

# 16. Cyber-Physical Security of Connected & Autonomous Vehicles

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# Outline

- Background
- Attacker-defender interaction
- Basics of game theory\*

# Background

- Application layer
- Network layer
- System level
- Privacy leakage

# Challenge: cyber-physical security for CAVs

- Adversaries that maliciously compromise (disconnect or pollute) information flow
- Why people do this? Beyond the scope of this talk...
- But people can do and have done this...



**Engineers who hacked into L.A. traffic signal computer, jamming streets, sentenced**

29 San Francisco Rail System Hacker Hacked

NOV 16

The San Francisco rail system was hacked by a team of researchers who used a computer to control the city's traffic lights. The team, which included members from the University of Michigan and the University of Washington, was able to gain access to the system's network and change the timing of traffic lights. The hack was discovered in October 2015 and the researchers were sentenced to prison in January 2017.

MIT  
Technology  
Review

Intelligent Machines

**Researchers Hack Into Michigan's Traffic Lights**

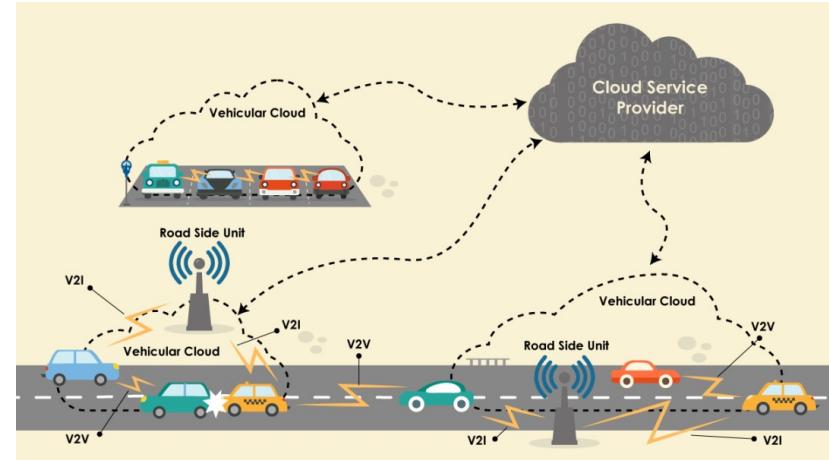
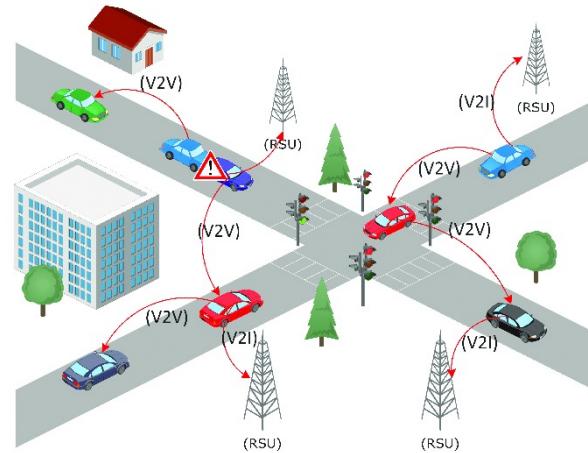
**Transport** 当“车联网”遇上“黑客”，安全难题怎么破？

2019-05-18 17:21:24 来源：新华网

Bygga in säkerhet i anslutna fordon och intelligenta transportsystem

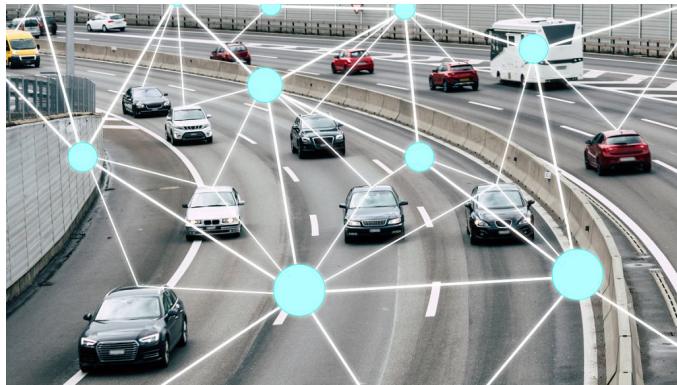
# Vulnerabilities

- To achieve automated cooperative driving, vehicles need to have access to each other's information.
- Such information enhances the ability of the autonomous vehicle to plan ahead and make better decisions to improve the overall safety and performance of the vehicle.
- One possible way of achieving inter-vehicle communication is through vehicular ad hoc networks (VANETs).



