Inverse-Inverse Reinforcement Learning. How to Hide Strategy from an Adversarial Inverse Reinforcement Learner

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Main Idea. Detecting utility maximization $\equiv$ Checking linear feasibility

How to make checking linear feasibility difficult?

Radar Context:

Cognitive radar $\rightarrow$ Choose optimal waveform for target tracking

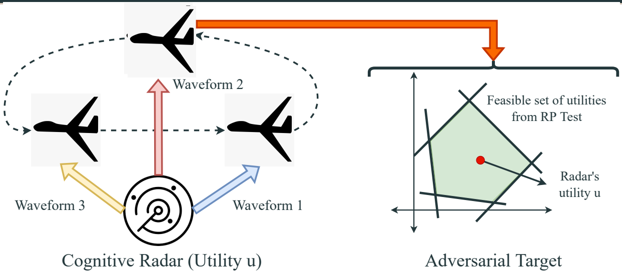
Adversarial Target $\rightarrow$ Malicious maneuvers to 'estimate' radar's utility

How to spoof adversarial attacks on radar's utility function?

Ans. **Cognition Masking**

Intelligently perturbed radar actions successfully hide radar's utility

Background. Cognitive Radar and Revealed Preference



Cognitive Radar [1–3]: Optimal waveform adaptation.
For target maneuvers (**probe**) $\{\alpha_k\}_{k=1}^K$, radar chooses waveforms (**response**) $\{\beta_k\}_{k=1}^K$ that maximize utility u:

$$\beta_k = \text{argmax}_{\beta \in \mathbb{R}_+^m} u(\beta), \ \ \alpha_k' \beta \leq 1 \tag{1}$$

Radar Bayesian tracker: Linear Gaussian dynamics
(i) α_k: state noise covariance
(ii) β_k: observation noise covariance
(iii) $\alpha_k' \beta_k \leq 1$ (1): Bound on radar SNR $\equiv$ Bound on radar's asymptotic predicted Kalman **precision** [3]
'Choose best waveform subject to resource constraints'

Utility Estimation via Revealed Preference (RP):
RP Test [4, 5] : For dataset $\mathbb{D} = \{\alpha_k, \beta_k\}_{k=1}^K$, linear feasibility test is **equivalent** to checking for utility maximization (1):

$$\text{RP}(u, \mathbb{D}) \leq 0, \ \ u = \{u_k, \lambda_k\} \in \mathbb{R}_+^{2m}, \tag{2}$$

$$u_{\text{est}}(\beta) = \min_k \{u_k + \lambda_k \alpha_k' (\beta - \beta_k)\} \tag{3}$$

What if $\mathbb{D}$ is noisy?
RP Test (2) generalizes to statistical hypothesis test to detect feasibility [6] (discussed in slide 4).

Cognition Masking
How to mitigate adversarial RP test and ensure poor reconstruction of radar's utility function

Result 1. Deterministic Inverse RP for Masking Cognition

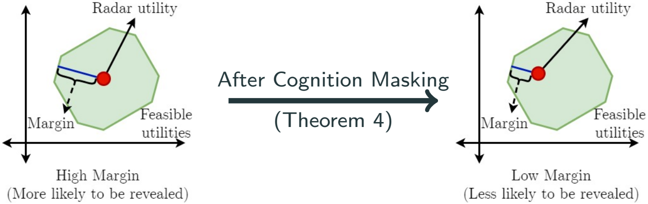
Assumption: "Radar and adversary have accurate probe-response measurements."

Adversarial target $\overset{\text{IRL}}{\rightarrow}$ RP Feasibility test (2) (Set-valued estimate of radar's utility)

How to rank utility functions in the feasible set?

