Large Sample Ecodriving Experiment
Preliminary Results

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Summary

• A study of 3 driver feedback screens
  – One-month periods
  – Average 5.8% improvement
  – Range 4-7% improvement by screen type
The HMI Feedback Loop

1. Context
2. HMI points of influence

A Broken Feedback Loop
The HMI Feedback Loop

1. Context
2. HMI points of influence

\[ h_0: \text{Feedback} \rightarrow \text{MPG improvement} \]
Past PH&EV Center Projects With Eco-driving Feedback

1. 2009 Scangauge field test (~6 drivers, 6 months).

2. 2008-9 Prius field test with V2Green Gridpoint website (~60 households, 1 month each).

3. 2009-10 UC Davis custom HMI (~40 drivers, 1 month each)
Notes on Methodology

• Experimental design:
  – Natural driving
  – Avoid social biases
  – Randomization
  – Supplement measurement with surveys and interviews
  – Individual specificity
Notes on Methodology

• Analysis
  – Model-based analysis
    • Presumes trip-patterns are constant – looks for changes within trip types
    • Mixed-effects models makes individual-level estimates using trips as repeated observations
    • Predictive model trained on baseline driving predicts neutral outcome in treatment phase based on trip-specific factors.
      – Prediction residual = behavior change + error.
      – Primary model factors are distance, drive-cycle, weather (temperature), vehicle
Ecodrive I-80 Study

- ORNL/DOE Study of 150 drivers along the San Francisco-Reno I-80 Corridor ending in early 2013.
  - Internal Controls based on 1 month off/on design
  - Experimental Comparison of three feedback metrics developed from NHTSA*
  - Currently 72 drivers, 95,000 miles in 3000 hours of driving.

<table>
<thead>
<tr>
<th>Direct Fuel Economy Value</th>
<th><img src="image" alt="MPG" /></th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbolic “Leaf” representation</td>
<td><img src="image" alt="Leaf" /></td>
</tr>
<tr>
<td>Acceleration level</td>
<td><img src="image" alt="Acceleration" /></td>
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</tbody>
</table>
Trip-types

Drive-cycle cluster descriptions (based on k-means clustering)

Average Distance and Speed

Average gp100m Fuel Consumption

- speed_mean
- miles
- gp100m
Results by Drive-cycle

Increasing Distance and Average Speed
Results by Interface Design

Average Savings (%)
- 4.2
- 6.7
- 6.8

Average Reduction in Fuel Consumption (Gallons Saved per Trip)
Conclusions

*This is a 50% dataset*

- Feedback has a significant influence on consumption
  1. Large variation by trip-type - low efficiency trips have higher effects
  2. Moderate variation by interface style (50% improvement between interfaces)
  3. Average reduction of 5.8% overall in 38k miles of driving with the interface on.
Future Directions

• Investigating changes over time, and mechanisms to keep drivers engaged

• Collaborations with municipal agencies (carbon reduction strategies)

• Inclusion of behavioral strategies into state/ federal policy
Thank you.
Questions?

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Fuel Economy in Context

1. Context
2. HMI points of influence
3. Other Model Factors

**On-Road MPG**

**Legislation & Policy**
- Speed Limits
- Enforcement
- CAFE

**Purchase Decisions**
- Interest in MPG
- Advertising
- Fuel Price (*)

**Land-use**
- Drive Cycles
- Roadway Design
- Signal timing

**Technology**
- Drivetrain Efficiency
- Real-time Optimization

**Driving Style**
- Education
- Information
- Traffic Pressure (*)
- Savings Goals

(*) Not currently in the driving model
Applied Behavioral Model (TPB, EMGDB)

Fuel Economy

Interface

Goals

Attitudes

Social Norms

Personality

Perceived Control

Ability to Influence Outcome

Behavior

Fuel Economy

Interface

Goals

Attitudes

Social Norms

Personality

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Ability to Influence Outcome

Behavior
Upcoming MTC ‘Smart Driving’ Study

• MTC-funded study of 250 Bay Area drivers for 1 year.
  – Safety + Efficiency
  – Real-time dashboard extensions using Android phones
  – 4 distinct feedback designs to be tested
  – Remote data collection
Predictive Model Code

- Using R
- Packages: nlme, ggplot2
- Estimated a Random effects model using the person-vehicle unit as the grouping factor

```r
p0 <- clustData[clustData$phase=='p0' & clustData$miles > 0.25 & clustData$grade < 1 & clustData$grade >= 1,]
p1 <- clustData[clustData$phase=='p1' & clustData$miles > 0.25 & clustData$grade < 1 & clustData$grade >= 1,]
lme0 <- lme(gp100m ~ abs(72-temp_est)+as.factor(trip) + grade, data = p0, random=-1|as.factor(combo))
summary(lme0)
p1$gp100m_p <- predict(lme0, p1)
p1$gp100m_r <- p1$gp100m-p1$gp100m_p #predicted savings (negative residual = saved gp100m)
summary(p1$gp100m_r)
```
The First Real-Time Feedback Device - 1915

Early mechanical MPG indicator designed for vehicle maintenance and fuel quality concerns.

For example, the driver of a motor car can tell by a glance at an indicator on the dash whether his car is operating at its normal rate of eighteen miles per gallon of gasolene, or at only fifteen miles per gallon, which latter reading would instantly tell him that some condition of operation required attention. For instance his last supply of gasolene might have been of a poor grade, the carbureter might require adjustment, the valves need grinding or some other part require attention that would cause a lowering of the fuel efficiency of the engine.