

# Traffic Flow Theory in the Era of Autonomous Vehicles

**Michael Zhang**

**University of California Davis**

**A Presentation at**

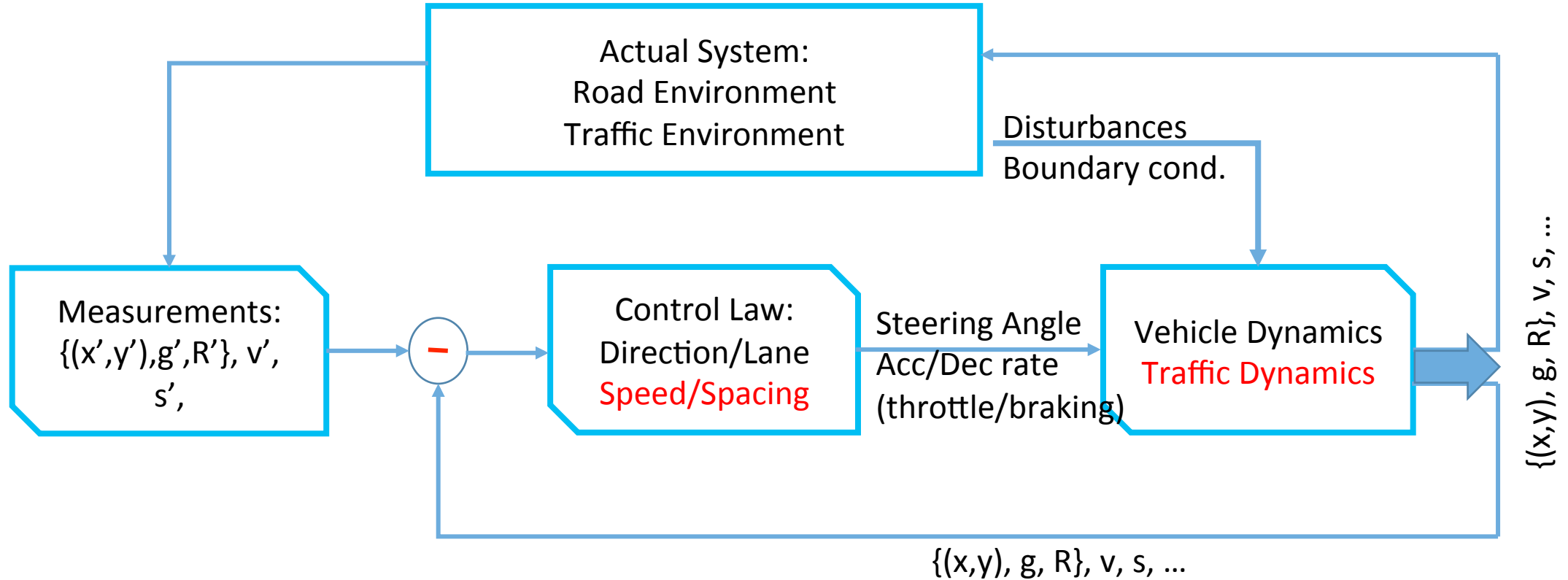
**The Symposium Celebrating 50 Years of Traffic Flow Theory,**

**August 11-13, 2014, Portland, Oregon USA**

# Outline

- From individual driving to traffic flow
- Prominent features of traffic flow
- Models of traffic flow-human driven vehicles
- Models of traffic flow-autonomous vehicles
- The future of traffic flow

# The Driving Task as Feedback Control



# Human Drivers vs Autonomous Vehicles From A Control Perspective

## Human Drivers

- Sensing is imprecise but more versatile
- Response is slower but more robust
- Best at processing fuzzy information and is highly adaptive
- Strength: handles complex tasks such as lane tracking, obstacle avoidance more easily

## Autonomous Vehicles (Robo Cars)

- Sensing is more precise but less versatile
- Response is faster but less robust
- Best at exercising precise controls and is less adaptive:
- Strength: handles procedural tasks such as speed control, car following more easily

# The Essence of Traffic Flow Theory is to Infer

- The Speed-Spacing Control Law of Each Driver

$$v \downarrow n (t) = \{?\}(s \downarrow n (t), \dots, E)$$

$E = \{\text{speed limits, grades, radius, surface conditions, visibility, ....}\}$

- And the collective dynamics of an OPEN “Many-Particle” Dynamical System with “random” insertions and removals (reflecting **LANE CHANGE** interactions) controlled by these driver control laws

$$\{x \downarrow n (t) = v \downarrow n (t), n = 1, 2, \dots, N\}$$

# Example: The California Motor Code Rule

- For every 10 mph of speed, leave one car length of space
- This translates to

$$s(t) - l = v(t)/10 \quad l \equiv T v(t)$$

or

$$v(t) = s(t) - l/T$$

with speed limits

$$v(t) = \min\{V_{\downarrow f}, s(t) - l/T\}$$

# If Human Drivers are Identical Robots

with super fast reaction time and vehicles capable of infinite acceleration and deceleration

- Micro model
- $$\begin{aligned} \dot{x}(t) &= v(t) & a(t) &= \begin{cases} 0, & v(t) \geq V \\ -\frac{v(t) - V}{T}, & v(t) < V \end{cases} & v(t) &= V \frac{u(t) - v(t)}{T} \end{aligned}$$

