Automobile Sensing and Intelligent Transportation Systems 1

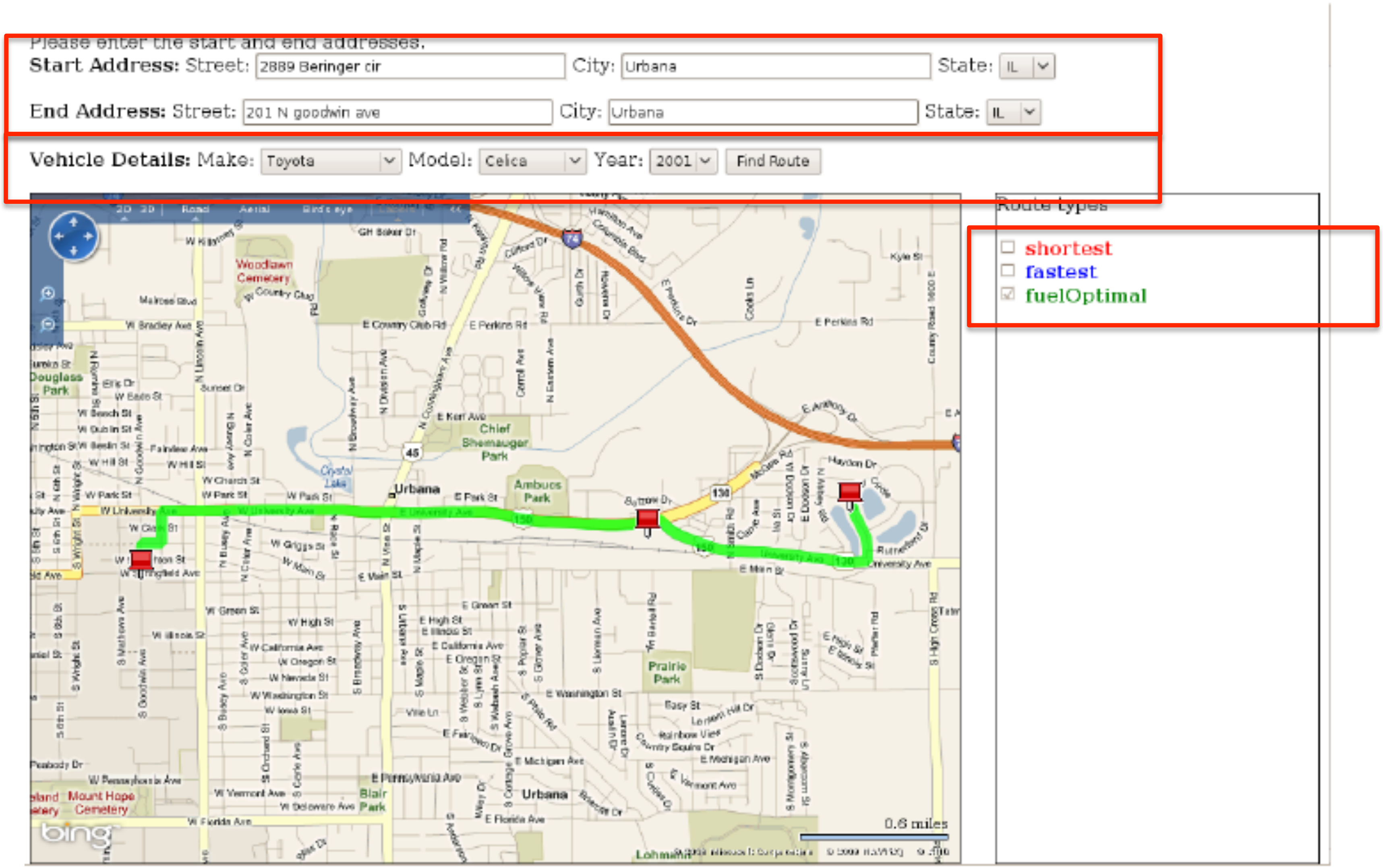
CSE 40437/60437-Spring 2015

Prof. Dong Wang

Papers

Paper1: Raghu K. Ganti, Nam Pham, Hossein Ahmadi, Saurabh Nangia, and Tarek F. Abdelzaher, "GreenGPS: a Participatory Sensing Fuel-efficient Maps Application," In *Proceedings of the 8th international conference on Mobile systems, applications, and services (MobiSys)*, 2010

Green GPS Map Interface



Key Points

- GreenGPS uses participatory sensors to determine a ***fuel-efficient route*** between two arbitrary end-points.
- Utilizes the OBD-II interface to retrieve data from sensing automobiles
- The most fuel-efficient route is **not always the shortest or fastest**

Green GPS Goals

- **Long term Goal:**
  - Develop a fuel efficient navigation service using participatory sensing to influence routing decisions of individuals
- **Short term Goal:**
  - Accurate fuel consumption prediction model
  - Experimental deployment to analyze fuel savings, average savings of 10%

Why Green GPS?

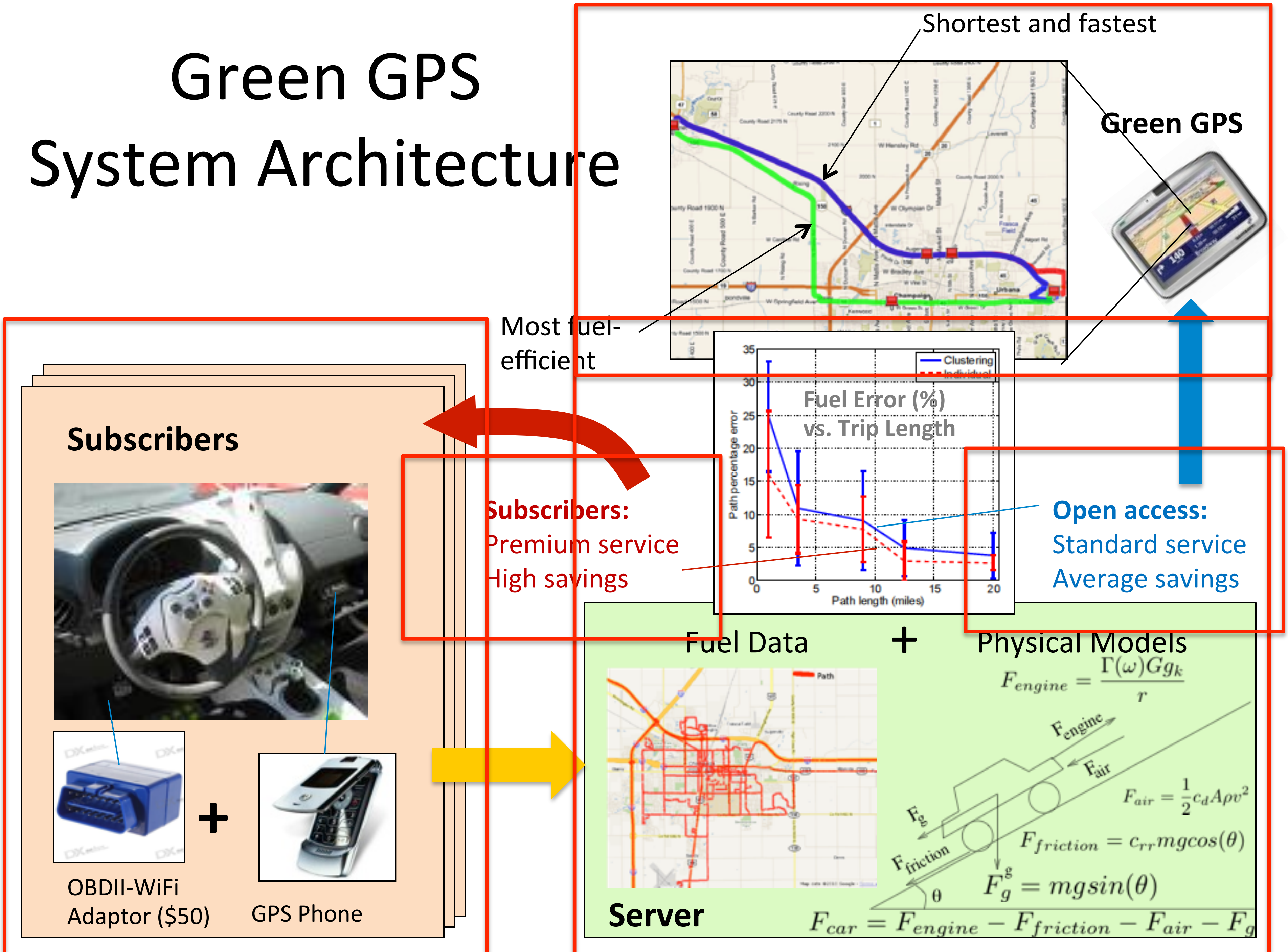
- 200 million light vehicles on the streets
- Each driven 12000 miles annually on average
- Average MPG (Miles Per Gallon) is 20.3 miles/gallon
- **118 Billion Gallons of Fuel per year!**
- **Savings of 1% = One Billion Gallons (2~3 Billion $)**

* The above data are from Environment Protection Agency (EPA) Statistics

Share your thoughts

- How would you design such an green navigation service using participatory sensing paradigm?
  - Assume you have a group of participants (drivers). Each of them has a smartphone with GPS, WiFi and Bluetooth, etc.)
  - You can get the parameters of their vehicles (e.g., current speed, total fuel consumption, fuel consumption rate, time, etc.) through a special on board device (OBD-II)
- What are the key challenges of designing this service?

