

Lecture 12

- Common mistakes to avoid.
- Reconciling intractability.

Following are some common mistakes I have encountered in the context of reductions and the class **NP**.

(1) Mistake: equating **NP** with “hard”

Simply because a problem is in **NP**, it does not necessarily mean that the problem is computationally hard. Folks sometimes mistakenly say, “the problem is in **NP**, therefore it is hard.” Another way to say this is: it is ok to assume that **NP** \neq **NP**-complete; it is weird to assume **NP** = **NP**-complete.

Recall that “ $q \in \mathbf{NP}$ ” establishes an *upper-bound* computational hardness for the problem q only. The problem q may be really easy, and be $\in \mathbf{NP}$. For example, there is a linear-time algorithm for **SHORTPATH**, and it is indeed the case that **SHORTPATH** $\in \mathbf{NP}$. Also consider the following problem: given as input a sorted array $A[1, \dots, n]$ and an item i , is i in $A[1, \dots, n]$? Both of the following are true: (i) there is an algorithm that runs in time, and therefore space, $O(\lg n)$ for this problem, and, (ii) this problem $\in \mathbf{NP}$. However, under the customary assumption that **L** \neq **NP**, this problem $\notin \mathbf{NP}$ -complete.

To reiterate, “ $\in \mathcal{C}$ ” expresses an upper-bound hardness for a problem only.

(2) Mistake: NP is “non-polynomial time”

NP stands for “Non-deterministic Polynomial time.” Not “non-polynomial time.” Whether $\mathbf{P} \neq \mathbf{NP}$, i.e., whether there exist problems for which there are efficient non-deterministic polynomial-time algorithms, but not deterministic polynomial-time algorithms, is of course a famous open problem.

(3) Mistake: a problem is NP-hard implies that no polynomial-time algorithm exists for it

A problem q may be **NP**-hard, and in **NP**. We do not know whether $\mathbf{P} \stackrel{?}{=} \mathbf{NP}$. In the (admittedly unlikely) event that $\mathbf{P} = \mathbf{NP}$, there exists a polynomial-time algorithm for such a q . It is best to not be lazy, and say something like the following fully:

*The problem is **NP**-hard, and under the customary assumption that $\mathbf{P} \neq \mathbf{NP}$, no polynomial-time algorithm exists for it.*

(4) Mistake: assuming $\mathbf{NP} = \mathbf{P} \cup \mathbf{NP}$ -complete

It is a mistake, or at least, weird, to assume that the only two subclasses of **NP** are **P** and **NP**-complete. Rather, it is conjectured widely, under the customary assumption $\mathbf{P} \neq \mathbf{NP}$, that there are problems “between” **P** and **NP**-complete. A well-known example is **ISO**: given as input a pair of graphs, $\langle G_1, G_2 \rangle$, is G_1 isomorphic to G_2 ? Recall that we considered **SUBGRAPHISO** before: whether a subgraph of a given graph is isomorphic to another graph. **ISO** asks whether the two are isomorphic to one another. **ISO** is in **NP**, but widely conjectured to not be **NP**-hard. It is conjectured also that **ISO** is not in **P**.

Another example is **PRODTWOPRIMES**, which we have discussed earlier: whether, given an input natural number, it is the product of two primes. We know that **PRODTWOPRIMES** $\in \mathbf{NP} \cap \mathbf{co-NP}$, and therefore unlikely to be **NP**-complete. It is conjectured that **PRODTWOPRIMES** is not in **P**.

Indeed, we can think of each of ISO and PRODTWOPRIMES as inducing their own complexity classes which are “between” **P** and **NP**-complete. For example, we could consider ISO-completeness under \leq_c . Consider AUTO: given a graph G , does there exist an isomorphism between G and itself that is not the identity mapping? It is possible to show that $\text{AUTO} \leq_c \text{ISO}$ and $\text{ISO} \leq_c \text{AUTO}$. Thus, AUTO is ISO-complete under \leq_c .

In summary: assuming that **NP** comprises only **P** and **NP**-complete would be unconventional, and would induce considerable skepticism.

(5) Mistake: assuming that an instance of a problem in NP has only a few certificates, or even one certificate

Consider the following claim.

