

MULTILAYER SENSOR NETWORK FOR INFORMATION PRIVACY

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MOTIVATIONS

With the ubiquitous adoption of Internet of Things (IoT) devices like on-body sensors, smart home appliances, and smart phones, massive amounts of data are being collected by service providers.

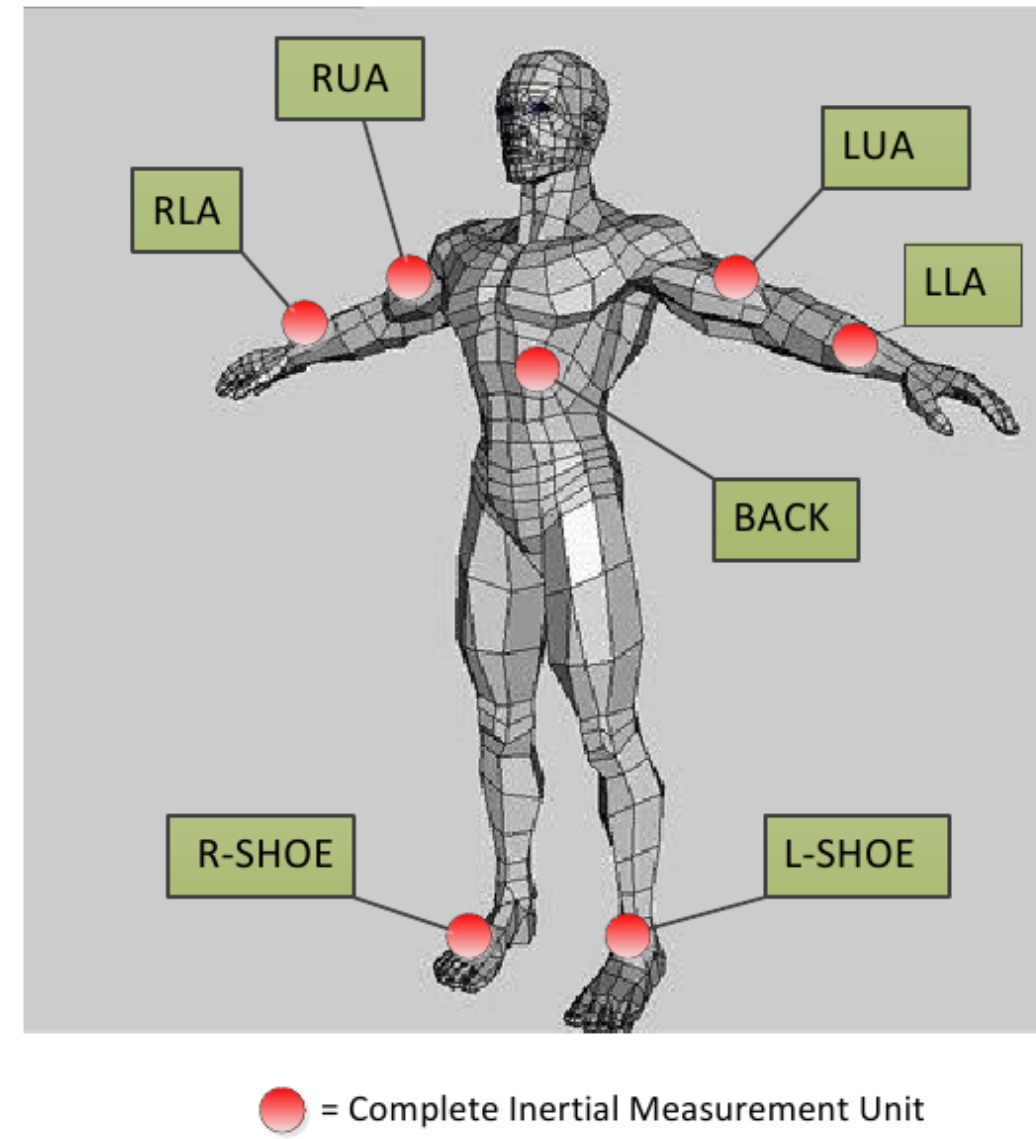


Fig. 1: Information privacy in on-body sensor network (UCI dataset).