Green GPS
System Architecture

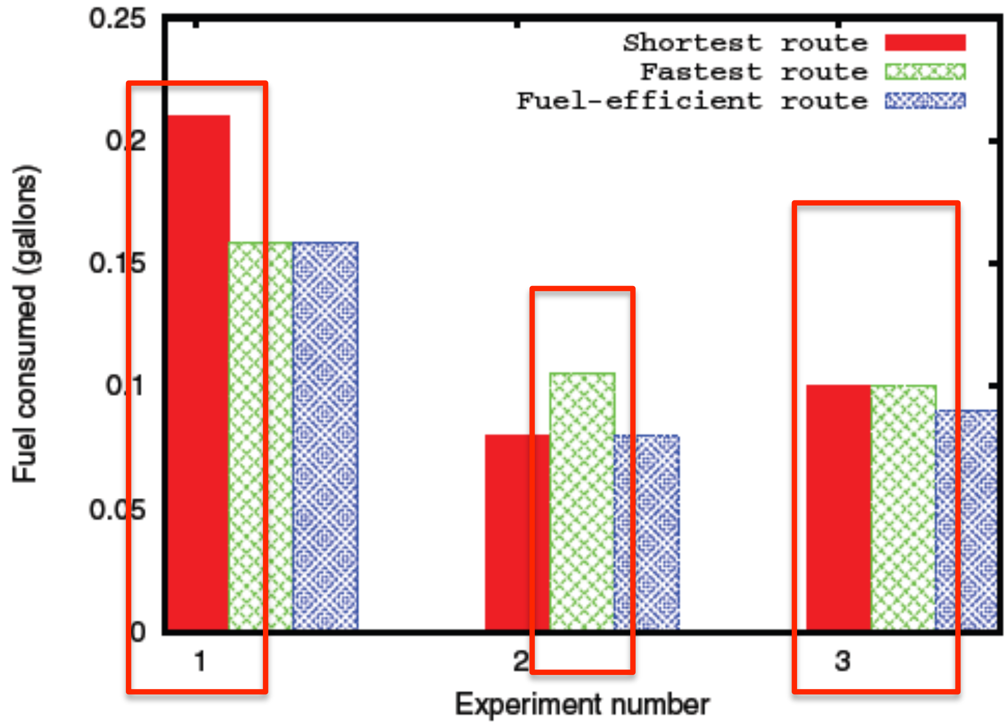


Small Scale Feasibility Study

- Three different cars and drivers between Urbana-Champaign landmarks
  - Shopping Center, author's office and football stadium
  - Shortest and fastest routes calculated using MapQuest (http://www.mapquest.com/)

Small Scale Results

- Average of 11% overhead for always taking the “fastest” route
- Average of 11.5% overhead for “shortest”

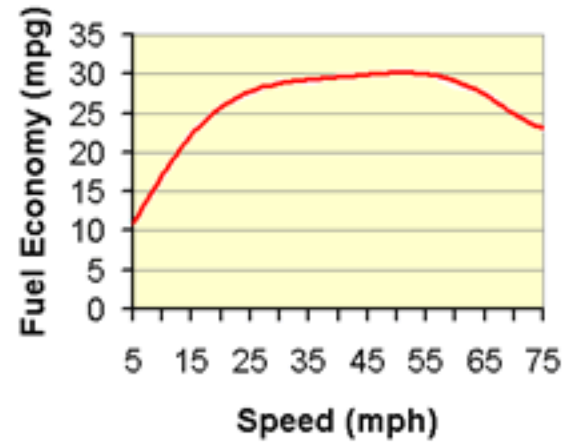


Simply choosing the shortest or the fastest route will not always be fuel-optimal.

GreenGPS: Fuel Efficient Routing

- Fuel efficient route different from shortest or fastest route ->**Why?**
  - Congestion, number of traffic regulators -> shortest may not be fuel efficient
  - MPG vs. speed is non-linear OR fastest route might be longer -> fastest may not be fuel efficient
- Individuals record fuel-related sensor data from their daily commutes
- Share the sensor data in a community to build fuel map of a given area

Source: US EPA



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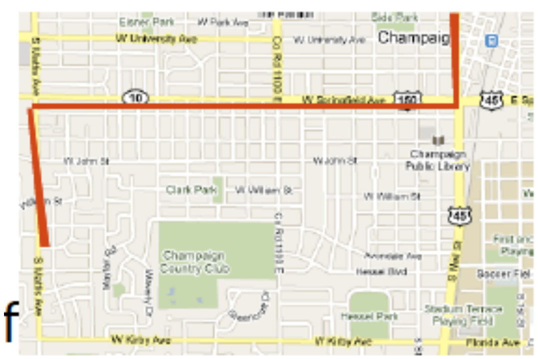


On Board Diagnostic (OBD-II) System

- Cars manufactured after 1996 equipped with On Board Diagnostic (OBD-II) System
- OBD measures engine parameters (e.g., fuel consumption, RPM, speed, etc.)
- Commercial OBD scanners available
- An estimated 200 millions cars and light trucks are on the roads in U.S

Cell phone

+

Wireless OBD

=

Large scale car sensor network

GreenGPS Users

- **Members (Subscribers):**
  - Have OBD-II Equipment
  - Upload their data to the service

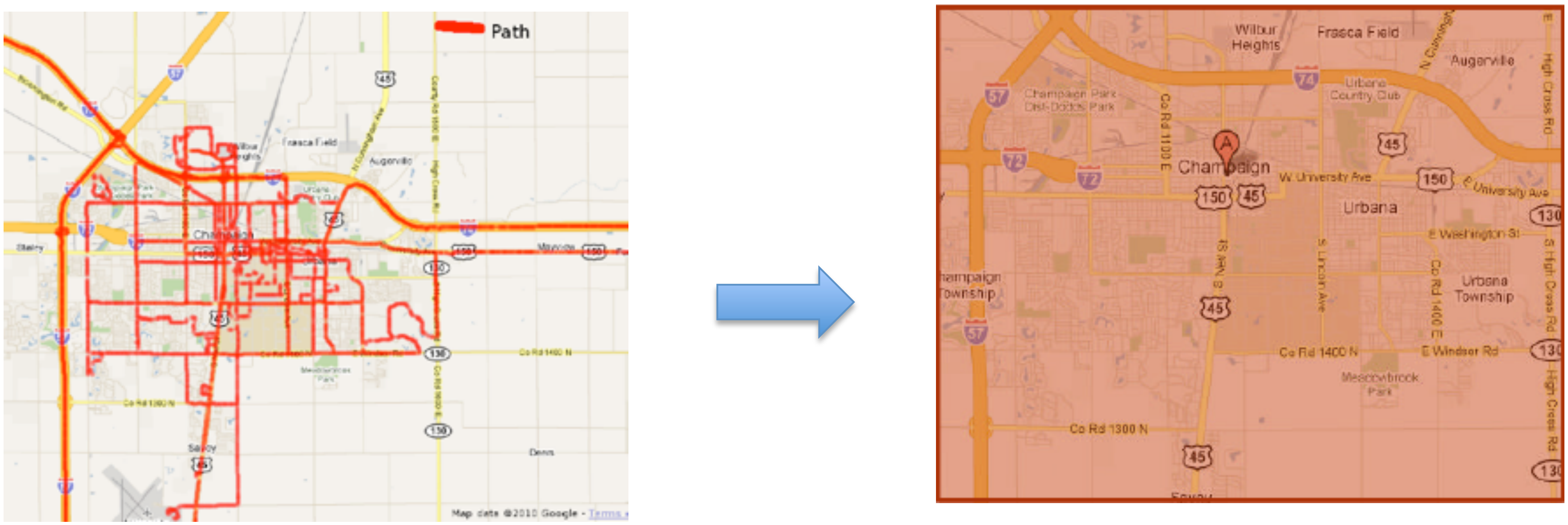
Why members can normally get better estimation on their fuel consumptions?

  - Just query fuel efficient routes from GreenGPS
  - Does not share their measurements
  - Approximate answers based on the average estimation based on car's make, model, year

Fuel Consumption Modeling

- **Ideal scenario:** all cars collect data on a LOT of streets
- **Current situation:** few individuals with OBD scanners
- **Challenge:** sparse deployment and data to model complex phenomena
- **Question:** Can we generalize a few measurements on a few cars to predict fuel consumption of *an arbitrary car* on *an arbitrary street*?

Sampling Regression Modeling Framework

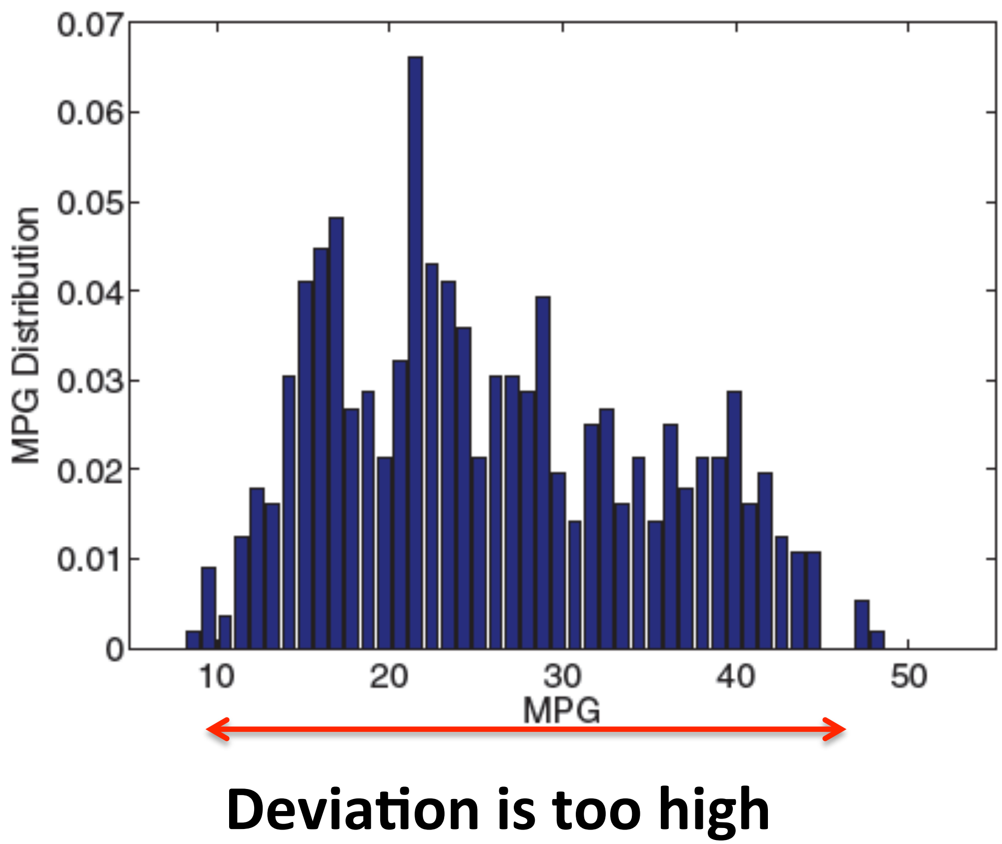


Fuel consumptions of few cars on a few streets to predict fuel consumption of any car on any street?

Use data from existing cars and streets to build generalized models (data cube) to predict fuel consumption of other cars on other streets.

