# New Independent Source Extractors with Exponential Improvement 

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#### Abstract

We study the problem of constructing explicit extractors for independent general weak random sources. For weak sources on $n$ bits with min-entropy $k$, perviously the best known extractor needs to use at least $\frac{\log n}{\log k}$ independent sources [Rao06, BRSW06]. In this paper we give a new extractor that only uses $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ independent sources. Thus, our result improves the previous best result exponentially. We then use our new extractor to give improved network extractor protocols, as defined in [KLRZ08]. The network extractor protocols also give new results in distributed computing with general weak random sources which dramatically improve previous results. For example, we can tolerate a nearly optimal fraction of faulty players in synchronous Byzantine agreement and leader election, even if the players only have access to independent $n$-bit weak random sources with min-entropy as small as $k=\operatorname{poly} \log (n)$.

Our extractor for independent sources is based on a new condenser for somewhere random sources with a special structure. We believe our techniques are interesting in their own right and are promising for further improvement.


[^0]
## 1 Introduction

Motivated by the enormous applications in computation that rely on the use of truly uniform random bits (e.g, algorithm design, distributed computing and cryptography), and the fact that random sources in practice are rarely uniform, the broad area of randomness extraction studies the problem of converting a weakly random source into a distribution that is close to uniform. Here we measure the randomness in a random source $X$ by the standard min-entropy.

Definition 1.1. The min-entropy of a random variable $X$ is

$$
H_{\infty}(X)=\min _{x \in \operatorname{supp}(X)} \log _{2}(1 / \operatorname{Pr}[X=x])
$$

For $X \in\{0,1\}^{n}$, we call $X$ an $\left(n, H_{\infty}(X)\right)$-source, and we say $X$ has entropy rate $H_{\infty}(X) / n$.
Given an $n$-bit weak source $X$, a randomness extractor takes $X$ as the input and outputs a distribution that is close to uniform in statistical distance. Ideally, one would like to construct a deterministic extractor that works for any source with enough min-entropy. However, it is not hard to show that no deterministic extractor can work for all sources with min-entropy as large as $n-1$. Instead, what we can construct is an extractor that uses an additional short uniform random seed. This is called a (strong) seeded extractor.

Definition 1.2. A function Ext : $\{0,1\}^{n} \times\{0,1\}^{d} \rightarrow\{0,1\}^{m}$ is a strong $(k, \varepsilon)$-(seeded) extractor if for every source $X$ with min-entropy $k$ and independent $R$ which is uniform on $\{0,1\}^{d}$,

$$
(\operatorname{Ext}(X, R), R) \approx_{\varepsilon}\left(U_{m}, R\right)
$$

where $U_{m}$ is the uniform distribution on $m$ bits independent of $R$, and $\approx_{\varepsilon}$ denotes the two distributions are within $\epsilon$ to each other in statistical distance.

The seed $R$ is generally much shorter than the source, say only $O(\log n)$ bits. Although the extractor needs an additional random seed, it already suffices for some applications (e.g., simulating randomized algorithms with weak sources) just by trying all possible seeds, which only blows up the running time by a poly $(n)$ factor. Besides this direct application, seeded extractors have found many other applications in computer science and nowadays we have explicit constructions with almost optimal parameters (e.g. [GUV09]). However, for applications such as distributed computing and cryptography, it is not clear how to use this trick. Instead, we need extractors that only use weak sources as inputs.

One kind of extractors that fits into this category is independent source extractors. These are extractors that take as input several independent weak sources, and output a distribution that is close to uniform. Indeed, these extractors are used in [KLRZ08, KLR09] to construct network extractor protocols that can be used to run distributed computing and cryptographic applications with weak random sources.