The observed data can be exploited for

- Public information: exercise logs for health monitoring,
- Private information: users' private behaviors, habits, emotion and medical condition,

PROBLEM FORMULATION

With training samples $(\mathbf{X}_i, p_i, q_i)_{i=1}^l$, an optimization problem is proposed to find $\mathbf{G} = \{\mathbf{G}^m\}_{m=1}^M$ so as to

- minimize the regularized empirical risk of detecting public hypothesis p ,
- keep the regularized empirical risk of detecting q above a given privacy threshold θ .

$$\begin{aligned} \min_{\mathbf{G} \in \mathcal{G}, \mathbf{w}_\alpha} & \frac{1}{l} \sum_{i=1}^l \phi(p_i \langle \mathbf{w}_\alpha, \Phi(\mathbf{Z}_i) \rangle_{\mathcal{H}}) + \frac{\lambda_\alpha}{2} \|\mathbf{w}_\alpha\|_2^2, \\ \text{s.t.} & \min_{\mathbf{w}_\beta} \sum_{k \in \{-1, 1\}} \frac{1}{2|S_k|} \sum_{i \in S_k} \phi(q_i \langle \mathbf{w}_\beta, \Phi(\mathbf{Z}_i) \rangle_{\mathcal{H}}) + \frac{\lambda_\beta}{2} \|\mathbf{w}_\beta\|_2^2 \geq \theta \end{aligned}$$

where $\phi(\cdot)$ is a convex loss function, $\Phi(\cdot)$ is a feature map, S_k with $k \in \{-1, 1\}$ contains the indexes of the training sample with label $q_i = \{-1, 1\}$, respectively, \mathbf{w}_α and \mathbf{w}_β are the fusion center decision rules for the public and private hypothesis, respectively.