- Traffic Stream Model (steady-state)

$$V(s) = \min\{V, s/T\}$$

- Macro (continuum) model (in vehicle coordinate)

$$s_t - v n = 0, \quad v = V(s)$$

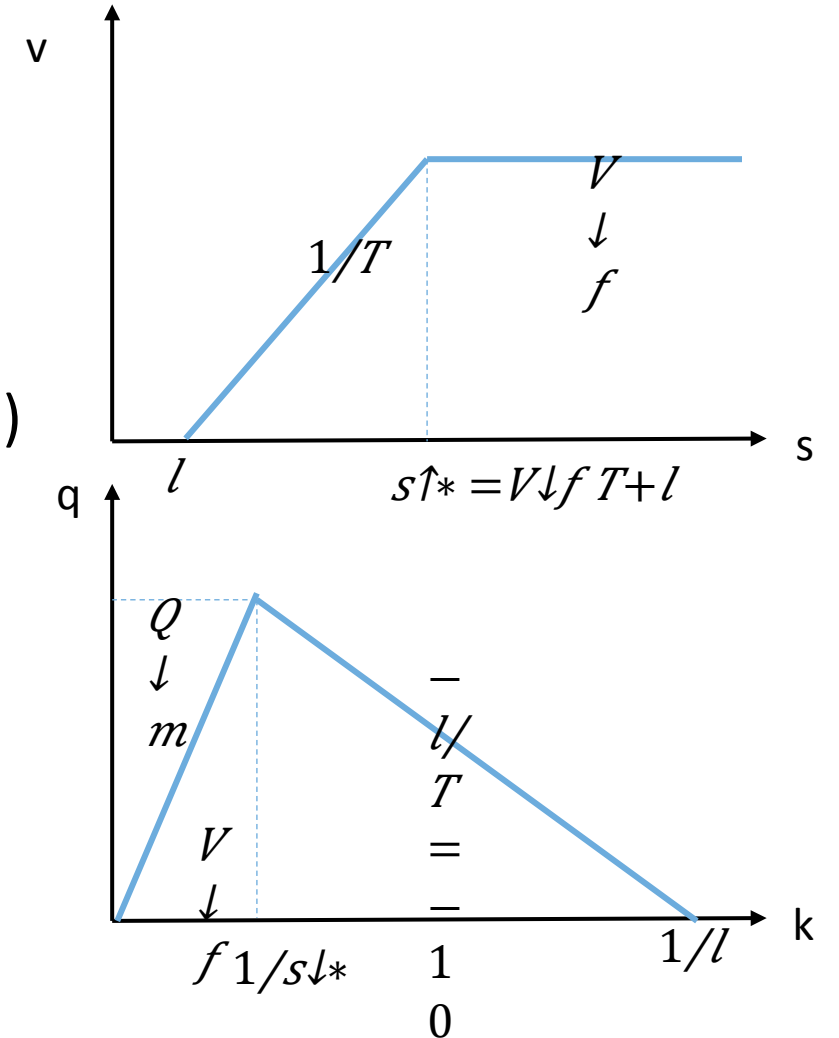
# What are These Models and what phenomena do they produce?

- Micro model: “linear” CF model of Pipes
  - Acceleration waves
  - Deceleration waves
- Stream model: Triangular FD
  - Capacity: 2640 pcphpl ( $l=20\text{ft}$ ,  $T=1.36\text{sec}$ ,  $Vf=60\text{mph}$ )
  - Jam wave speed: -10 mph

- Macro model: LWR with Triangular FD

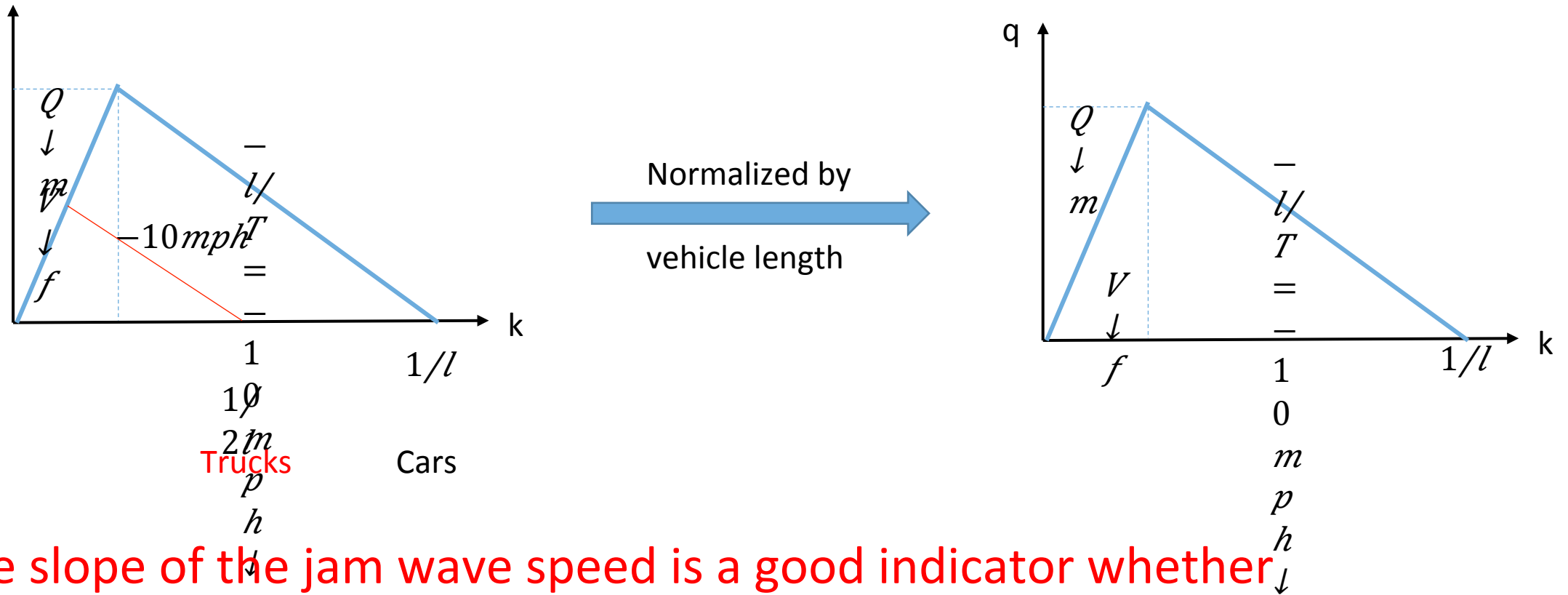
$$k \downarrow t + Q \downarrow x(k) = 0$$

- Shock waves
- Expansion (acceleration) waves





# When All Vehicles Follow the Same Rule



The slope of the jam wave speed is a good indicator whether drivers of different type of vehicles follow the same driving rule or not

# In reality, human drivers

- Differ from each other in driving ability and habits
- Cannot assess motion and distances precisely
- Respond with delay and finite acceleration/deceleration
- Do not follow rules exactly