The study of independent source extractors dates back to the well known Lindsey's lemma, which gives an extractor for two independent $(n, k)$ sources with $k>n / 2$. Besides the applications in distributed computing and cryptography, independent source extractors are themselves interesting objects since they strongly resemble some properties of random functions. For example, using the probabilistic method, one can show that with high probability a random function is a deterministic extractor for just two independent sources with logarithmic min-entropy. Thus,
constructing explicit independent source extractors is also closely related to the general problem of derandomization. However, although researchers have spent considerable efforts on this problem [CG88, BIW04, $\mathrm{BKS}^{+} 05$, Raz05, Bou05, Rao06, BRSW06, Li11], the known constructions are far from achieving optimal parameters. Currently the best explicit extractor for two independent $(n, k)$ sources only achieves min-entropy $k=0.49 n$ [Bou05], the best explicit extractor for three independent $(n, k)$ sources only achieves min-entropy $k=n^{1 / 2+\alpha}$ for an arbitrary constant $\alpha>0$ [Li11], and the best explicit extractor for independent $(n, k)$ sources requires $O(\log n / \log k)$ sources [Rao06, BRSW06].

### 1.1 Network extractor protocols

One application of independent source extractors is in distributed computing with imperfect randomness. Historically, Goldwasser, Sudan, and Vaikuntanathan [GSV05] were the first to consider this problem. They showed that it is possible to run distributed computing applications (e.g., Byzantine agreement) with imperfect randomness. However, they only considered fairly restricted weak sources. Kalai, Li, Rao and Zuckerman [KLRZ08] later improved this result to general weak random sources, where they also defined network extractor protocols.

The basic setting is, in a network with point to point or broadcast channels (synchronous or asynchronous), a set of players each has a private independent weak random source. They wish to communicate with each other so that at the end of the communication protocol, they end up with random strings that are close to being independent, uniform and private. However, some of the players are corrupted by an adversary, who is passive but otherwise can see every message transmitted in the network and has unlimited computational power. The protocol has to ensure that in the end, a large fraction of the honest players end up with private and uniform random strings. Below we give the formal definition of a network extractor protocol. For simplicity, in this paper we only consider the synchronous model.

We assume that $p$ total players communicate with each other via point-to-point channels in order to perform a task, of which an unknown $t$ are faulty. We allow Byzantine faults: faulty players may behave arbitrarily and even collude adversarially. In other words, we assume that the faulty players are controlled by an adversary. We assume that the the adversary can see all communication in the channels. This is called the full information model.

In a synchronous network, all communication takes place in rounds and every message transmitted at the beginning of a round is guaranteed to reach its destination at the end of the round. We allow rushing in this case: the faulty players may wait for all honest players to transmit their messages for a particular round, and then decide what to transmit for their own messages.

We now introduce some notation. Player $i$ begins with a sample from a weak source $x_{i} \in\{0,1\}^{n}$ and ends up with a hopefully uniform string $z_{i} \in\{0,1\}^{m}$. Let $b$ be the concatenation of all the messages that were sent during the protocol. We use capital letters such as $Z_{i}$ and $B$ to denote these strings viewed as random variables.
Definition 1.3. [KLRZ08] [Network Extractor] A protocol for $p$ players is a $(t, g, \epsilon)$ network extractor for min-entropy $k$ if for any min-entropy $k$ independent sources $X_{1}, \ldots, X_{p}$ over $\{0,1\}^{n}$ and any choice of $t$ faulty players, after running the protocol, the number of players $i$ for which

$$
\left|\left(B, Z_{i}\right)-\left(B, U_{m}\right)\right|<\epsilon
$$

is at least $g$. Here $U_{m}$ is the uniform distribution on $m$ bits, independent of $B$, and the absolute value of the difference refers to statistical distance.

