

# A Game Theoretic Analysis of LQG Control under Adversarial Attack

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# Motivation

- Deep reinforcement learning<sup>1</sup>
  - ▶ DNN function approximator for complex control tasks
  - ▶ Wide-range of promising applications
  - ▶ Inherits vulnerability of DNN<sup>2,3</sup>
- Need for adversarial reinforcement learning



<sup>1</sup>Mnih et al., 2015. Human-level control through deep reinforcement learning.

<sup>2</sup>Szegedy et al., 2013. Intriguing properties of neural networks.

<sup>3</sup>Huang et al., 2016. Adversarial attacks on neural network policies.

- Attack techniques: Generate adversarial examples<sup>3-5</sup>
- Defense techniques: Use perturbations in the training<sup>6</sup>
- Game formulations: Capture the strategic interaction
  - ▶ Variants of stochastic game<sup>6-8</sup>
  - ▶ Stackelberg game + POMDP or LQG<sup>9,10</sup>
  - ▶ Cheap talk game + Linear dynamic system<sup>11</sup>

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<sup>3</sup> Huang et al., 2016. Adversarial attacks on neural network policies.

<sup>4</sup> Lin et al., 2017. Tactics of adversarial attack on deep reinforcement learning agents.

<sup>5</sup> Behzadan and Munir, 2017. Vulnerability of deep reinforcement learning to policy induction attacks.

<sup>6</sup> Pinto et al., 2017. Robust adversarial reinforcement learning.

<sup>7</sup> Horák et al., 2017. Manipulating adversary's belief: A dynamic game approach to deception by design for proactive network security.

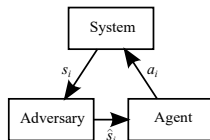
<sup>8</sup> Gleave et al., 2020. Adversarial policies: Attacking deep reinforcement learning.

<sup>9</sup> Osogami, 2015. Robust partially observable Markov decision process.

<sup>10</sup> Sayin et al., 2019. Hierarchical multistage Gaussian signaling games in noncooperative communication and control systems.

<sup>11</sup> Saritas et al., 2017. Nash and Stackelberg equilibria for dynamic cheap talk and signaling games.

# Adversarial LQG control



- *N*-stage LQG:

$$s_{i+1} = \alpha_i s_i + \beta_i a_i + z_i, \text{ given } \alpha_i \neq 0, \beta_i \neq 0$$

$$\hat{s}_i = \pi_i s_i + c_i$$

$$a_i = \kappa_i \hat{s}_i + \rho_i$$

$$r_i = R_i(s_i, a_i) = -\theta_i s_i^2 - \phi_i a_i^2, \text{ given } \theta_i > 0, \phi_i > 0$$

$$S_1 \sim b_1 \triangleq \mathcal{N}(\mu_1, \sigma_1^2), \text{ given } \mu_1, \sigma_1^2 > 0$$

$$Z_i \sim \mathcal{N}(0, \omega_i^2), \text{ given } \omega_i^2 > 0$$

$$C_i \sim \mathcal{N}(0, \delta_i^2)$$

# Adversarial LQG control

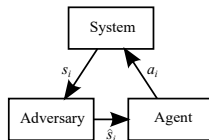
- Belief of the agent in the beginning of  $i$ -th stage  $b_i \triangleq \mathcal{N}(\mu_i, \sigma_i^2)$ : Posterior distribution of  $S_i$  after observing  $\{(\hat{s}_k, a_k)\}_{k=1}^{i-1}$
- Belief update  $b_i \rightarrow b_{i+1}$ :

$$\mu_{i+1} = \Lambda_\mu(b_i, \pi_i, \delta_i^2, \hat{s}_i, a_i) = \alpha_i \frac{\pi_i \sigma_i^2 \hat{s}_i + \mu_i \delta_i^2}{\pi_i^2 \sigma_i^2 + \delta_i^2} + \beta_i a_i$$
$$\sigma_{i+1}^2 = \Lambda_\nu(b_i, \pi_i, \delta_i^2) = \frac{\alpha_i^2 \sigma_i^2 \delta_i^2}{\pi_i^2 \sigma_i^2 + \delta_i^2} + \omega_i^2$$

- Adversarial manipulation constraints:

$$-\infty < \varepsilon' \leq \pi_i \leq \varepsilon < \infty, \text{ given } \varepsilon', \varepsilon$$
$$I(\hat{S}_i; S_i) = \frac{1}{2} \log \frac{\pi_i^2 \sigma_i^2 + \delta_i^2}{\delta_i^2} \geq \frac{1}{2} \log \lambda > 0, \text{ given } \lambda > 1$$