Rank via **Margin** of RP test - **max. perturbation to fail RP test** (based on [7])

$$\boxed{\text{Margin}_{\mathbb{D}}(u) = \max_{\epsilon \geq 0} \epsilon, \quad \text{RP}(u, \mathbb{D}) + \epsilon \geq 0, \quad u \in \text{Feasible set}}$$



- Margin: Closeness to edge of feasible set (infeasibility of RP test)
- Center of feasible set: **max. margin**, edge of feasible set: **zero margin**
- $\uparrow$ Margin $\iff$ $\uparrow$ Goodness-of-fit to RP test
- **Deterministic** Cognition masking: Deliberately perturb radar's response to push radar's utility **towards** edge of feasible set from RP test

Deterministic Inverse IRL for Masking Cognition

Suppose radar faces adversarial constraints $\{\alpha_k'\beta \leq 1\}_{k=1}^K$. The radar's *deterministic* I-IRL algorithm to hide its utility u is:

Step 1. Choose margin $\epsilon_{\text{thresh}} \in \mathbb{R}_+$
Step 2. Compute naive response β_k^* (1)
Step 3. Compute optimal perturbation $\{\delta_k^*\}$ for I-IRL:

$$\{\delta_k^*\} = \underset{\{\delta_k\}\in\mathbb{R}^m}{\operatorname{argmin}} \underbrace{\sum_{k=1}^{K} \|\delta_k\|_2^2}_{\text{(Radar's degradation)}} \quad , \quad \underbrace{\text{Margin}_{\{\alpha_k,\beta_k^*+\delta_k\}}(u) \leq \epsilon_{\text{thresh}}}_{\text{(Mitigating adversarial RP Test)}} \tag{4}$$

Step 4. Transmit engineered sub-optimal responses $\{\beta_k^* + \delta_k^*\}$.

Summary

Deterministic I-IRL: Small margin ϵ_{thresh}

$\iff$ Closer to failing RP test (2)

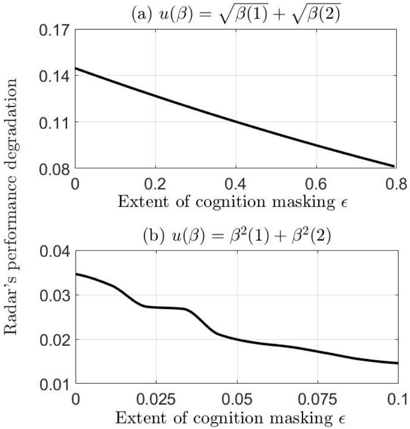
$\iff$ Larger deviation from radar's optimal strategy

- Margin Constraint in (4) is non-convex (bilinear).

Current research: *Formulate convex relaxations of bi-linear constraints in* (4).

Numerical Results: Deterministic Inverse IRL

- Simulation-based datasets to illustrate I-IRL for 2 utility functions
- Parameters: Time horizon $K = 50$, Probe/Response dimension $m = 2$



Key Insights:

- **Small deviation** from *optimal strategy* masks utility by a large extent.
- Radar's performance degradation ↑ with ϵ.

Result 2. Stochastic Inverse RP for Masking Cognition

Assumption: "Adversary has *noisy* measurements of the radar's response."

$$\text{(Adversary side): } \hat{\beta}_k = \beta_k + w_k, \;\; w_k \sim f_w \;\; (f_w \text{ known to radar}) \tag{5}$$

Adversarial target $\xrightarrow{\text{IRL}}$ Feasibility *Detector* (see also [3] for details)

$$H_0: \text{ RP Test (2) has a feasible solution for } \{\alpha_k, \beta_k\}$$

$$H_1: \text{ RP Test (2) has NO feasible solution for } \{\alpha_k, \beta_k\}$$

IRL Feasibility Detector : $\boxed{\phi^*(\widehat{\mathbb{D}}) \lesseqgtr_{H_0}^{H_1} F_L^{-1}(1-\eta)}$ $(\widehat{\mathbb{D}} = \{\alpha_k, \hat{\beta}_k\}),$ (6)

$$\phi^*(\widehat{\mathbb{D}}): \max_{\{\bar{u}>0\}} \text{Margin}_{\bar{u}}(\widehat{\mathbb{D}}), \text{ r.v. } L := \max_{j,k} \alpha_j'(w_j - w_k),$$

$$\eta: \text{ Adversary chosen bound for } \mathbb{P}(H_1|H_0)$$

"*Radar is non-cognitive if margin is under a threshold*"