The main goal of the network extractor protocol is to tolerate as many faulty players as possible (ideally a linear fraction), and to achieve $g$ as close to $p-t$ as possible. In [KLRZ08], for any constant $0<\beta<1$, the authors constructed a $1 / \beta+1$ round $\left(t, p-(1.1+1 / \beta) t, 2^{-k^{\Omega(1)}}\right)$ network extractor protocol for min-entropy $k \geq 2^{\log ^{\beta} n}$. Using this network extractor, they obtained synchronous Byzantine agreement protocols that tolerate roughly $1 / 4$ fraction of faulty players for weak sources with $k \geq n^{\beta}$ and that tolerate roughly $1 /(3+1 / \beta)$ fraction of faulty players for weak sources with $k \geq 2^{\log ^{\beta} n}$. For leader election they obtained similar results. Note that for $k \geq 2^{\log ^{\beta} n}$, if $\beta$ is small, although the protocol can still tolerate a linear fraction of faulty players, the fraction is quite small.

### 1.2 Our results

In this paper, we obtain new independent source extractors for general $(n, k)$ sources that significantly improve the previous best results [Rao06, BRSW06]. Specifically, we have the following theorem.

Theorem 1.4. For every $n, k \in \mathbb{N}$ with $k>\log ^{4} n$ there exists a polynomial time computable function IExt : $\left(\{0,1\}^{n}\right)^{t} \rightarrow\{0,1\}^{m}$ with $m=\Omega(k)$ and $t=O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ such that if $\left(X_{1}, \cdots, X_{t}\right)$ are $t$ independent $(n, k)$ sources, then

$$
\operatorname{IExt}\left(X_{1}, \cdots, X_{t}\right) \approx_{\epsilon} U_{m},
$$

where $\epsilon=1 / \operatorname{poly}(k)$.
Thus, for $(n, k)$ sources, our extractor only needs roughly $O\left(\log \left(\frac{\log n}{\log k}\right)\right)$ sources to output a distribution that is close to uniform. Compared to the previous best result which uses $\Omega(\log n / \log k)$ sources, this is an exponential improvement.

We also show that our extractor works in a weaker setting, namely, when we only have a constant number of independent $(n, k)$ sources and two independent $k$-block sources ${ }^{1}$ with $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ blocks of size $n$.

Theorem 1.5. There exists an absolute constant $c>0$ such that for any $n, k \in \mathbb{N}$ with $k>\log ^{10} n$ there exists a polynomial time computable function BExt : $\{0,1\}^{c n} \times\{0,1\}^{\text {tn }} \times\{0,1\}^{\text {tn }} \rightarrow\{0,1\}^{m}$ with $m=\Omega(k)$ and $t=O\left(\log \left(\frac{\log n}{\log k}\right)\right)$
$+O(1)$ such that if $X=\left(X_{1}, \cdots, X_{c}\right)$ are $c$ independent $(n, k)$ sources and $Y=\left(Y_{1} \circ \cdots \circ Y_{t}\right), W=$ $\left(W_{1} \circ \cdots \circ W_{t}\right)$ are 2 independent $(k, \cdots, k)$ block sources, then

$$
\operatorname{BExt}(X, Y, W) \approx_{\epsilon} U_{m},
$$

where $\epsilon=1 / \operatorname{poly}(k)$.
Next, we apply our extractor to the network extractor protocols in [KLRZ08]. By using our improved independent source extractor, we also obtain improved network extractor protocols and protocols for Byzantine agreement/leader election with weak random sources. Specifically, we have

Theorem 1.6. There exists a constant $c>1$ such that for every $n, k, p, t \in \mathbb{N}$ with $k>\log ^{c} n$, there is an explicit 2 -round $(t, p-3.1 t, 1 / \operatorname{poly}(k))$ network extractor protocol for $(n, k)$ sources.

[^1]Theorem 1.7 (Synchronous Byzantine Agreement). There exists a constant $c_{1}>1$ such that for any constants $\alpha>0$ and $c_{2}>1$ the following holds. Assume $p$ players each has access to an independent $(n, k)$-source with $k>\log ^{c_{1}} n$ and $k>p^{1 / c_{2}}$, then there exists an explicit (in $n$ ) synchronous $O(\log p)$ expected round protocol for Byzantine Agreement in the full information model that tolerates $(1 / 5-\alpha) p$ faulty players.