# Adversarial LQG control

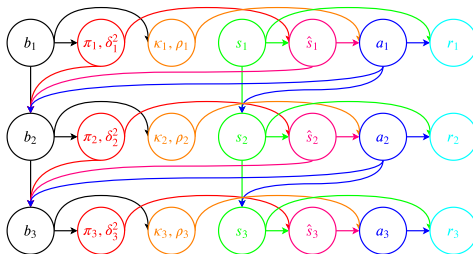


- Asymmetric information
  - ▶ The adversary manipulates the system states.
  - ▶ The agent chooses actions based on the manipulated observations.
- Conflicting objectives
  - ▶ The agent aims at improving the control reward.
  - ▶ The adversary aims at degrading the control reward.

## Question

*How to formulate the interaction of players with asymmetric information in an LQG control?*

# Adversarial LQG game



- In the beginning of the  $i$ -th stage
  - ▶ Adversarial strategy:  $g_i(\pi_i, \delta_i^2 | b_i)$  or  $(\pi_i, \delta_i^2) = g_i(b_i)$
  - ▶ Agent strategy:  $f_i(\kappa_i, \rho_i | b_i)$  or  $(\kappa_i, \rho_i) = f_i(b_i)$
- Running follows the LQG equations
- In the end of the  $i$ -th stage
  - ▶ Adversary reveals the chosen parameters  $(\pi_i, \delta_i^2)$  to the agent
  - ▶ Both players update the next belief  $b_{i+1}$

# Subgame perfect equilibrium

- Strategies  $(g^{N*}, f^{N*})$  form an SPE.
- Value function of a subgame starting from the  $i$ -th stage:

$$V_i^N(b_i) = E_{b_i, g_i^{N*}, f_i^{N*}} \left( \sum_{j=i}^N R_j(S_j, A_j) \right)$$

- Backward dynamic programming:

$$\begin{aligned} V_i^N(b_i) &= \min_{g_i} E_{b_i, g_i, f_i^*} \{ R_i(S_i, A_i) \\ &\quad + V_{i+1}^N(\mathcal{N}(\Lambda_\mu(b_i, \Pi_i, \Delta_i^2, \hat{S}_i, A_i), \Lambda_\nu(b_i, \Pi_i, \Delta_i^2))) \} \\ &= \max_{f_i} E_{b_i, g_i^*, f_i} \{ R_i(S_i, A_i) \\ &\quad + V_{i+1}^N(\mathcal{N}(\Lambda_\mu(b_i, \Pi_i, \Delta_i^2, \hat{S}_i, A_i), \Lambda_\nu(b_i, \Pi_i, \Delta_i^2))) \} \end{aligned}$$



# Single-stage ALQG game

## Proposition 1

Let  $N = 1$ . An SPE *always exists* and consists of  $(f_1^*, g_1^*)$ , where  $(\kappa_1^*, \rho_1^*) = f_1^*(b_1) = (0, 0)$  for any belief  $b_1$ ; and  $g_1^*$  can be any adversarial strategy subject to constraints.

## Theorem 1

Let  $N \geq 2$ . If  $\varepsilon' \neq \varepsilon$  or if  $\varepsilon' = \varepsilon = 0$ , then there is *no* pure strategy SPE for the ALQG game. If  $\varepsilon' = \varepsilon \neq 0$ , then there is a *unique* pure strategy SPE. The SPE strategies for  $1 \leq i \leq N$  are given by

$$\begin{aligned}\tilde{\theta}_{N+1} &= \hat{\theta}_{N+1} = 0; \\ \tilde{\theta}_i &= \theta_i + \tilde{\theta}_{i+1}\alpha_i^2 - \frac{\tilde{\theta}_{i+1}^2\alpha_i^2\beta_i^2}{\phi_i + \tilde{\theta}_{i+1}\beta_i^2}; \\ \hat{\theta}_i &= \theta_i + \hat{\theta}_{i+1}\alpha_i^2 - \left( \frac{\tilde{\theta}_{i+1}^2\alpha_i^2\beta_i^2}{\phi_i + \tilde{\theta}_{i+1}\beta_i^2} + (\hat{\theta}_{i+1} - \tilde{\theta}_{i+1})\alpha_i^2 \right) \frac{\lambda - 1}{\lambda}; \\ (\pi_i^*, \delta_i^{2*}) &= g_i^*(b_i) = \left( \varepsilon, \frac{\varepsilon^2\sigma_i^2}{\lambda - 1} \right); \\ (\kappa_i^*, \rho_i^*) &= f_i^*(b_i) = \left( -\frac{\tilde{\theta}_{i+1}\alpha_i\beta_i(\lambda - 1)}{(\phi_i + \tilde{\theta}_{i+1}\beta_i^2)\lambda\varepsilon}, -\frac{\tilde{\theta}_{i+1}\alpha_i\beta_i\mu_i}{(\phi_i + \tilde{\theta}_{i+1}\beta_i^2)\lambda} \right).\end{aligned}$$

