

Assignment 1

● Graded

Group

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[View or edit group](#)

Total Points

48 / 50 pts

Question 1

Derivation

10 / 10 pts

✓ + 10 pts A valid derivation showing that a linear model suffices to solve the problem.

– 2 pts Minor mistakes

+ 0 pts Completely wrong or else unanswered

Question 2

Code

34 / 35 pts

+ 0 pts No rubric -- see comments for mark breakup

💬 + 34 pts GROUP NO: 27

Grading scheme for code:

Dimensionality dd: $dd < 550$ (5 marks), $550 \leq dd < 1000$ (4 marks), $dd \geq 1000$ (3 marks)

Train time tt (in sec): $tt < 5$ (10 marks), $5 \leq tt < 10$ (9 marks), $10 \leq tt < 20$ (8 marks), $20 \leq tt < 50$ (7 marks), $tt \geq 50$ (6 marks)

Map time mt (in sec): $mt < 0.1$ (10 marks), $0.1 \leq mt < 0.2$ (9 marks), $0.2 \leq mt < 0.5$ (8 marks), $0.5 \leq mt < 1$ (7 marks), $mt \geq 1$ (6 marks)

Error rate ee: $ee < 0.1$ (10 marks), $0.1 \leq ee < 0.2$ (8 marks), $ee > 0.2$ (6 marks)

dd = 528.0 : 5 marks

tt = 2.162 sec : 10 marks

mt = 0.145 sec : 9 marks

ee = 0.006 : 10 marks

TOTAL: 34 marks

Question 3

Report

4 / 5 pts

✓ + 5 pts Description of the hyperparameters in the chosen method and how the hyperparameters were tuned.

– 2 pts Insufficient or missing details of hyperparameters e.g. missing grid values if grid search was used.

+ 0 pts Completely wrong or else unanswered.

💬 – 1 pt -1 for not specifying method for hyperparameter tuning

No questions assigned to the following page.

CS771A Introduction to Machine Learning

Assignment 1

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Question 1:

By giving a detailed mathematical derivation (as given in the lecture slides), show how a CAR-PUF can be broken by a single linear model. Give derivations for a map $\phi : \{0, 1\}^{32} \rightarrow \mathbb{R}^D$ mapping 32-bit 0/1-valued challenge vectors to D-dimensional feature vectors (for some $D > 0$) so that for any CAR-PUF, there exists a D-dimensional linear model $W \in \mathbb{R}^D$ and a bias term $b \in \mathbb{R}$ such that for all CRPs (c, r) with $c \in \{0, 1\}^{32}, r \in \{0, 1\}$, we have

$$\frac{1 + \text{sign}(W^T \phi(c) + b)}{2} = r$$

Solution 1:

First we will find a linear model to break a single PUF.

An Attacker can see responses on a few challenges and use ML to predict responses on other challenges. It does not if using 32 bit or 64 bit challenges.

t_i^u : time at which the upper signal leaves the i^{th} - MUX.

t_i^l : time at which the lower signal leaves the i^{th} - MUX.

t_1^u and t_1^l depend on $t_0^u, t_0^l, p_1, q_1, r_1, s_1$ and c_1 .

c_1 dictates which previous delay t_0^u and t_0^l will get carried forward and p_1, q_1, r_1, s_1 gives us delay introduce in the i^{th} - MUX itself.

$$\begin{aligned} t_1^u &= (1 - c_1) \cdot (t_0^u + p_1) + c_1 \cdot (t_0^l + s_1) \\ t_1^l &= (1 - c_1) \cdot (t_0^l + q_1) + c_1 \cdot (t_0^u + r_1) \end{aligned}$$

let us use shorthand $\Delta = t_i^u - t_i^l$ denotes lag.

All that matter is, for a single PUF whether Δ_{31} is less then 0 or not.

$$\begin{aligned} \Delta_1 &= (1 - c_1) \cdot (t_0^u + p_1 - t_0^l - q_1) + c_1 \cdot (t_0^l + s_1 - t_0^u - r_1) \\ &= (1 - 2c_1) \cdot \Delta_0 + (q_1 - p_1 + s_1 - r_1) \cdot c_1 + (p_1 - q_1) \end{aligned}$$

No questions assigned to the following page.

$$\Delta_1 = \Delta_0.d_1 + \alpha_1.d_1 + \beta_1$$

$$\text{where, } \alpha_1 = \frac{(p_1 - q_1 + r_1 - s_1)}{2} \quad \& \quad \beta_1 = \frac{(p_1 - q_1 + r_1 - s_1)}{2}$$

$$d_i = (1 - 2c_i) \Rightarrow d_i = \{-1, 1\}$$

$$\Delta_i = d_i.\Delta_{i-1} + \alpha_i.d_i + \beta_i \quad \dots[\Delta_{-1} = 0]$$

$$\Delta_0 = \alpha_0.d_0 + \beta_0$$

$$\Delta_1 = \alpha_0.d_2.d_1.d_0 + (\alpha_1 + \beta_0).d_2.d_1 + (\alpha_2 + \beta_1).d_2 + \beta_2$$

A pattern begins can be seen in these equations:

$$\begin{aligned} \Delta_{31} &= w_0.x_0 + w_1.x_1 + \dots + w_{31}.x_{31} + \beta_{31} \\ &= w^T X + b \end{aligned}$$

$$\begin{aligned} x_i &= d_i.d_{i+1}.d_{i+2} \dots d_{31} \\ w_i &= \alpha_i + \beta_{i-1} \quad \text{for } (i > 0) \\ w_0 &= \alpha_0 \end{aligned}$$

If $\Delta_{31} < 0$, upper signal wins and answer is 0. And if $\Delta_{31} > 0$, then the lower signal wins and the answer is 1.

$$\Rightarrow \frac{\text{sign}(w^T X + b) + 1}{2}$$

This means if we find w, b parameters then we can predict response to any challenge. Similarly, we can show the proof for the 2^{nd} PUF (reference PUF).

