Advanced Cryptography — Final Exam Solution

Serge Vaudenay

3.8.2019

- duration: 3h
- any document allowed
- a pocket calculator is allowed
- communication devices are not allowed
- the exam invigilators will <u>**not**</u> answer any technical question during the exam
- readability and style of writing will be part of the grade

The exam grade follows a linear scale in which each question has the same weight.

1 Security of Key Agreement

We consider a key agreement scheme defined by

- one PPT algorithm setup $(1^s) \rightarrow pp$ which generates public parameters pp;
- two probabilistic polynomially bounded interactive machines A and B with input pp and producing a secret output K (denoted by K_A for A and by K_B for B).

Correctness implies that the following game outputs 1 with probability 1.

- 1: $setup(1^s) \rightarrow pp$
- 2: make A(pp) and B(pp) interact with each other and output K_A and K_B
- 3: output $1_{K_A=K_B}$

Q.1 Give a formal definition for the security against key recovery under passive attacks.

Given an adversary A, we consider the following game with security parameter s.
1: setup(1^s) → pp
2: make A(pp) and B(pp) interact with each other and output K_A and K_B; define transcript as the list of exchanged messages
3: run A(pp, transcript) → K
4: output 1_{K=KA=KB}
The protocol is secure against key recovery under passive attack if for any PPT adversary A, the above game returns 1 with negligible probability.

Q.2 Formalize how to define the Diffie-Hellman protocol under this setting.

In the Diffie-Hellman protocol, we assume that pp is of form pp = (q, g) where g generates a (multiplicatively denoted) group of order q. The algorithm A works as follows:

1: pick $a \in \mathbb{Z}_q^*$ at random 2: $\mathsf{pk}_A \leftarrow g^a$ 3: send pk_A 4: receive pk_B 5: **if** $\mathsf{pk}_B \not\in \langle g \rangle - \{1\}$ **then** abort 6: $K \leftarrow \mathsf{pk}_B^a$ 7: **return** K (private output) The algorithm B works as follows: 1: pick $b \in \mathbb{Z}_q^*$ at random 2: $\mathsf{pk}_B \leftarrow g^b$ 3: receive pk_A 4: **if** $\mathsf{pk}_A \notin \langle g \rangle - \{1\}$ **then** abort 5: send pk_B 6: $K \leftarrow \mathsf{pk}_A^b$ 7: **return** K (private output)

Q.3 Formally prove that the Diffie-Hellman protocol is secure in the sense of the previous question if and only if the computational Diffie-Hellman problem is hard.

By plugging the algorithms A and B in the security game, we obtain 1: setup $(1^s) \rightarrow (q, g)$ 2: pick $a \in \mathbf{Z}_q^*$ at random 3: $\mathsf{pk}_A \leftarrow g^a$ 4: pick $b \in \mathbf{Z}_q^*$ at random 5: $\mathsf{pk}_B \leftarrow g^b$ 6: $if \operatorname{pk}_A \notin \langle g \rangle - \{1\}$ then abort 7: $K_B \leftarrow \operatorname{pk}_A^b$ 8: $if \operatorname{pk}_B \notin \langle g \rangle - \{1\}$ then abort 9: $K_A \leftarrow \operatorname{pk}_B^a$ 10: $run \mathcal{A}(pp, pk_A, pk_B) \rightarrow K$ 11: output $1_{K=K_A=K_B}$ Clearly, the two if are useless and we always have $K_A = K_B = g^{ab}$. Hence, the game simplifies to 1: setup $(1^s) \rightarrow (q, g)$ 2: pick $a \in \mathbf{Z}_q^*$ at random 3: pick $b \in \mathbf{Z}_{a}^{*}$ at random 4: $run \mathcal{A}(q, g, g^a, g^b) \to K$ 5: output $1_{K=a^{ab}}$ which is the computational Diffie-Hellman problem (CDH). An adversary answers 1 in the security game with the same probability as in the CDH game.

- Q.4 We now consider security against Alice's key recovery under active attacks as defined by the following game:
 - 1: $\operatorname{setup}(1^s) \to \operatorname{pp}$ 2: $\operatorname{st}_A \leftarrow \operatorname{pp}$, $\operatorname{finished}_A \leftarrow \operatorname{false}$ 3: $\operatorname{st}_B \leftarrow \operatorname{pp}$, $\operatorname{finished}_B \leftarrow \operatorname{false}$ 4: $\operatorname{run} \mathcal{A}^{\operatorname{OA,OB}}(\operatorname{pp}) \to K$ 5: $\operatorname{output} 1_{K=K_A}$ and $\operatorname{finished}_A$

OA(x): 6: if finished_A then return 7: $st_A \leftarrow (st_A, x)$

- 8: run $A(\mathsf{st}_A)$ to get private output st_A and next message y
- 9: if y non-final then return y
- 10: finished_A \leftarrow true
- 11: $K_A \leftarrow \mathsf{st}_A$
- 12: return y

And the same for oracle OB. Prove that the Diffie-Hellman protocol is insecure in this sense.