Claim 83. *Suppose q is a problem in **NP**. Then, an instance of q of size n that is true may have $\Omega(2^n)$ certificates.*

Recall that a certificate is some efficiently-sized evidence for the true-ness of the instance. E.g., for an instance of SAT, a certificate is a satisfying assignment. What is the worst-case number of satisfying assignments that an instance of SAT may have? The answer is $\Theta(2^n)$ and therefore $\Omega(2^n)$. Given any n , consider the formula $x_1 \vee x_2 \vee \dots \vee x_n$. Then, all but one of the assignments to $\langle x_1, \dots, x_n \rangle$ is satisfying. Thus, we have $2^n - 1 = \Theta(2^n)$ satisfying assumptions.

Thus, there is nothing surprising that there may be exponentially many certificates for an instance of a decision problem, even one that is **NP**-complete.

Following is an example of a piece of work that suggests that we should be surprised by this.



An excerpt:

[The problem]... is **NP**-complete. ... We show... [the problem] is in fact much harder than **NP**-complete; it is not just intractable, but unsolvable. ... [possesses] a number of [certificates] which is at least exponential...

Again: there is nothing surprising with the number of certificates being exponential in the size of the instance.

Aside (and not part of the course): instead of a decision problem, which is a function whose co-domain is $\{0, 1\}$, we could instead generalize to a *counting* problem, which maps a set of problem-instances to a non-negative integer which is the number of certificates. E.g., we could map every instance of

SAT or VERTEXCOVER to the number of satisfying assignments, or number of different vertex cover sets of size k . It should be easy to observe that if the decision version is **NP**-hard, then such a counting version of the problem is **NP**-hard. There is a complexity class that is associated with these kinds of counting problems. It is written “ $\#P$,” pronounced “sharp-P.”

(6) Mistake: when we reduce problem A to problem B , where B is NP-complete, that implies that A is hard

This mistake is similar to Mistake (1) above, in which we think that $A \in \mathbf{NP}$ means that A is hard. Here, we are considering a reduction $A \leq B$. This is the kind of mistake with which the use of “ \leq ” for a reduction comes in handy to clarify what a reduction actually achieves. A reduction from A to B is written $A \leq B$. And as that indicates, we have shown only that B is an upper-bound for A . That is, we have said nothing about how hard A is. We have said something about how easy A is only.

An example of such a “reduction in the wrong direction” mistake:

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Trapdoor Computational Fuzzy Extractors and Stateless Cryptographically-Secure Physical Unclonable Functions

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Abstract—We present a fuzzy extractor whose security can be reduced to the hardness of Learning Parity with Noise (LPN) and can efficiently correct a constant fraction of errors in a biometric source with a “noise-avoiding trapdoor.” Using this computational fuzzy extractor, we present a stateless construction of a cryptographically-secure Physical Unclonable Function. Our construction requires no non-volatile (permanent) storage, secure or otherwise, and its computational security can be reduced to the hardness of an LPN variant under the random oracle model. The construction is “stateless” because there is no information stored between subsequent queries, which mitigates attacks against the PUF via tampering. Moreover, our stateless construction corresponds to a PUF whose outputs are free of noise because of internal error-correcting capability, which enables a host of applications beyond authentication. We describe the construction, provide a proof of computational security, analysis of the security parameter for system parameter choices, and present experimental evidence that the construction is practical and reliable under a wide environmental range.

Index Terms—Fuzzy extractor, physical unclonable function, learning parity with noise, ring oscillators, physically obfuscated keys

1 INTRODUCTION

1.1 Background and Motivation

SILICON Physical Unclonable Functions (PUFs) are a promising innovative primitive that are used for authentication and secret key storage without the requirement of secure memory or expensive tamper-resistant hardware [26], [25]. This is possible, because instead of storing secrets in digital memory, PUFs derive secrets from the physical characteristics of the integrated circuit (IC). Silicon PUFs rely on the fact that even though the mask and manufacturing process is the same among different ICs, each IC is actually slightly different due to normal manufacturing variability. PUFs leverage this variability to derive “secret” information that is unique to the chip (a silicon “biometric”). Due to the manufacturing variability, one cannot manufacture two chips with identical secrets, even with full knowledge of the chip’s design. PUF architectures that exploit different types of manufacturing variability have been proposed. In addition to gate delay, there are PUFs that use the power-on state of SRAM, threshold voltages, and many other physical characteristics to derive the secret. The informal requirements for a PUF are:

- 1) Upon being given a challenge, the PUF produces a response, and no other data about the internal functionality of the PUF is revealed.
- 2) Large enough challenge-response space such that an adversary cannot enumerate all challenge-response pairs within reasonable time.
- 3) An adversary given a polynomial number of challenge-response pairs cannot predict the response to a new, randomly chosen challenge.
- 4) Not feasible to manufacture two PUFs with the same responses to all challenges.