## Corollary 1

If  $\varepsilon' = \varepsilon \neq 0$ , the value function induced by the unique pure strategy SPE is

$$V_i^N(b_i) = -\tilde{\theta}_i \mu_i^2 - \hat{\theta}_i \sigma_i^2 - \sum_{j=i+1}^N \hat{\theta}_j \omega_{j-1}^2.$$

## Observations

- A rational adversary will always apply a manipulation with the largest variance.
- The value function  $V_i^N$  consists of two separable terms of  $\mu_i$  and  $\sigma_i^2$ .

# Time-invariant model

- Time-invariant parameters:  $\alpha_i = \alpha \neq 0$ ,  $\beta_i = \beta \neq 0$ ,  $\omega_i^2 = \omega^2 > 0$ ,  $\theta_i = \theta > 0$ , and  $\phi_i = \phi > 0$  for  $i \geq 1$
- Define the mapping  $L : \mathbb{R}_{\geq 0}^2 \rightarrow \mathbb{R}_{\geq 0}^2$  as

$$L(x, y) = \left( \theta + \frac{\phi \alpha^2 x}{\phi + \beta^2 x}, \theta + \frac{\phi \alpha^2 x}{\phi + \beta^2 x} \frac{\lambda - 1}{\lambda} + \alpha^2 y \frac{1}{\lambda} \right).$$

## Proposition 2

Let  $\lambda > \alpha^2$ . Then the mapping  $L$  admits a least fixed point  $(\tilde{\theta}, \hat{\theta}) \in \mathbb{R}_{\geq 0}^2$ , for which

$$\lim_{n \rightarrow \infty} L^n(0, 0) = L(\tilde{\theta}, \hat{\theta}) = (\tilde{\theta}, \hat{\theta}).$$

# Time-invariant model

## Theorem 2

Let  $\lambda > \alpha^2$ ,  $\varepsilon' = \varepsilon \neq 0$ , and  $N \rightarrow \infty$ . Then the ALQG game of the time-invariant model has a stationary SPE in pure strategies as: For  $i \geq 1$ ,

$$\begin{aligned}(\pi_i^*, \delta_i^{2*}) &= g_i^*(b_i) = \left( \varepsilon, \frac{\varepsilon^2 \sigma_i^2}{\lambda - 1} \right); \\(\kappa_i^*, \rho_i^*) &= f_i^*(b_i) = \left( -\frac{\tilde{\theta} \alpha \beta (\lambda - 1)}{(\phi + \tilde{\theta} \beta^2) \lambda \varepsilon}, -\frac{\tilde{\theta} \alpha \beta \mu_i}{(\phi + \tilde{\theta} \beta^2) \lambda} \right).\end{aligned}$$

## Corollary 2

Let  $b_1 \triangleq \mathcal{N}(\mu_1, \sigma_1^2)$  with *bounded* mean and variance. For the stationary SPE in pure strategies, the expected average reward per stage in steady state is *independent* of the initial belief:

$$\lim_{N \rightarrow \infty} \frac{V_1^N(b_1)}{N} = -\hat{\theta} \omega^2.$$

## Theorem 3

Let  $N \geq 2$ ,  $\varepsilon' < 0 < \varepsilon$ , and  $\check{\theta}_{N+1} = 0$ . Then for  $1 \leq i \leq N$ ,

$$\check{\theta}_i = \theta_i + \check{\theta}_{i+1}\alpha_i^2 - (\check{\theta}_{i+1} - \tilde{\theta}_{i+1})\alpha_i^2 \frac{\lambda - 1}{\lambda}.$$

