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# The Role of Driver Attributes in Understanding Driver Behavior

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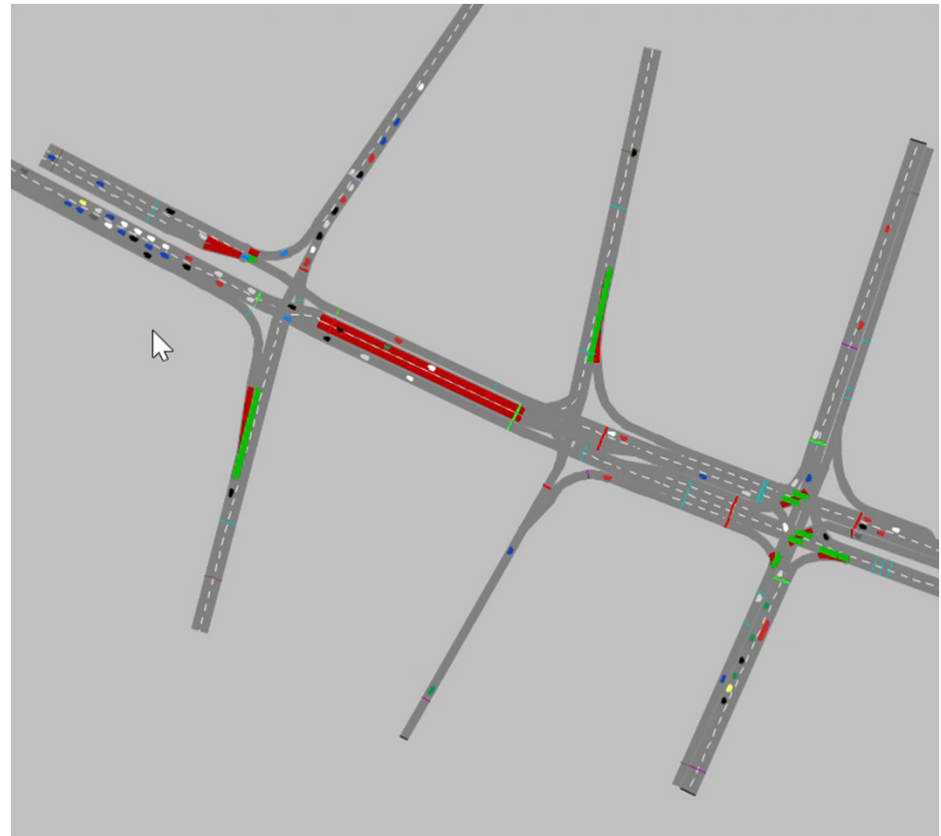
# Outline

- Motivation
- Data
- Research Question 1
  - Methods
  - Results
  - Summary
- Research Question 2
  - Methods
  - Results
  - Summary
- Conclusions

This research focuses on the application of the SHRP2 NDS **dataset to improve transportation operations decision support systems.**