The man-in-the-middle attack is breaking the protocol. We consider the adversary: Input: (q, g)1: pick $c \in \mathbb{Z}_q^*$ 2: $OA() \rightarrow pk_A$ 3: $OA(g^c)$ 4: **return** pk_A^c (Note that the interaction with Bob is useless in this security model.)

- **Q.5** Based on some attacks seen in the course, formalize security against key recovery under *active* attacks making $K_A = K_B$. Prove that Diffie-Hellman is secure by assuming that the problem defined by the following game is hard:
 - 1: setup $(1^s) \rightarrow pp = (q, g)$ 2: pick $x, y \in \mathbb{Z}_q^*$ 3: $\mathcal{B}(pp, g^x, g^y) \rightarrow (u, v, w)$ 4: return $1_{u^x = v^y = w}$ and $u, v, w \in \langle g \rangle$ and $w \neq 1$

where g generates $\langle g \rangle$ of order q, with neutral element 1.

The output of the security game is now $1_{K=K_A=K_B}$ and finished_A and finished_B. We want to prove that the protocol is secure. Let \mathcal{A} by an adversary against the protocol. We define \mathcal{B} as follows: $\mathcal{B}(pp, X, Y)$: 1: run $\mathcal{A}^{OA,OB}(pp) \rightarrow w$ and simulate the oracles as follows: OA(): simulate A choosing Xnext OA(x): set $v \leftarrow x$ OB(x): set $u \leftarrow x$ and simulate B choosing Y2: return (u, v, w)When \mathcal{B} is put in its game, the simulation of the selection of the public keys of A and B are perfect. It is also clear that the winning conditions in both games are equivalent. So, they have the same advantage. If the game that \mathcal{B} plays is hard, then it must be the case that \mathcal{A} has a negligible advantage.

2 Advantage Amplification

Let $X_1, \ldots, X_n, Y_1, \ldots, Y_n$ be 2n independent Boolean variables. We assume that X_1, \ldots, X_n are identically distributed and that Y_1, \ldots, Y_n are identically distributed. We assume that the statistical distance between the distributions of X_i and Y_j is ε . Given distinguisher, i.e. a Boolean algorithm \mathcal{A} (with unbounded complexity), we define $X = \mathcal{A}(X_1, \ldots, X_n)$ and $Y = \mathcal{A}(Y_1, \ldots, Y_n)$. We are interested in \mathcal{A} which maximizes the statistical distance between the distributions of X and Y. We denote by d the statistical distance and we identify random variables by their distributions when computing distances, by abuse of notation.

Q.1 Prove that $d(X, Y) = d((X_1, ..., X_n), (Y_1, ..., Y_n)).$

We know from the course that for any \mathcal{A} $d(X,Y) \leq d((X_1,\ldots,X_n),(Y_1,\ldots,Y_n))$ and equality can be reached by using the likelihood ratio. We actually known that $\mathcal{A}(z_1,\ldots,z_n) = 1_{\Pr[X_1=z_1,\ldots,X_n=z_n] < \Pr[Y_1=z_1,\ldots,Y_n=z_n]}$ reaches the equality case.

Q.2 Assume that $\Pr[X_i = 1] = 0$.

Q.2a Give the distributions of X_i and Y_j .

We have $\Pr[X_i = 1] = 0$ and $\Pr[X_i = 0] = 1$. Due to the statistical distance of ε , we have $\Pr[Y_j = 1] = \varepsilon$ and $\Pr[Y_j = 0] = 1 - \varepsilon$.

Q.2b Compute d(X, Y) in terms of ε and n.

We compute the statistical distance by regrouping all (z_1, \ldots, z_n) by their Hamming weight.

$$d(X,Y) = \frac{1}{2} \sum_{z_1,\dots,z_n} |\Pr[X_1 = z_1,\dots,X_n = z_n] - \Pr[Y_1 = z_1,\dots,Y_n = z_n]|$$

= $\frac{1}{2} (1 - (1 - \varepsilon)^n) + \frac{1}{2} \sum_{h=1}^n \binom{n}{h} \varepsilon^h (1 - \varepsilon)^{n-h}$
= $1 - (1 - \varepsilon)^n$

In the sum, only the (0, ..., 0) case makes the first probability nonzero. This is the h = 0 case.