Theorem 1.8 (Leader Election). There exists a constant $c_{1}>1$ such that for any constants $\alpha>0$ and $c_{2}>1$ the following holds. Assume $p$ players each has access to an independent $(n, k)$-source with $k>\log ^{c_{1}} n$ and $k>p^{1 / c_{2}}$, then there exists an explicit (in $n$ ) synchronous $\log ^{*} p+O(1)$ round protocol for leader election that tolerates $(1 / 4-\alpha) p$ faulty players.

Note that here we can tolerate a nearly optimal fraction of faulty players (for Byzantine agreement, the optimum is $1 / 3$ fraction and for leader election, the optimum is $1 / 2$ fraction), even for weak sources with min-entropy as small as $k=\operatorname{polylog}(n)$. These results dramatically improve previous results.

## 2 Overview of The Constructions and Techniques

Here we give a brief overview of our constructions and the techniques. To give a clear description of the ideas, we shall be informal and imprecise sometimes.

### 2.1 Independent source extractor

Similar as in [Rao06, BRSW06], our extractor is obtained by repeatedly condensing somewhere random sources (SR-source for short). Take an $(n, k)$ source $X$ and a strong seeded extractor Ext with seed length $O(\log n)$, by applying Ext to $X$ with all possible choices of the seed, we obtain an SR-source with $N=\operatorname{poly}(n)$ rows such that at least one row (in fact, most of the rows) is (close to) uniform. The condenser in [Rao06, BRSW06] reduces the number of rows in the SR-source from $N$ to $N / k^{0.9}$ each time, while consuming a constant number of independent $(n, k)$ sources. Once the number of rows decreases to $k^{0.9}$, extraction becomes easy with an additional two independent $(n, k)$ sources. This results in a total number of $O\left(\frac{\log n}{\log k}\right)$ sources.

The decreasing of the number of rows from $N$ to $N / k^{0.9}$ is inherently limited by the techniques in [Rao06, BRSW06]. In this paper, however, by using a new condenser, we can reduce the number of rows in the SR-source much faster. Specifically, each time by consuming just one independent $(n, k)$ source, our condenser reduces the number of rows in the SR-source from $N$ to $N^{3 / 4}$. If $N \gg k$ then $N^{1 / 4} \gg k^{0.9}$. Note that initially $N=\operatorname{poly}(n)$, thus especially for small $k$ such as $k=\operatorname{polylog}(n)$, our condenser performs much better than the condenser in [Rao06, BRSW06].

Once we have this condenser, we can use it repeatedly to reduce the number of rows in the SRsource to say $k^{5}$. At this time we can use the extractor in [Rao06, BRSW06] to extract random bits with a constant number more of independent sources. Since initially $N=\operatorname{poly}(n)$, the condensing process uses $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ sources. Thus our extractor uses $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ sources.

We now describe our condenser. Unfortunately, to get this super efficiency we have to sacrifice some generality. Unlike the condenser in [Rao06, BRSW06], our condenser does not work for a general SR-source, but it works for SR-sources with some special structure. We now explain in more details. As mentioned before when we take a strong seeded extractor Ext with seed length $O(\log n)$ and applies it to a source $X$ with all possible choices of the seed, we obtain a SR-source
with poly $(n)$ rows such that most of the rows are (close to) uniform. Ignoring the error, now suppose these rows are indeed uniform, and moreover, these rows are independent. We note that it is not clear at all that we can achieve this (in fact, it's impossible to achieve with just one weak source), but for now let us assume that we can indeed get such an SR-source. Now we want to reduce the number of rows in the SR-source while still keeping it to be an SR-source with the same structure, what can we do?

We will now borrow some ideas from a distributed computing problem. Imagine that in the SR-source, each row is associated with a player, and each player has a string that is supposed to be uniform and independent, which is the corresponding row in the SR-source. Those rows that are uniform and independent are associated with honest players, since their strings are indeed uniform and independent. The other rows are associated with faulty players, since their strings may not be uniform and may depend arbitrarily on the honest players' strings. Now we want to select a committee from the players, which has size much smaller than the number of players and which has roughly the same fraction of honest players. This problem is very similar to our condenser problem. On the other hand, this is a well-studied problem in leader election [RZ01, Fei99]. In particular, Feige [Fei99] gave a beautiful lightest bin protocol to solve this problem.