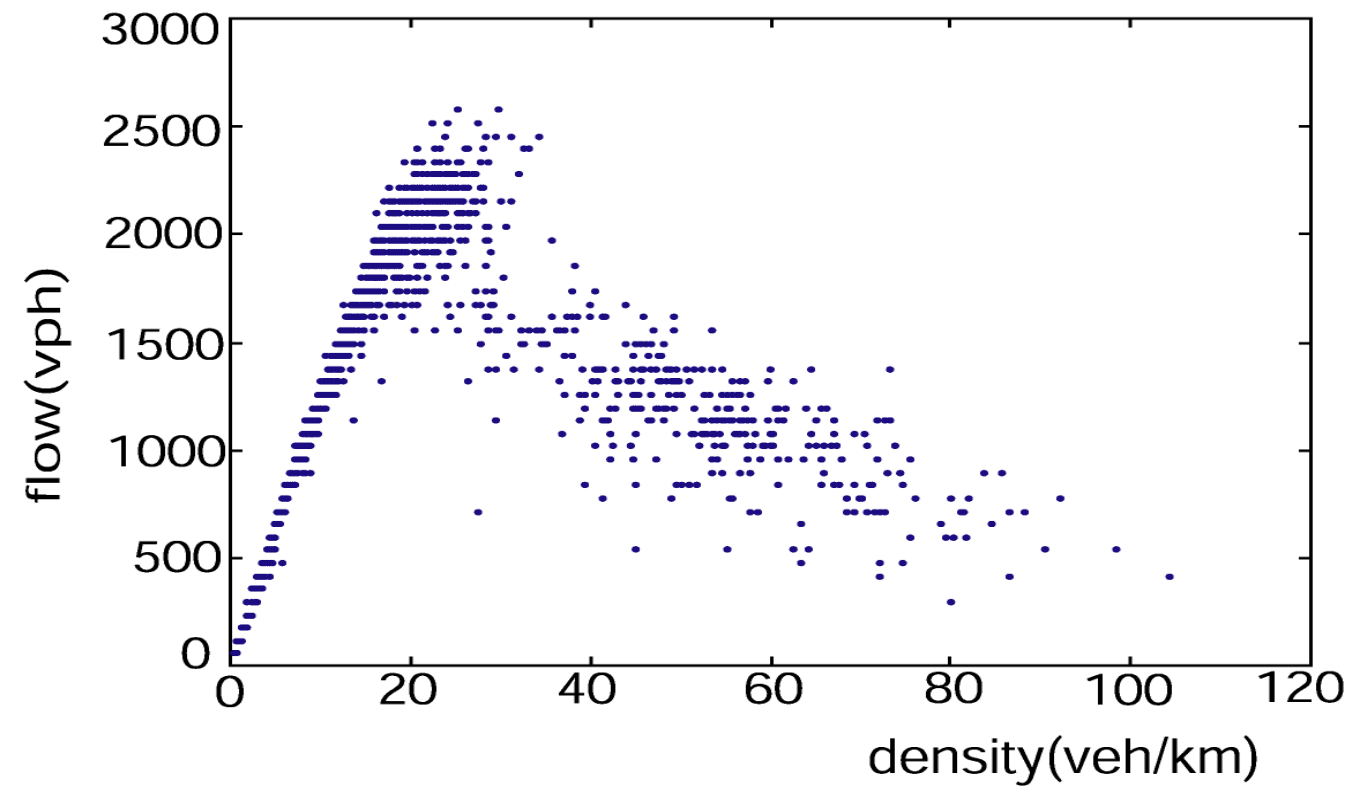
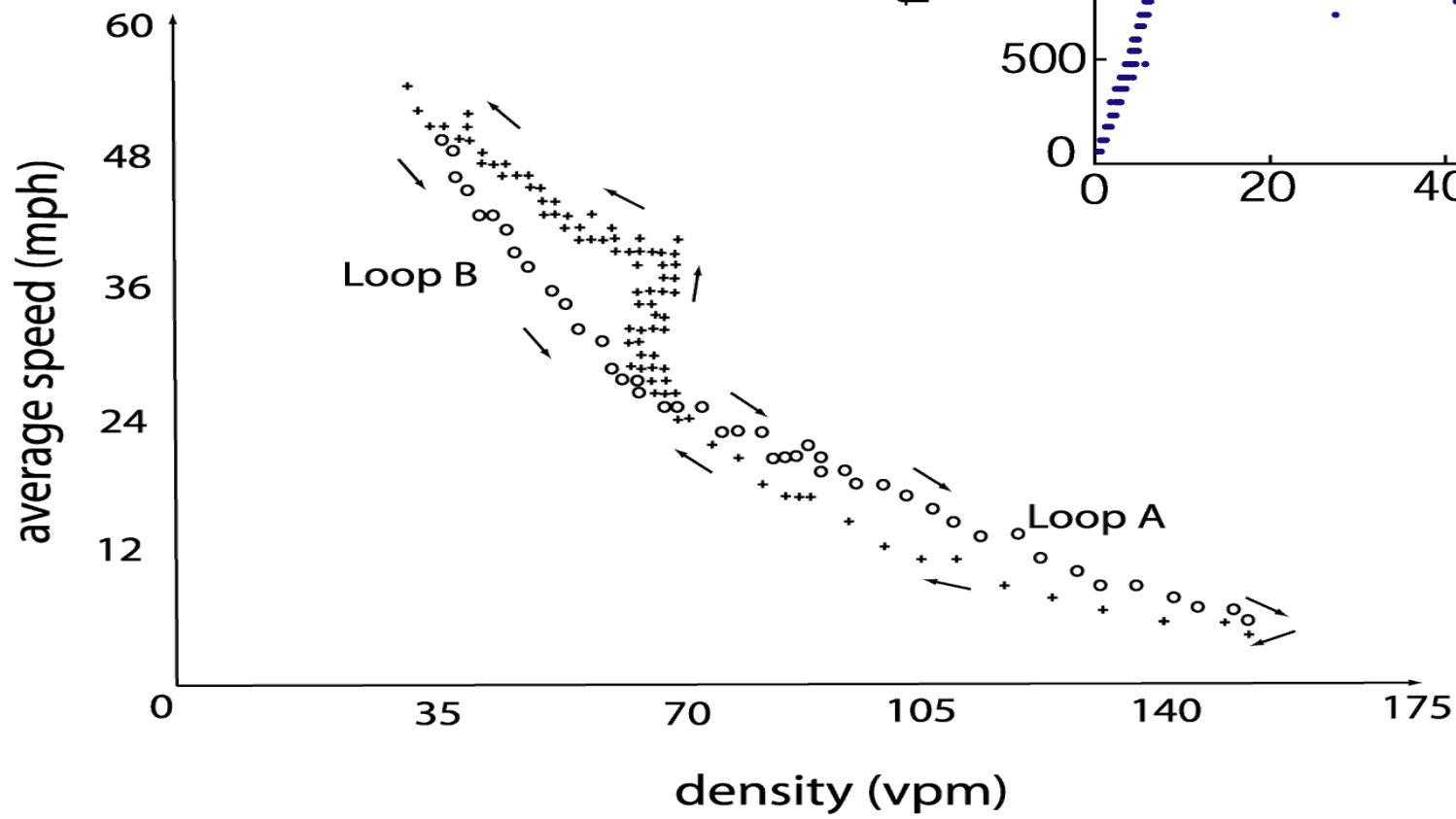
## Consequence:

Traffic flow in the real world is much more complex

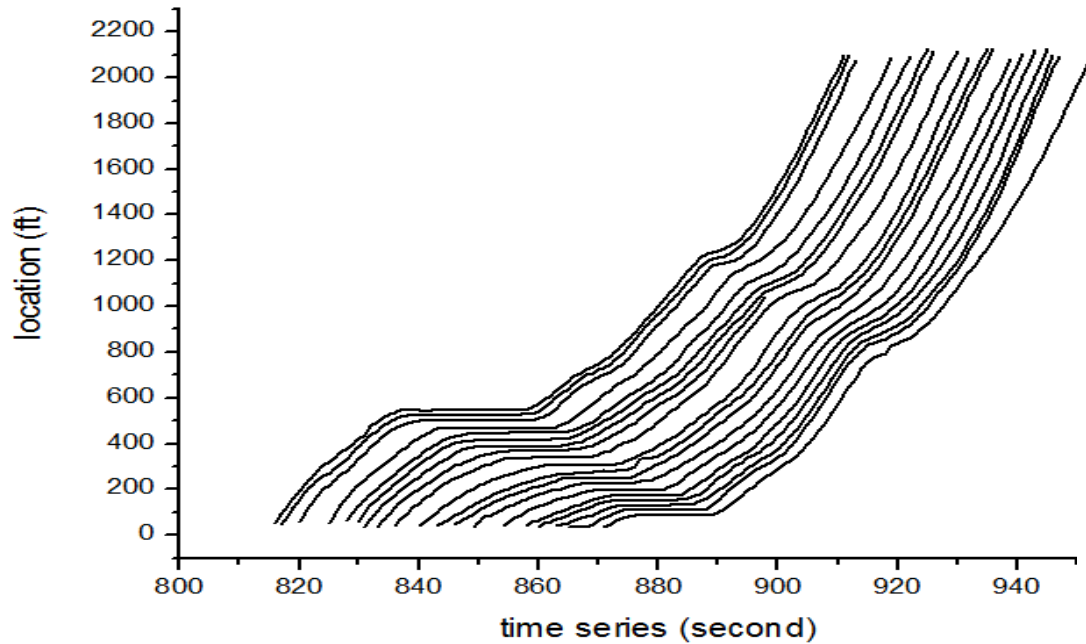
# Prominent Features of Real Traffic Flow

- [Phase transitions](#)
- [Nonlinear waves](#)
- [Stop-and-Go Waves \(periodic motion\)](#)