# Motivation

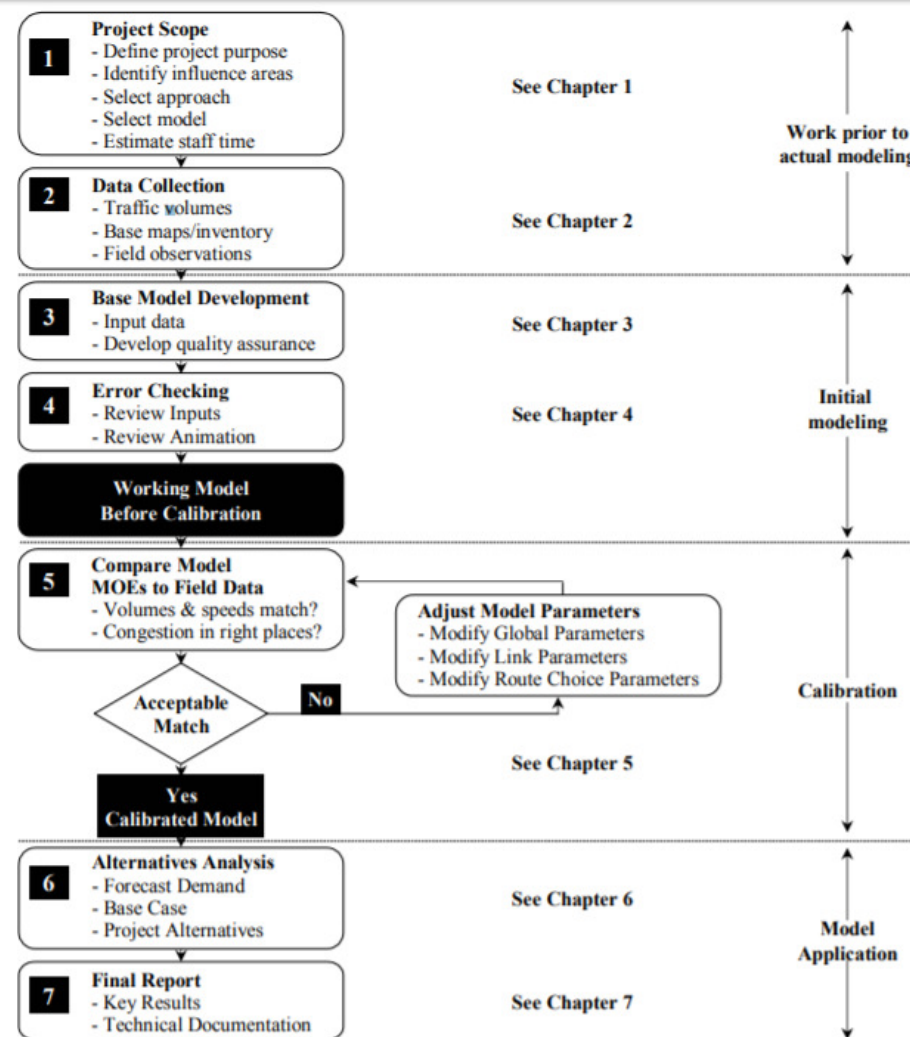
- Decision making tool
- Comprised of sub-models
- Car-following models: sub-second level acceleration behavior
- Traditional application: benefits estimation



# Motivation

Required data:

- Demand
- Geometric
- Control
- Driver behavior



Developed by the FHWA Traffic Analysis Tools Team and later adapted from *Advanced Corsim Training Manual*, Short, Elliott, Hendrickson, Inc., Minnesota Department of Transportation, September 2003.