# Vulnerabilities

- Although VANET technologies have matured over time, they are still riddled with security issues.
- Faults in software components can potentially lead to devastating effects for autonomous vehicles and other vehicles sharing the roadway.
- Thus, it is important to design the system to be robust, secure against malicious attacks, privacy preserving, and fault tolerant.



# Vulnerabilities

- We group the security attacks on CAVs as application layer, network layer, system level, and privacy leakage attacks.
- All these attacks can potentially impact the string stability of the system, and compromise the safety and privacy of the passengers of the CAV stream.
- Such attacks can be launched by either an outsider or insider adversary.
- While leveraging state-of-the-art security architectures can potentially limit the capabilities of outsider attacks, there can still be disruptive insider attacks.

# Vulnerabilities

- Application layer
  - Network layer
  - System level
  - Privacy leakage
- 
- Amoozadeh, M., Raghuramu, A., Chuah, C. N., Ghosal, D., Zhang, H. M., Rowe, J., & Levitt, K. (2015). Security vulnerabilities of connected vehicle streams and their impact on cooperative driving. *IEEE Communications Magazine*, 53(6), 126-132.

# Application layer

- Application layer attacks affect the functionality of a particular application such as CACC beaconing, or message exchange in the platoon management protocol.
- In a message **falsification** attack, the adversary starts listening to the wireless medium and, upon receiving each beacon, manipulates the content meaningfully and rebroadcasts it
- In a **spoofing** attack, the adversary impersonates another vehicle in the stream in order to inject fraudulent information into a specific vehicle.
- In a **replay** attack, the adversary receives and stores a beacon sent by a member of the stream and tries to replay it at a later time with malicious intent.

# Application layer

- How to address application layer attacks?
- For outsiders (invader):
  - Prevent unauthorized outsiders from intruding
  - State-of-the-art security architectures employing a strong cryptographic system
  - Digital signatures provide data integrity for beacon messages and protect them from unauthorized change.
  - But many practical challenges involved in deployment, implementation, and standardization
- For insiders (spy):
  - Not very much can be done with cryptography & authentication.
  - Main solution: misbehavior/anomaly detection techniques
  - Multiple sources of data for cross verification
  - False negative and false positive rates.

# Network layer

- Network layer attacks have the potential to affect the functioning of multiple user applications.
- (Distributed) denial-of-service (DoS/DDoS) attack
  - CAVs have a tamper-proof hardware security module (HSM), which is responsible for storing digital keys as well as performing all cryptographic operations, such as message signing/verification, encryption, and hashing. A **botnet** can target this limitation to overwhelm an autonomous vehicle and make its HSM unavailable.
  - **Radio jamming** to deliberately disrupt communications over small or wide geographic areas.

# System-level attacks

- Another type of attack is tampering with vehicle hardware or software, which can be done by a malicious insider at the manufacturing level or by an outsider in an unattended vehicle (e.g., by replacing or altering certain vehicle sensors).
- Even if the communication channel is secure, and a state-of-the-art security architecture is deployed in the VANET if the onboard hardware/software is tampered with or faulty, the input information to the system will not be accurate.
- One possible solution is to use tamper-proof sensors.
- If a tamper-proof version is not available or too expensive to deploy on a large scale, the misbehavior detection techniques discussed below can be useful.

# Privacy leakage attacks

- An **eavesdropping** attack extracts valuable information about the CAVs such as its trace by linking position data, and use it for her own benefit.
- Eavesdropping is a type of passive attack, and hence is difficult to detect, especially in broadcast wireless communication.
- However, it is possible to prevent the success of eavesdropping by using encryption to achieve data privacy or using anonymity techniques to achieve identity and location privacy.

# A philosophical question

Why would people do such bad things?