METHODOLOGY

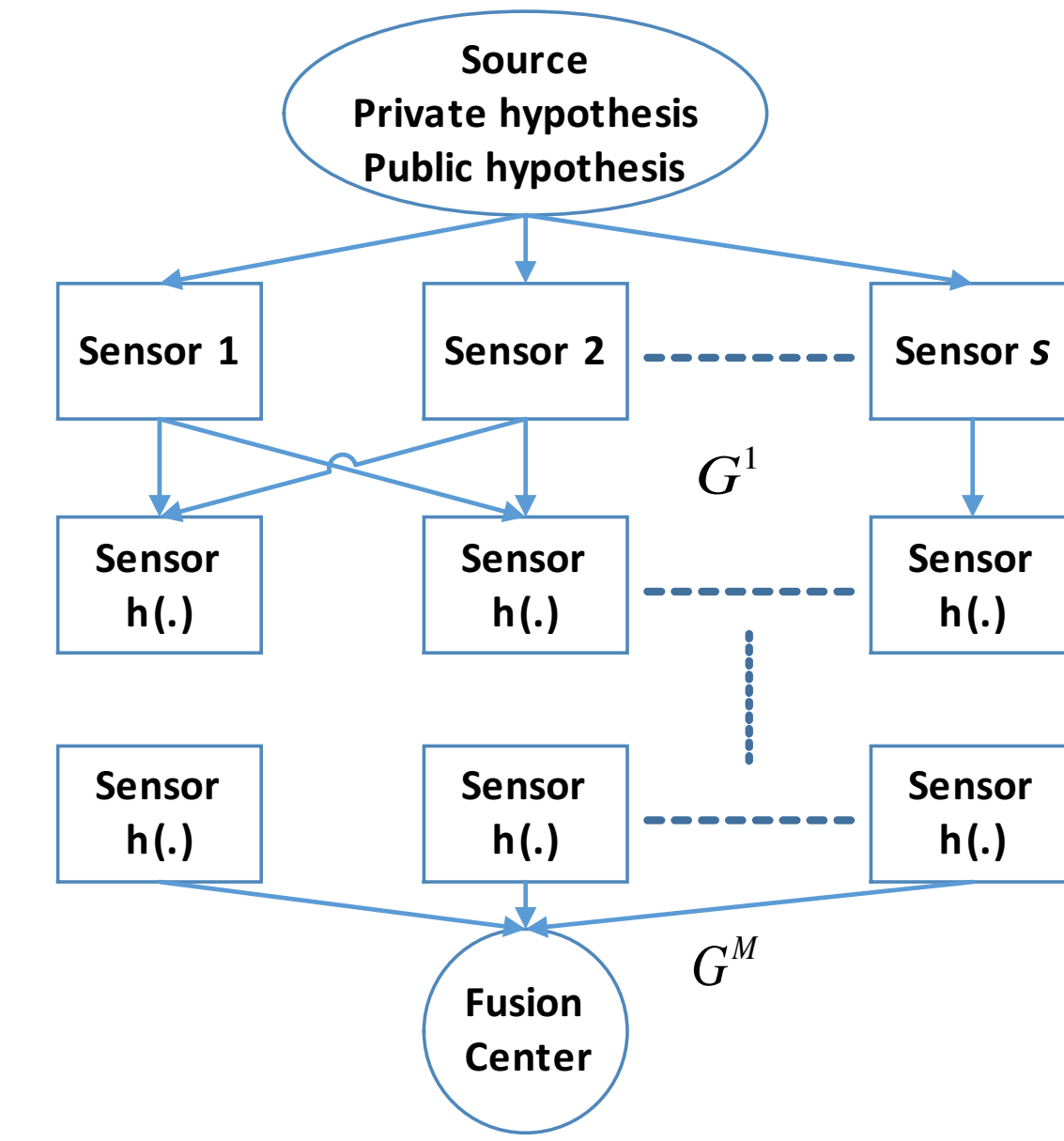


Fig. 2: Information privacy using a multilayer network.

After a repeated linear and nonlinear distortion of the observed data, the distorted data at the fusion center is

$$\mathbf{Z}(\mathbf{X}) = \mathbf{G}^M h(\mathbf{G}^{M-1} h(\dots h(\mathbf{G}^1 \mathbf{X}))).$$

The target of the weighting matrices $\{\mathbf{G}^m\}_{m=1}^M$ is to:

- Extract the public hypothesis related feature.
- Distort the privacy hypothesis related feature.

THE PROPOSED ALGORITHM

1. Finding the threshold θ :

In the dual formulation, the best empirical risk of detecting the private hypothesis q under the worst case \mathbf{G} is

$$\begin{aligned} \max_{\mathbf{G} \in \mathcal{G}, \beta} & - \sum_{k \in \{-1, 1\}} \frac{1}{2|S_k|} \sum_{i \in S_k} \phi^*(-2|S_k|\beta_i) \\ & - \frac{1}{2\lambda_\beta} (\mathbf{q} \circ \beta)^T \mathbf{K}(\mathbf{G}, \mathbf{X}) (\mathbf{q} \circ \beta) \end{aligned}$$

Let the objective value be θ^* , then we chose $\theta = p\theta^*$, $p \in [0, 1]$.

2. Optimizing the weighting matrices:

- (a) Without constraint on $\{\mathbf{G}^m\}_{m=1}^M$: gradient descent with line search such that the constraint is satisfied.
- (b) Positive semi-definite constraints on $\{\mathbf{G}^m\}_{m=1}^M$: modified mirror descent method to obtain a closed-form solution for gradient updating.