Motivation

Behavioral data

Control data

Geometric data

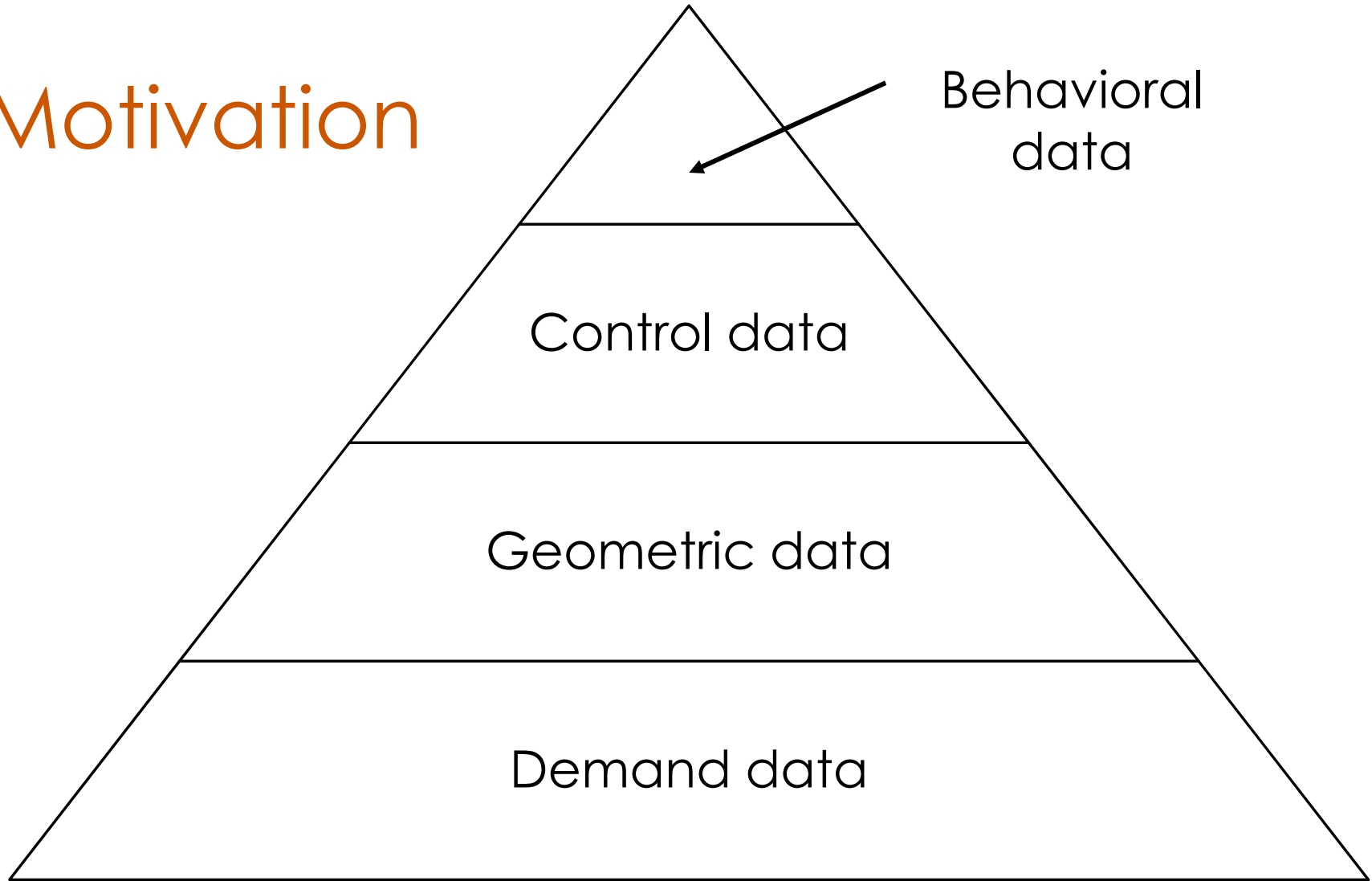
Demand data

Motivation

Data

Research Questions

Conclusions



# Motivation

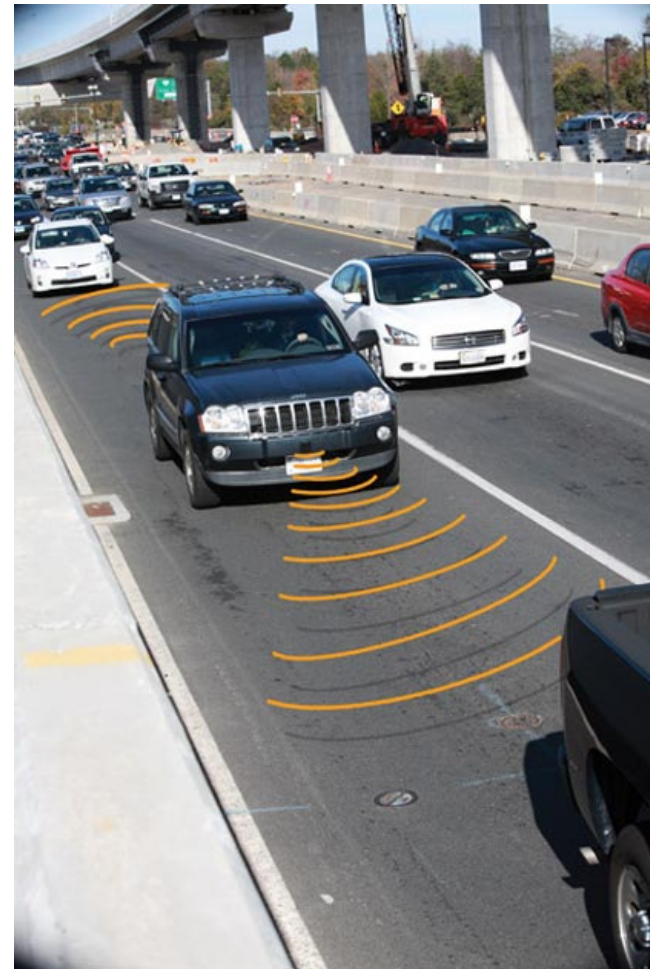
- Emerging applications of microsimulation results:
  - Modeling mixed-fleet vehicle interactions
  - Emissions modeling (MOVES)
  - Risk-based crash modeling (SSAM)