Simple Prediction: Average MPG

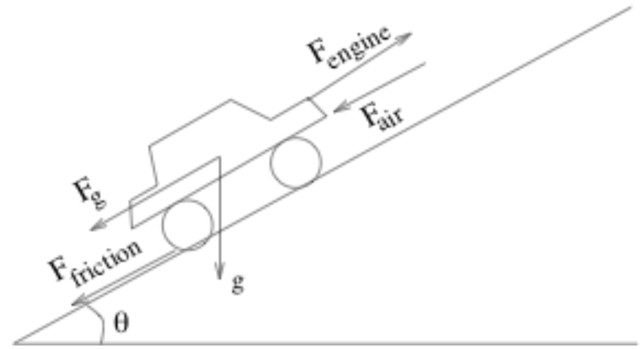
- Uniform distribution of mpg and high standard deviation (standard deviation= 9.12 mpg)



Nearly Uniform

Model Structure Deviation

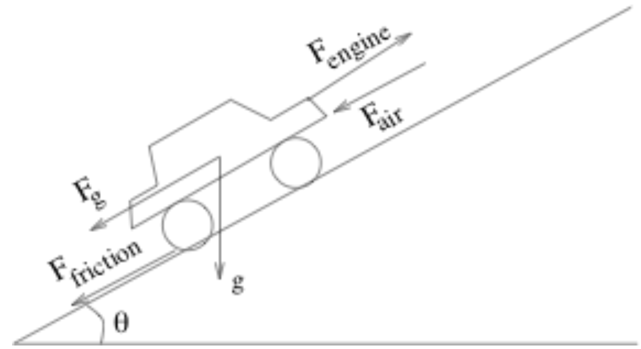
- **Simple model** for fuel consumption derived from physics principles



- What kind of features/parameters should we consider in order to predict the fuel consumption of a trip for a given car?

Model Structure Deviation

- **Simple model** for fuel consumption derived from physics principles



- Approximate based on easily measurable parameters (e.g., stop signs, speed limits)

$$gpm = k_1 m \bar{v}^2 \frac{ST + \nu TL}{\Delta d} + k_2 m \frac{\bar{v}^2}{\Delta d} + k_3 m cos(\theta) + k_4 A \bar{v}^2 + k_5 m sin(\theta)$$

\# of stop signs | # of traffic lights | Distance traveled | Average speed | Weight of the car | Car front area | Slope

Individual Car Models

- Split data into 1 mile segments (segment length determined empirically)
- Individual models: how can we predict a car's fuel consumption on a different path?

Car make	Car model	Car year	Cumulative Error %
Hyundai	Santa Fe	2008	2.89
Honda	Accord	2003	0.89
Ford	Contour	1999	0.83
Ford	Focus	2009	0.12
Ford	Taurus	2001	0.75
Toyota	Corolla	2009	0.75

One Size Fits All?

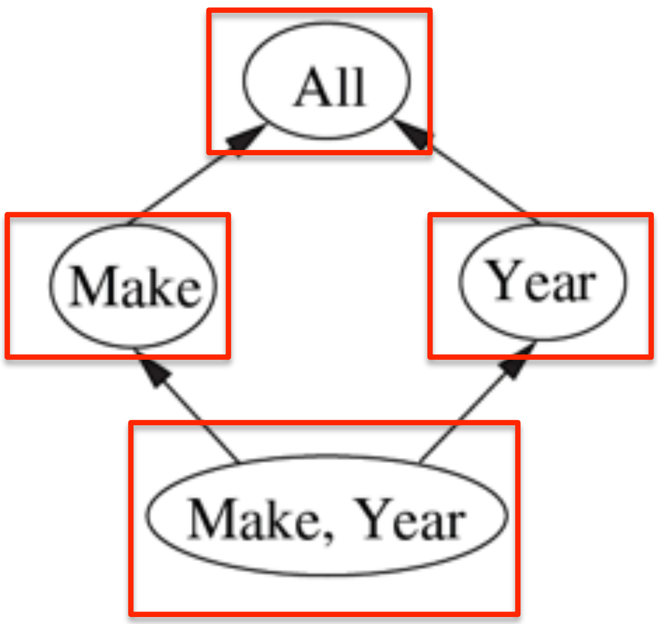
- Generalize: Use model computed from all data to predict fuel consumption of a car that lacks previously measured values

Car make	Car model	Car year	Cumulative Error %
Hyundai	Santa Fe	2008	23.63
Honda	Accord	2003	15.3
Ford	Contour	1999	91.4
Ford	Focus	2009	27.35
Ford	Taurus	2001	24.85
Toyota	Corolla	2009	89.97

Fuel consumption of different cars is different: one size did not fit all!

Generalization Hierarchy

- Derive a hierarchy for prediction using the sampling regression framework when data for a specific car is missing



Q: What if a car is encountered for which we do not have data on its (make, year)?

Q: What if there are no models corresponding to either make or year for the car?

Example: 2001 compact Ford is modeled differently from a 2001 mid-size Ford, a 2002 compact Ford or a 2001 compact Toyota.

Generalization Hierarchy Evaluation Results

- Evaluate model performance using this framework

Car make	Car model	Car year	Mean error %
Hyundai	Santa Fe	2008	0.73
Honda	Accord	2003	1.01
Ford	Contour	1999	1.42
Ford	Focus	2009	2.7
Ford	Taurus	2001	3.38
Toyota	Corolla	2009	1.28

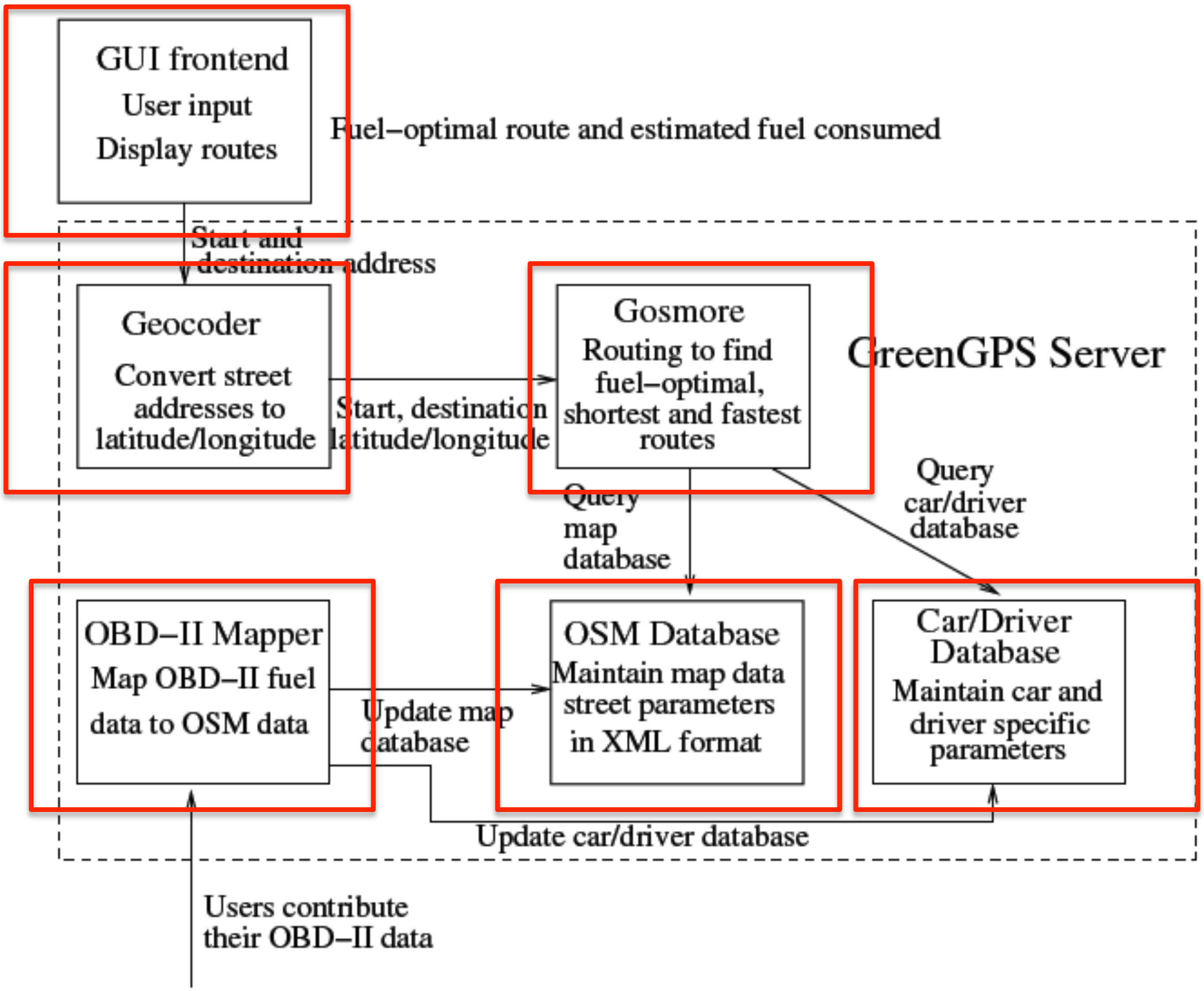
Hierarchical generalization addressed the sparse data and modeling challenge!

Green GPS System Implementation

- Open Street Map (OSM) database
- Routing: think of it as weighted Dijkstra’s algorithm with weights as fuel consumption on road segments
- Microsoft Bing maps based interface for input and output route display
- Preliminary system:

http://green-way.cs.illinois.edu/GreenGPS.html

GreenGPS Modules

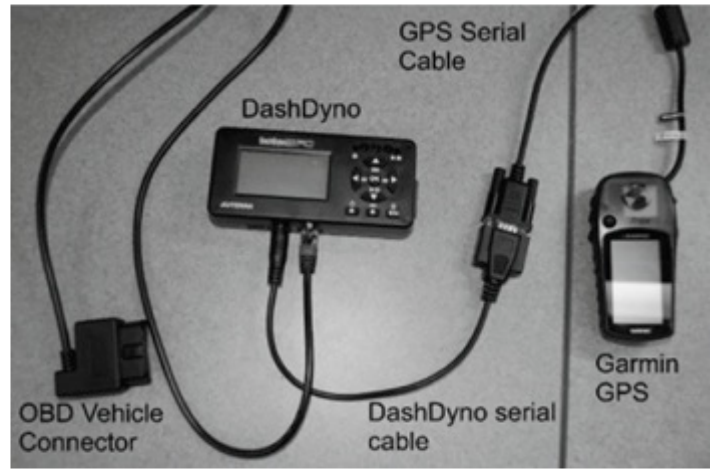


Evaluation

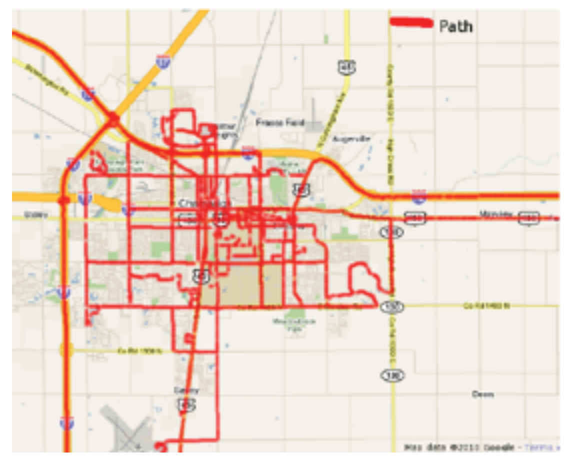
- Performed in two stages
  - Stage 1 – Use to predict **end-to-end** fuel consumption for long routes
  - Stage 2 – Evaluate potential fuel savings **of an individual** using GreenGPS