RESULT ON UCI ACTIVITY RECOGNITION

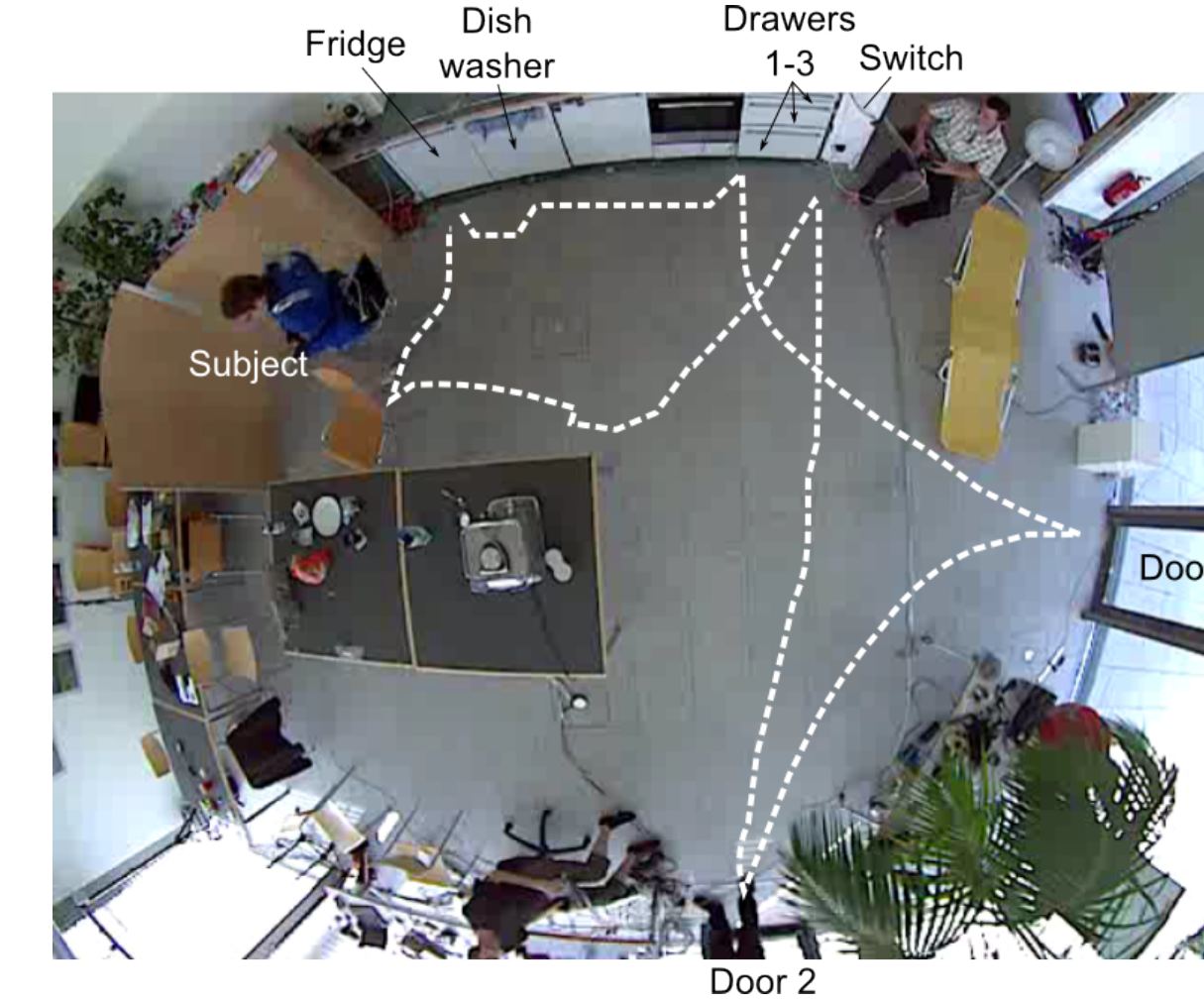


Fig. 3: The UCI OPPORTUNITY activity recording room.

Sensors	Inertial measurement
Public hypothesis	open or close a door ?
Private hypothesis	walking or standing ?