Accurately calibrated car-following  
models VERY important towards robust  
results of these analyses

# Motivation

## Two primary obstacles

- Complex optimization problem
- Availability of appropriate data
  - Loop detector
  - Aerial
  - IRV (SHRP 2)



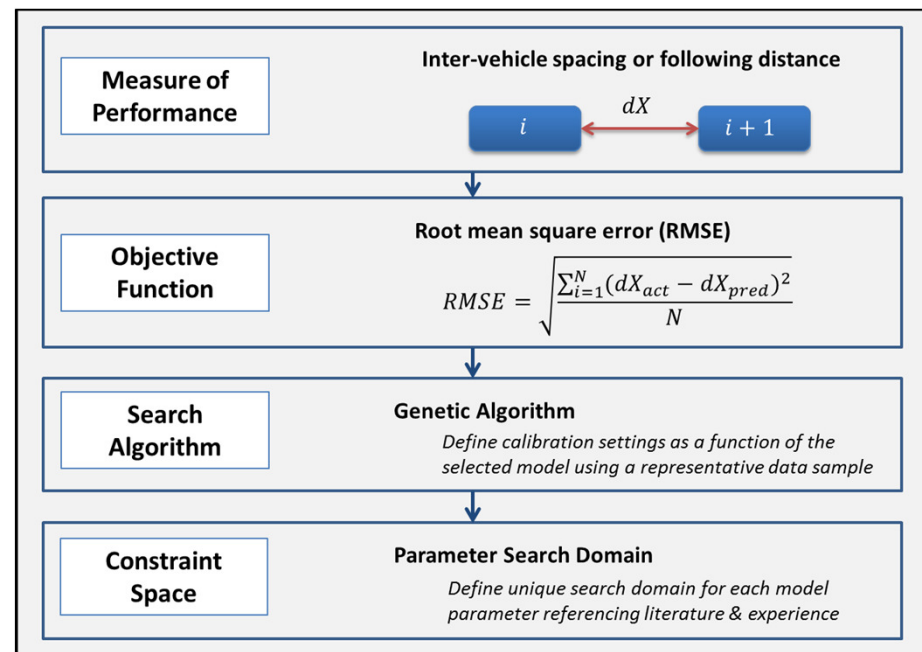
# Data

- Wyoming Implementation Assistance Program
- Filter data: clear weather on freeways
- 691 trip sample
- 82 drivers



# Data – Calibration Method

- Identify three CFMs
  - Safety distance CFM
  - Psychophysical CFM
  - Social force CFM
- Identify segments of CF
- Calibrate each trip
  - **Calibrated parameter sets used as surrogates for driver behavior**



