## Trapdoor Sampling

March 26, 2013
Scribe: Yuan Kang

## 1 Trapdoor Sampling MP12

The GPV Signature scheme assumes that we can generate trapdoor matrices. This process has two steps:

1. Construct a special purpose, "easy lattice", $G,{ }^{1}$ that is not random at all, as described in the handout, and
2. Show how to sample a nearly-uniform $A$, together with a trapdoor that "maps" $A$ to $G$

The "easy lattice" is $G \in \mathbb{Z}_{q}^{n \times m^{\prime}}, m^{\prime}=\lceil n \log (q)\rceil$, such that:
(a) It is easy to sample $\mathcal{D}_{\mathcal{L}_{\vec{u}}^{\perp}(G), s}$ for any $\vec{u} \in \mathbb{Z}_{q}^{n}$ and parameter $s \geq 2 \sqrt{n}$. ${ }^{2}$
(b) Given $[\vec{s} G+\vec{e}]$, with small $\|\vec{e}\|_{\infty}<\frac{q}{4}$, one can efficiently recover $\vec{s}$.

### 1.1 Step (2): Mapping $A$ to $G$

Definition 1. As in the first property, denote:

$$
m^{\prime}=\lceil n \log (q)\rceil
$$

In addition denote

$$
m^{\prime \prime}=\lceil n \log (q)+\sqrt{n}\rceil
$$

and

$$
m=m^{\prime}+m^{\prime \prime}=\lceil 2 n \log (q)+\sqrt{n}\rceil
$$

Let $A \in \mathbb{Z}^{n \times m}$ denote

$$
A=[\underbrace{\bar{A}}_{m^{\prime \prime}} \mid \underbrace{A_{1}}_{m^{\prime}}]
$$

A matrix $R \in \mathbb{Z}_{q}^{m^{\prime \prime} \times m^{\prime}}$ is a trapdoor of $A$ iff

- $R$ is "small"
- $\underbrace{A_{1}}_{n \times m^{\prime}}=\underbrace{G}_{n \times m^{\prime}}-\underbrace{\bar{A}}_{n \times m^{\prime}} \underbrace{m^{\prime \prime} \times m^{\prime}}_{n \times m^{\prime \prime}}$. In matrix notation: $A=[\bar{A} \mid G]\left(\begin{array}{cc}I & -R \\ 0 & I\end{array}\right)$

The algorithm to generate $(A, R)$ proceeds as follows:

[^0]- Choose $R \in \mathbb{Z}_{q}^{m^{\prime \prime} \times m^{\prime}}$, where each entry in $R$ is chosen at random from the discrete Gaussian, $\mathcal{D}_{\mathbb{Z}, \sqrt{n}} . R$ is the trapdoor, and note that it is "small," for example with high probability, we have for all $\vec{x}$, that $\|\vec{x} R\|_{\infty} \leq\|\vec{x}\|_{\infty} 2 n \log (q)$, and the same applies for $\|.\|_{2}$ (so $S_{1}(R)<$ $2 n \log (q))$.
- To choose $A$, first draw a uniform matrix $\bar{A} \in_{R} \mathbb{Z}_{q}^{n \times m^{\prime \prime}}$, then set

$$
\begin{aligned}
A & =[\bar{A} \mid G]\left(\begin{array}{cc}
I & -R \\
0 & I
\end{array}\right) \\
& =[\bar{A} \mid G-\bar{A} R] \in \mathbb{Z}_{q}^{n \times\left(m^{\prime}+m^{\prime \prime}\right)}
\end{aligned}
$$

Fact 1. A is nearly uniform. Recall that $f_{\bar{A}}=\bar{A} \vec{x} \bmod q$ is a strong seeded extractor, and the columns of $R$ have high min-entropy, so $\bar{A} R$ is nearly uniform, even given $\bar{A}$.

Fact 2. If we can solve LWE for $G$, then $R$ lets us also solve for $A$. ${ }^{3}$ Given input $\vec{b}=\vec{s} A+\vec{e}$, where we denote $\vec{e}=[\underbrace{\vec{e}_{1}}_{m^{\prime \prime}} \mid \underbrace{\overrightarrow{e_{2}}}_{m^{\prime}}]$, we have

$$
\begin{aligned}
\vec{b}\left(\begin{array}{cc}
I & R \\
0 & I
\end{array}\right) & =\left(\vec{s} A+\left[\vec{e}_{1} \mid \vec{e}_{2}\right]\right)\left(\begin{array}{cc}
I & R \\
0 & I
\end{array}\right) \\
& =\vec{s}[\bar{A} \mid G]\left(\begin{array}{cc}
I & -R \\
0 & I
\end{array}\right)\left(\begin{array}{cc}
I & R \\
0 & I
\end{array}\right)+\left[\vec{e}_{1} \mid \vec{e}_{2}\right]\left(\begin{array}{cc}
I & R \\
0 & I
\end{array}\right) \\
& =\vec{s}[\bar{A} \mid G]+\left[\vec{e}_{1} \mid \vec{e}_{1} R+\vec{e}_{2}\right]
\end{aligned}
$$