These requirements correspond to what has been sometimes called a strong PUF in the literature.

The silicon PUF approach is advantageous over standard secure digital storage for several reasons:

- Since the “secret” is derived from physical characteristics of the IC, the chip must be powered on for the secret to reside in digital memory. Any physical attack attempting to extract digital information from the chip therefore must do so while the chip is powered on.
- Authentication of devices and secure communication to devices do not require embedding and permanently storing secrets in the device. Devices therefore do not require non-volatile memory, which is more expensive and not available in all manufacturing processes. For example, EEPROMs require additional mask layers, and battery-backed RAMs require an external always-on power source.

PUFs can therefore serve as one way to address the growing counterfeit electronics problem [29].

For authentication, PUFs usually adopt a simple challenge-response protocol. An entity, call it the verifier, collects challenge-response pairs in a secure location when in possession of the PUF. At any later point of time, to authenticate a remote device, the verifier sends a challenge to the device and asks for the response.¹ If

1. To defeat man-in-the-middle attacks, challenges should not be repeated.

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The first sentence of the abstract is:

We present [our approach] whose security can be reduced to the hardness of [some problem that is presumed to be hard]...

Such a reduction would establish nothing about the security of their approach. What they need is a reduction in the other direction: from the hard problem to their approach. Because, presumably what they want is to say that their security is lower-bounded by the difficulty of solving that other problem. Which is a good segue to the next common mistake...

(7) Mistake: if a problem is NP-hard, then every instance of that problem is hard

A notion such as NP-hard only captures the *worst-case* hardness of a problem. That is, under the customary assumption $\mathbf{P} \neq \mathbf{NP}$, if a problem is NP-hard, then this means that there exists *some instances* of the problem that are hard. Not every instance is necessarily hard. Indeed, most instances of a problem that is NP-complete, for example, may be easy, and only very few may be hard. This is an observation that is leveraged by real-world tools such as SAT solvers. It is easy to conceive of entire classes of SAT, all of whose instances are easy. And hardness is not necessarily correlated with the size of an instance. E.g., for SAT, for every instance-size n , one can easily come up with instances of SAT that are easy to decide.

Even for a problem such as HALT which is undecidable, we certainly have classes of instances for which the problem is certainly decidable. Thus, \mathcal{C} -hard captures only the worst-case, not every case, and not even the average, or expected, case.

We can indeed conceive, and folks have proposed and used an “average-case” kind of reduction. In such a reduction, the idea is roughly to establish that if we were to pick an instance randomly, then it is hard. But the customary \leq_k which is used to show that a problem is NP-hard does not establish anything like that.

(8) Mistake: not addressing the “if” part of the “if and only if” property of a Karp-reduction

Recall that $A \leq_k B$ requires proof of the following property for the underlying mapping, m from instances of A to instances of B : an instance i of A is **true** if and only if an instance of B is **true**. A common mistake is to present a mapping that satisfies the “only if” property only, and neglect the “if.”

Consider, for example, the following mapping from ISO and SUBGRAPHISO. We know that $\text{ISO} \leq_k \text{SUBGRAPHISO}$ because $\text{ISO} \in \mathbf{NP}$ and $\text{SUBGRAPHISO} \in \mathbf{NP}$ -hard. Our proposed mapping is: given an instance $\langle G_1, G_2 \rangle$ of ISO, simply output $\langle G_1, G_2 \rangle$ as our instance of SUBGRAPHISO. So we are claiming that the identity mapping works as a Karp-reduction from ISO to SUBGRAPHISO. This is false.