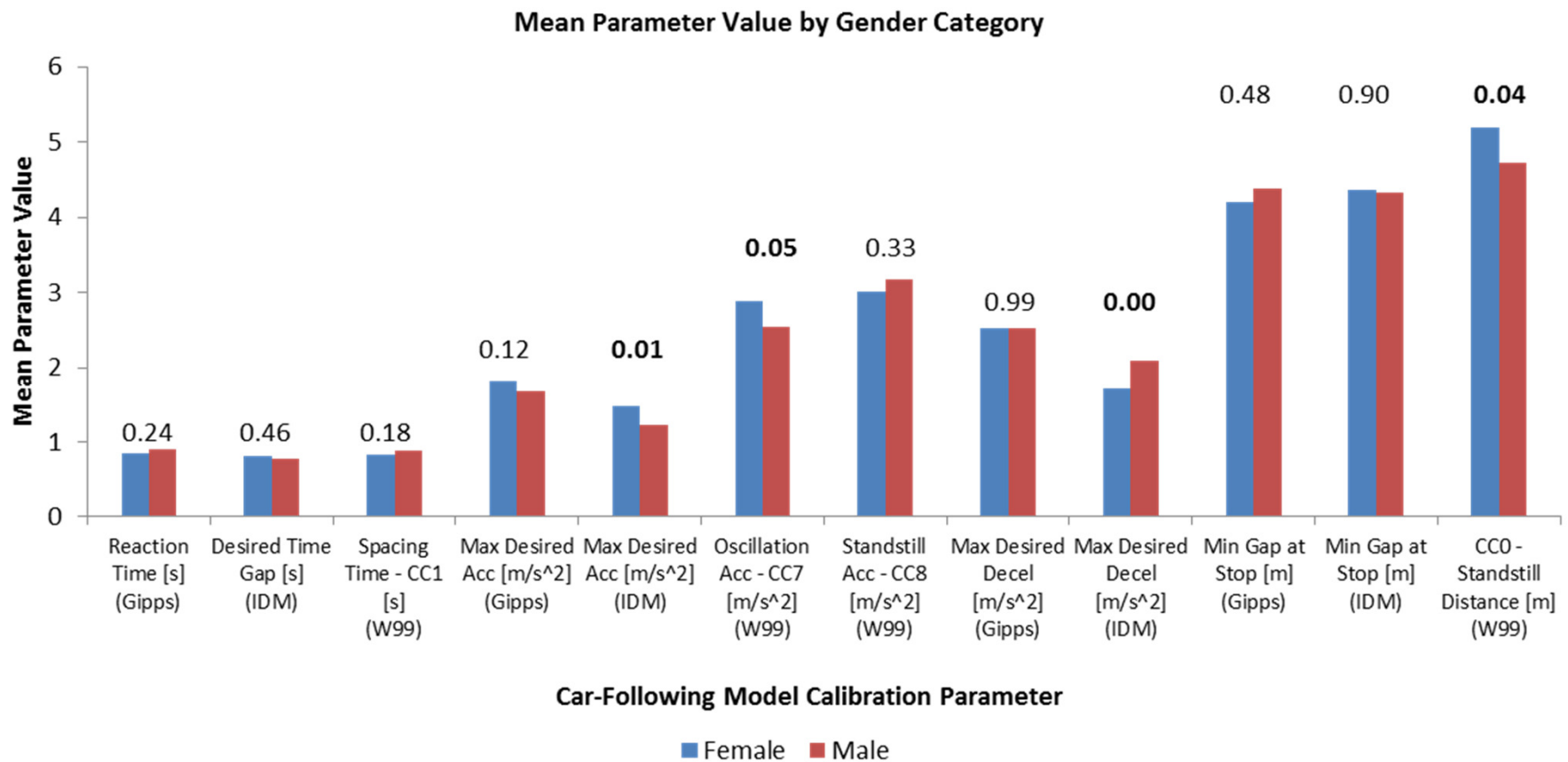
# Research Questions

- Q1: Do different hypothesized groups of drivers exhibit statistically significant differences in driving behavior?
- Q2: Do different subgroups of drivers behave sufficiently similarly to be considered one homogenous group of drivers?