# Attacker-defender interaction

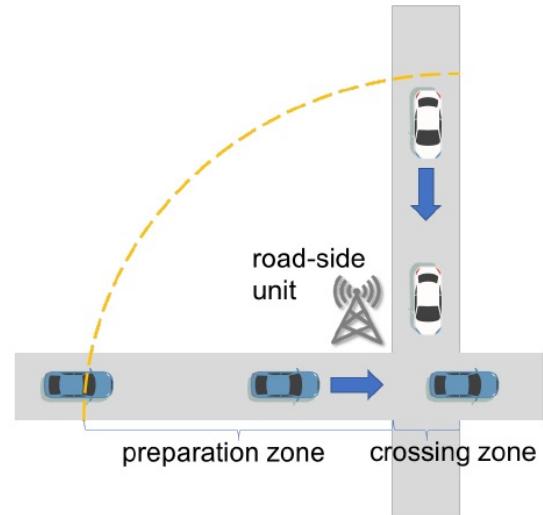
- Baseline setting
- Attacker model
- Defender model

# Baseline setting

- CAV intersection, FCFS
- Standard trajectory planning algorithm (road-side)
  - Generates trajectory to go
- Standard trajectory tracking algorithm (road-side)
  - Generates target speed
- Standard car-following/collision avoidance system (onboard)
  - Generates engine torque

# Problem formulation

- Two one-way routes without turning
- Radius of preparation zone =  $L$
- Initial conditions  $x_i^k(0), v_i^k(0) = \bar{v}$ 
  - $x_i^k(0) - x_{i+1}^k(0) \geq d$  (safe)
  - $|L - x_i^k(0)| + |L - x_j^{-k}(0)| \geq d$  (safe)
  - $\bar{v}$  = nominal speed
- Furthermore, we assume that in the absence of attacks, every vehicle can keep traveling at constant speed  $\bar{v}$  and cross the intersection safely.
- Safely = satisfying the distance constraint



# Research questions

- How to create an accident by falsification or spoofing?
- How many pieces of information have to be spoofed to create an accident?
- How much redundant information is needed to detect spoofing?
- To what extent can we recover spoofed information?

# Attacker

- Attacking modes
  - DoS: erase certain pieces of information
  - Spoofing: modify certain pieces of information
  - Manipulation: modify instructions
- Budget
  - Probability of erasure/modification
  - # of erasures/modifications
- Objective
  - DoS: maximize efficiency loss
  - Spoofing: create accident

# Defender

- Defending actions
  - Increase safety margin
  - Detect spoofed data
  - Recover erased/spoofed data
  - Activate backup sensing
  - Increase security level
- Budget
  - Probability of successful detection
  - # of nodes with increased security
  - # of backup sensing
- Objective
  - Avoid accident
  - Optimize efficiency

# Attacking modes

- DoS: suppose the attacker can erase the information of  $a$  vehicles per time step.
  - Simultaneously erase  $x_i^k(t)$  and  $v_i^k(t)$
  - When state of vehicle  $i$  is erased, vehicle  $i + 1$  switches to ACC mode and relies on onboard sensing for vehicle following. This leads to an inter-vehicle spacing  $d' > d$ .
  - This leads to an increase in travel time
  - Attacker wants to maximizes this increase
  - Which vehicle to erase?

# Attacking modes

- Spoofing: create non-existent vehicle to cause “phantom” delay
  - Inject information  $\xi(t)$  (position) and  $v(t)$  (speed) of a phantom vehicle
  - This misleads the RSU to induce an unnecessary spacing between vehicles
  - Attacker wants to maximize the induced delay
- Falsification: modify state observation
  - Modify  $x_i^k(t)$  and  $v_i^k(t)$
  - Creates accidents
  - That is, drive the system to an unsafe state

# Attacker's decision-making problem

- Data:
  - CAV parameters
- Decision variable
  - Which piece information to attack
  - When to attack
- Constraint:
  - Budget
  - Technological
- Objective
  - Compromise safety
  - Compromise efficiency