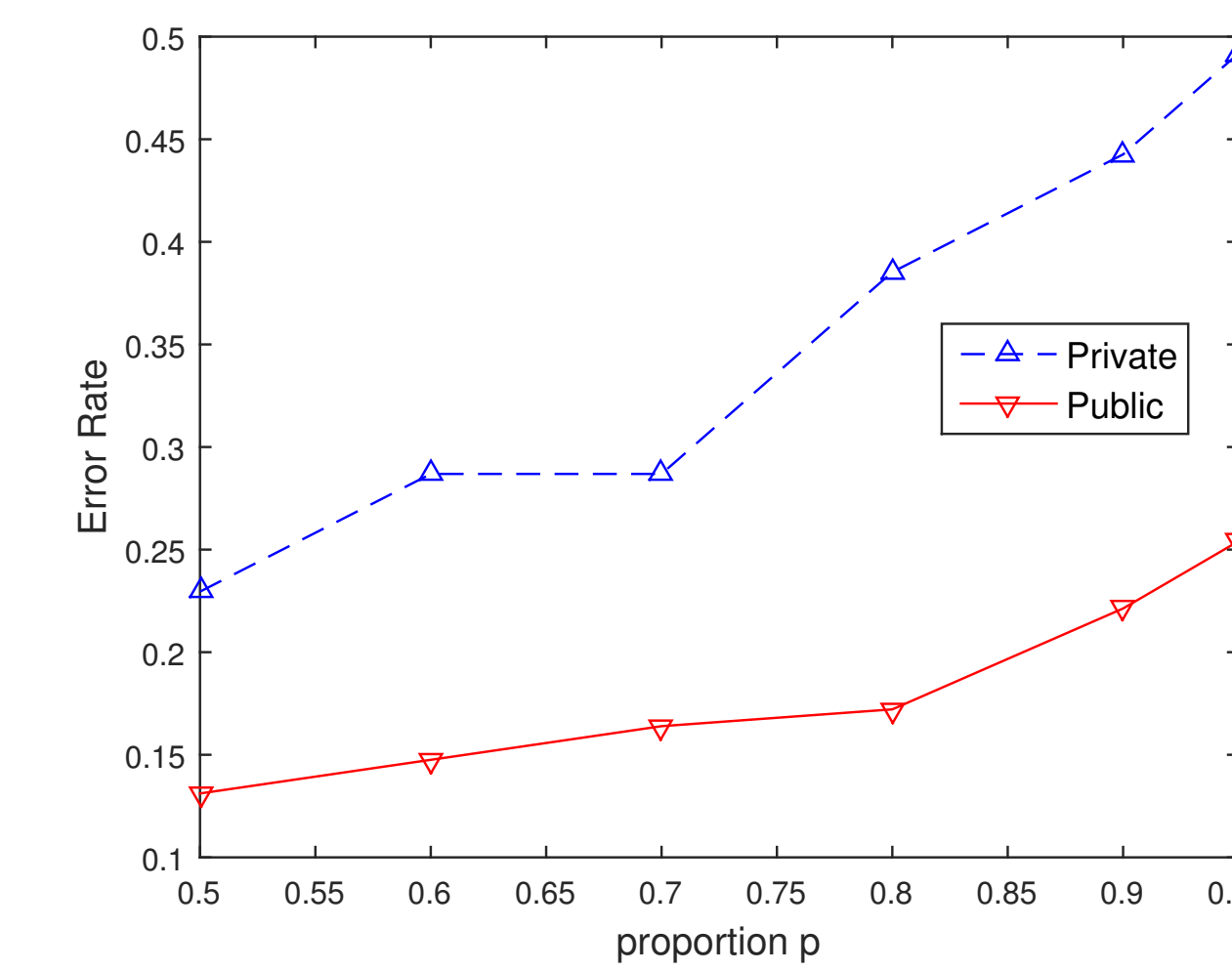


Fig. 4: The impact of the proportion p on public and private hypothesis test.

RESULT ON DALLAS ACTION RECOGNITION

Sensors	Inertial measurement+Kinetic camera
Public hypothesis	Boxing action existence ?
Private hypothesis	Baseball action existence ?