Preliminary Deployment

- **DashDyno** – OBD scanner with GPS to collect location tagged car sensor data
- **16** different compact and mid-sized sedans, e.g., Ford, Toyota, Honda
- Over **1000 miles** of data collected
- Users record sensor data and GPS on SD card and upload to the backend server



DashDyno

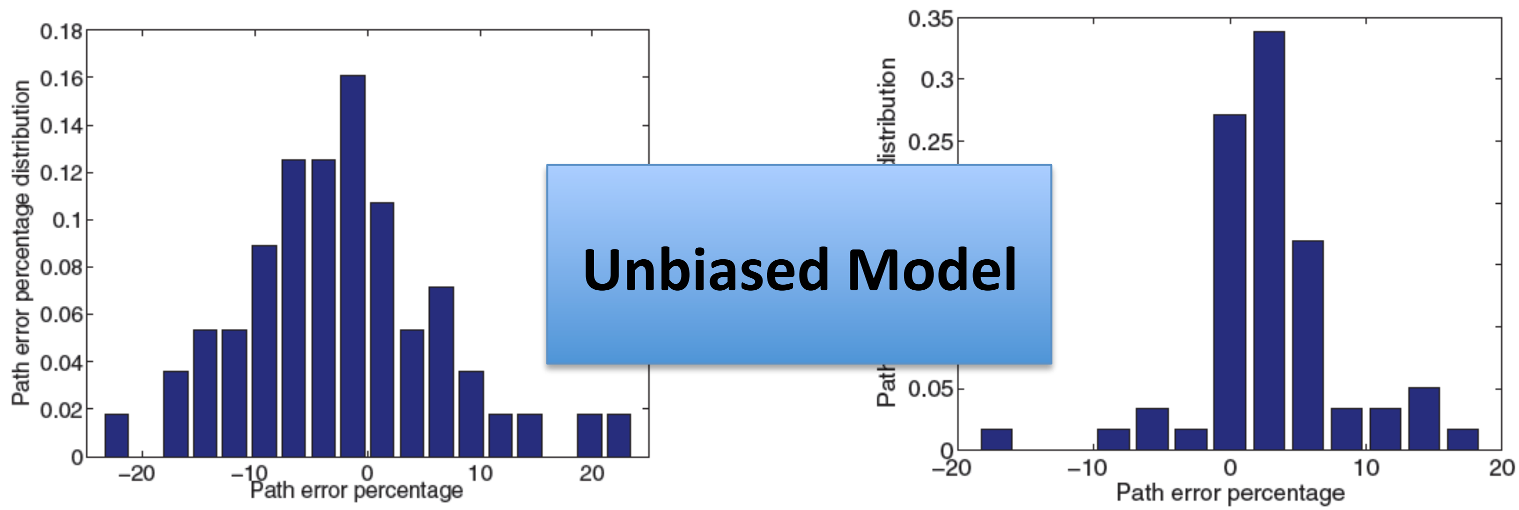


Coverage map

Cars Used in Experiments

Car make	Car model	Car year	Miles driven
Ford	Taurus	2001	135
Toyota	Solara	2001	45
BMW	325i	2006	70
Toyota	Prius	2004	140
Ford	Taurus	2001	136
Ford	Focus	2009	95
Toyota	Corolla	2009	45
Honda	Accord	2003	102
Ford	Contour	1999	22
Honda	Accord	2001	18
Pontiac	Grand Prix	1997	25
Honda	Civic	2002	11
Chevrolet	Prizm	1998	16
Ford	Taurus	2001	10
Mazda	626	2001	9
Toyota	Celica	2001	120
Hyundai	Santa Fe	2008	22

Model Accuracy



- Left: Remove the path but calculating prediction from **the same car on different paths**
- Right: Remove all data from that car and use **hierarchical method** to find an appropriate model
- Both version have normal distribution with a **near zero mean (long term savings)**
- Path error is **reduced with the length** of the travel

Fuel Savings Evaluation

- Experiments on five cars, each does *four round-trips* between 2 landmarks in Urbana-Champaign on *fastest* and *shortest* routes
- GreenGPS predicts fuel efficient route between fastest and shortest **always correctly**

Car Details	Landmarks	GreenGPS Route	Savings %
Honda Accord 2001	H1 to Mall	Shortest	31.4
	H1 to Gym	Shortest	19.7
Ford Taurus 2001	H2 to Restaurant	Shortest	26
Toyota Celica 2001	H2 to Work	Fastest	10.1
Nissan Sentra 2009	H3 to CUPHD	Fastest	8.4
Honda Civic 2002	Grad to Work	Fastest	18.7

Average fuel savings across 5 cars

Lessons Learnt

Experience with GreenGPS

- Data cleaning is important
  - Sometimes GPS would not provide/record data to DashDyno
  - Some cars used metric while others used imperial systems
  - Need to filter complete datasets
- Privacy
  - User activity is traced via GPS
  - User can turns this off but this affects data
- What incentives should be provided to the user?
  - Need to mitigate sparse data
  - Free gas or mutual benefits or more? (e.g., 1 mile -> 1 dollar)

Limitations

- What important limitations do you observe about GreenGPS service?

Limitations

- GreenGPS should eventually be **a real-time service** since traffic condition changes quickly over time. This paper does not explore time dimension!
- Fuel consumption is also a function of **driver's behavior** (e.g., abrupt break and acceleration), which is totally ignored in the paper due to the small sample size of the users

Limitations

- Cars used in the experiments are mostly compact and mid-sized sedans. A **broader range of vehicles** (e.g., SUVs, minivans, light trucks) should also be considered.
- Experiments have been done in a quiet college town. Hence it is not clear if the model will be accurate for **large cities** (where traffic and road conditions can be quite different)

Conclusions

- Demonstrate the use of participatory sensing system to predict fuel consumption of **an arbitrary car on an arbitrary street**
- Show a **6%** on average savings vs **shortest route** and **13%** savings over **fastest route**
- Demonstrate how to generalize sparse samples of high dimensional spaces to develop models of complex non-linear phenomena-> **one size does not fit all!**

Papers

Paper2: Koukoumidis, Emmanouil, Li-Shiuan Peh, and Margaret Rose Martonosi. "Signalguru: leveraging mobile phones for collaborative traffic signal schedule advisory." Proceedings of the 9th international conference on Mobile systems, applications, and services. ACM, 2011 (Best Paper Award).


Cars are big polluters & energy hogs
• Produce 32% of total $C0_2$.
• Consume 28% of USA's total energy.
• 10 times the energy for computing infrastructure.
* Source: US Environmental Protection Agency (http://www.epa.gov/)

Traffic Signals - GLOSA

- Traffic signals:
  - (+) Provide safety.
  - (-) Enforce a stop-and-go movement pattern.
    - Increases fuel consumption by 17%*.
    - Increases CO_2 emissions by 15%*.

* Source: Audi Travolution Project

- Solution: Green Light Optimal Speed Advisory (GLOSA).

w/o GLOSA: 

with GLOSA: 

Need to know the schedule of traffic signals.

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers				


9

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗
Vehicular countdown timers				

Thailand

Design: Damjan Stankovich


Design: Thanva Tivawong

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗
Vehicular countdown timers	$	✓	✓	✗

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗
Vehicular countdown timers	$	✓	✓	✗
Road-side speed message signs	$$	✓	✗	✓

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗
Vehicular countdown timers	$	✓	✓	✗
Road-side speed message signs	$$	✓	✗	✓
Audi Travolution				

Audi Travolution

Signal Schedule Advisory Systems

	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗
Vehicular countdown timers	$	✓	✓	✗
Road-side speed message signs	$$	✓	✗	✓
Audi Travolution	$$$	✓	✓	✓

Signal Schedule Advisory Systems

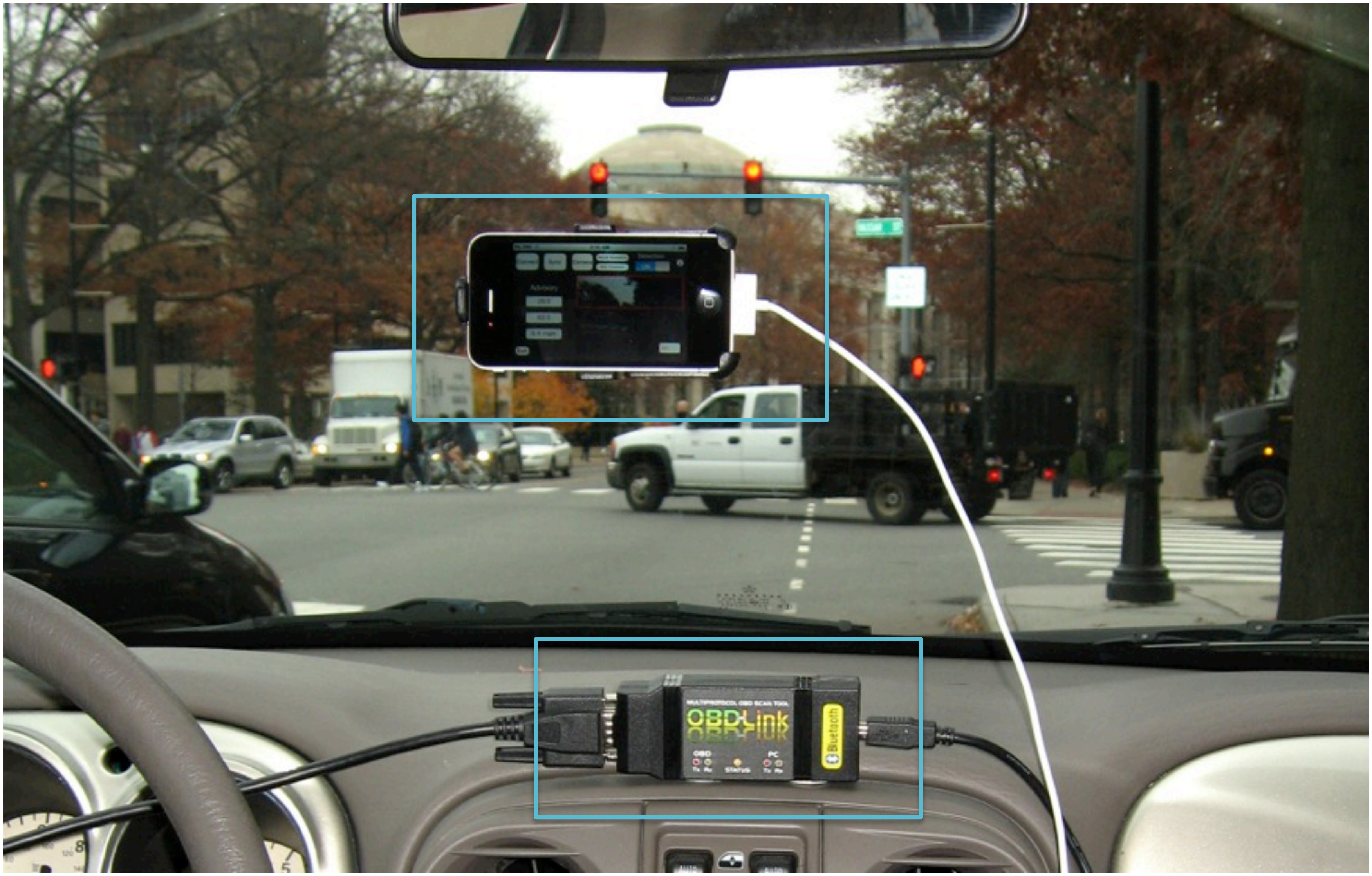
	Infrastructure Cost	Predictability	Continuous Advisory	Advance Advisory
Pedestrian countdown timers	$	✗	✓	✗
Vehicular countdown timers	$	✓	✓	✗
Road-side speed message signs	$$	✓	✗	✓
Audi Travolution	$$$	✓	✓	✓
SignalGuru	None	✓	✓	✓