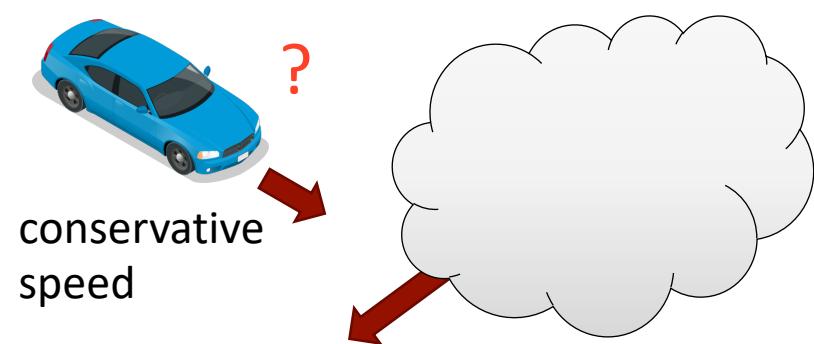
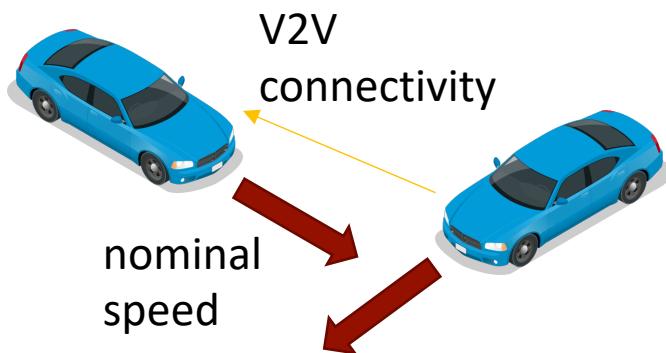
# Defending modes

- Proactive actions:

- Increase security investment (e.g. hardware)
- Improved encryption technology
- Maintain safety margins

- Reactive actions:

- Isolate detected malicious information
- Switch to or activate redundant information sources
- Intervene the trajectories of neighboring vehicles



# Defender's decision-making problem

- Data:
  - CAV parameters
  - Observed data
- Decision variable
  - Proactive actions
  - Reactive actions
- Constraint:
  - Budget
  - Performance
- Objective
  - Ensure safety
  - Improve efficiency

# Question:

How about the attack and defense for a CACC-based vehicle platoon?

# Attacker-defender interaction

- Let's summarize the setting...
- Two decision makers have conflicting objectives
- One side's decision will influence the gain/loss of the other side
- Both sides have some extent of expectation/belief of the behavior of the other side
- --> Game!



# Why game theory?

Multiple decision makers + conflicting objectives  
= game theory

# Basics of game theory\*

- Formulation
- Strategy
- Equilibrium

# Game vs. optimization

## Optimization

- A single decision maker
- A single objective function
- Optimal solution: no other solution can improve objective value

## Game

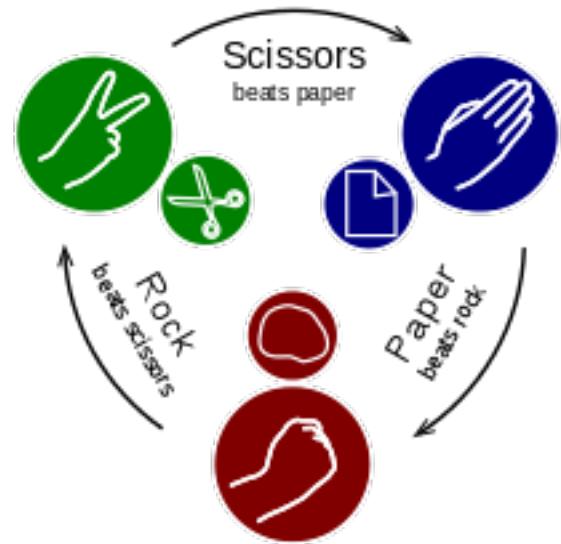
- Two (or multiple) decision makers (players)
- Two players have different (typically conflicting) objectives
- Equilibrium: neither player can improve its utility by unilaterally varying its action

# Strategic-form game

- Set of players  $i \in \mathcal{I} = \{1, 2, \dots, I\}$
- Pure-strategy space  $S_i$
- Space of pure strategies  $S = \prod_{i=1}^I S_i$
- Payoff function  $u_i: \prod_{j=1}^I S_j \rightarrow \mathbb{R}$
- Strategy profile  $s = (s_1, s_2, \dots, s_I)$
- Zero-sum game:  $\sum_{i=1}^I u_i(s) = 0$  for all  $s$ .
- Common knowledge: all players know the structure of the strategic form and other players' knowledge.

