

# Private Consensus: A Building Block for Secure Distributed Control

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# A Building Block for Distributed Control



Load balancing

Sensor fusion



Filtering

Flocking



Distributed coordination

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Iterative Consensus Problem

- ▶ N agents
- ▶ Initial states  $v(0) = [\theta \downarrow 1, \dots, \theta \downarrow N]$
- ▶ Agents interact & update states
  - ▶  $v(t+1) = P(t) v(t)$
  - ▶  $P(t)$ : Matrix capturing communication and update rule

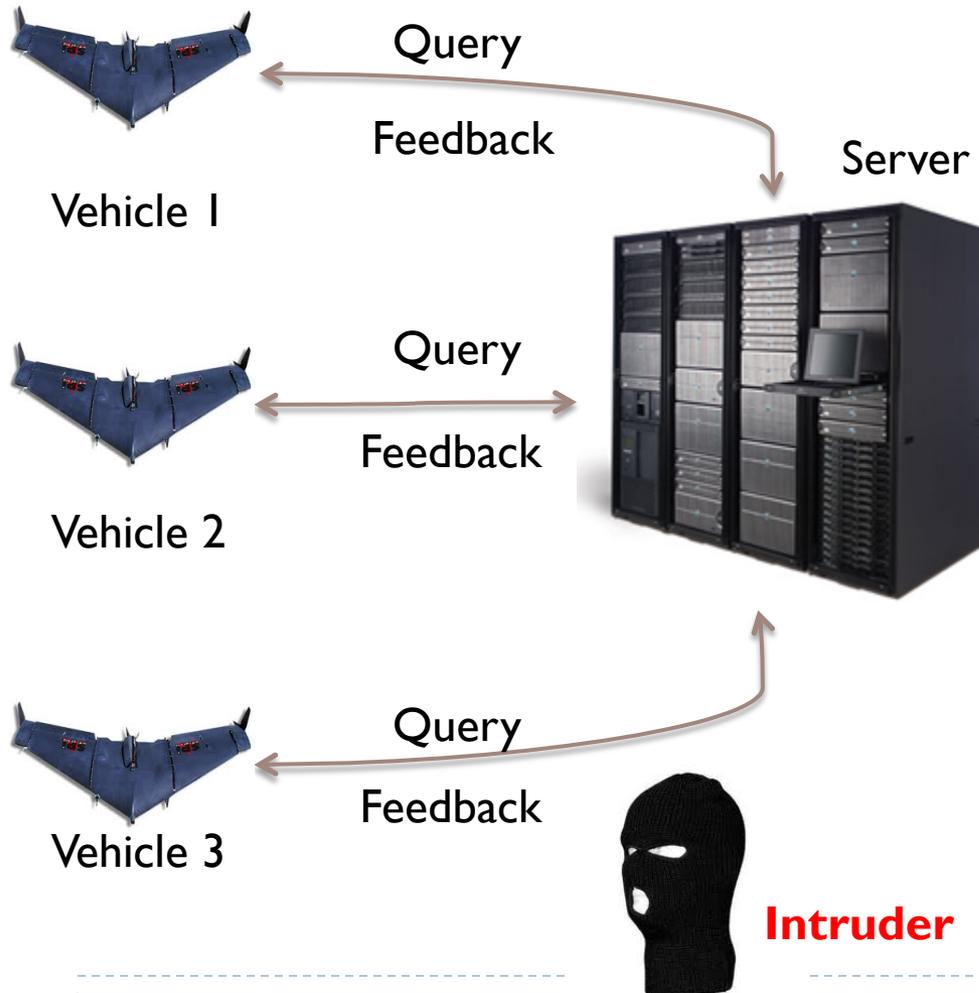
▶ Goal 1: **Converge**

$$\lim_{t \rightarrow \infty} v(t) = v(0)$$

▶ Average of the initial values

▶ Equal spacing

# A Use Case



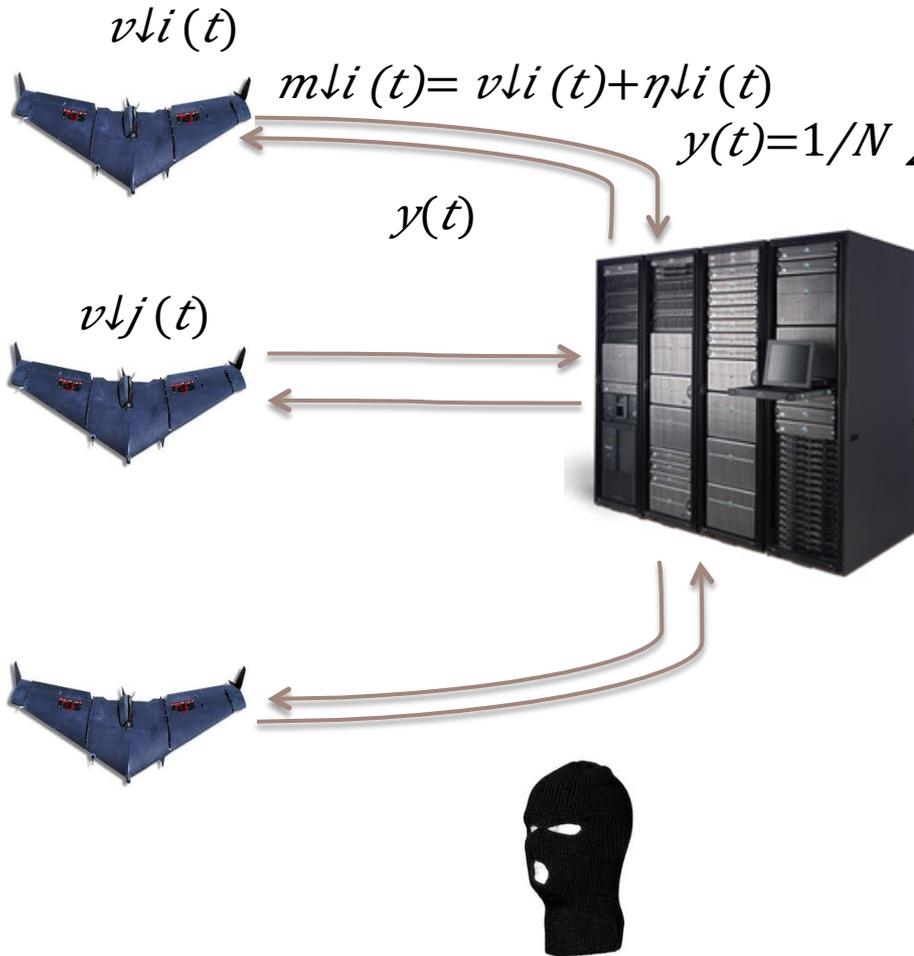
- ▶ N vehicles require move in a group while protecting their locations
- ▶ **Private consensus on velocities**
- ▶ Private data: initial velocity
- ▶ Vehicles send query, server computes feedback, vehicles' local controller updates state based on feedback
- ▶ **Eventually all vehicles move with same velocity (consensus)**
- ▶ Intruder can **see all messages** as well as **server's states** (honest but curious)