- Radar **can no more** manipulate margin of RP test.
- Can *at best* manipulate $\mathbb{P}(H_1|\{\alpha_k, \beta_k\}, u)$ (Cond. Type-I error prob.)
- **Stochastic** Cognition masking: Deliberately perturb radar's response to mitigate IRL detector (**increase** conditional Type-I error probability).

Stochastic Inverse IRL for Masking Cognition

Adversary's sensor is noisy; everything else the same as deterministic case. Radar's *stochastic* I-IRL algorithm is:

Step 1. Choose sensitivity parameter $\lambda > 0$

Step 2. Compute naive response β_k^* (1)

Step 3. Compute optimal perturbation $\{\delta_k^*\}$ for I-IRL:

$$\{\delta_k^*\} = \underset{\{\delta_k\} \in \mathbb{R}^m}{\operatorname{argmin}} \sum_{k=1}^{K} \Big(\underbrace{u(\beta_k^*) - u(\beta_k^* + \delta_k))}_{\text{(Radar's deliberate performance loss)}} - \lambda \underbrace{\mathbb{P}(H_1 | \{\alpha_k, \beta_k^* + \delta_k\}, u)}_{\text{(Mitigating adversarial IRL detector)}} \tag{7}$$

Step 4. Transmit engineered sub-optimal responses $\{\beta_k^* + \delta_k^*\}$

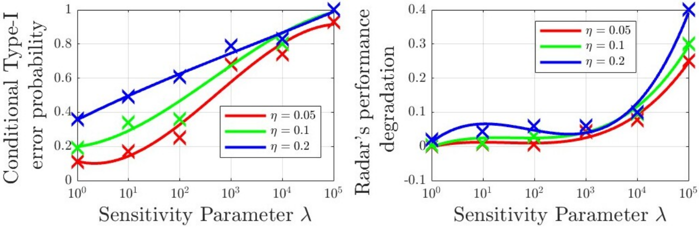
(7)*: Ensuring low margin of RP Test with high probability*

Summary

- **Stochastic I-IRL**: Trade-off between $\uparrow$ *QoS* and $\uparrow$ *adversarial obfuscation*.
- Radar can only <u>estimate</u> $\mathbb{P}(H_1 | H_0, u)$ (7) via Monte-Carlo methods.
- Stochastic approximation based algorithms like **SPSA [8]** can be used for implementing optimization problem (7).
- SPSA $\rightarrow$ Fewer (only 2) computations/update wrt finite diff. methods.

Numerical Results: Stochastic Inverse IRL

- Simulations for a single utility function $u(\beta) = \sqrt{\beta_1} + \sqrt{\beta_2}$
- Parameters: Time horizon $K = 50$, Probe/Response dimension $m = 2$



Key Insights:

- Small *performance loss* sufficiently confuses IRL detector (large cond. Type-I error).
- **Both** adversarial confusion and radar's performance degradation $\uparrow$ with λ.
- Interestingly, performance degradation $\downarrow$ with η (error bound).

Remark: Inverse IRL results on slides 3,6 can be extended to the case where radar hides is system constraints and adversary dictates the radar's utility function, for e.g. , beam allocation (Th. 3 in paper).

Result 3. Finite Sample Effects for Inverse IRL

Stochastic I-IRL (slide 6) adapts deterministic I-IRL to strategy 'detector'.

Key Idea. Sufficient statistics for existence of strategy in terms of observation noise.

What if radar has noisy measurements of the adversary's probes?

Prob. bounds for Deterministic I-IRL (slide 3) to mask strategy effectively?

Recall: Deterministic I-IRL maintains feasibility margin of IRL test **less than** ϵ_{thresh} (4).