Share your thoughts

- How would you design such a speed advisory system using smartphones in cars?

- What are the key challenges you can envision?

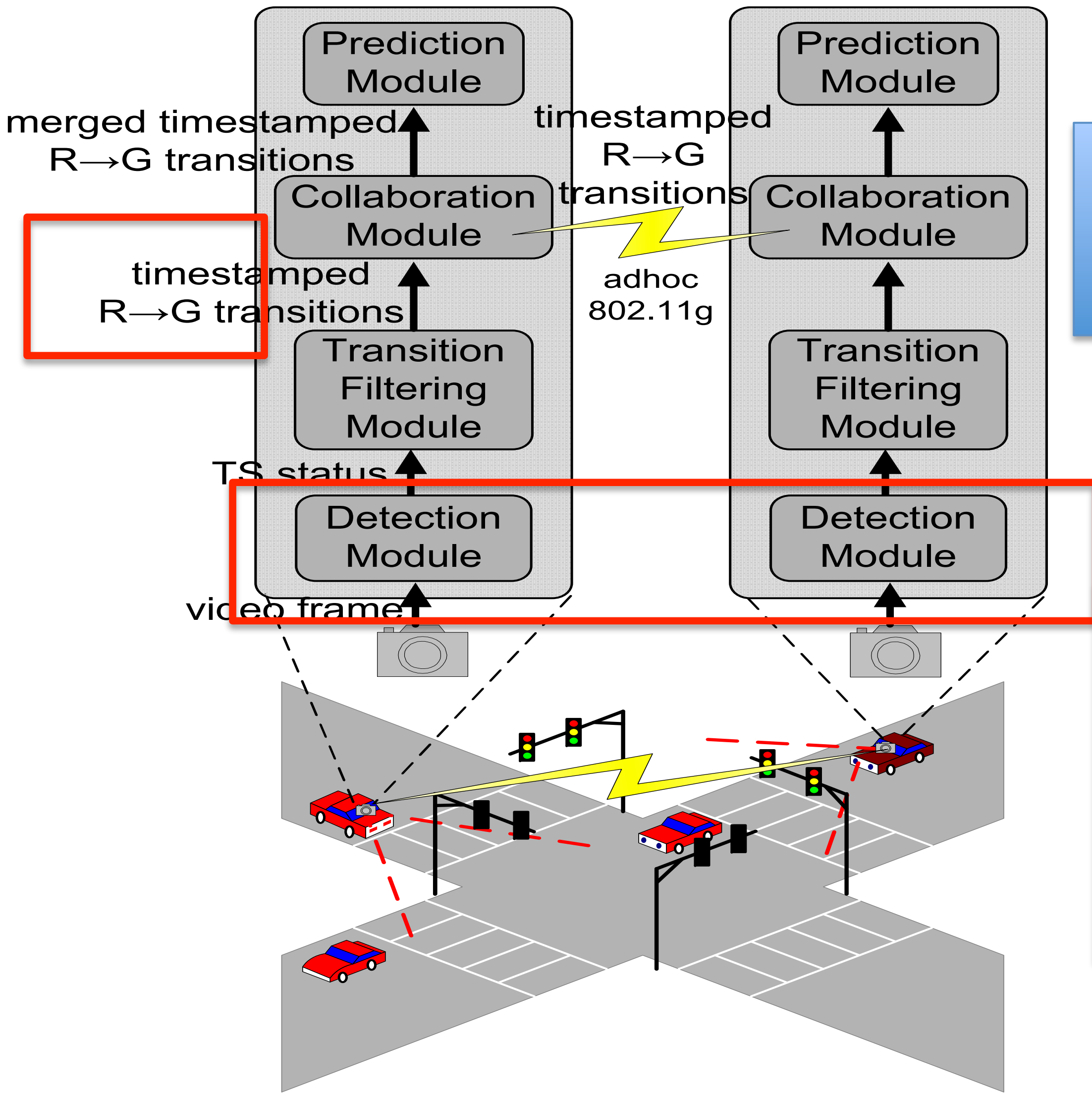
SignalGuru Approach



Challenges

- Commodity cameras. Low video resolution:
  - iPhone 4: 1280 × 720 pixels.
  - iPhone 3GS: 640 × 480 pixels
- Limited processing power.
  - But need high video processing frequency.
- Uncontrolled environment.
- Traffic-adaptive traffic signals.
  - Singapore traffic signal system using inductive loop detectors
- Non-challenge: Energy.

SignalGuru Architecture

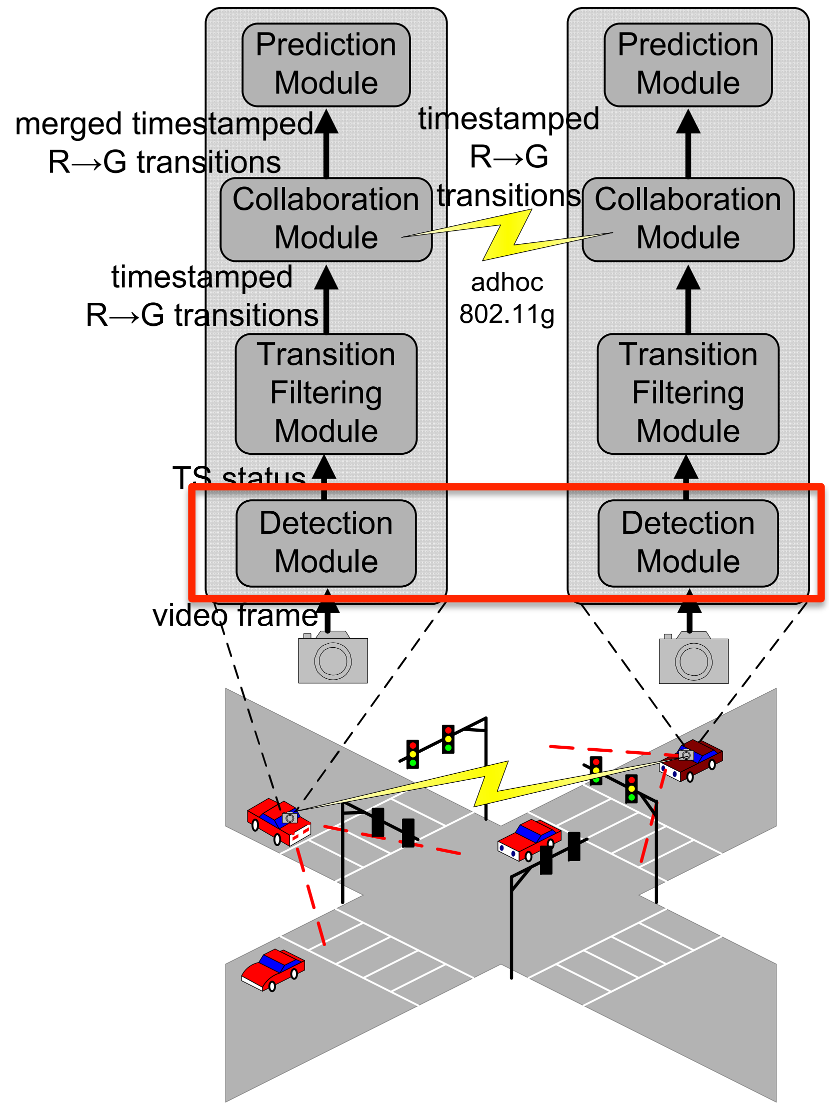


Q: Why detect R->G transitions (instead of G->Y, Y->R)?

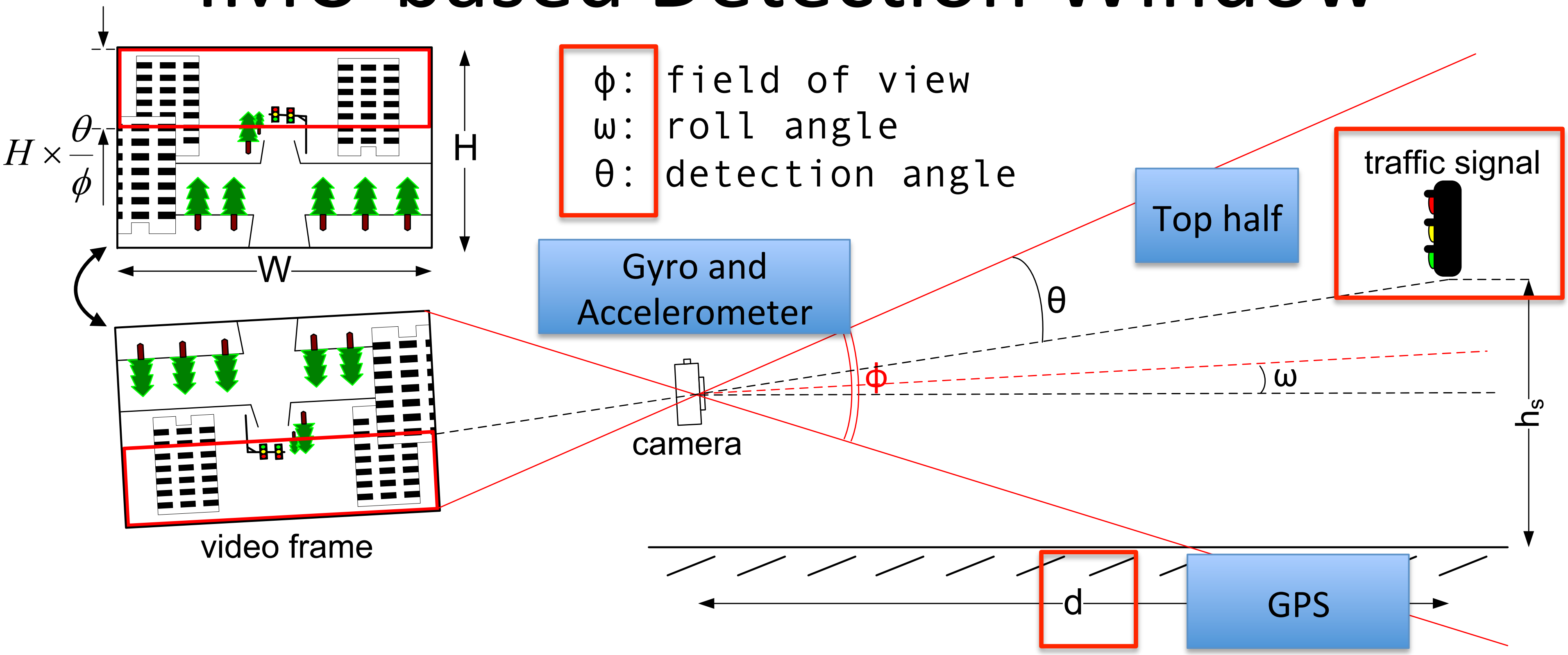
A: Cars stop at red lights and have a higher chance to capture R->G transition

