## Lecture Notes 9

## 22 Proving a Predicate is Hard-Core

We continue the proof of Lemma 3 of section 21. Recall that $f$ is a strongly one-way and length preserving function, and that

$$
\begin{aligned}
g(x, r) & \stackrel{\text { df }}{=}(f(x), r) \\
b(x, r) & \stackrel{\text { df }}{=} x \cdot r \bmod 2 .
\end{aligned}
$$

We showed in Lemma2 that $g$ is strongly one-way. We want to show that $b$ is a hard core for $g$.
Assume to the contrary that $b$ is not a hard core for $g$. Then there exists a p.p.t. algorithm $G$ that predicts $b$ with non-negligible advantage $\varepsilon_{G}(n)$. Thus, there is a polynomial $p(\cdot)$ such that

$$
\begin{equation*}
\operatorname{Pr}\left[G\left(f\left(U_{n}\right), X_{n}\right)=b\left(U_{n}, X_{n}\right)\right] \geq \frac{1}{2}+\frac{1}{p(n)} \tag{1}
\end{equation*}
$$

for all $n$ in an infinite set $N$.
To complete the proof of Lemma 3, we will do two things:

- We will construct an algorithm $A$ that on input $y$ attempts to invert $f$.
- We will show that, for some polynomial $q(\cdot), A$ has success probability greater than $\frac{1}{q(n)}$ at inverting $f$ on length $n$ inputs for all sufficiently large $n$ in the infinite set $N$. This contradicts the assumption that $f$ is strongly one-way.

We construct $A$ now and defer the analysis of its success probability to the next lecture.

### 22.1 Using $G$ to invert $f$

How can $G$ help us to invert $f$ ? A priori it doesn't seem to be much help to have a predictor for only a single predicate when our algorithm $A$ is supposed to correctly output a length- $n$ string in $f^{-1}(y)$. It's not at all obvious how to use $G$, and several tricks are involved.

Using $b$ to extract bits of $x$ : Let $e^{i}$ be the unit vector with a 1 -bit in position $i$ and 0 's elsewhere. As before, we treat strings in $\{0,1\}^{*}$ as bit-vectors, so $x_{i}$ is the $i^{\text {th }}$ bit of $x$. It follows from the definition of Boolean dot product that $b\left(x, e^{i}\right)=x \cdot e^{i} \bmod 2=x_{i}$.

Fact

$$
\begin{equation*}
b(x, r) \oplus b\left(x, r \oplus e^{i}\right)=x_{i} . \tag{2}
\end{equation*}
$$

This follows because

$$
\begin{align*}
b(x, r) \oplus b(x, s) & =\left(\bigoplus_{j=1}^{n} x_{j} \cdot r_{j}\right) \oplus\left(\bigoplus_{j=1}^{n} x_{j} \cdot s_{j}\right) \\
& =\bigoplus_{j=1}^{n}\left(x_{j} \cdot\left(r_{j} \oplus s_{j}\right)\right) \\
& =b(x, r \oplus s) \tag{3}
\end{align*}
$$

Taking $s=r \oplus e^{i}$, equation 3 gives

$$
\begin{equation*}
b(x, r) \oplus b\left(x, r \oplus e^{i}\right)=b\left(x, r \oplus\left(r \oplus e^{i}\right)\right)=b\left(x, e^{i}\right)=x_{i} \tag{4}
\end{equation*}
$$

as desired.
First idea for $A$ : For each $i=1, \ldots, n$, use $G$ to guess $b(x, r)$ and $b\left(x, r \oplus e^{i}\right)$ for random $r$, then use equation 4 to guess $x_{i}$, i.e., guess $x_{i}=G(y, r) \oplus G\left(y, r \oplus e^{i}\right)$. Repeat this procedure to obtain polynomially many guesses of $x_{i}$ and choose the majority value. Return $x=x_{1} \ldots x_{n}$ as the guess for $f^{-1}(y)$.

If $G$ is correct about $b$ on both calls, then $x_{i}$ is correct. As long the probability that both calls on $G$ are correct is greater than $\frac{1}{2}+\frac{1}{\text { poly }}$, repetition will amplify this probability to be sufficiently close to 1 so that the probability of all $n$ bits of $x$ being correct is also close to 1 . Unfortunately, this is only the case when $G$ 's success probability is $\frac{3}{4}+\frac{1}{\text { poly }}$, that is, its advantage is a little bit greater than $\frac{1}{4}$. All we know about our $G$ is that it satisfies inequality 1 , so its advantage is only $\frac{1}{p(n)}$.