Q.2c Give an asymptotic equivalent of the minimal n such that $d(X, Y) \ge \frac{1}{2}$ in terms of ε , when $\varepsilon \to 0$.

 $1-(1-\varepsilon)^n \ge \frac{1}{2}$ is equivalent to $n \ge -\frac{\ln 2}{\ln(1-\varepsilon)}$. So, the minimal n is $n \sim \frac{\ln 2}{\varepsilon}$.

Q.3 Assume now that $\Pr[X_i = 1] = \frac{1}{2}(1 - \varepsilon)$ and $\Pr[Y_i = 1] = \frac{1}{2}(1 + \varepsilon)$. **Q.3a** Show that $\mathcal{A}(z_1, \ldots, z_n) = \mathbb{1}_{z_1 + \cdots + z_n < \frac{n}{2}}$ makes d(X, Y) maximal.

> Let $h = z_1 + \dots + z_n$. We have $\Pr[X_1 = z_1, \dots, X_n = z_n] = 2^{-n}(1 - \varepsilon)^h (1 + \varepsilon)^{n-h}$ $\Pr[Y_1 = z_1, \dots, Y_n = z_n] = 2^{-n}(1 + \varepsilon)^h (1 - \varepsilon)^{n-h}$ So, $\Pr[X_1 = z_1, \dots, X_n = z_n] < \Pr[Y_1 = z_1, \dots, Y_n = z_n]$ is equivalent to $(1 - \varepsilon)^h (1 + \varepsilon)^{n-h} < (1 + \varepsilon)^h (1 - \varepsilon)^{n-h}$, which is equivalent to $(1 + \varepsilon)^{n-2h} < (1 - \varepsilon)^{n-2h}$, which is equivalent to $h < \frac{n}{2}$. Hence, the suggested \mathcal{A} is actually equivalent to the optimal algorithm based on the likelihood ratio. We know it

Q.3b Given that $\Pr[X_1 + \dots + X_n < \frac{n}{2}] = \Pr[Y_1 + \dots + Y_n > \frac{n}{2}]$, prove that for n odd, we have $d(X, Y) = |1 - 2\Pr[X_1 + \dots + X_n < \frac{n}{2}]|$.

Actually, d(X,Y) is the advantage which is $d(X,Y) = |\Pr[Y_1 + \dots + Y_n < \frac{n}{2}] - \Pr[X_1 + \dots + X_n < \frac{n}{2}]|$. For n odd, we have $\Pr[Y_1 + \dots + Y_n < \frac{n}{2}] = 1 - \Pr[Y_1 + \dots + Y_n > \frac{n}{2}]$ which gives the answer.

Q.3c Compute the expected value and the variance of $X_1 + \cdots + X_n$.

makes d(X, Y) maximal.

TT7 7

We have	$E(X_1 + \dots + X_n) = n \cdot E(X_i) = \frac{n}{2}(1 - \varepsilon)$
and	$V(X_1 + \dots + X_n) = n \cdot V(X_i) = \frac{n}{4}(1 - \varepsilon^2)$
because $V(X_i) = E(X_i)(1 - E(X_i)).$	

Q.3d By approximating $X_1 + \cdots + X_n$ to a normal distribution, give an asymptotic equivalent to n so that d(X, Y) is a constant.

For $\Pr[X_1 + \dots + X_n < \frac{n}{2}]$ to be constant, we need $\frac{n}{2}\varepsilon$ and $\sqrt{\frac{n}{4}(1-\varepsilon^2)}$ of same order of magnitude. This means $n \sim \frac{\text{cste}}{\varepsilon^2}$. It is interesting to observe that to amplify the statistical distance with close-

to-unbiased distributions, it is harder than for close-by distributions which are heavily biased. Nice solution from a student: we apply the upper-tail Chernoff bound with $\delta = \frac{\varepsilon}{1-\varepsilon}$ which says

$$\Pr[X_1 + \dots + X_n > (1+\delta)\mu] \le e^{-\frac{\delta^2}{2+\delta}\mu}$$

hence $\Pr[X_1 + \dots + X_n > \frac{n}{2}] \le e^{-\frac{\varepsilon^2}{2(2-\varepsilon)}n}$. So, with $n > \frac{4}{\varepsilon^2}$, we get $\Pr[X_1 + \dots + X_n > \frac{n}{2}] \le e^{-1}$.