Detection Module

- Detects signal current status (Red/Yellow/Green) from video.
- Activated based on its GPS location (<50m) to the intersection
- Process a new frame every 2sec.
- Main features:
  – Bright color.
  – Shape (e.g., round, arrow).
  – Within black housing.
  – Location in frame (detection window).



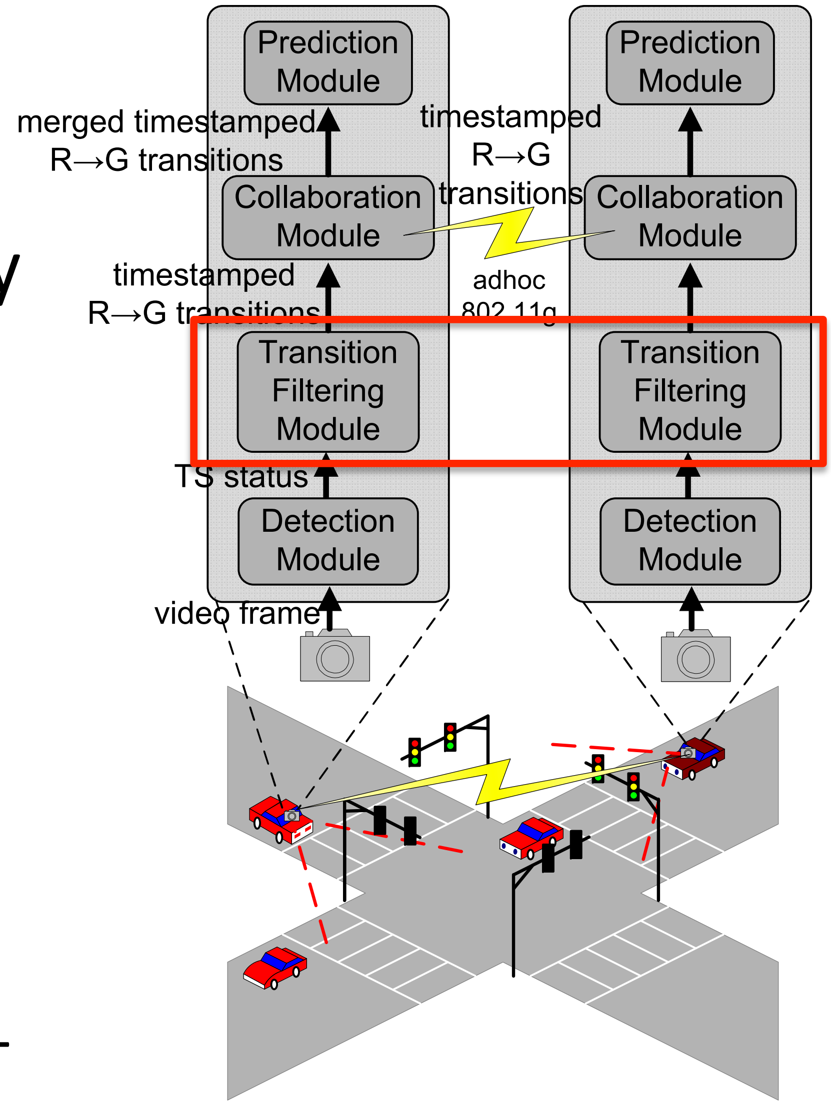
IMU-based Detection Window



- Roll angle ω is calculated by gyro and accelerometer (inertial measurement unit-IMU) data.
- Process only area within detection window.
- Cuts off half of the image:
  - Processing time reduced by **41%**.
  - Misdetection rate reduced by **49%.**

Transition Filtering Module

- The raw detection of traffic signals and their color transitions (R->G) given by the detection module is fairly noisy.
  - Many things can be misclassified as traffic signals (e.g., signs on bus, cars, etc.)
- Q: How could we filter out noise (i.e., avoid false positives) in the transition detection?
  - False positives pollute the prediction scheme (e.g., R->R->G->R->R)



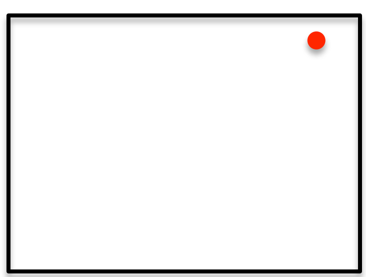
Transition Filtering Module

- Filters out false positives.
- Low Pass Filter:

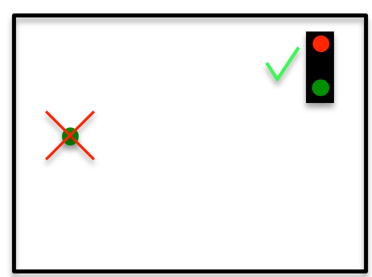
  …→R→R→R→~~G~~→R→R→…

  …→G→G→G→~~R~~→G→G→…

- Colocation filter.
  - Red and Green bulbs should be colocated.