There is a continuum of SPEs in behavioral strategies. Each SPE in the  $i$ -th stage consists of a behavioral strategy  $g_i^*$  and a pure strategy  $f_i^*$  satisfying

$$\mathbb{S}(g_i^*|b_i) \triangleq \left\{ (\pi_i, \delta_i^2) : \pi_i \neq 0, \varepsilon' \leq \pi_i \leq \varepsilon, \delta_i^2 = \frac{\pi_i^2 \sigma_i^2}{\lambda - 1} \right\};$$

$$\|\mathbb{S}(g_i^*|b_i)\| \geq 2;$$

$$E_{g_i^*}(\Pi_i) = 0;$$

$$(\kappa_i^*, \rho_i^*) = f_i^*(b_i) = \left( 0, -\frac{\tilde{\theta}_{i+1}\alpha_i\beta_i\mu_i}{\phi_i + \tilde{\theta}_{i+1}\beta_i^2} \right).$$

## Corollary 3

Let  $\varepsilon' < 0 < \varepsilon$ . For any SPE in behavioral strategies, we have

$$V_i^N(b_i) = -\tilde{\theta}_i \mu_i^2 - \check{\theta}_i \sigma_i^2 - \sum_{j=i+1}^N \check{\theta}_j \omega_{j-1}^2.$$

## Observations

- It is sufficient for the agent to use a pure strategy.
- Although the adversary cannot use  $\pi_i = 0$ , the behavioral strategy  $g_i^*$  needs to achieve zero-mean of the random coefficient  $\Pi_i$ .
- A rational adversary will always use a manipulation with the largest variance.
- The value function  $V_i^N$  consists of two separable terms of  $\mu_i$  and  $\sigma_i^2$ .
- Stronger adversary  $\Rightarrow$  The value function of an SPE in behavioral strategies  $\leq$  The value function of a pure strategy SPE.

- Define the mapping  $J : \mathbb{R}_{\geq 0}^2 \rightarrow \mathbb{R}_{\geq 0}^2$  as

$$J(x, y) = \left( \theta + \frac{\phi \alpha^2 x}{\phi + \beta^2 x}, \theta + \alpha^2 x \frac{\lambda - 1}{\lambda} + \alpha^2 y \frac{1}{\lambda} \right).$$

## Proposition 3

Let  $\lambda > \alpha^2$ . Then the mapping  $J$  admits a least fixed point  $(\tilde{\theta}, \check{\theta}) \in \mathbb{R}_{\geq 0}^2$ , for which

$$\lim_{n \rightarrow \infty} J^n(0, 0) = J(\tilde{\theta}, \check{\theta}) = (\tilde{\theta}, \check{\theta}).$$



# Time-invariant model

## Theorem 4

Let  $\lambda > \alpha^2$ ,  $\varepsilon' < 0 < \varepsilon$ , and  $N \rightarrow \infty$ . Then the ALQG game of the time-invariant model has a stationary SPE in behavioral strategies as: For  $i \geq 1$ ,

$$\begin{aligned} g_i^* \left( \pi_i = \varepsilon', \delta_i^2 = \frac{\varepsilon'^2 \sigma_i^2}{\lambda - 1} \middle| b_i \right) &= \frac{\varepsilon}{\varepsilon - \varepsilon'}; \\ g_i^* \left( \pi_i = \varepsilon, \delta_i^2 = \frac{\varepsilon^2 \sigma_i^2}{\lambda - 1} \middle| b_i \right) &= -\frac{\varepsilon'}{\varepsilon - \varepsilon'}; \\ (\kappa_i^*, \rho_i^*) &= f_i^*(b_i) = \left( 0, -\frac{\tilde{\theta} \alpha \beta \mu_i}{\phi + \tilde{\theta} \beta^2} \right). \end{aligned}$$

## Corollary 4

Let  $b_1 \triangleq \mathcal{N}(\mu_1, \sigma_1^2)$  with *bounded* mean and variance. For the stationary SPE in behavioral strategies, the expected average reward per stage in steady state is

$$\lim_{N \rightarrow \infty} \frac{V_1^N(b_1)}{N} = -\check{\theta} \omega^2.$$

- **Theorem 5:** Let  $N \geq 2$ . If  $0 = \varepsilon' < \varepsilon$  or if  $\varepsilon' < \varepsilon = 0$ , there is *no* SPE for the ALQG game.
- **Theorem 6:** Let  $N = 2$ . If  $0 < \varepsilon' < \varepsilon$  or if  $\varepsilon' < \varepsilon < 0$ , there is a *unique* SPE in behavioral strategies for the ALQG game: For any belief  $b_1 \triangleq \mathcal{N}(\mu_1, \sigma_1^2)$ ,

