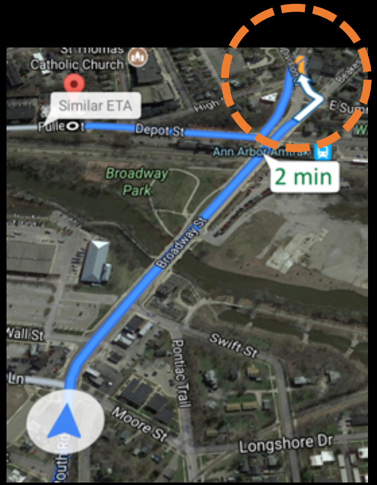
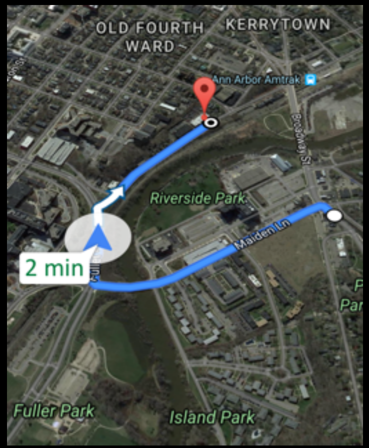
Use Case

– ◆ –

- Adapting TurnsMap for Navigation Systems
  - User study of **564** participants



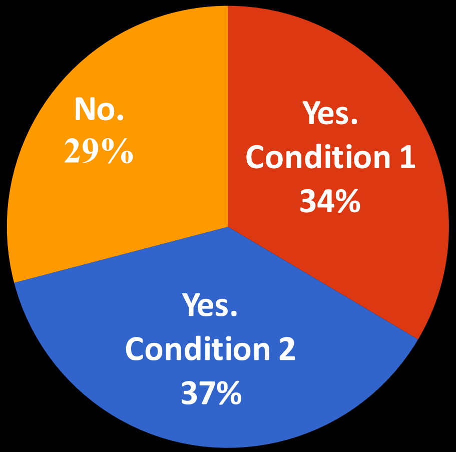
Two **unprotected** left turns



- Replace unprotected left turns with right turns by altering trip route

Would you prefer a navigation app that can help you avoid unprotected left turns?

I will use it if it has similar ETA



I'll use even with a prolonged ETA

Analyze Intersections, Worldwide

- Unprotected intersection is a common issue and shares the same nature across the world
- Future work: how to adapt to the local driving pattern

Future Directions

Multi-Modal Sensing

- Break the barrier --- free access of in-vehicle network (IVN) data
  - CAN-bus data's format is proprietary to car OEMs
  - LibreCAN: Automated CAN-bus Data Translator

Multi-Modal Sensing

“People who are really serious about software should make their own hardware”

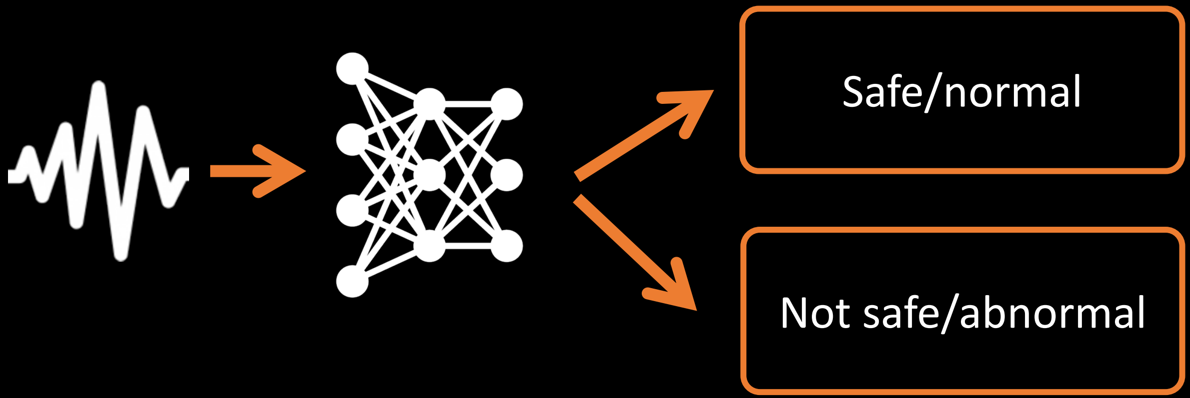
--- Alan Kay & Steve Jobs

- Customized sensory platform
  - Scalable, reliable and light-weight sensory platforms

Image courtesy: https://www.aloriumtech.com/wp-content/uploads/2016/06/xlr8prod_obl_left_600x400.png

Human-centric System Design

- Bridging state-of-the-art research and engaging product
  - Crucial for safety-critical applications and large-scale data collection
  - Requires engaging system implementation
- Enabling safety features, e.g., detection of driving with intoxication, irregular emotion



Better Coexistence, Better Future

- Horse carriage → automobile → fully-automated cars

Better Coexistence, Better Future

- Horse carriage → automobile → fully-automated cars
- Transportation, re-invented
  - Achieving better coexistence of human-driven cars and self-driving Cars

Thank You!