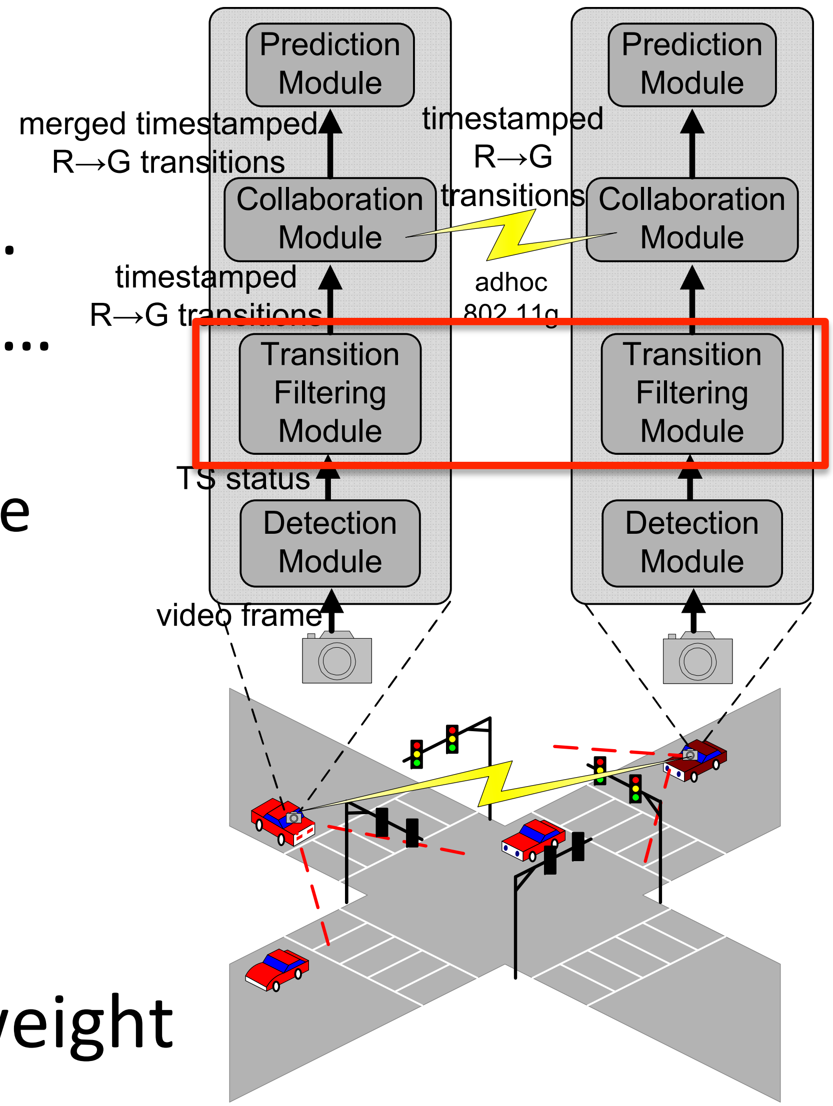


frame i



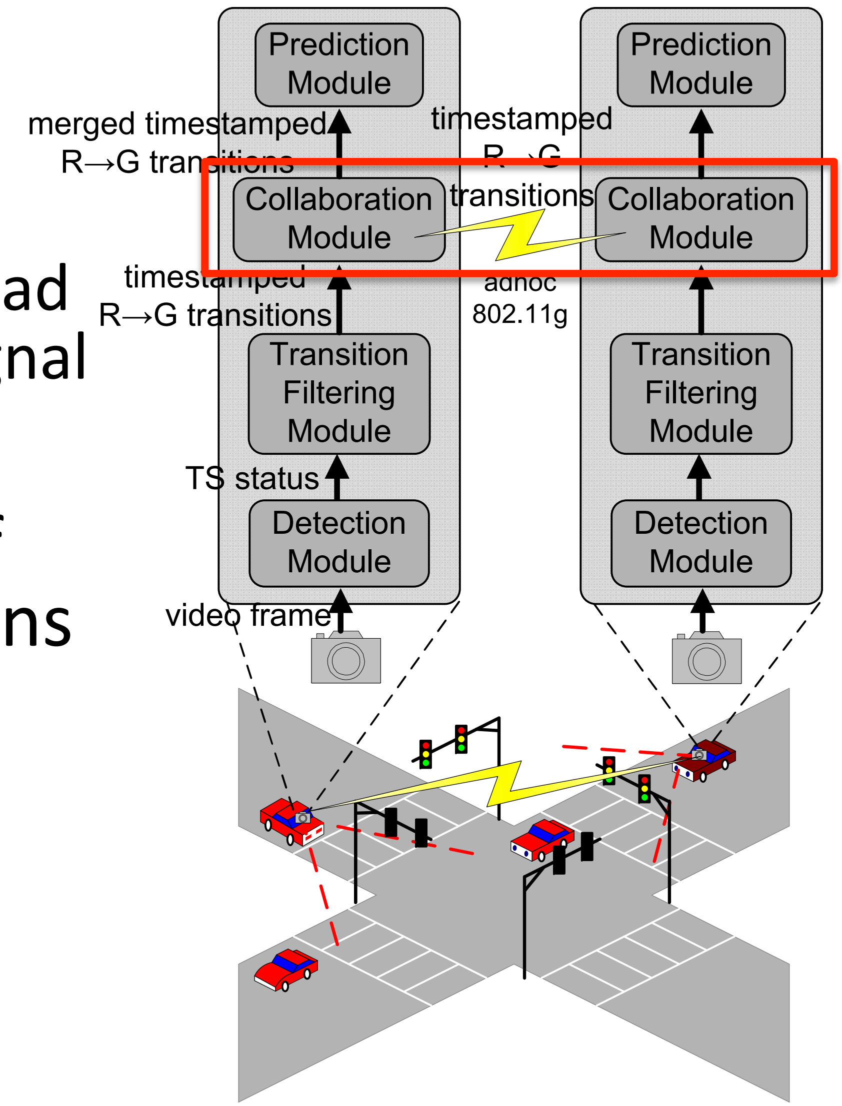
frame i+1

- Filters compensate for lightweight but noisy detection module.



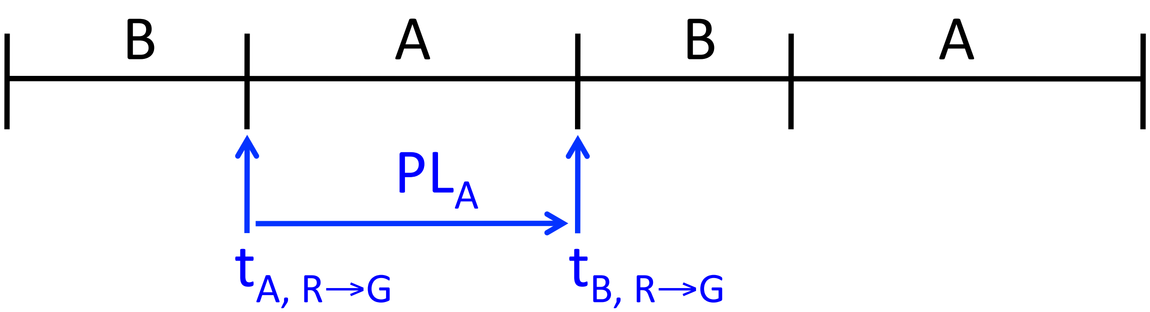
Collaboration Module

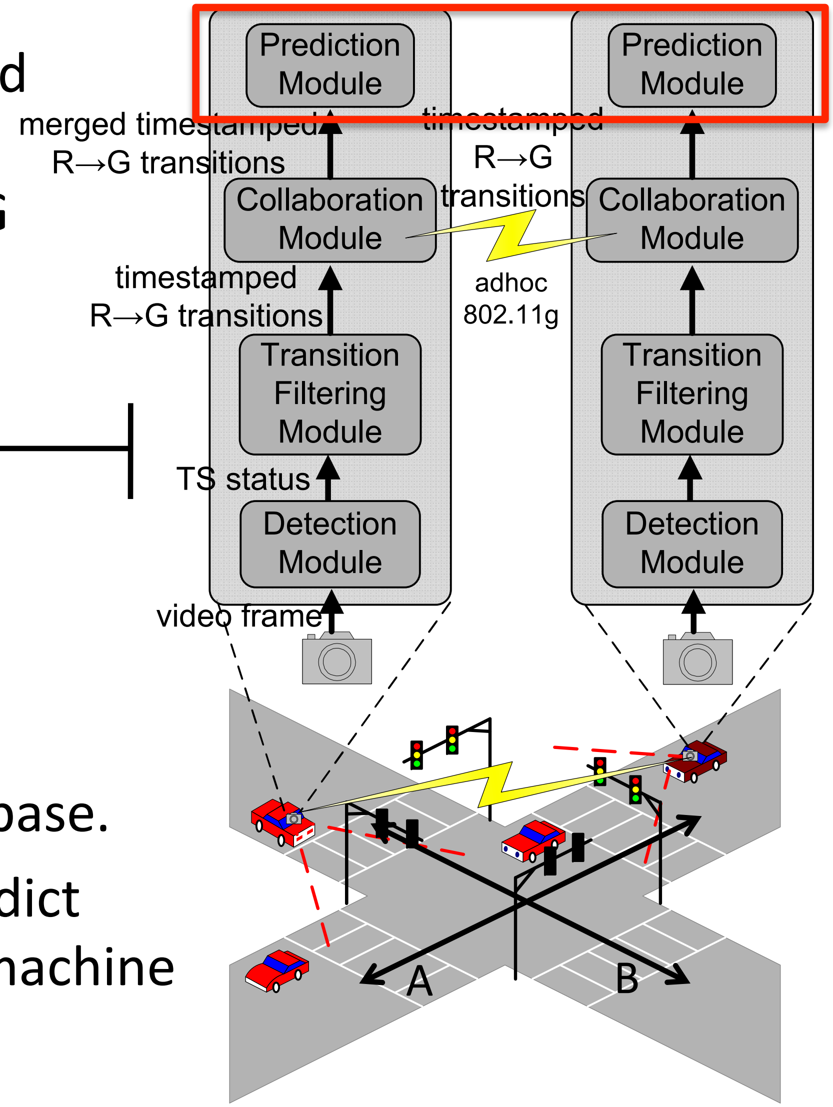
- Why?
  – A node is limited in its vision
  – A node needs information ahead of time before it "sees" the signal
- No central server.
- Real-time adhoc exchange of time-stamped R→G transitions (last 5 cycles)
- Collaboration:
  – Improves mutual information.
  – Enables advance advisory.



Prediction Module

- Add to timestamp of phase A's detected R→G transition ($t_{A,\, R \to G}$) the predicted Phase Length of A (PL_A) to predict R→G transition for B ($t_{B,\, R \to G}$).





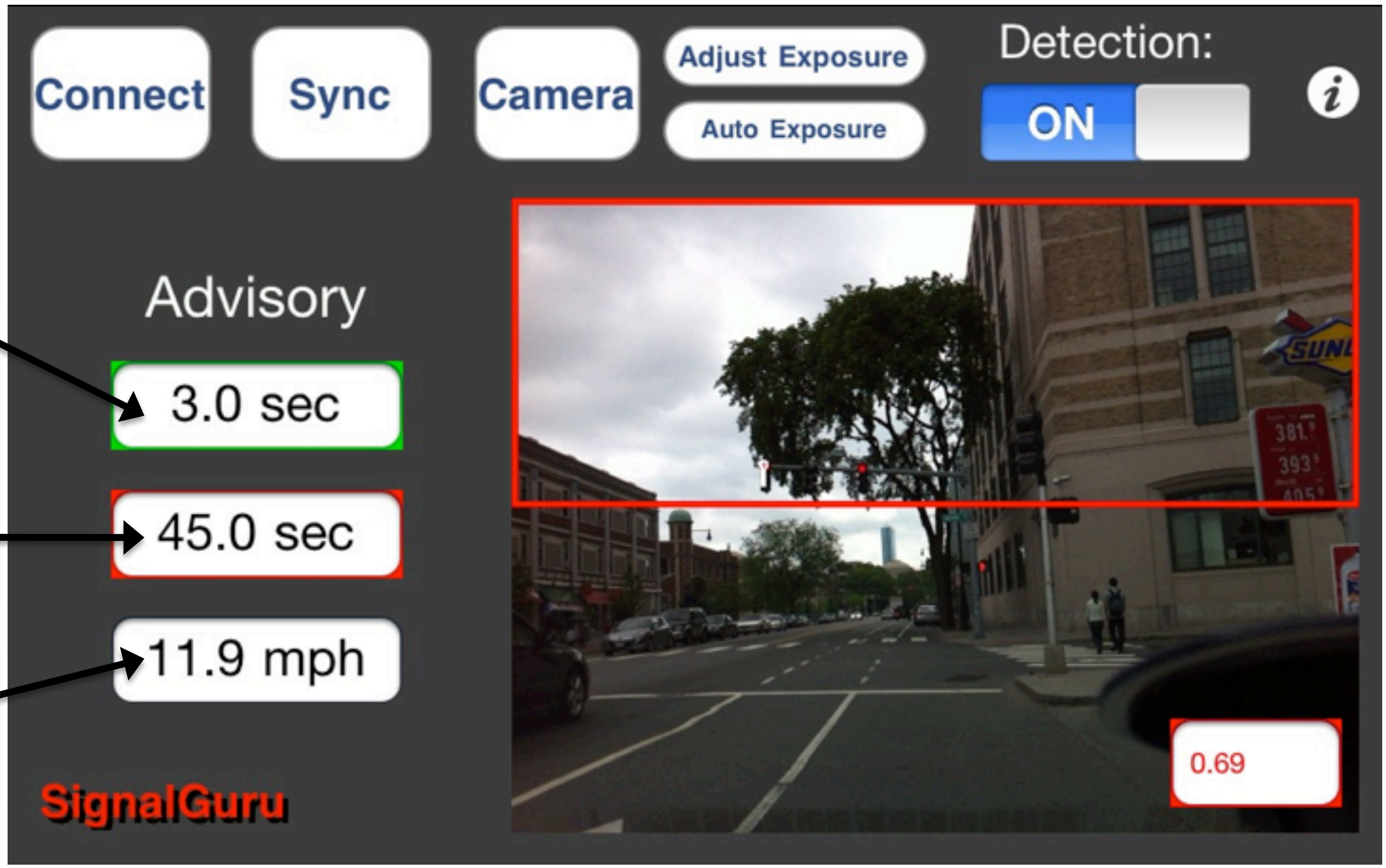
- Phase Length prediction:
  - **Pre-timed signals**: Look-up in database.
  - **Traffic-adaptive traffic signals**: Predict based on history of settings using machine learning (SVR).

SignalGuru/GLOSA iPhone Application

Residual amount of time in sec until the traffic signal turns green.