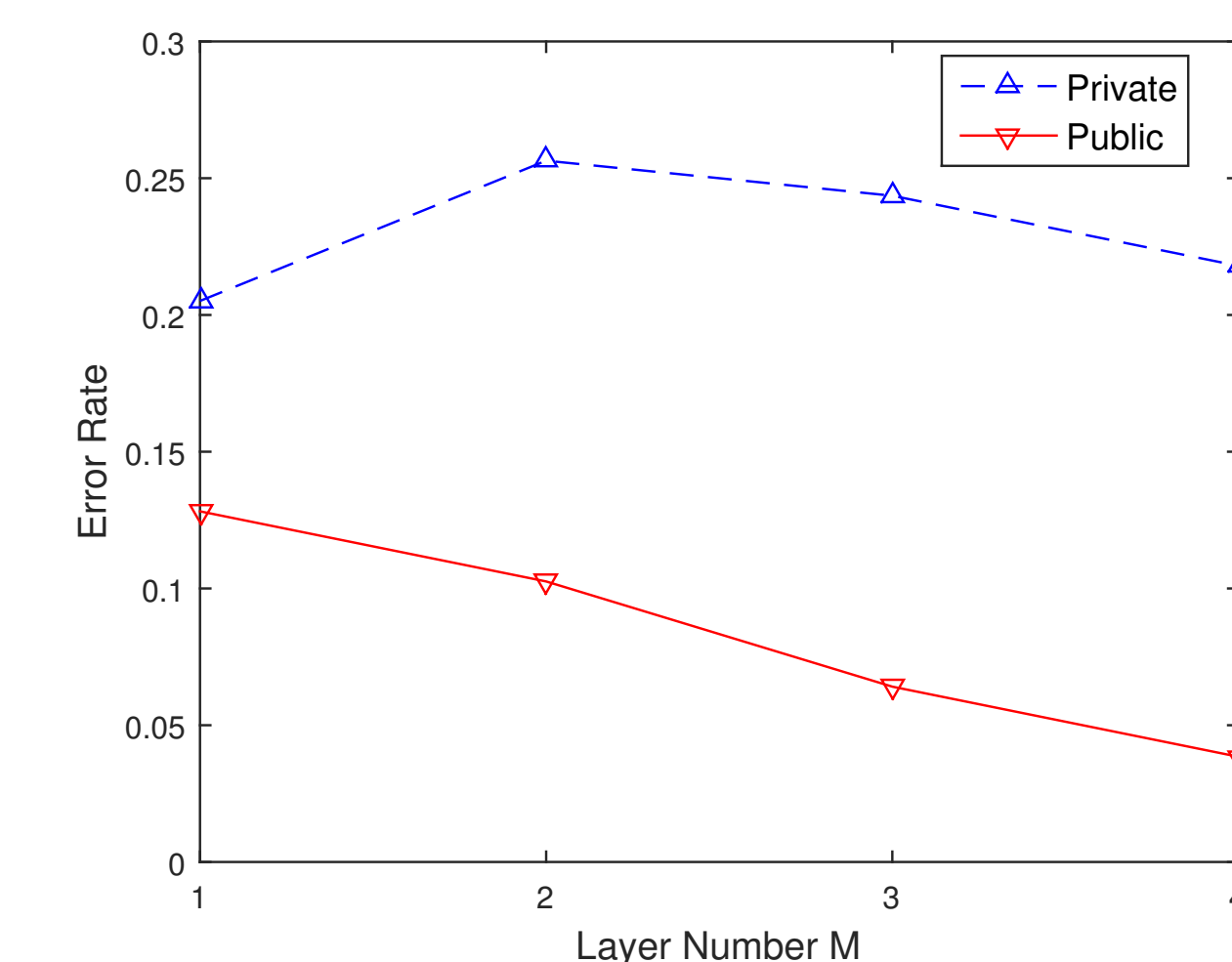


Fig. 5: Inertial sensor and kinetic camera.

- Note: 25% is the worst error rate for this four action setting.

REAL IMAGE EXPERIMENT



Fig. 6: Image experiment. The presence or absence of a gun and cash are the public and private hypothesis, respectively.