The lightest bin protocol is as follows. Take $r$ bins and each player uses his random string to randomly select a bin. The players who select the lightest bin (the bin selected by the fewest number of players) form the selected committee. The idea is that, since the strings of the honest players are uniform and independent, by a Chernoff bound with high probability the honest players are roughly evenly distributed into each bin. Thus, no matter how the faulty players' strings depend on the honest players' strings, in the lightest bin the fraction of faulty players cannot be much larger than the original fraction of faulty players.

Back to our condenser problem, we can use the same lightest bin protocol to select a subset of the rows, such that with high probability the "good" rows (rows that are originally uniform and independent) in this subset has roughly the same fraction. Now we take another independent ( $n, k$ ) source $X^{\prime}$ and apply the strong seeded extractor Ext to $X^{\prime}$ using each row in the selected subset as the seed. Ignoring the error, and assume that $k$ is larger than the size of the subset times the output size of the extractor, one can show that with high probability conditioned on the fixing of the original SR-source, the outputs of the extractor which correspond to the good rows are also uniform and independent. Moreover, these outputs are now a deterministic function of the new source $X^{\prime}$ (since the original SR-source is fixed). This corresponds to one round in the original lightest bin protocol in leader election. Note that after we select the subset of rows, we need to use a new source $X^{\prime}$ to get another SR-source for the next "round". This is because in the lightest bin protocol the faulty players' strings can depend arbitrarily on the honest players' strings in the same round, but cannot depend on the honest players' strings in future rounds. Thus, by consuming one independent source we have obtained a new SR-source with fewer rows and the same structure as the original SR-source. We can now iterate the above process. This gives our condenser.

Note that if the good rows in the SR-source are indeed uniform and independent, then by a Chernoff bound we can take the number of bins to be $r=N / \log N$ and each time we can reduce the number of rows from $N$ to $\log N$. This is how [Fei99] achieves a leader election protocol with $\log ^{*} p+O(1)$ rounds, where $p$ is the number of players. Back to our extractor problem, in one step we can reduce the number of rows in the SR-source from $N=\operatorname{poly}(n)$ to $O(\log n)$. Thus, as long as $k \geq \operatorname{poly} \log (n)$ we can use the extractor in [Rao06, BRSW06] to extract random bits from the SR-source and ONE additional $(n, k)$ source. This will give us an extractor for $(n, k)$ sources with
$k$ as small as polylog $(n)$ that uses just a constant number of sources!
This sounds really great, except that we cannot achieve an SR-source such that the good rows are indeed uniform and independent. What we can achieve now is that every pair of the good rows is close to being uniform and independent. In other words, ignoring the error, we can achieve pairwise independence in the good rows. Thus, we cannot apply the Chernoff bound in the analysis. Luckily, by pair-wise independence we can still apply Chebysev's inequality, which guarantees that in one step we can take the number of bins to be $r=N^{1 / 4}$ and reduce the number of rows in the SR-source from $N$ to $N^{3 / 4}$. This is our actual condenser.

So now the question is how to obtain an SR-source such that the good rows are close to being pair-wise independent. For this, we need the definition of a non-malleable extractor.

