

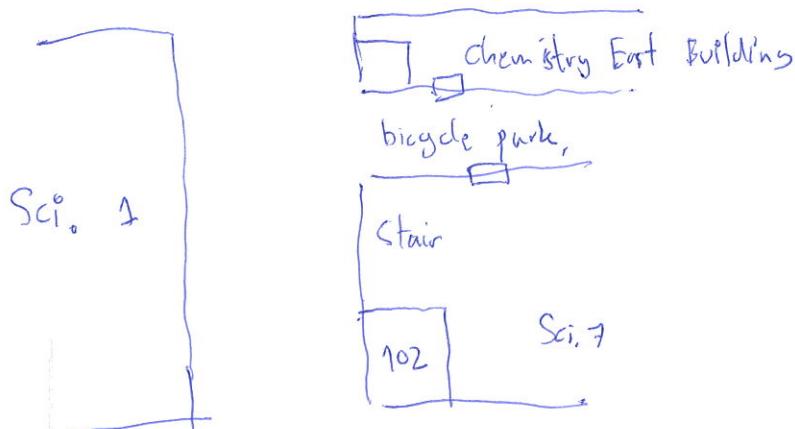
# 4810 - 1184 Algorithms for Information Security and Privacy.

Instructor: Vorapong Suppakitpaisarn, vorapong@isas.u-tokyo.ac.jp  
(International Center for IST)

I sometimes discuss about our international activities at classes.

Office Hour: Thursday 15:00 - 16:30

How to get at my office? Room 137, Chemistry East Building.



First room after you get into the building.

The room has no room number at the gate!!

## Class Schedule

- |          |  |
|----------|--|
| 9/25     | Course Introduction, PAC Learning                      |
| 9/26 (F) | Differential Privacy : Laplacian Mechanism             |
| 10/09    | Differential Privacy : Exponential Mechanism           |
| 10/15 16 | Differential Privacy : Composition, Small DB algorithm |
| 10/22 23 | Differential Privacy : Private PAC Learning            |
| 10/29 30 | Countermeasures for Linking Attack                     |
| 11/26    | Midterm Examination<br>[30% to grade]                  |

11/13

No class ~~Fri 10/13~~

[ Day for cancelled classes]

11/20

Optional Class: Introduction to Abstract Algebra.

12/27

Calculation on Elliptic Curve Cryptosystem

12/3

Discrete Logarithm Problems

12/30

Elliptic Curve Cryptography Protocol

12/17

Identity-based Cryptosystems

12/23, 1/1

No class. [ Holiday ]

1/8

Final Examinations [70% of credits]

Please inform me if you are not available on 11/6 or 1/8 before 10/9.

Relationship with other courses

focusses on security

Introduction to cryptography  
( Prof. Phong Nguyen )  
2018 S

Contemporary cryptography  
( Prof. Tsugoshi Takeagi )  
2017 A

This course  
2018 A

Focus on Speed.

Approximation Algorithms  
with Applications  
2018 S

(Me)

Network Optimizations  
2018 A

## Differential Privacy

Name	Weight
Alice	40
Bob	60
Charles	80
Doe	60

Private Information.

$$\downarrow$$

Average Weight = 60 } public information

$$Charles = 80$$

Information leakage!!!

Idea: Add noise to public information

$$\begin{cases} \text{Average Weight} = 60 \\ \text{public information} \end{cases}$$

$\Rightarrow$

$$\begin{cases} \text{Average Weight} + \text{noise} = 55 \\ \text{public information} \end{cases}$$

By the noise, it is impossible to predict Charles' weight.

## Linking Attack

Data published by government

Name	Age	Occupation
Alice	25	Student
Bob	30	Student
Charles	30	Banker

Data that hospitals give to machine learners.

[They want to find the diabetic potential of each person.]

Name	Age	Occupation	Diabetes
Alice	25	Student	✓
Bob	30	Student	✗
Charley	30	Banker	✗

Don't publish ↗

- We do not want people to know that Alice has Diabetes.
- We know from public information that the only 25-year-old is Alice.
- We know from hospital information that the only 25-year-old has diabetes.

11.

Alice has diabetes. ☹

87% of US citizens can be uniquely identified by sex, birth date, and city [Sweeney 2002]

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## Elliptic Curve Cryptography (ECC)

- Alternative choice to RSA
- Used in industrial web services (Google, Facebook, Microsoft)
- Have features that RSA does not have. [forward secrecy]
- Have better security level.

NIST Standard 2020

RSA 1024 bits

→ ECC 160 bits.

(National Institute of Standards  
and Technology )

security parameter

[larger → more secure]

[larger → more memory consumption]

[Bos et al.]