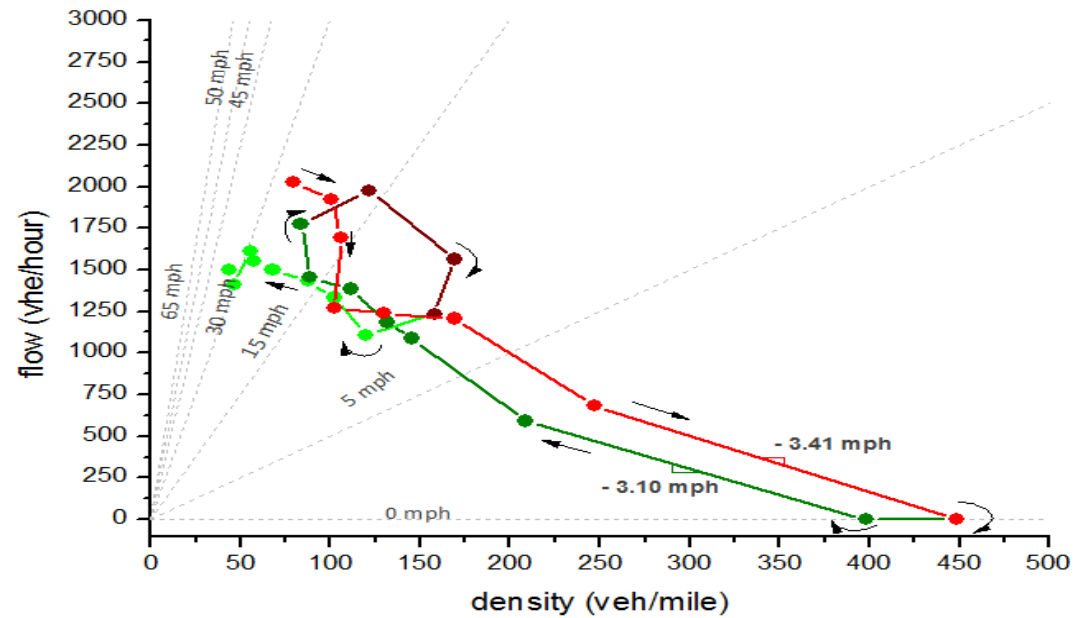
# Phase transitions



# Nonlinear waves

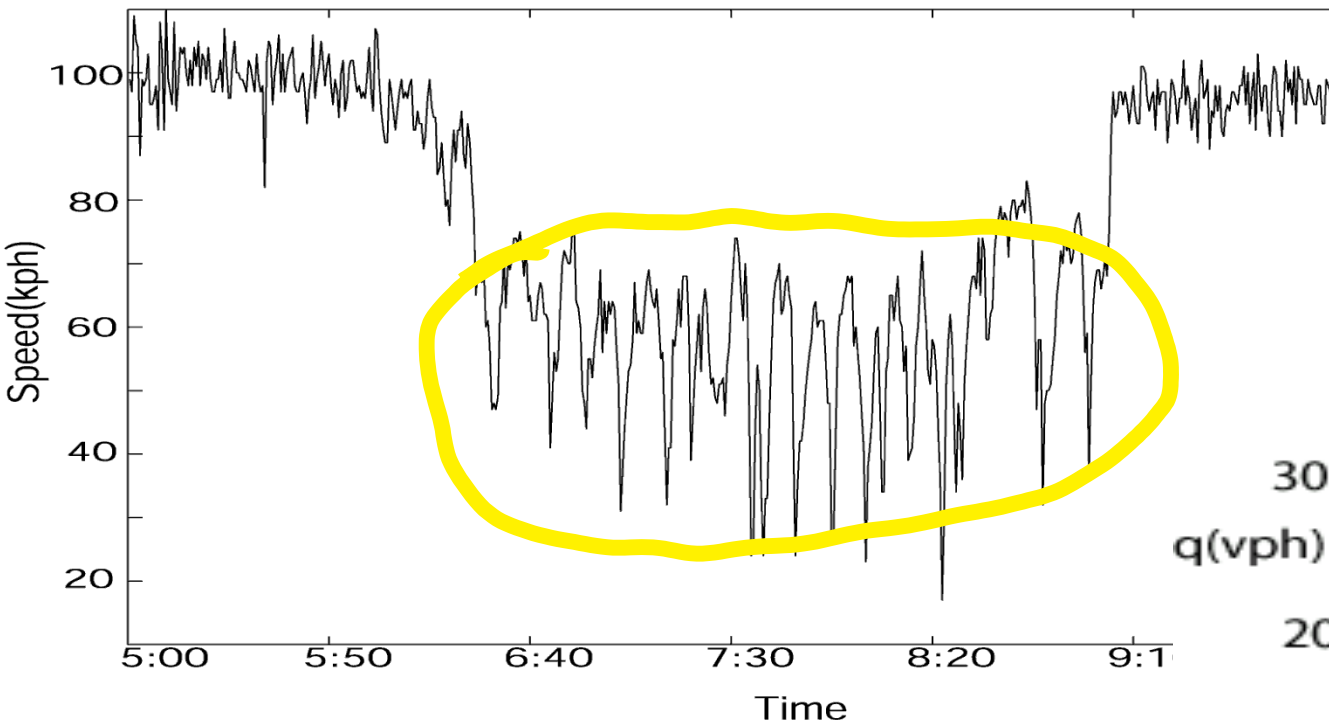


Vehicle platoon traveling through two shock waves

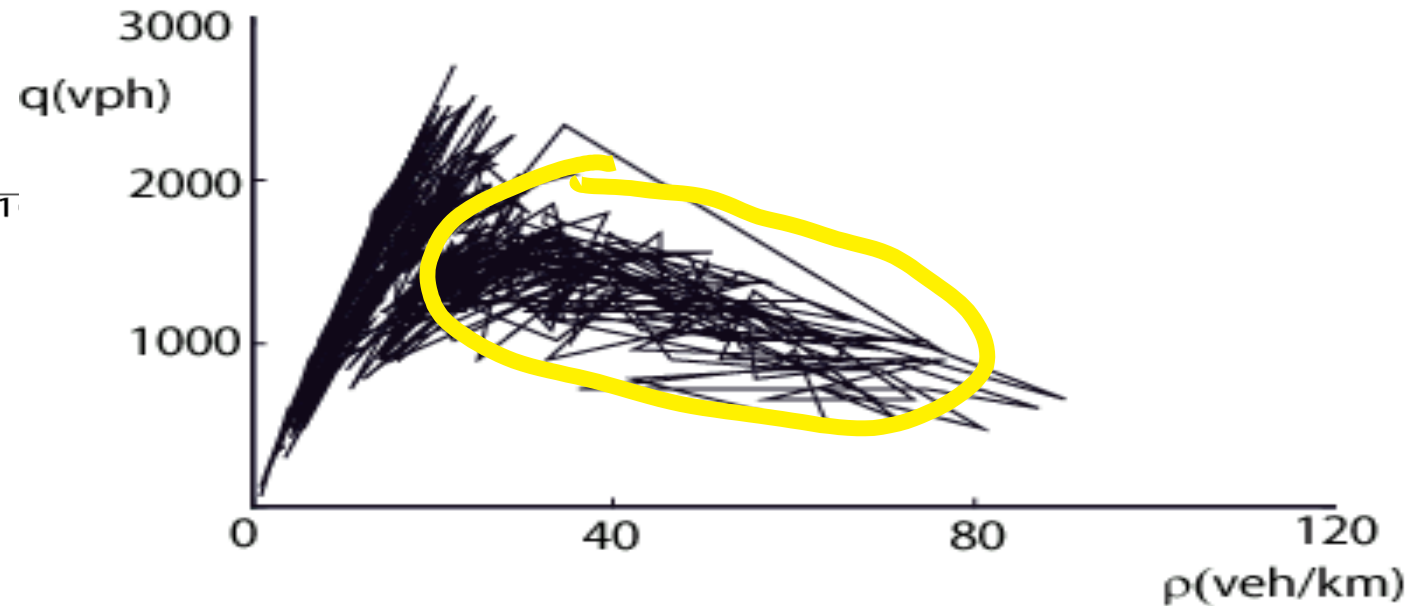


flow-density phase plot

# Stop-and-Go Waves (Oscillations)



Scatter in the phase diagram is closely related to stop-and-go wave motion



# Some Classical Traffic Models

- Microscopic

- Modified Pipes' model
- Newell' Model
- Bando' model

$$x_n = \min \{ v_f, (s_n(t) - l) / \tau \}$$

$$x_n(t + \tau) = v_f \left[ 1 - \exp \left\{ -\lambda (s_n(t) - l) / v_f \right\} \right]$$

$$\dot{x}_n(t) = a \left[ (u_*(s_n) - x_n)(t) \right], \quad a = 1 / \tau$$

$$\rho = 1 / s, \quad u_*(s) = v_*(\rho), \quad q = \rho v, \quad q_*(\rho) = \rho v_*(\rho)$$