# Q1 – Methods

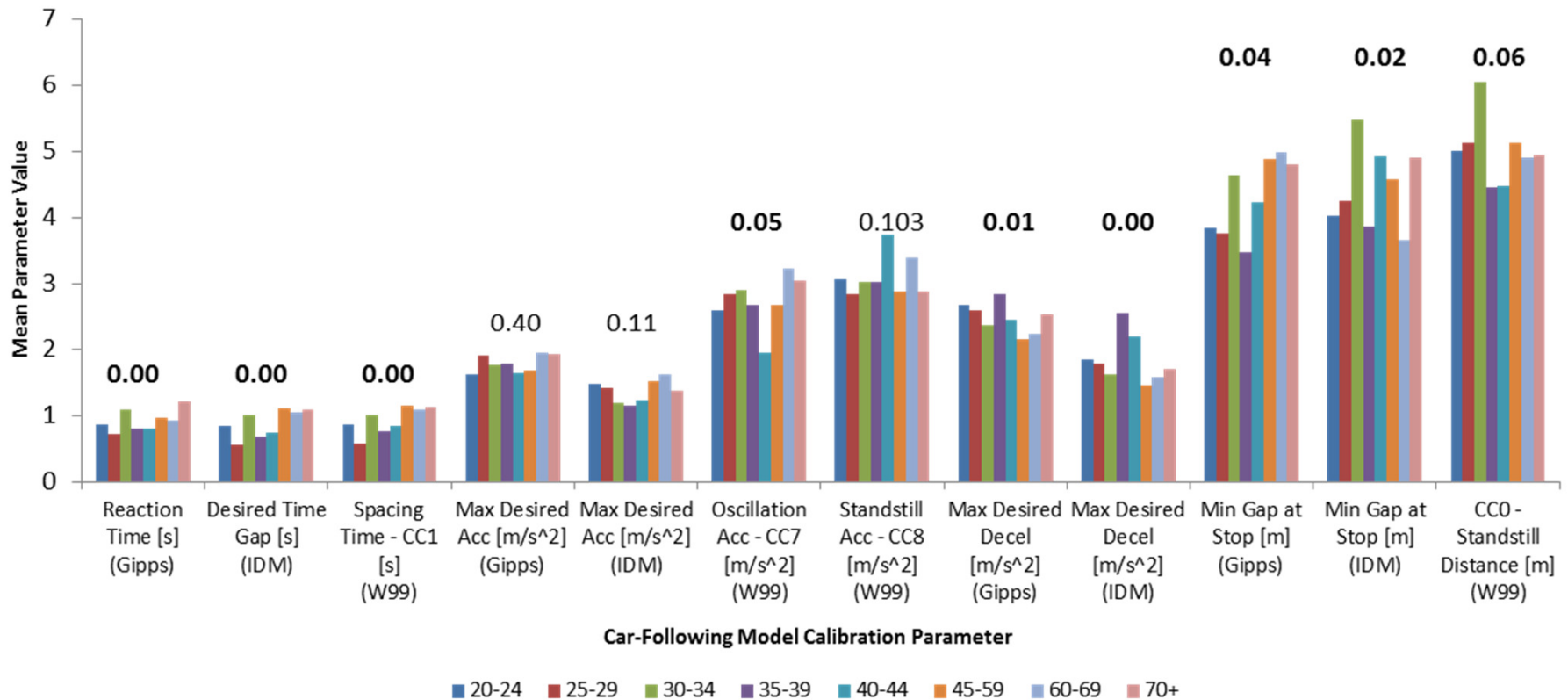
- Identify set of critical driver attributes:
  - Gender
  - Age
  - Income
  - Miles driven last year
- Divide each attribute into subgroups
- ANOVA test

# Q1 – Results



# Q1 – Results

Mean Parameter Value by Age Category



## Q1 – Summary

- Significant differences in driver behavior between hypothesized subgroups:
  - Miles driven last year
  - Age
  - Income
- Differences in behavior attributable to gender not statistically significant

# Research Questions

- Q1: Do different hypothesized groups of drivers exhibit statistically significant differences in driving behavior?
- Q2: Do different subgroups of drivers behave sufficiently similarly to be considered one homogenous group of drivers?