# Example: Rock paper scissors

- Two players  $i \in \{1,2\}$
- Pure strategy space  $S_i = \{R, P, S\}$  for  $i = 1, 2$
- Space of pure strategies  $S = \{R, P, S\}^2$
- Payoff function  $u_i: \{R, P, S\}^2 \rightarrow \{-1, 0, 1\}$  #
- Strategy profile  $s = (s_1, s_2)$
- Zero-sum game:  $\sum_{i=1}^I u_i(s) = 0$  for all  $s$
- Common knowledge: rules for the game; simultaneous move



# Mixed strategy

- A mixed strategy  $\sigma_i$  is a probability distribution over pure strategies.
- Each player's randomization is statistically independent of others'.
- Space of player  $i$ 's mixed strategies =  $\Sigma_i$
- Mixed strategy profile  $\sigma = (\sigma_1, \sigma_2, \dots, \sigma_I)$
- Space of mixed strategy profiles  $\Sigma$
- Payoff  $u_i(\sigma_i) = \sum_{s \in S_i} (\prod_{j=1}^I \sigma_j(S_j)) u_i(s)$

# Example: Rock paper scissors

- Randomized action (mixed strategy)

$$\sigma_i = \{p_R^i, p_P^i, p_S^i\}$$

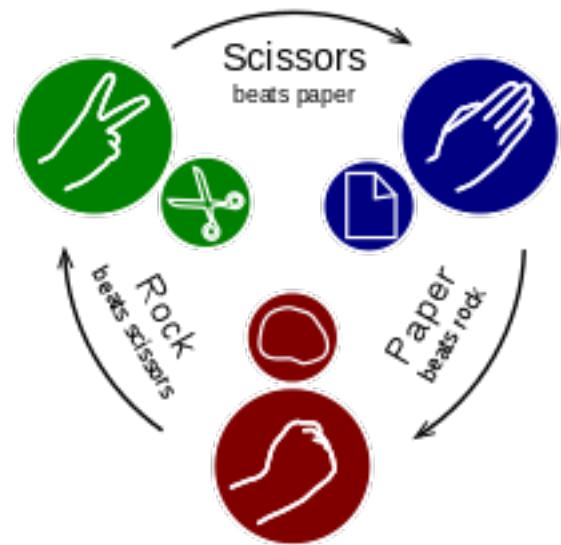
$$\sigma_i \geq 0, \|\sigma_i\|_1^1 = 1$$

- Player  $i$ 's mixed strategy space  $\Sigma_i = ? \#$

- Mixed strategy profile  $\sigma = (\sigma_1, \sigma_2)$

- Space of mixed strategy profiles  $\Sigma$

- Payoff  $u_i(\sigma_i) = \sum_{s \in S_i} (\prod_{j=1}^I \sigma_j(s_j)) u_i(s)$



# Dominated strategies

- Pure strategy  $s_i$  is strictly dominated for player  $i$  if there exists  $\sigma'_i \in \Sigma_i$  such that

$$u_i(\sigma'_i, s_{-i}) > u_i(s_i, s_{-i}) \text{ for all } s_{-i} \in S_{-i}$$

- The strategy  $s_i$  is weakly dominated if
  - $u_i(\sigma'_i, s_{-i}) \geq u_i(s_i, s_{-i})$  for all  $s_{-i} \in S_{-i}$
  - There exists  $-i$  such that  $u_i(\sigma'_i, s_{-i}) > u_i(s_i, s_{-i})$
- Iterated (strict) dominance: process of elimination of dominated strategies
- Only a small portion of games can be solved by iterated dominance
- R-P-S: dominated strategy exists?

# Nash equilibrium

- Provides solutions to general games
- A Nash equilibrium is a profile of strategies such that each player's strategy is an optimal response to the others'
- Mathematically, a mixed-strategy profile  $\sigma^*$  is a Nash equilibrium if for all players  $i$

$$u_i(\sigma_i^*, \sigma_{-i}^*) \geq u_i(s_i, \sigma_{-i}^*) \text{ for all } s_i \in S_i$$

- Similarly, a pure-strategy Nash equilibrium is  $s^*$  such that for all players  $i$

$$u_i(s_i^*, s_{-i}^*) \geq u_i(s_i, s_{-i}^*) \text{ for all } s_i \in S_i$$

# Nash equilibrium

- A Nash equilibrium is strict if each player has a unique best response to others'
- That is,  $s^*$  is a strict equilibrium if and only if for all  $i$  and for all  $s_i \neq s_i^*$ 
$$u_i(s_i^*, s_{-i}^*) > u_i(s_i, s_{-i}^*)$$
- A strict equilibrium must be a pure-strategy equilibrium
- If one round of iterated dominance yields a unique strategy profile  $s^*$ , then  $s^*$  must be a unique Nash equilibrium
- Any Nash-equilibrium strategy profile puts weight only on strategies that are not strictly dominated