- Macroscopic continuum

- LWR model
- Payne-Whitham model
- Aw-Rascle, Zhang model

$$\rho_t + q_*(\rho)_x = 0$$

$$\rho_t + (\rho v)_x = 0, \quad v_t + (v v)_x + \frac{c_0^2}{\rho} \rho_x = \frac{v_*(\rho) - v}{\tau}$$

$$\rho_t + (\rho v)_x = 0, \quad v_t + (v - c(\rho)) v_x = \frac{v_*(\rho) - v}{\tau}$$

$$c(\rho) = -\rho v'_*(\rho)$$

- v-s (speed-spacing) relation is central to all these models

# The Difficulty of Modeling Real Flow

- Each driver is different
- Driving rules are hidden
- Sensing is imprecise
- Behavior is adaptive, nonlinear, and perhaps inconsistent
- (Driving environment is complex)



# When Robo Cars Take Over the Road

- Behavior is uniform and consistent
- Sensing and control is more precise
- Rules are always obeyed
- (Driving environment is still complex)

More importantly, driving rules are by design, leaving room for optimizing flow and safety  Feedback Control Problem

# Traffic Flow Theory For Robo Cars- Longitudinal Control

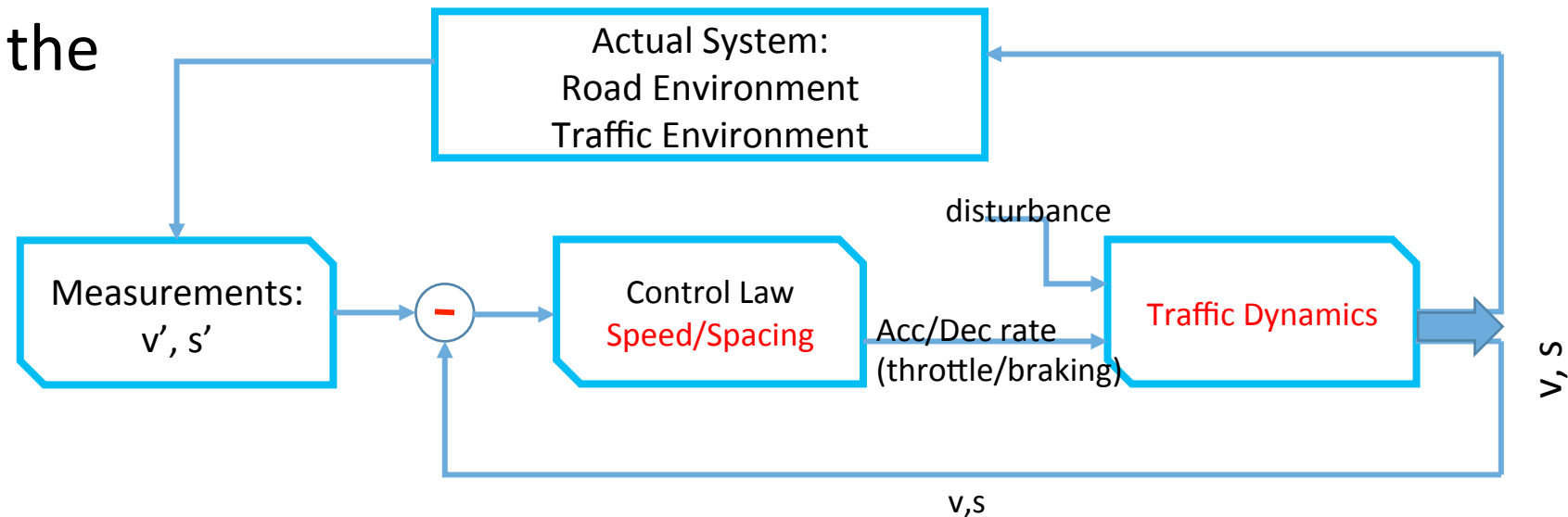
- Example RoboCar#1

$$a(t+\tau) = k \downarrow r \{V(s) - v\}, V(s) = \min\{V \downarrow f, s/T\}$$

- Human:  $\tau=1-2s$ ,  $T=1.36-2s$ ; Robo Car:  $\tau=0.4-0.6s$ ,  $T=0.8-1.2s$ ,  
Capacity:  $\approx 1/T$ , +70%,

- But this may be too

rosy a prediction in the  
initial deployment  
stage (liability)