- ▶ **Privacy: Intruder cannot guess vehicles initial velocity, and therefore its current position,** with any high degree of confidence

# Private Iterative Consensus Problem

- ▶ Requirements: Achieve **consensus** while **protecting privacy** of  $V(0)$
- ▶ Randomization for privacy  $\rightarrow$  probabilistic convergence
  - ▶ A mechanism is **(1-b) probability** and **r-radius accuracy** if for any initial state  $v(0)$  all executions starting from  $v(0)$ , converges to within  $r$  of  $v(0)$  with probability **(1-b)**
- ▶ Differential privacy [**Dwork et al. 2006**]
  - ▶ Privacy of individuals participating in statistical databases
- ▶ We adapt differential privacy to continuous computations:
  - ▶ Two initial states  $\mathbf{v}(0)$  and  $\mathbf{v}'(0)$  are  **$\delta$ -adjacent** if there exists  $j$  such that  $v \downarrow j(0) - v' \downarrow j(0) \leq \delta$  and for all other agents  $v \downarrow i(0) = v' \downarrow i(0)$
  - ▶ If for any sequence of observations  $\beta$  & any  **$\delta$ -adjacent** initial states  $v(0), v'(0)$   
 $Pr[\text{Execution from } v(0) \text{ produces } \beta] / Pr[\text{Execution from } v'(0) \text{ produces } \beta] \leq e^{\epsilon \delta}$
  - ▶ Then, the randomized mechanism has  $\epsilon$ -differential privacy.