For working PUF, let us assume $(\Delta w)_{31}$

For reference PUF, let us assume $(\Delta r)_{31}$

In the given question, we require a linear model to break two PUF whose time difference $|(\Delta w)_{31} - (\Delta r)_{31}|$ is smaller than some unknown $\tau > 0$

$$\Rightarrow |(\Delta w)_{31} - (\Delta r)_{31}| < \tau$$

So, now we will prove Melbo wrong and give a single linear model to break such combination of PUF.

$$\begin{aligned} (\Delta w)_{31} &= w_0.x_0 + w_1.x_1 + \dots + w_{31}.x_{31} + \beta_{31} \\ &= w^T X + b \quad \dots[b = \beta_{31}] \end{aligned}$$

$$\Rightarrow \begin{pmatrix} w_0 & w_1 & w_2 & \dots & w_{31} & \beta_{31} \end{pmatrix} \begin{pmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_{31} \\ 1 \end{pmatrix}$$

$$w_i = \alpha_i + \beta_{i-1} \quad \text{for } (i > 0, I \in I)$$

α_i & β_i are system constant for working PUF.

No questions assigned to the following page.

$$\begin{aligned}
(\Delta r)_{31} &= v_0.x_0 + v_1.x_1 + \dots + v_{31}.x_{31} + \beta_{31} \\
&= v^T X + b \quad \dots [b = B_{31}]
\end{aligned}$$

$$\Rightarrow \begin{pmatrix} v_0 & v_1 & v_2 & \dots & v_{31} & B_{31} \end{pmatrix} \begin{pmatrix} x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_{31} \\ 1 \end{pmatrix}$$

$$v_i = A_i + B_{i-1} \quad \text{for } (i > 0, i \in I)$$

A_i & B_i are system constant for reference PUF.

given -

$$|(\Delta w) - (\Delta r)| \leq \tau \rightarrow 1$$

$$|(\Delta w) - (\Delta r)| > \tau \rightarrow 0$$

From the lecture notes we know :

$$(\Delta w) = u^T .x + P$$

$$(\Delta r) = v^T .x + Q$$

$$|(\Delta w) - (\Delta r)| = |(u - v)^T .x + (P - Q)|$$

$$|(\Delta w) - (\Delta r)| - \tau = |(u - v)^T .x + (P - Q)| - \tau$$

as far as bit is concerned, it will be :

$$\frac{1 + \text{sign}(|(u - v)^T .x + (P - Q)| - \tau)}{2}$$

So we can see that above expression is for a generalized linear model

Now, we can prove that $\text{sign}(|a| - b)$ is same as $\text{sign}(a^2 - b^2)$

So, we can say that

$$\text{sign}(|(u - v)^T .x + (P - Q)| - \tau) = \text{sign}(((u - v)^T .x + (P - Q))^2 - \tau^2)$$

$$\text{let } (u - v) \rightarrow \alpha \text{ \& } (P - Q) \rightarrow \beta$$

$$\Rightarrow \text{sign}((\alpha^T .x + \beta)^2 - \tau^2)$$

$$\alpha^T .x = \text{can be expanded as } \rightarrow (\alpha_1.x_1 + \alpha_2.x_2 + \alpha_3.x_3 + \dots + \alpha_{32}.x_{32})$$

$$\Rightarrow \text{sign}((\alpha_1^2.x_1^2 + \alpha_2^2.x_2^2 + \alpha_3^2.x_3^2 + \dots + \alpha_{32}^2.x_{32}^2) + C)$$

also value of $(x_1, x_2 \dots x_{32})$ is either (1 or -1) so value of $(x_1^2, x_2^2 \dots x_{32}^2)$ will be 1 only

So Now,

$$\Rightarrow \text{sign}\left(\sum_{\substack{i,j=1 \\ i \neq j}}^{32} \alpha_i . \alpha_j . x_i . x_j + C\right)$$

No questions assigned to the following page.

Question 3:

LinearSVC		
Loss	Accuracy	time
Hinge	98.93	51s
Squared hinge	99.19	1m 1s

Table 1: Changing the loss hyperparameter in LinearSVC (hinge vs squared hinge)

c	LinearSVC	
	Accuracy	Time
100	99.2	1m 38s
1	99.16	1m 1s
0.01	98.65	6s

c	Logistic Regression	
	Accuracy	Time
100	99.31	3s
1	99.07	3s
0.01	96.35	2s

Table 2: Changing the c hyperparameter in LinearSVC and LogisticRegression to high/low/medium values

tol	LinearSVC	
	Accuracy	Time
High	97.21	25s
Medium	99.04	59s
Low	99.19	1m 18s

tol	Logistic Regression	
	Accuracy	Time
High	99.07	1s
Medium	99.07	2s
Low	99.07	3s

Table 3: Changing the tol hyperparameter in LinearSVC and LogisticRegression to high/low/medium values

Penalty	LinearSVC		Logistic Regression	
	Accuracy	Time	Accuracy	Time
l1	99.1425	12m 40s	N/A	N/A
l2	99.19	1m	99.07	2s

Table 4: Changing the penalty (regularization) hyperparameter in LinearSVC and LogisticRegression (l2 vs l1)