Residual amount of time in sec until the traffic signal turns red again.

Recommended GLOSA speed.

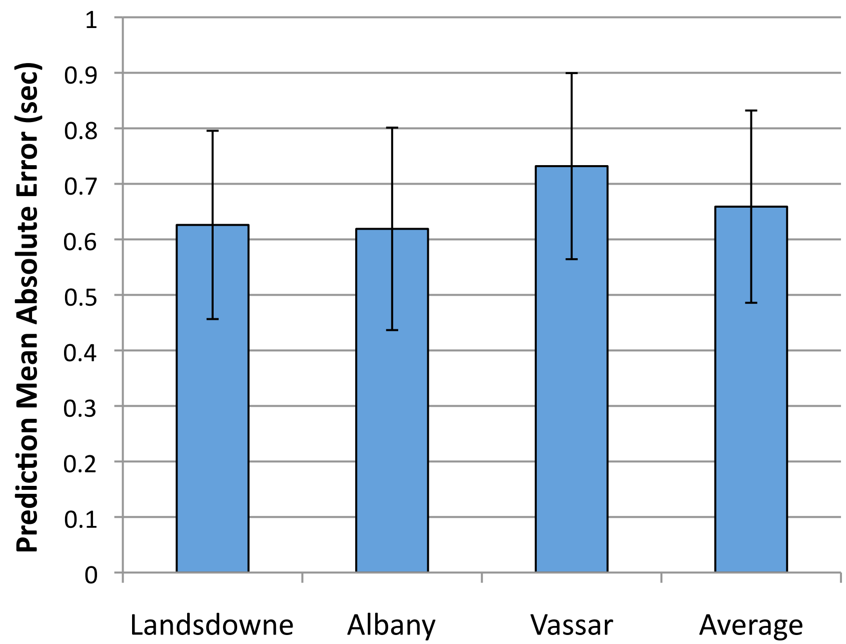


SignalGuru Evaluation

SignalGuru Evaluation

Cambridge: Prediction Accuracy Evaluation

Cambridge (MA, USA)



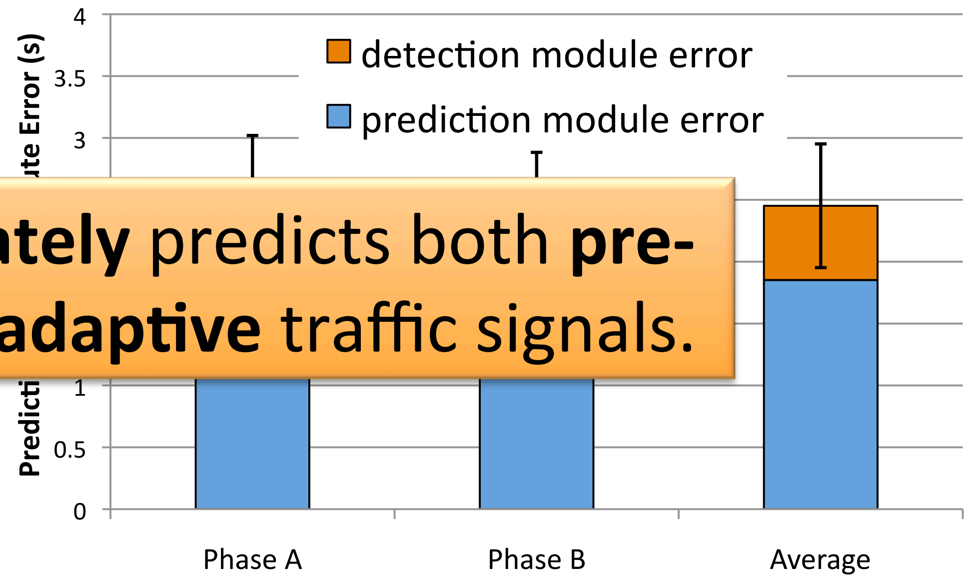
- Pre-fixed traffic signals
- Experiment on Massachusetts Ave:
  - 5 cars over 3 hours.
  - 1 pedestrian node serves as the relay nodes

$\text{Error}_{\text{Average}}$ = 0.66sec (2%).

The error was solely caused by the detection phase of SignalGuru

Singapore: Prediction Accuracy Evaluation

Singapore

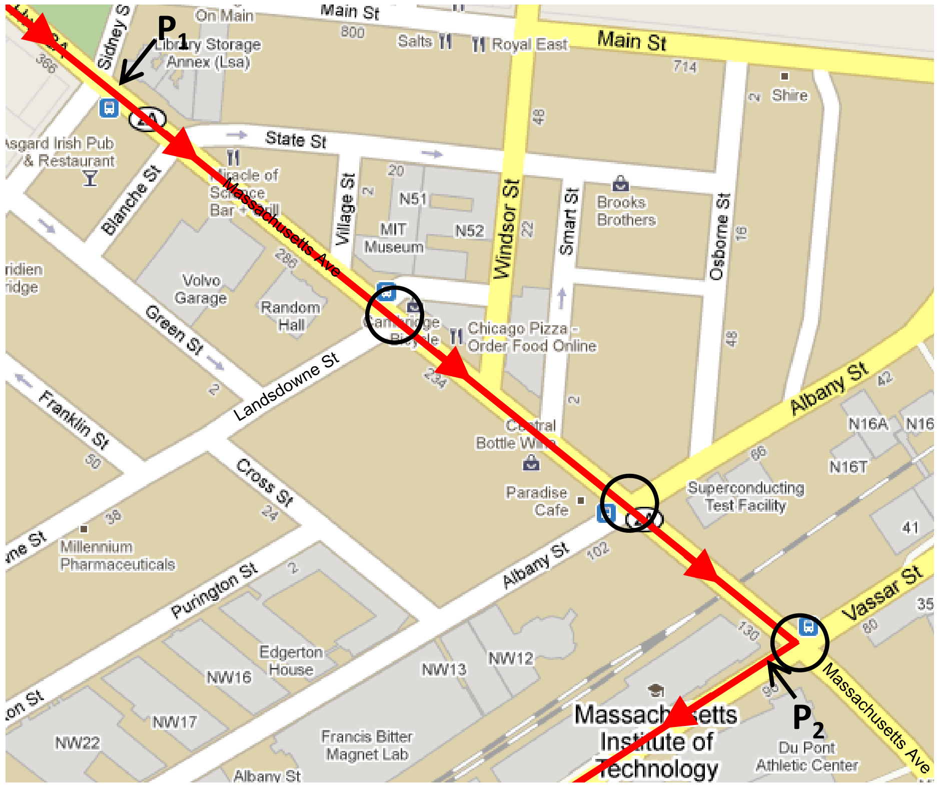


SignalGuru **accurately** predicts both **pre-timed** and **traffic adaptive** traffic signals.

- Traffic-adaptive traffic signals
- Experiment in downtown:
  - 8 cars over 30 min.
  - 2 signals, 26 transitions.

- **$\text{Error}_{\text{Average}}$ = 2.45sec (3.8%).**
  - **$\text{Error}_{\text{Transition Detection}}$ = 0.60sec (0.9%).**
  - **$\text{Error}_{\text{Phase Length Prediction}}$ = 1.85sec (2.9%).**

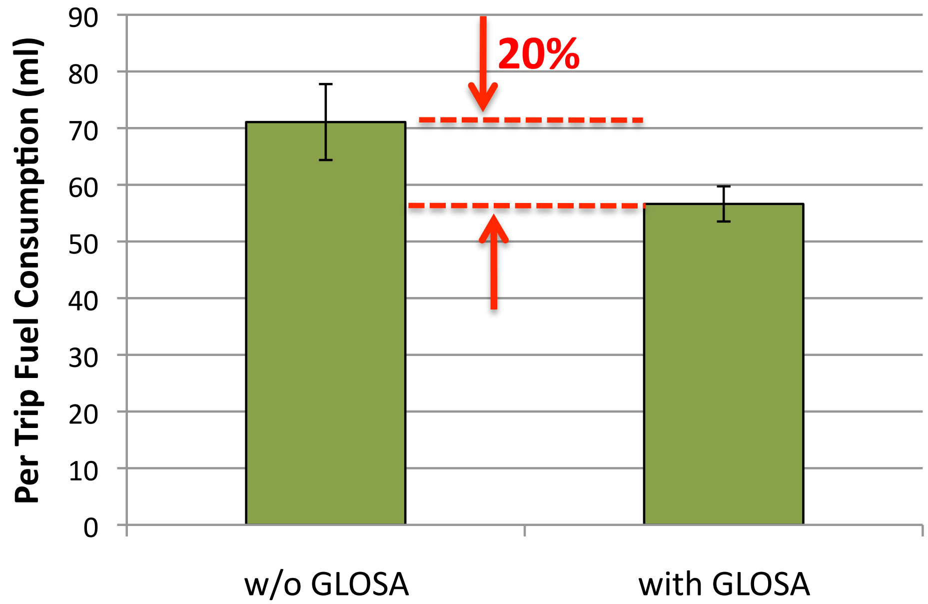
Evaluation: GLOSA Fuel Savings



- Trip: P_1 to P_2 through 3 signalized intersections.
- 20 trips to measure fuel consumption.


2.4L Chrysler
PT Cruiser '01
SignalGuru/GLOSA-
enabled iPhone
Scan Tool
OBD-LINK device
OBDWiz software (IMAP)

Evaluation: GLOSA Fuel Savings



- Without GLOSA driver made on average 1.7/3 stops.

Average fuel consumption reduced by 20.3%.
Mpg improved by 24.5% (16.1->20.1 mpg).

Limitations

- What limitations do you observe about Signal Guru?

Limitations

- The paper did not discuss the issue of user's adaptability to this technology.
  - It might change user's driving behavior
  - It might affect the car that is behind you

- It does need sufficient cars with the SignalGuru app to participate and share their detected signal transition traces

Limitations

- The prototype has only been tested on limited number of roads in two cities
  - Large city and busy roads may introduce more noise
- The privacy issue has not been discussed
  - People are sharing their GPS traces with each other

Other related applications

- Traffic Signal-Adaptive Navigation
  - Suggest better route to avoid long-waiting traffic signals
- Red Light Duration Advisory
  - Driver can switch off engine to save fuel and decrease environment impact during long wait red lights
- Imminent Red Light Advisory
  - Let the driver know the residual amount of time before the signal turns red to avoid unnecessary speeding
- Red Light Violation Advisory
  - Warns the driver when they are about to violet red lights using the signals detected and accelerometers on the phone

Conclusions

- With selective accelerometer- and gyro-based image detection and filtering near real-time, the accurate image processing can be supported.
- SignalGuru predicts accurately both pre-timed and traffic-adaptive traffic signals.
- SignalGuru-based GLOSA helps save 20% on gas.