In particular, considering only the last $m^{\prime}$ entries, we have

$$
\vec{b}\binom{R}{I}=\vec{s} G+\underbrace{\left(\vec{e}_{1} R+\vec{e}_{2}\right)}_{\vec{e}^{\prime}}
$$

As long as $\left\|\overrightarrow{e^{\prime}}\right\|_{\infty} \leq\left\|\vec{e}_{1}\right\|_{\infty} 2 n \log (q)+\left\|\vec{e}_{2}\right\|_{\infty}<\frac{q}{4}$, we can recover $\vec{s}$ from $\vec{s} G+\overrightarrow{e^{\prime}}$. The first inequality follows from the choice of a "small" $R$, and the second inequality is true as long as $\left\|\vec{e}_{1}\right\|_{\infty},\left\|\vec{e}_{2}\right\|_{\infty} \ll \frac{q}{n \log (q)}$.
Fact 3. If we can sample from $\mathcal{D}_{\mathcal{L}_{\vec{u}}^{\perp}(G), s}$, then using $R$, we can sample $\mathcal{D}_{\mathcal{L}_{\vec{u}}^{\perp}(A), s^{\prime}}$, where $s^{\prime}$ is not much bigger than $s$.

- First attempt: Draw $\vec{z} \leftarrow \mathcal{D}_{\mathcal{L}_{\vec{u}}^{\perp}(G), s}$, output $\vec{x}=\binom{R}{I} \vec{z}$. This "almost works"; we have $A \vec{x}=A\binom{R}{I} \vec{z}=G \vec{z}=\vec{u}$, and $\|\vec{x}\|_{\infty} \leq\|R \vec{z}\|_{\infty}+\|\vec{z}\|_{\infty} \leq(2 n \log (q)+1)\|\vec{z}\|_{\infty}$, as needed for SIS. But if $\vec{z}$ is a spherical Gaussian, then $\vec{x}$ is an ellipsoid Gaussian. Even worse, the covariance of $\vec{x}$ has the shape $s^{2}\binom{R}{I}\left[R^{T} \mid I\right]$, so after enough samples, we can get the shape of $R$ and recover $R$ itself.
- Better attempt: Use"perturbation" Pei10. Roughly, choose $\vec{p}$ from an ellipsoid that cancels out that of $\vec{x}$, and output $\vec{p}+\vec{x}$ :

[^1]- Define the covariance matrix $\Sigma=\underbrace{s^{2} I}_{\text {what we aim for }}-\underbrace{\binom{R}{I}\left[R^{T} \mid I\right]}_{\text {the "shape" of } \vec{x}}$. Note that s must be large enough so that $\Sigma$ is positive (else it cannot be a covariance matrix). Specifically, we need to have $s>1+S_{1}(R)$.
- Sample from the ellipsoid discrete Gaussian $\vec{p} \leftarrow \underbrace{\mathcal{D}_{\mathbb{Z}^{m}, s \sqrt{n}} \sqrt{\Sigma}}_{\text {"perturbation" }}$
- Calculate the syndrome $\vec{v}=\vec{u}-A \vec{p} \bmod q$
- Sample $\vec{z} \leftarrow \mathcal{D}_{\mathcal{L}_{\overrightarrow{\vec{v}}}^{\perp}(G), 2 \sqrt{n}}$, then set $\vec{x}=\binom{R}{I} \vec{z}$
- Output $\vec{y}=\vec{x}+\vec{p}$

Clearly we have $A \vec{y}=A \vec{x}+A \vec{p}=\vec{v}+A \vec{p}=\vec{u}$. Moreover, $\vec{p}$ has covariance $4 n \Sigma$, and $\vec{x}$ has covariance $4 n\binom{R}{I}\left[R^{T} \mid I\right]$, so if they were independent, we would expect their covariance matrices to add, and we get $4 n\left(\binom{R}{I}\left[R^{T} \mid I\right]+\Sigma\right)=4 n s^{2} I$.
They are not quite independent, since the mean of $\vec{z}$ depends on $\vec{p}$, but only via $A \vec{p}$ in $\vec{v}$, which does not give much information about $\vec{p}$. We can think of first choosing $\vec{v}$ at random, then drawing $\vec{p}$ from the discrete Gaussian. Once $\vec{v}$ is fixed, $\vec{p}$ and $\vec{x}$ are independent and their covariances add; since we choose $\vec{z}$ from a Gaussian wider than $\eta_{\epsilon}\left(\mathcal{L}^{\perp}(A)\right)$, for a negligible $\epsilon$, the covariance behaves as we expect.