# A Randomized Mechanism

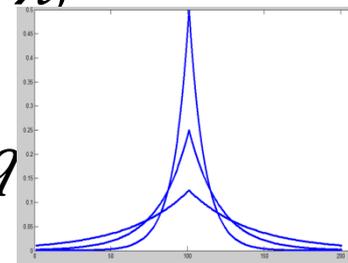


▶  $\epsilon$ : Security parameter

▶  $\lambda \in (0, 1)$ ,  $q \in (0, \lambda)$

▶  $\eta_i(t) \sim Lap(q)$

▶ **Decaying noise**



▶  $y(t)$  feedback from server

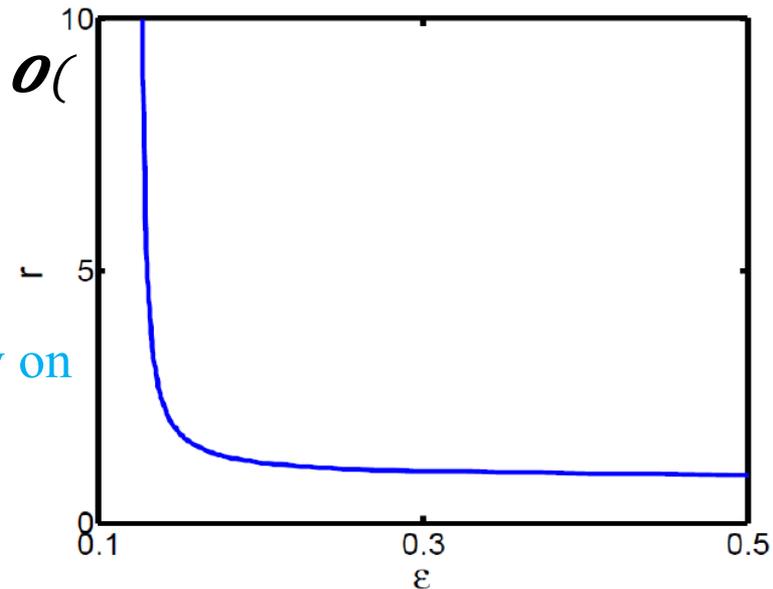
▶ **Local control law**

▶  $v_i(t+1) = (1-\lambda)v_i(t) + \lambda y(t)$

# Main Result

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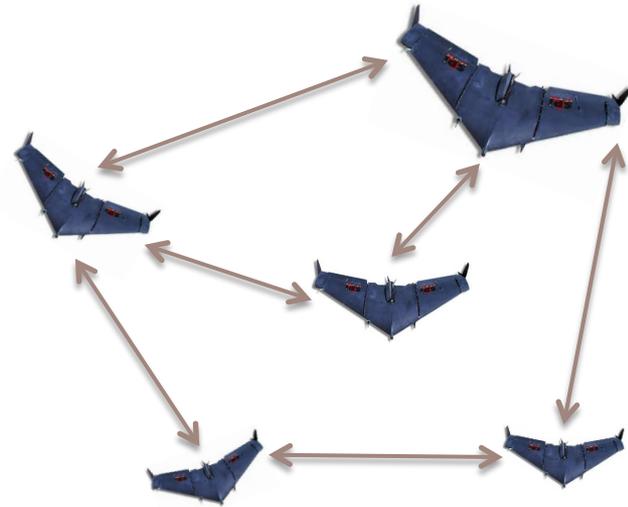
- ▶ **Theorem.** For any  $\epsilon$ ,  $N$  and  $b$ , our mechanism achieves **(1-b) probability** accuracy for **radius  $\mathcal{O}(1/\epsilon\sqrt{bN})$**  and  **$\epsilon$ -differential privacy**.
- ▶ **Remark.** For a given level of probabilistic guarantee (1-b), the accuracy **depends inversely on privacy ( $\epsilon$ )**,  **$\sqrt{b}$** , and **directly on  $\sqrt{N}$**
- ▶ **Lessons.**
  - ▶ Initially distort private data with large noise & progressively decay the noise level; **noise should converge slower than the system's inertia so as to cover the trail of dynamics**
  - ▶ Proof technique relies on **constructing bijection between two sets of executions** starting from adjacent start states