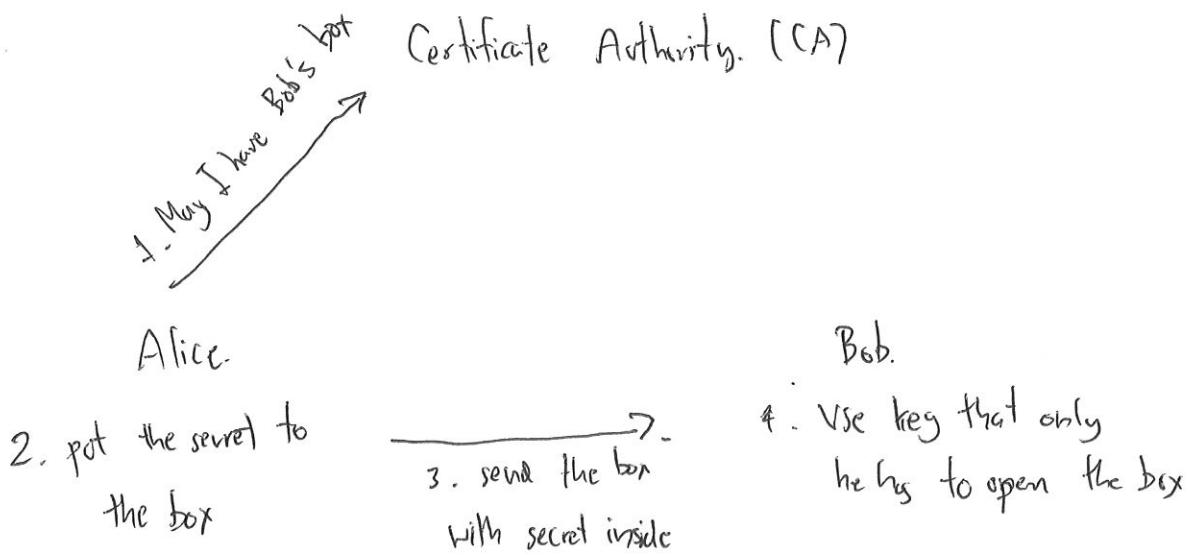
at least until 2014

much after that

[vn likely before 2028]

ECC is used in computation environment with limited memory .

## Public Key Cryptography



Alice has to contact Bob at everytime she send a message to a new person.  
CA

Inefficient ...

## Identity-Based Cryptosystem



Know Bob's e-mail address

1. Create Bob's box using Bob's e-mail address.
2. Put the secret into the box



Has a key generated from his e-mail address

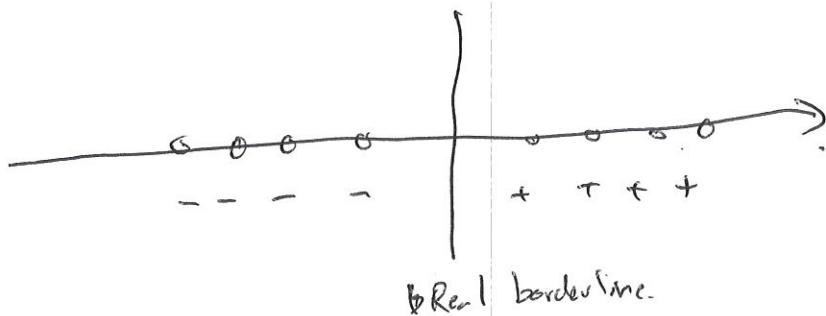
3. send the box with secret inside

4. Use key to open the box

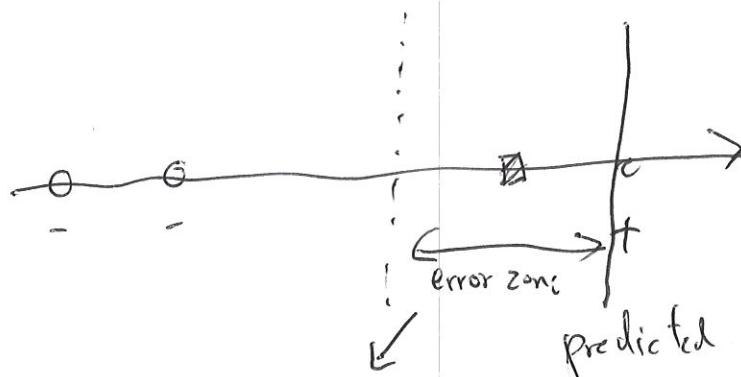
Only task of Certificate Authority is to generate Bob's key!!

## Probably Approximately Correct Learning (PAC Learning)

- Our graduate School is selecting students based on their entrance exam score. (assumption).
- We do not publish or give entrance examination score to students. You have to pay 300 yen to know your score.
- We want to know the borderline.



When we have  
a lot of information.



There have not been any + come from this zone.

predicted borderline  $\rightarrow$  smallest score we know that pass to the school.

Question: What is the probability that we have error zone by  $\pm 10$  points.  
When we conduct a sample independently for  $m$  times.

Assumption: The full score is 1000.

Prob. Probability that a sample is  $i$  is  $1/1000$   
for all  $i$ .

Probability that we have a sample between (real border)  $\pm \epsilon$  and (real border  $\pm 2\epsilon$ ) is  $10/1000$ .

Prob. that we don't is  $\frac{99}{100}$

Prob. that we don't for  $m$  times is  $\left(\frac{99}{100}\right)^m$ .

We will have a prediction with at most  $2\epsilon$  points error is  $1 - \left(\frac{99}{100}\right)^m$ .  
Approximately  
Probably.

at most  $k$  points error is  $1 - \left(1 - \frac{k}{1000}\right)^m$

Important inequality:  $1+x \leq e^x$  for all  $x \in \mathbb{R}$

$$1-x \leq e^{-x}$$

$$1-e^{-x} \leq -x$$

$1-e^{-x} \approx -x$  when  $x$  is small

$$\left(1 - \frac{k}{1000}\right)^m \leq e^{-\frac{km}{1000}}$$

$$1 - \left(1 - \frac{k}{1000}\right)^m \geq 1 - e^{-\frac{km}{1000}} \approx \frac{k}{1000} \cdot m.$$

maximum error in precision.

# times we do sampling

We will

IF we allow machine learning algorithms to have.

- o larger error (approximately)

- o ~~less~~ more fine  $\epsilon$

we have more chances to attain it.

(probably)

Question:

In our discussion, we assume that  $\Pr[\text{sample} = i] = \frac{1}{1000}$  for all  $i$ .

Show that the whole discussion still works for all probability distribution over  $P$ .

□