Want to bound: $\boxed{\mathbb{P}(\text{Margin}_{\{\alpha_k+w_k,\tilde{\beta}_k^*\}}(u) \not\leq \epsilon_{\text{thresh}})}$, where $w_k \rightarrow$ Radar sensor's measurement noise, $\tilde{\beta}_k^* \rightarrow$ I-IRL response (4). Assume i.i.d $w_k \sim \mathcal{N}(\mathbf{0}, \Sigma)$.

Finite Sample Complexity for Deterministic I-IRL

Consider the radar choosing I-IRL responses according to (4) and observes adversary's probes in noise. Then, under mild conditions, the probability that deterministic I-IRL fails to mask the radar's strategy is given by:

$$\mathbb{P}(\text{Margin}_{\{\alpha_k+w_k,\tilde{\beta}_k^*\}}(u) > \epsilon_{\text{thresh}}) \leq 1 - \frac{T\ e^{-\psi^2(\widehat{\mathbb{D}})/2}}{\psi(\widehat{\mathbb{D}})\sqrt{2\pi}},\ \widehat{\mathbb{D}} = \{\alpha_k + w_k, \beta_k\}_{k=1}^T,$$

$\psi(\cdot)$ (8) is proportional to Lipschitz constant of radar's constraint, range of allowable probes, and inversely proportional to Lipschitz constant of radar's utility function.

Remark. Above error bound is loose, currently investigating tighter convergence rates.

Conclusion and Extensions

Summary:

- Radar **counter**-countermeasure to mitigate an adversarial countermeasure
- Cognition Masking: *Deliberately perturb optimal radar waveforms to sufficiently reduce margin of RP test and 'hide' radar's utility.*
- Sub-optimality in response trades-off between Privacy and Performance
- Methodology inspired from adversarial obfuscation [9] in deep learning and differential privacy [10]

Extensions (Current research):

1. *Online IRL.* Current strategy hiding idea is offline (since IRL via Afriat's Theorem is intrinsically offline). Bandit approach for approximating IRL detector?
2. *Meta-confusion.* Vary the low margin constraint over time for 'robust' adversarial mitigation.
3. *Semi-parametric.* Jointly optimize over response perturbations and variance of additive Laplacian noise for robust I-IRL.
4. **Counter**-(counter-)^{n}measure: What if adversary knows radar's spoofing strategy? *Game theoretic approach?*

Thank You!

Miscellaneous

FAQs

- **How justified is the constrained utility maximization abstraction for radar operation?**

Quite prevalent in literature:

(i) Multi-UAV network [11]: Utility $\rightarrow$ Fairness and downlink data rate, Constraint $\rightarrow$ Transmission power, Cramer-Rao bound on localization accuracy
(ii) Q-RAM (Resource Allocation) [12]: Utility $\rightarrow$ QoS for tracking and search, Constraint $\rightarrow$ Bandwidth, Short-term and Long-term constraints
(iii) Radar Tracking with ECM [13]: Utility $\rightarrow$ Neg. of weighted mean of radar energy and dwell time, Constraint $\rightarrow$ 4% Cap on lost tracks due to ECM

FAQs

- **Is conditional Type-I probability the only I-IRL metric for adversarial obfuscation in stochastic I-IRL?**

No fixed formula, does need more work. Some intuitive alternatives: (a) Use deterministic I-IRL as is. Formulate concentration inequalities for margin of the noisy dataset.

(b) Manipulate the average margin instead of margin. BUT, might be underplaying robustness of IRL detector.

(c) [**Speculative**] Use a neural network to learn IRL method on the fly and disrupt ECM.

Remark: I-IRL hinges delicately on IRL methodology.

Other heuristic ideas to hide utility?

FAQs

- **What's next after IRL, and inverse IRL? I2-IRL?**

Game-theoretic formulation.

Key challenge: Formulate a utility function in terms of both adversary probes and radar response.

Anticipated outcome: Inverse game theory - Detecting play from the Nash equilibrium of a game between adversary and radar.

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