# Nash equilibria

- Nash equilibria are consistent predictions of how game will be played in the sense that if all players predict a particular Nash equilibrium, then no player has an incentive to play differently.
- Many games have multiple Nash equilibria
- A Nash equilibrium is played if there exists some mechanism that leads all players to expect the same equilibrium
- Focal point: a priori preference for certain equilibria
- Risk dominance: Pareto-dominant equilibrium

# Example: Rock paper scissors

- Does this game have a pure-strategy NE?

# Existence of mixed-strategy equilibrium

- **Theorem:** Every finite strategic-form game has a mixed-strategy equilibrium.
- Remember that a pure-strategy equilibrium is an equilibrium in degenerate mixed strategies.
- The theorem does not assert the existence of an equilibrium with nondegenerate mixing.
- R-P-S: no pure-strategy equilibrium, but with mixed-strategy equilibrium #

# Cournot game

- So far we have motivated the solution concepts of dominance, iterated dominance, and Nash equilibrium by supposing that
  - players predict opponents' play by introspection and deduction
  - common knowledge
- Cournot adjustment process: an alternative approach to introspection for explaining why Nash equilibria are played

# Cournot game: definition

- Players take turns choosing their actions
- Each player's each action is a best response to the history of actions
- Suppose two players 1 and 2
  - Player 1 moves first and chooses  $a_1^0$
  - Player 2 responds with  $a_2^1 = r_2(a_1^0)$
  - Player 1 then responds with  $a_1^2 = r_1(r_2(a_1^0))$
  - If  $a_1^k \rightarrow a_1^*$  and  $a_2^k \rightarrow a_2^*$ , then  $a_2^* = r_2(a_1^*)$  and  $a_1^* = r_1(a_2^*)$
  - $(a_1^*, a_2^*)$  is a Nash equilibrium

# Cournot game: convergence

- If  $(a_1^k, a_2^k) \rightarrow (a_1^*, a_2^*)$  for all  $(a_1^0, a_2^0)$  within a neighborhood of  $(a_1^*, a_2^*)$ , the equilibrium is **asymptotically stable**.
- If  $(a_1^k, a_2^k) \rightarrow (a_1^*, a_2^*)$  for all  $(a_1^0, a_2^0)$  in the action space, the equilibrium is **globally stable**.

# Existence of Nash equilibrium in infinite games

- **Theorem:** Consider a strategic-form game whose strategy space  $S_i$  are nonempty compact convex subsets of an Euclidean space. If the payoff functions  $u_i$  are continuous in  $s$  and quasi-concave in  $s_i$ , then there exists a pure-strategy Nash equilibrium.

# Quasiconvex and quasiconcave

- A function  $f: S \rightarrow \mathbb{R}$  defined on a convex subset  $S$  of a real vector space is quasiconvex if for all  $x, y \in S$  and  $\lambda \in [0,1]$  we have

$$f(\lambda x + (1 - \lambda)y) \leq \max \{f(x), f(y)\}$$

- A function  $f: S \rightarrow \mathbb{R}$  defined on a convex subset  $S$  of a real vector space is quasiconcave if for all  $x, y \in S$  and  $\lambda \in [0,1]$  we have

$$f(\lambda x + (1 - \lambda)y) \geq \max \{f(x), f(y)\}$$

# Existence of Nash equilibrium in infinite games

- **Theorem:** Consider a strategic-form game whose strategy spaces  $S_i$  are nonempty compact subsets of a metric space. If the payoff functions  $u_i$  are continuous, then there exists a Nash equilibrium in mixed strategies.
- If payoff functions are discontinuous, mixed strategies may not exist.

# Security game between CAV attacker & defender

- Players
- Strategy spaces
- Payoffs
- Common knowledge
- Pure strategy
- Mixed strategy
- Equilibrium



# Summary questions

- What types of attacks do CAVs face?
- For CAVs, how does cyber security influence physical safety?
- What are the actions and objectives for CAV attackers and defenders?

# Next time

- Cyber-physical security of network systems.