Second idea for $A$ : Same as first idea, except instead of using $G$ to guess $b(x, r)$, we just use a random bit $\hat{b}(r)$. Thus, we guess that $x_{i}=\hat{b}(r) \oplus G\left(y, r \oplus e^{i}\right)$. This of course doesn't work since the probability of being correct is exactly $\frac{1}{2}$ and we get no advantage. But if we somehow had an oracle that would give us the correct value for $\hat{b}(r)=b(x, r)$, then this idea would indeed work since then the advantage at guessing $x_{i}$ would be the same as $G$ 's advantage at guessing $b$.

Third idea for $A$ : We generate a small $\left(O(\log n)\right.$-sized) set of random strings $R_{0}$ and corresponding guesses for $\hat{b}(r)$ for each $r \in R_{0}$. From $R_{0}$, we deterministically generate a polynomial set of strings $R$ and corresponding values for $\hat{b}(r), r \in R$. By the way the construction will work, if $\hat{b}(r)$ is correct for all $r \in R_{0}$, then $\hat{b}(r)$ is correct for all $r \in R$. Since the number of strings in $R_{0}$ for which we require correct guesses is only $O(\log n)$, it follows that the probability of all $O(\log n)$ guesses being correct is at least $\frac{1}{\text { poly }}$ since $2^{O(\log n)}=\operatorname{poly}(n)$.

The strings in $R$ are uniformly distributed over $\{0,1\}^{n}$, but they are only pairwise independent. However, this turns out to be sufficient for the construction to work.

How to generate $R_{0}$ and $R$ : Let $\ell=\left\lceil\log _{2}\left(2 n \cdot p(n)^{2}+1\right)\right\rceil$.

1. Select $s^{1}, \ldots, s^{\ell} \in\{0,1\}^{n}$ uniformly and independently. Select $\sigma^{1}, \ldots, \sigma^{\ell} \in\{0,1\}$ uniformly and independently. Let $R_{0}=\left\{s^{1}, \ldots s^{\ell}\right\}$ and $\hat{b}\left(s^{i}\right)=\sigma^{i}, i=1, \ldots, \ell$.
2. Let $\mathcal{J}$ be the family of non-empty subsets of $\{1,2, \ldots, \ell\}$. For all sets $J \in \mathcal{J}$, compute

$$
r^{J}=\bigoplus_{j \in J} s^{j} \quad \text { and } \quad \rho^{J}=\bigoplus_{j \in J} \sigma^{j}
$$

Let $R=\left\{r^{J} \mid J \in \mathcal{J}\right\}$, and $\hat{b}\left(r^{J}\right)=\rho^{J}$ for all $J \in \mathcal{J}$.
Note that $r^{\{i\}}=s^{i}$ and $\rho^{\{i\}}=\sigma^{i}$, so indeed $R \supseteq R_{0}$.
Fact If $b\left(x, s^{j}\right)=\sigma^{j}$ for all $j \in\{1, \ldots, \ell\}$, then $b\left(x, r^{J}\right)=\rho^{J}$ for all $J \in \mathcal{J}$.
This follows because

$$
b\left(x, r^{J}\right)=b\left(x, \bigoplus_{j \in J} s^{j}\right)=\bigoplus_{j \in J} b\left(x, s^{j}\right)=\bigoplus_{j \in J} \sigma^{j}=\rho^{J} .
$$

The first equality is from the definition of $r^{J}$, the second comes from repeated use of equation 3 , the third uses the assumption that $\sigma^{j}$ is correct for all $j \in\{1, \ldots, \ell\}$, and the final equality is from the definition of $\rho^{J}$.

### 22.2 The complete algorithm for $A$

Here is the complete algorithm for $A$. On input $y$, let $n=|y|$ and $\ell=\left\lceil\log _{2}\left(2 n \cdot p(n)^{2}+1\right)\right\rceil$.

1. Uniformly and independently, select $s^{1}, \ldots, s^{\ell} \in\{0,1\}^{n}$ and $\sigma^{1}, \ldots, \sigma^{\ell} \in\{0,1\}$.
2. For all non-empty $J \subseteq\{1,2, \ldots, \ell\}$, compute

$$
r^{J}=\bigoplus_{j \in J} s^{j} \quad \text { and } \quad \rho^{J}=\bigoplus_{j \in J} \sigma^{j}
$$

3. For all $i \in\{1, \ldots, n\}$, for all non-empty $J \subseteq\{1, \ldots, \ell\}$, compute

$$
z_{i}^{J}=\rho^{J} \oplus G\left(y, r^{J} \oplus e^{i}\right) .
$$

4. For all $i \in\{1, \ldots, n\}$, let $z_{i}=$ majority $_{J}\left\{z_{i}^{J}\right\}$.
5. Output $z=z_{1} \ldots z_{n}$.