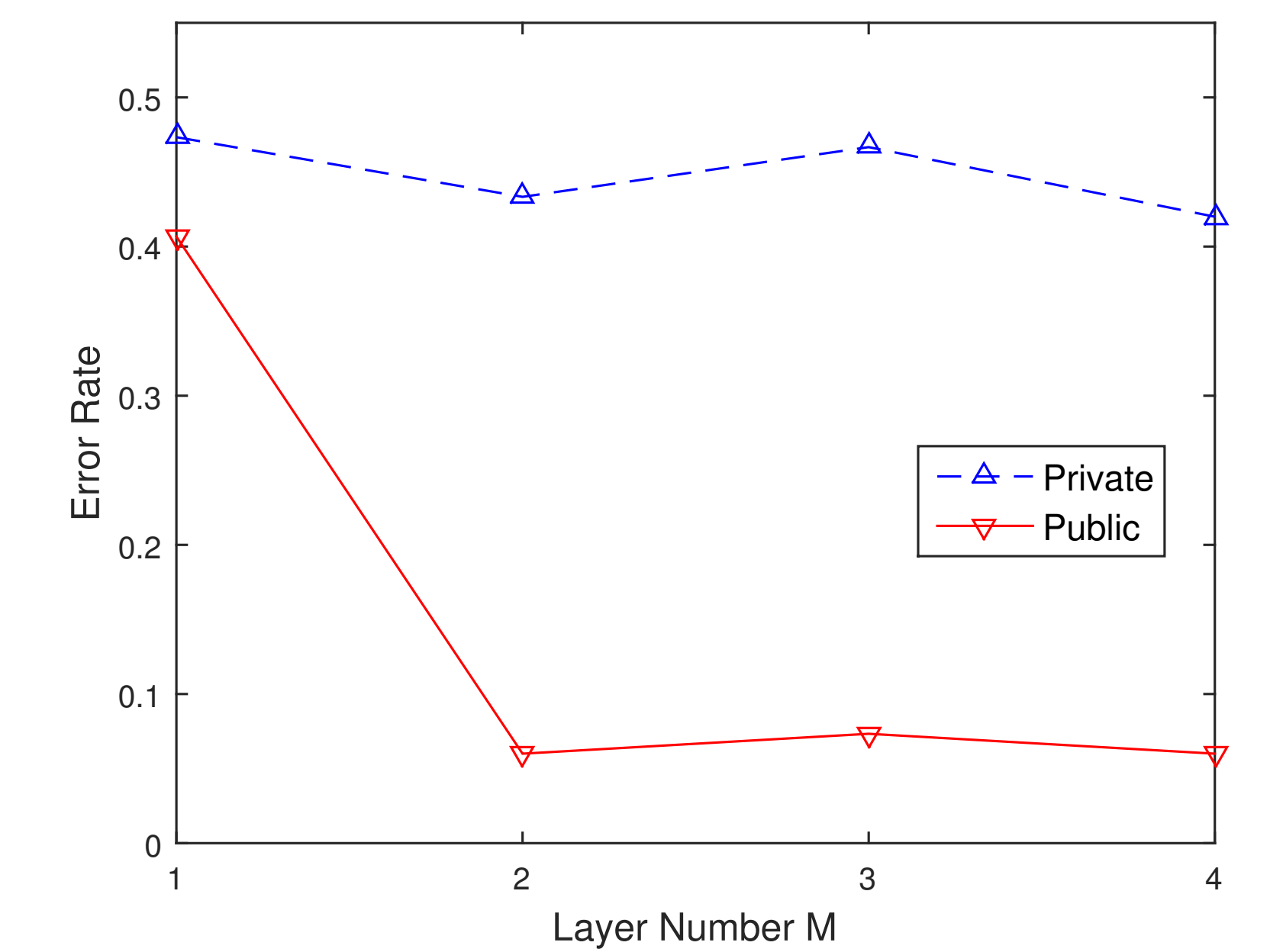


Fig. 7: One type of gun and cash.