Q & A

Image courtesy: http://onebigphoto.com/intersection-new-york/

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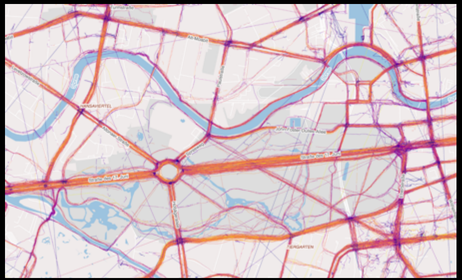
Backup Slides

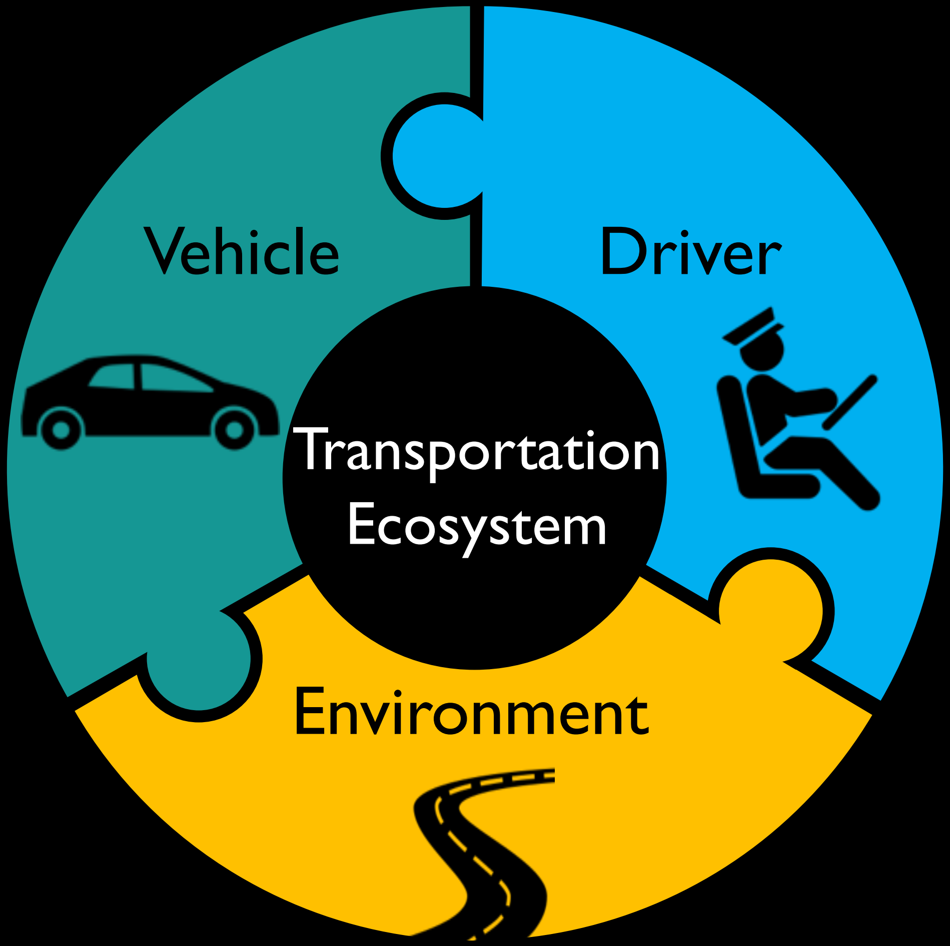
Sensing vehicle dynamics

Driving behavior modeling



Transportation safety

Privacy Protection



Thesis Statement

1. Understanding driving pattern in large-scale based on mobile sensor data

2. Using this understanding for enhancing transportation safety

ToDo: why it is a pressing issue?