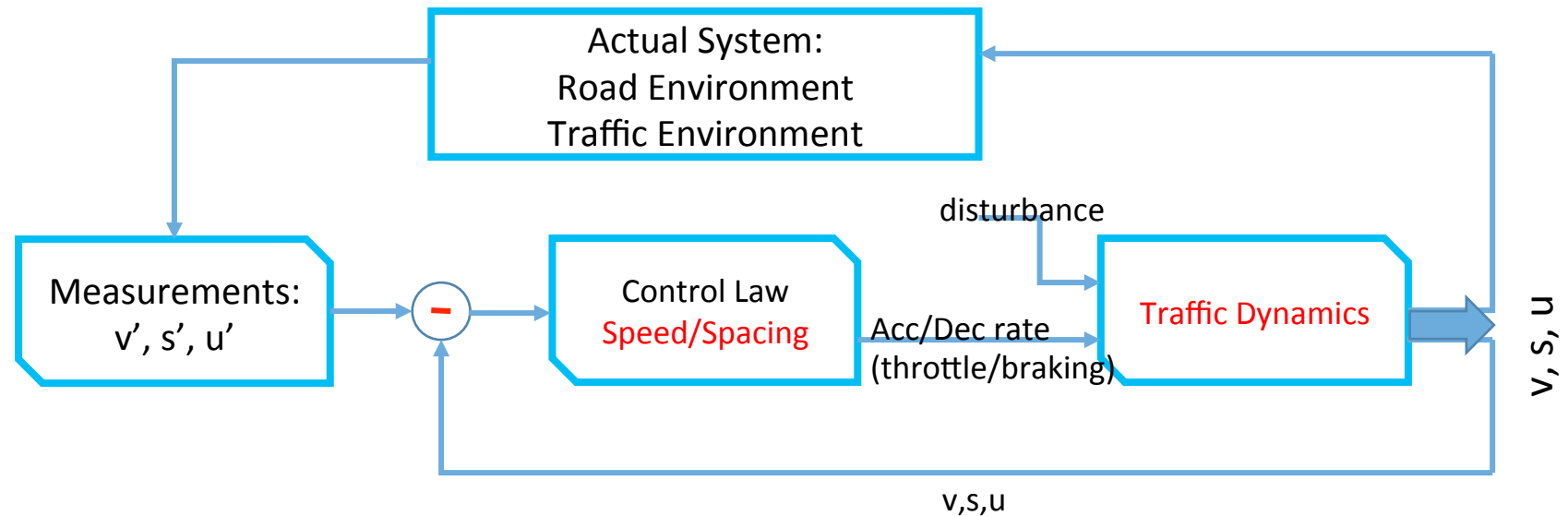


# Example RoboCar#2

$$a(t+\tau) = k_1 r \{V(s) - v\} + k_2 v \{u - v\}$$

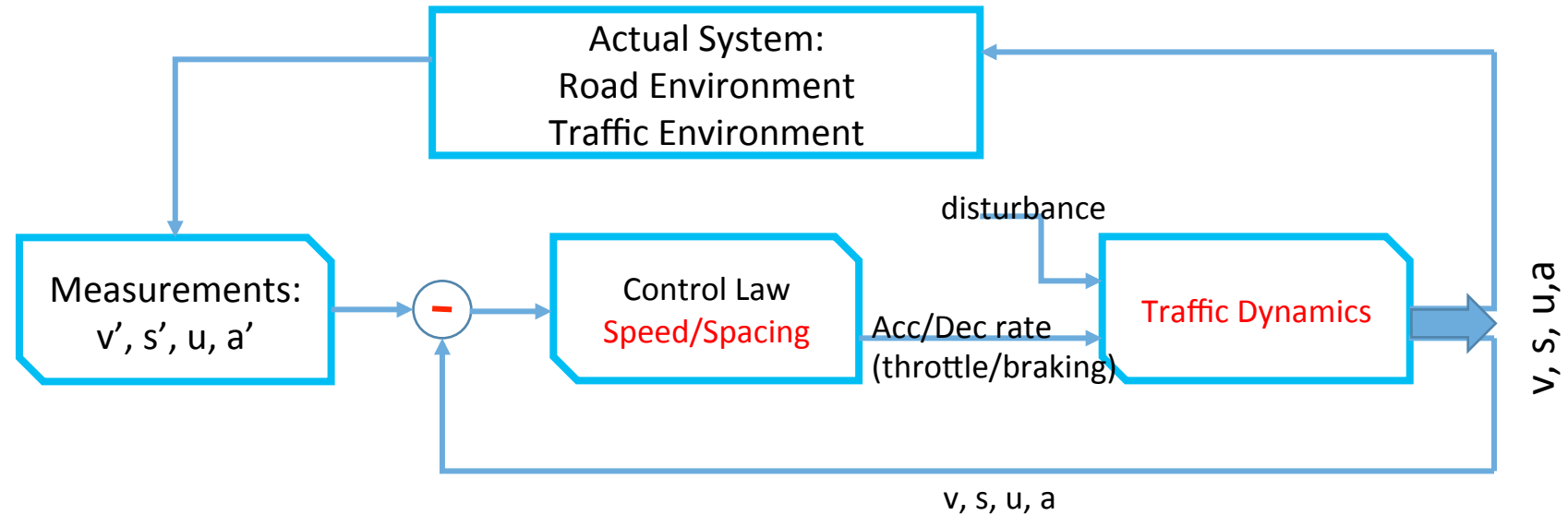
Faster response and higher throughput than RoboCar#1