## Q2 - Methods

### Clustering

- Expectation Maximization algorithm

### Attribute Selection

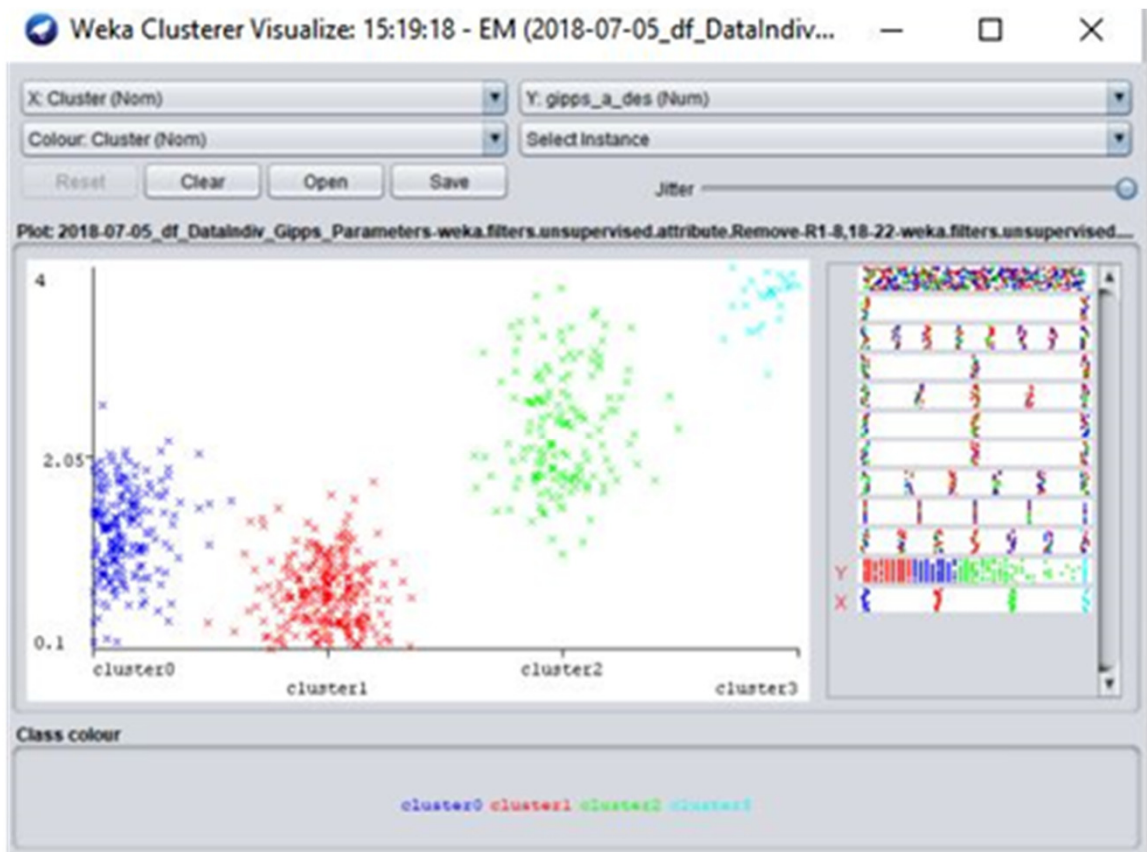
- CfsSubsetEval algorithm

### Classification

- ZeroR algorithm
- OneR algorithm
- PART Decision Rules algorithm
- J48 Decision Tree algorithm



## Q2 - Methods



Assign each trip to a cluster using calibrated parameters

Classify each trip into a cluster ID using driver attributes

## Q2 - Results

- Most commonly selected attributes
  - Age
  - Income
  - Marital status
- Least commonly selected attributes
  - Gender
  - Work status
  - Living status

## Q2 – Desired Velocity Results

<b>Model Calibration Parameter</b>	<b>Optimal Clusters</b>	<b>Baseline Accuracy Rate</b>	<b>Best Model Accuracy Rate</b>	<b>% Difference (from baseline)</b>	<b>Best Model</b>
<b>Gipps</b>	5	229	360	57%	J48
<b>IDM</b>	5	194	332	71%	J48
<b>W99</b>	4	288	412	43%	PART

## Q2 – Standstill Distance Results

Model Calibration Parameter	Optimal Clusters	Baseline Accuracy Rate	Best Model Accuracy Rate	% Difference (from baseline)	Best Model
Gipps	6	172	182	6%	PART
IDM	4	316	311	-2%	PART
W99	6	163	201	23%	OneR

## Q2 – Summary

- Evidence that some drivers behave sufficiently similar to one another—and sufficiently different from drivers belonging to a different group—to be considered a homogenous group of drivers
- Driver specific attributes can be carefully utilized to classify drivers into homogenous driver groups

# Conclusions

- A modeler may not need to model every single driver differently to properly calibrate the driving behavior component of microsimulation.
- Modelers may be able to improve the realism of their models, by accounting for heterogeneity, without significantly increasing the complexity of their effort.

# Future Work

- Census-level demographics data can be used to divide the driving population into homogenous groups of driving behavior.
- Future work:
  - Calibrate each homogenous group of drivers.
  - Develop new framework for the calibration of a microsimulation network using the proportion of expected drivers belonging to a homogenous driver group.

# Thank you! Any Questions?

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