This mapping satisfies the “only if” property. That is, if $\langle G_1, G_2 \rangle \in \text{ISO}$, then $\langle G_1, G_2 \rangle \in \text{SUBGRAPHISO}$. Why? Because G_2 is a subgraph of itself. However, the “if” property is not satisfied. That is, it is possible that G_1 is subgraph isomorphic to G_2 , but not isomorphic to G_2 . It is easy to come up with an example of this. Thus, the identity mapping does not work as a Karp-reduction from ISO to SUBGRAPHISO.

To reiterate: one must consider both “if” and “only if.” Not the latter only.

(9) Mistake: adopting a function that is not computable in polynomial-time as a Karp-reduction

The other important property for the mapping that underlies $A \leq_k B$ is that it must be computable in polynomial-time. A common mistake is to propose a mapping that is not computable in polynomial-time in the worst-case, and then conclude that $A \leq_k B$.

For example, consider reducing VERTEXCOVER to SETCOVER. An instance of VERTEXCOVER is $\langle \langle V, E \rangle, k \rangle$. An instance of SETCOVER is $\langle G, \mathcal{S}, k' \rangle$. Consider the following function, call it m , from the set of instances of VERTEXCOVER to SETCOVER:

- Corresponding to each edge, $e \in E$, an item $i_e \in G$.

- A couple of negative examples from research: the work to the left (which won a prestigious award) has an exponential-time reduction to Integer Linear Programming (ILP), and the work to the right has an exponential-time reduction to SAT.

(10) Mistake: equating NP-complete and NP-hard

NP-hard is a lower-bound on computational hardness only. **NP**-complete is an upper- and lower-bound. There are problems that are **NP**-hard that are not **NP**-complete. An example is **HALT**. Following is another example that is more nuanced.

Let **VERTEXCOVEREXACT** be the following decision problem: given as input an undirected graph G and an integer k , does G have a vertex cover of size k and no smaller?

VERTEXCOVEREXACT is indeed **NP**-hard. However, it is unlikely to be in **NP**, and is therefore unlikely to be **NP**-complete. Why? Think about whether a **true** instance of **VERTEXCOVEREXACT** possesses an efficiently-sized certificate that can be verified efficiently. The “no smaller” part is the tricky part. More broadly, there are problems for which algorithms exist, which are “harder” than **NP**.

Note, however, that $\text{VERTEXCOVEREXACT} \leq_c \text{VERTEXCOVER}$. Because, given a polynomial-time algorithm for **VERTEXCOVER**, we can do a binary search on k to identify the smallest size of a vertex cover for G .

Aside (not part of the course): we can prove that **VERTEXCOVEREXACT** is complete for a particular class in the *polynomial hierarchy*. Also, we can prove that $\text{VERTEXCOVEREXACT} \in \mathbf{PSPACE}$.

(11) Mistake: equating NP and co-NP

co-NP comprises problems that are complements of problems in **NP**. It is unlikely that $\mathbf{NP} = \mathbf{co-NP}$, though it is indeed true that $\mathbf{NP} \cap \mathbf{co-NP} \neq \emptyset$. As a practical matter, however, one may argue that we do not need to carefully distinguish **NP** and **co-NP**, because an oracle for a problem q is also an oracle for its complement, \bar{q} , except with the output negated.

Dealing with intractable problems in practice

Given the customary assumption $\mathbf{P} \neq \mathbf{NP}$, we know that no efficient algorithm exists for a problem that is \mathbf{NP} -hard. Indeed, even if a problem is, for example, \mathbf{ISO} -hard, it is unlikely that an efficient algorithm exists for it. However, such problems arise quite frequently in practice, in every imaginable context in computing. For example, it was recognized in the early days of cloud computing that placing Virtual Machines (VMs) in servers is a kind of multi-dimensional bin packing problem, which is \mathbf{NP} -complete.

So what is one to do? In the following, we consider several possible approaches when confronted with a situation in which one is unable to conceive of an efficient algorithm.