$\tau = 0.4 - 0.6s$ ,  $T = 0.6 - 0.75s$



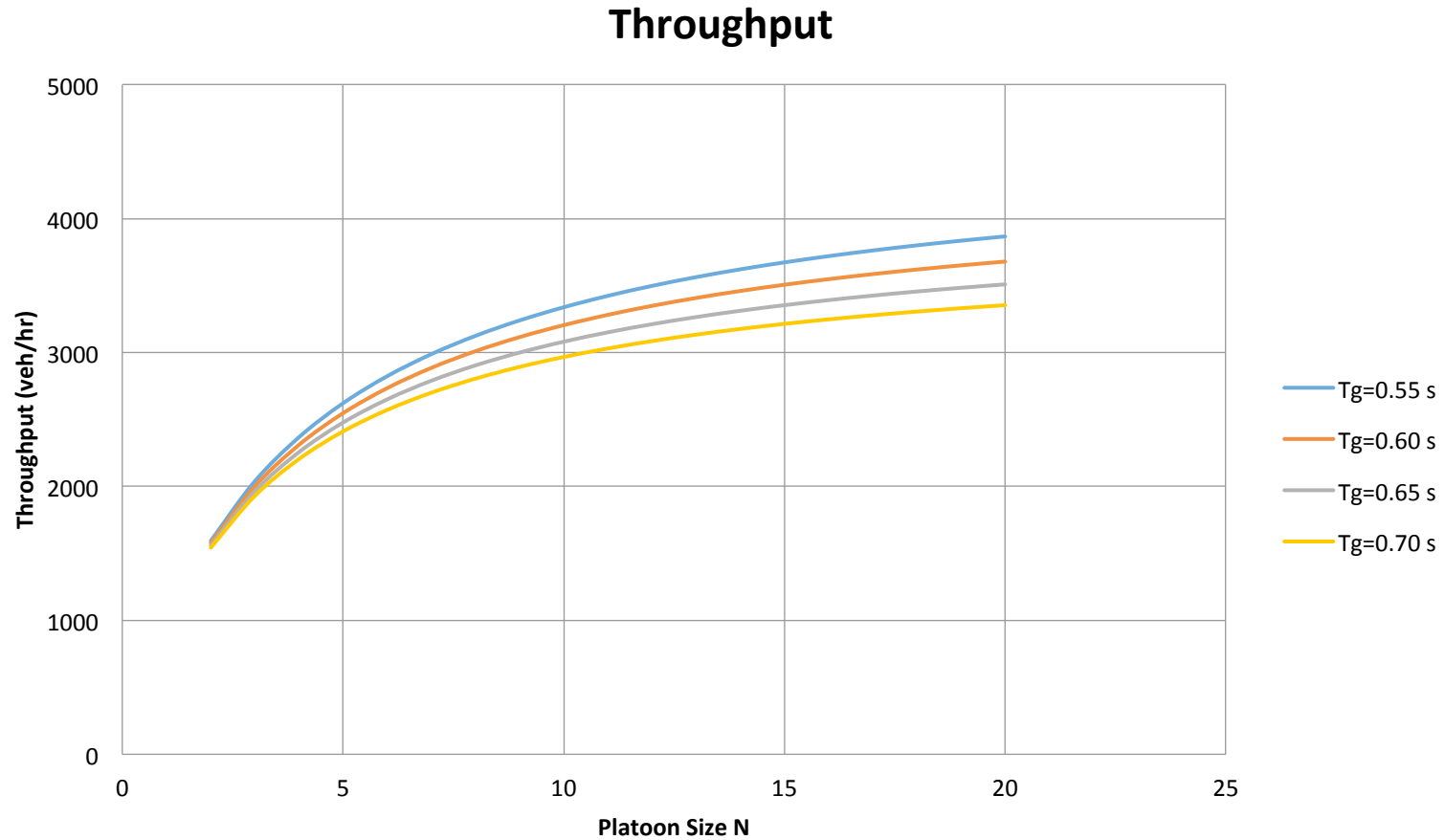
# Example RoboCar#3 (RoboCar#2 with V2V)

$$a(t+\tau) = k_a a(t) + k_r \{V(s) - v\} + k_v \{u - v\}$$



And the list goes on: you can come up with other models that meet safety and stability requirements

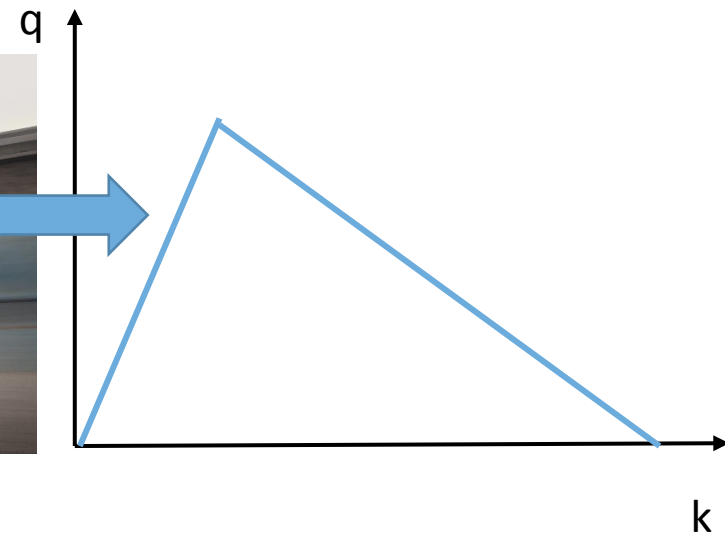
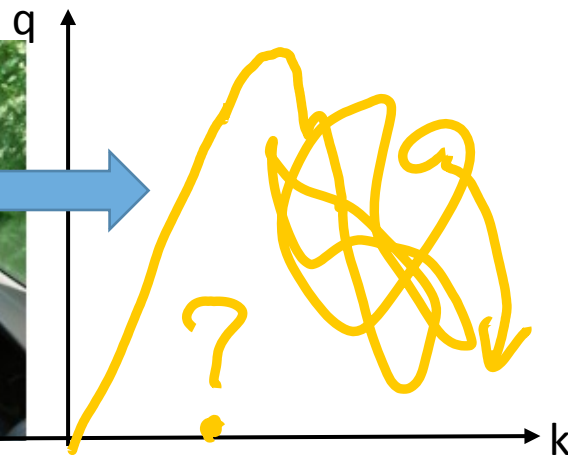
# Expected throughput with vehicle platooning



Throughput of CACC platooning with different platoon size and intra-platoon time gap setting

# Future of Traffic Flow Theory Research (1)

- Do the Arrival of Robo Cars Mean The End of Traffic Flow Research?
  - Automation creates uniformity and standardization, suppresses randomness:  
**From billions of drivers to a handful:** Google Car, GM Car, Toyota Car ....
  - Behavior of each Robo Car is consistent and known



From Human Drivers to Robots

# Future of Traffic Flow Theory Research (2)

- In the short term
  - design of driving models for Robo cars
  - Robo car friendly infrastructure
- In the intermediate term
  - Mixed traffic with Robo Cars,
  - Platooning of Robo Cars
  - Lightless intersections with in-vehicle signal control
  - Rich micro level data for understanding and modeling traffic, and validating traffic models

# Future of Traffic Flow Theory Research (3)

- In the long term, full automation of highway traffic
  - Optimal scheduling and pricing for congestion free networks
  - Robust Recovery from Disruptions
- New services and shared use of autonomous vehicles
  - Robo Taxi Services
  - Last and first-mile of transit (flexible transit)
  - Seamless integration of multiple modes
  - And the list goes on



# Concluding Remarks

Autonomous Vehicles will

- In the long run bring more order to traffic flow and simplify traffic flow theory
- Produce rich data for traffic flow research
- Brings a host of brand new research problems for modeling, design and operations of transportation systems