## 2 Trapdoor Delegation

Given a trapdoor, $R$, for $A \in \mathbb{Z}_{q}^{n \times m}$, generate a trapdoor, $R^{\prime}$, for an extension of $A, A^{\prime}=\left[A \mid A_{1}\right]$, where $A_{1} \in \mathbb{Z}_{q}^{n \times m^{\prime}}$ is an arbitrary matrix (eg. it can be random), and $m^{\prime} \geq\lceil n \log (q)\rceil$.

TDelegate $\left(A, R, A_{1}\right)$ :

- Calculate $\Delta=G-A_{1}$. Denote the columns of $\Delta$ by $\Delta=\left(\vec{\delta}_{1}\left|\vec{\delta}_{2}\right| \ldots \mid \vec{\delta}_{m^{\prime}}\right)$.
- For $i \in\left\{1,2, \ldots, m^{\prime}\right\}$, use $R$ to sample from $\mathcal{D}_{\mathcal{L}_{\hat{\delta}_{i}}^{\perp}(A), s}$, where $s=\left\lceil 2+S_{1}(R)\right\rceil \approx 2 n \log (q)>$ $\eta_{\epsilon}\left(\mathcal{L}^{\perp}(A)\right)$ for some negligible $\epsilon$. Denote $\overrightarrow{r^{\prime}}{ }_{i} \leftarrow \mathcal{D}_{\mathcal{L}_{\hat{\delta}_{i}}}(A), s$.
- Output the new trapdoor, $R^{\prime}=\left(\vec{r}^{\prime}| |{\overrightarrow{r^{\prime}}}_{2}|\ldots|{\overrightarrow{r^{\prime}}}_{m^{\prime}}\right) \in \mathbb{Z}_{q}^{n \times m^{\prime}}$.

By construction $A{\overrightarrow{r^{\prime}}}_{i}=\vec{\delta}_{i} \bmod q$, so $A R^{\prime}=\Delta$, and therefore we have

$$
A^{\prime}=\left(A \mid A_{1}\right)=(A \mid G-\Delta)=\left(A \mid G-A R^{\prime}\right)
$$

So $R^{\prime}$ is indeed a trapdoor for $A^{\prime}$. Also, $R^{\prime}$ is "small"; roughly, the size of each column of $R^{\prime}$ is approximately $\sqrt{m} s$, so $S_{1}\left(R^{\prime}\right) \approx \sqrt{m} S_{1}(R) \approx(n \log (q))^{\frac{3}{2}}$.

Note that if $\left(A, A_{1}\right)$ are random, the distribution of $\left(A^{\prime}, R^{\prime}\right)$ is the same as the output of TGen, except for larger parameters, $\tilde{m}=m+m^{\prime}$, and $S_{1}\left(R^{\prime}\right) \approx(n \log (q))^{\frac{3}{2}}$.

## References

[1] Daniele Micciancio and Chris Peikert. Trapdoors for Lattices: Simpler, Tighter, Faster, Smaller. In David Pointcheval and Thomas Johansson (editors) Advances in Cryptology, EUROCRYPT 2012, pages 700-718, Heidelberg, Germany, 2012. Springer.
[2] Chris Peikert. An Efficient and Parallel Gaussian Sampler for Lattices. In Tal Rabin (editor) Advances in Cryptology, CRYPTO 2010, pages 80-97, Heidelberg, Germany, 2010. Springer.


[^0]:    ${ }^{1}$ ie. it is easy to solve LWE or SIS
    ${ }^{2}$ Recall the definition $\mathcal{L} \stackrel{\rightharpoonup}{\vec{u}}(A)=\left\{\vec{x} \in \mathbb{Z}_{q}^{n} \mid A \vec{x}=\vec{u} \bmod q\right\}$

[^1]:    ${ }^{3}$ Given input $A, \vec{b}=\vec{s} A+\vec{e}$, for "secret" $\vec{s}$, and "small" $\vec{e}$, find $\vec{s}$.