Safety Evaluation of Protected Left-Turn Phasing and Leading Pedestrian Intervals on Pedestrian Safety

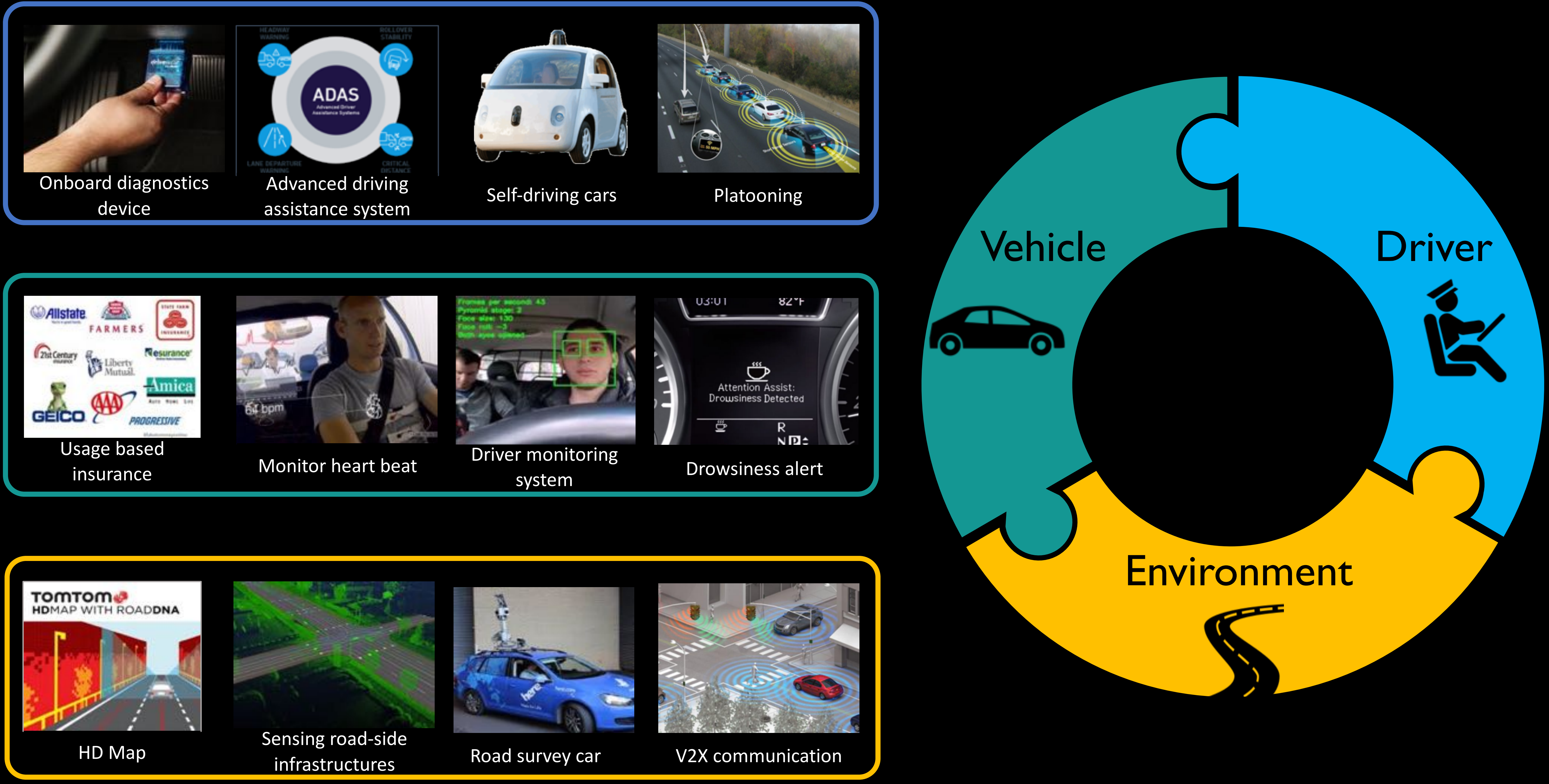
PUBLICATION NO. FHWA-HRT-18-044 OCTOBER 2018

U.S. Department of Transportation
Federal Highway Administration

Research, Development, and Technology
Turner-Fairbank Highway Research Center
6300 Georgetown Pike
McLean, VA 22101-2296

Pedestrian and Bicycle Safety

- Government efforts took about 2 years for collecting around 10 traces per intersetion.


ADAS
Onboard diagnostics device
Advanced driving assistance system
Self-driving cars
Platooning
Usage based insurance
Monitor heart beat
64 bpm
Driver monitoring system
Attention Assist: Drowsiness Detected
Drowsiness alert
TOMTOM
HDMAP WITH ROADDNA
HD Map
Sensing road-side infrastructures
Road survey car
V2X communication
Vehicle
Driver
Environment