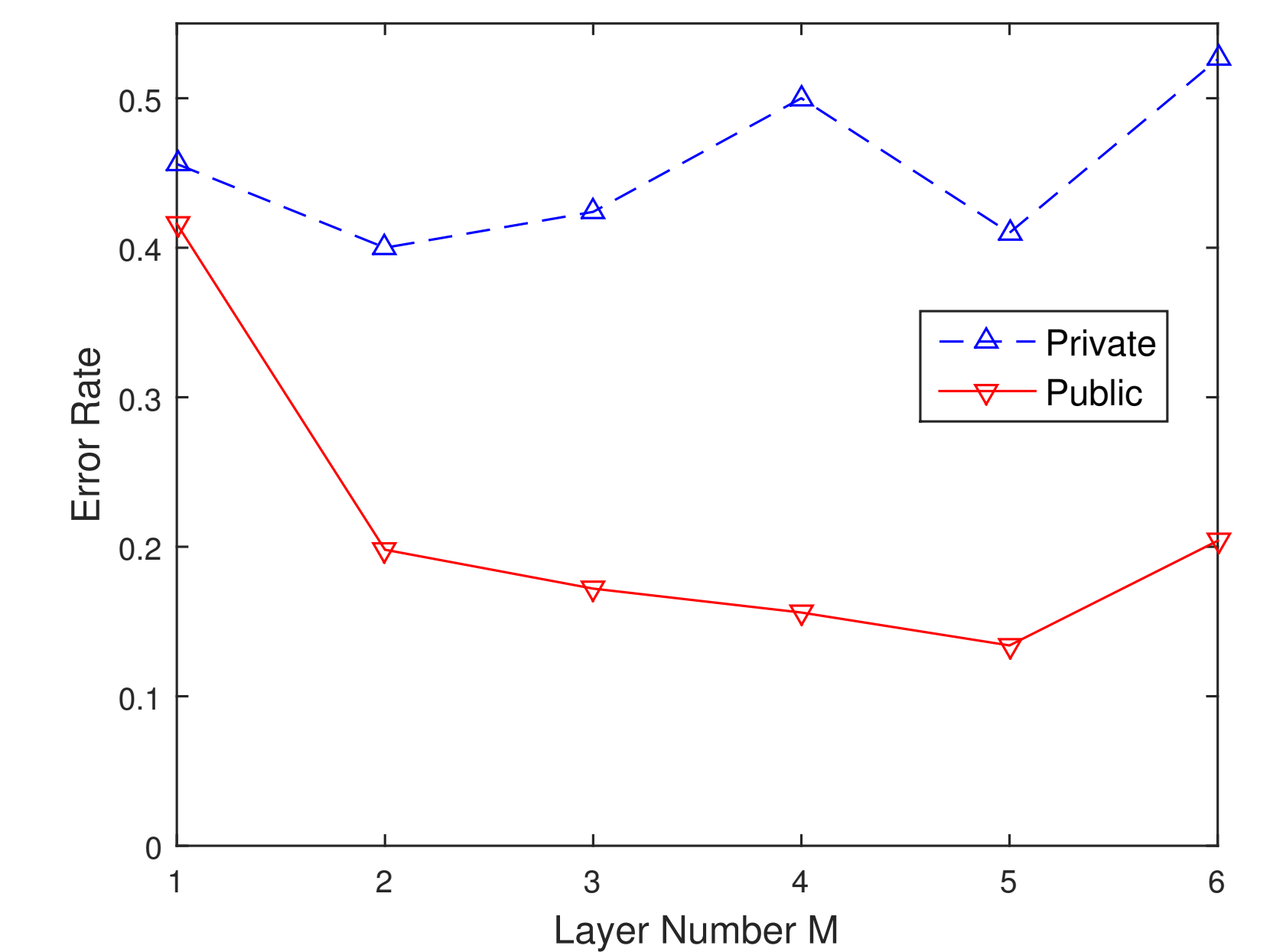


Fig. 8: Three types of gun and cash.

- Conclusion: A proper layer number M should be chosen to match the multilayer model and the dataset.