Efficient approximation

We have discussed some approximation algorithms that are efficient for problems whose decision versions are \mathbf{NP} -complete; for example, those for TSP and Vertex Cover. There is a rich theory that underlies efficient approximation, and a reduction all of its own called a “gap-preserving reduction,” which helps establish a lower-bound for the best approximation ratio we can achieve. For example, we can prove, via a gap-preserving reduction, that $\lg n$ is the best approximation ratio we can achieve with a polynomial-time algorithm for Set Cover under the assumption that $\mathbf{P} \neq \mathbf{NP}$. It is possible to sub-classify the class \mathbf{NP} based on how approximable a problem is.

The monograph of Arora and Lund is a great starting point: <https://www.cs.princeton.edu/~arora/pubs/chapter.ps>. You should find that document accessible now that you have taken this course.

Randomized algorithms

Even though a problem is not in \mathbf{P} , it is possible that it is not \mathbf{NP} -hard. For example, it may be in the class \mathbf{RP} : the class of decision problems for which there exists an *randomized* algorithm. For example, for a long time it was not known whether the problem of determining whether an integer is

prime is in **P**. It turns out that it is indeed in **P**, a discovery that was made in the mid-2000's. However, by then, we already knew that it is in **RP**, and the randomized Miller-Rabin primality test continues to be the most widely used algorithm, rather than the polynomial-time algorithm.

Thus, it may be worthwhile investigating whether a problem is in **RP**, if one is unable to devise a polynomial-time algorithm for it. However, it is conjectured that $\mathbf{RP} \subset \mathbf{NP}$, and therefore if you prove that your problem is indeed **NP**-hard, an efficient randomized algorithm is unlikely to exist.

Reduction to a problem such as SAT and model checking, and use of a constraint solver

If one is unable to conceive of an efficient, or really, any algorithm, for one's problem, then a possibility is to reduce a decision version to which the problem is polynomially related to the language of an off-the-shelf constraint solver. The right way to do this is to: (i) first identify a complexity class to which the problem belongs, and, (ii) carry out a Karp reduction to the problem the solver understands.

An example of such a solver is a SAT solver, which customarily takes as input an instance of CNFSAT, that is, a SAT formula in CNF. In my experience, reduction first to CIRCUIT-SAT, and then employment of the “textbook” reduction to CNFSAT is usually the most conceptually simple way to go about this. For example, consider VERTEXCOVER, which is the following decision problem: given as inputs (i) a graph G , and, (ii) a natural number k , does there exist a subset of vertices of G of size k that is a vertex cover for G ?

A reduction to CIRCUIT-SAT could be the following. Construct a circuit as follows.

- Take as input one wire per vertex.
- For each edge, $\langle u, v \rangle$, join the input wire that represents u and v with an OR gate. This captures the constraint that at least one of those must be in the vertex cover.

- Add a sub-circuit that performs an integer-sum of the input wires to the circuit, and compare the output of that sub-circuit to a circuit encoding of the integer k .
- Do an AND of the wires that are the outputs of each ‘edge’ sub-circuit, and the comparison-with- k sub-circuit. This is the output wire of the circuit.

The size of the above circuit is $O(n \lg n)$, where n is the size of the input graph. From this instance of CIRCUIT-SAT, we can generate an instance of CNFSAT in linear-time.

If our problem is not in **NP**, it may be, for example, in **PSPACE**. In this case, we could perform a reduction to model-checking, and deploy an off-the-shelf model-checker such as nuSMV. The proof that a problem is in **PSPACE** can be constructive: we prove it by producing an algorithm that takes auxiliary space only polynomial in the size of the input.

Via assumptions about the input, and heuristics

A final way we mention is somewhat “hacky.” And that is to simply make assumptions about the input so that we simply ignore hard instances. Recall that even if a problem is **NP**-hard, it is possible that only relatively few classes of input instances may be hard in practice. This is a feature that is exploited by solvers such as SAT solvers and model checkers. “Branch and bound” and “gradient descent” are algorithm design strategies that work as heuristics in this context. Thus, if it turns out that we can assume that hard instances do not arise in practice, even though the worst-case characterization of our problem may be that it is hard, we may have an efficient algorithm for large classes of inputs that are not hard.

A tricky part with this is that if a problem is indeed **NP**-hard, and we have an efficient algorithm driven, for example, by heuristics, then we may not get a strong sense for what classes of inputs our algorithm does not perform well. The reason is that if we do, then that would give us insight in to the separation of **P** from **NP**, which would be a major contribution to computing.