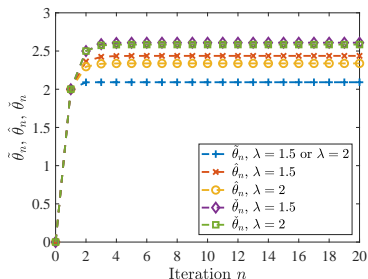
$$\begin{aligned}
 g_1^* \left( \pi_1 = \varepsilon', \delta_1^2 = \frac{\varepsilon'^2 \sigma_1^2}{\lambda - 1} \middle| b_1 \right) &= \frac{\varepsilon}{\varepsilon' + \varepsilon}; \\
 g_1^* \left( \pi_1 = \varepsilon, \delta_1^2 = \frac{\varepsilon^2 \sigma_1^2}{\lambda - 1} \middle| b_1 \right) &= \frac{\varepsilon'}{\varepsilon' + \varepsilon}; \\
 \kappa_1^* = f_1^*(b_1) &= \frac{-\theta_2 \alpha_1 \beta_1 E_{g_1^*}(\Pi_1) \sigma_1^2}{(\phi_1 + \theta_2 \beta_1^2) \left( E_{g_1^*}(\Pi_1^2) \left( \mu_1^2 + \frac{\lambda}{\lambda - 1} \sigma_1^2 \right) - E_{g_1^*}^2(\Pi_1) \mu_1^2 \right)}; \\
 \rho_1^* = f_1^*(b_1) &= -E_{g_1^*}(\Pi_1) \mu_1 \kappa_1^* - \frac{\theta_2 \alpha_1 \beta_1 \mu_1}{\phi_1 + \theta_2 \beta_1^2};
 \end{aligned}$$

$$V_1^2(b_1) = - \left( \theta_1 + \theta_2 \alpha_1^2 - \frac{\theta_2^2 \alpha_1^2 \beta_1^2}{\phi_1 + \theta_2 \beta_1^2} \right) \mu_1^2 - \theta_2 \omega_1^2 - (\theta_1 + \theta_2 \alpha_1^2) \sigma_1^2 \\ + \frac{\theta_2^2 \alpha_1^2 \beta_1^2 E_{g_1^*}^2(\Pi_1) \sigma_1^4}{(\phi_1 + \theta_2 \beta_1^2) \left( E_{g_1^*}(\Pi_1^2) \left( \mu_1^2 + \frac{\lambda}{\lambda-1} \sigma_1^2 \right) - E_{g_1^*}^2(\Pi_1) \mu_1^2 \right)}.$$

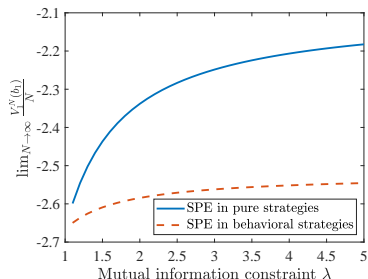
# Numerical results

Time-invariant LQG model parameters

| Parameter | $\mu_1$ | $\sigma_1^2$ | $\alpha$ | $\beta$ | $\omega^2$ | $\theta$ | $\phi$ |
|-----------|---------|--------------|----------|---------|------------|----------|--------|
| Value     | 0       | 1            | -0.5     | -1.5    | 1          | 2        | 1      |



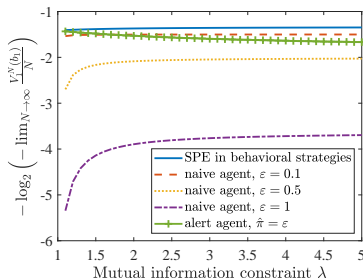
$\tilde{\theta}_n, \hat{\theta}_n, \check{\theta}_n$  computed as  $L^n(0,0)$  and  $J^n(0,0)$  v.s. the number of iterations  $n$ , for  $\lambda = 1.5$  and  $\lambda = 2$  ( $\lambda > \alpha^2$ ).



Expected average reward per stage v.s. mutual information constraint  $\lambda$ , for stationary SPEs in pure strategies and behavioral strategies.

# Numerical results

- Naive agent: Unaware of the adversary and take the optimal LQG strategy
- Alert agent: Assume an adversarial strategy and take the best response



Expected average reward per stage for stationary SPE in behavioral strategies, that for a naive agent, and that for an alert agent v.s. mutual information constraint  $\lambda$ .

- Adversarial LQG game
  - ▶ Strategic interaction
  - ▶ Asymmetric information
  - ▶ System dynamics
- Subgame perfect equilibria
  - ▶ Pure strategy SPE
  - ▶ Behavioral strategy SPE
- Improvement by considering strategic interactions
- Future work
  - ▶ Non-scalar state dynamic system
  - ▶ Relax the assumption that the adversarial strategy is revealed to the agent after each stage

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Thank you for your attention!