# Distributed Generalization

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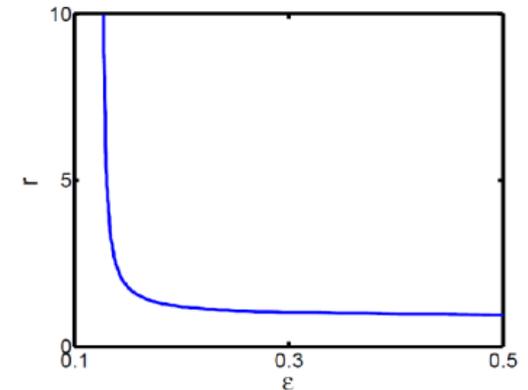
- ▶ Similar result for fully distributed algorithm (server-less) in which clients exchange information with their neighbors
  - ▶ Adversary can see **all messages** as well as **internal states** of a set (**C**) of compromised clients
  - ▶ Differential privacy of good clients



# Summary and Next Steps

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- ▶ A mechanism for private iterative consensus with **eavesdropping/honest but curious adversaries**
  - ▶ Shows trade-off between privacy and accuracy
  - ▶ Math framework for rigorous proofs



- ▶ **Next in PIC**

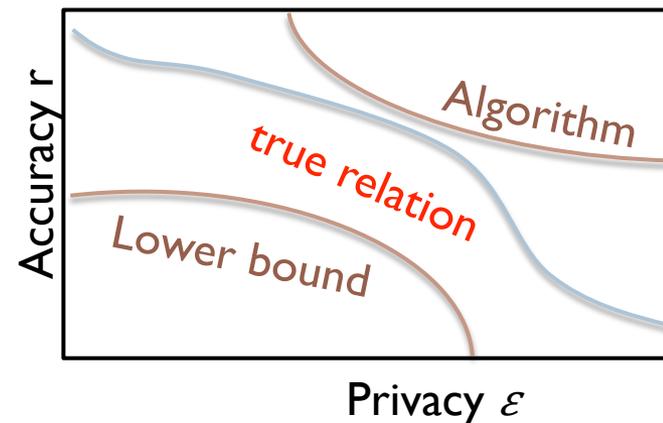
- ▶ **Lower bound** for same class of adversaries
  - ▶ **More powerful adversaries**: State corruption, Time varying  $C(t)$ ,
- ▶ **Problems requiring Safety & Convergence**
  - ▶ E.g. Maintain safe separation while converging to a formation
  - ▶ Monolithic models, distributed systems
- ▶ **Synthesizing secure protocols**
- ▶ **Proof automation [Barthe et al. 2012, Datta et al. 2012]**

# Relation to Science of Security

- ▶ Conflicting requirements for Private Consensus problem **Control Systems**
  - ▶ Differential Privacy **Security**
  - ▶ Accuracy **Control performance**
- ▶ Scientific Question: **“Is it possible to have  $\epsilon$ -differential privacy and r-accuracy for a given class of adversaries?”**
- ▶ Amenable to the standard scientific method? Hypothesis, experimentation, validation?

We believe, yes! **Proof is Data**

- ◆ **Hypothesis**: An algorithm or a conjecture for a lower bound
- ◆ **Experiments**: **Proofs and counter-examples based on specific classes of algorithms**. Try to come up with specific algorithms and lower bound proofs



# Questions / Comments?

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