Definition 2.1. [DLWZ11] A function nmExt : $\{0,1\}^{n} \times\{0,1\}^{d} \rightarrow\{0,1\}^{m}$ is a $(k, \varepsilon)$-non-malleable extractor if, for any source $X$ with $H_{\infty}(X) \geq k$ and any function $\mathcal{A}:\{0,1\}^{d} \rightarrow\{0,1\}^{d}$ such that $\mathcal{A}(r) \neq r$ for all $r$, the following holds. When $R$ is chosen uniformly from $\{0,1\}^{d}$ and independent of $X$,

$$
(\operatorname{nmExt}(X, R), \operatorname{nmExt}(X, \mathcal{A}(R)), R) \approx_{\varepsilon}\left(U_{m}, \operatorname{nmExt}(X, \mathcal{A}(R)), R\right) .
$$

Note that a non-malleable extractor is a stronger version of a strong extractor, in the sense that the output is required to be close to uniform conditioned on both the seed and the output on another different but otherwise arbitrarily correlated seed. Non-malleable extractors were originally introduced in [DW09] to study the problem of privacy amplification with an active adversary. We now claim that if we take a source $X$ and apply a non-malleable extractor nmExt to $X$ with all possible choices of the seed, then ignoring the error, we obtain an SR-source such that a large fraction of the rows are pair-wise independent. Indeed, for any seed $r$ if there exists a seed $r^{\prime} \neq r$ such that $n m \operatorname{Ext}(X, r)$ is not close to uniform conditioned on $n m \operatorname{Ext}\left(X, r^{\prime}\right)$, then we can let $\mathcal{A}(r)=$ $r^{\prime}$. The definition of a non-malleable extractor asserts that the fraction of these $r$ 's is small. Thus, for the rest of the seeds, the outputs of the non-malleable extractor are pair-wise independent.

Now this is very nice, except another problem. Currently the best explicit non-malleable extractor only works for $k=0.49 n$ [Li12c], while we need constructions for essentially any min-entropy. Thus, we switch to a relaxation of a non-malleable extractor, a non-malleable condenser.

Definition 2.2. [Li12a] A $\left(k, k^{\prime}, \epsilon\right)$ non-malleable condenser is a function nmCond : $\{0,1\}^{n} \times$ $\{0,1\}^{d} \rightarrow\{0,1\}^{m}$ such that given any $(n, k)$-source $X$, an independent uniform seed $R \in\{0,1\}^{d}$, and any (deterministic) function $\mathcal{A}:\{0,1\}^{d} \rightarrow\{0,1\}^{d}$ such that $\forall r, \mathcal{A}(r) \neq r$, we have that with probability $1-\epsilon$ over the fixing of $R=r$,

$$
\operatorname{Pr}_{z^{\prime} \leftarrow \mathrm{nm} \operatorname{Cond}(X, \mathcal{A}(r))}\left[\left.\mathrm{nm} \operatorname{Cond}(X, r)\right|_{\mathrm{nm}} \operatorname{Cond}(X, \mathcal{A}(r))=z^{\prime} \text { is } \epsilon-\operatorname{close} \text { to an }\left(m, k^{\prime}\right) \text { source }\right] \geq 1-\epsilon .
$$

Non-malleable condensers were introduced in [Li12a]. Note that it is indeed a relaxation of a non-malleable extractor in the sense that it only requires the output to have a certain amount of min-entropy. Once we have a non-malleable condenser nmCond, we can apply it to a source $X$ with all possible choices of the seed, and (ignoring the error) we obtain a source such that for a large fraction of the rows, each pair of the rows is a $k^{\prime}$-block source with 2 blocks of size $m$. Recently, Li [Li12b] constructed explicit non-malleable condensers for essentially any min-entropy, with error $\epsilon=1 / \operatorname{poly}(n)$ and seed length $d=O\left(\log ^{2} n\right)$ such that $k^{\prime}>\sqrt{m}$. However, this does not give us an SR-source. To fix this, we take several independent sources and from each one we obtain a
source with $N$ rows by applying the non-malleable condenser. For each source, let $S_{i} \subset[N]$ be the set of "good" rows. Now let $S=\cap S_{i}$ and $S$ still takes up a large fraction of [ $\left.N\right]$. Moreover, the good rows in $S$ are now aligned across these sources. Now for every $j \in S$, we apply the extractor in [Rao06, BRSW06] to all the row $j$ 's in these sources. Since each row is a $\left(m, k^{\prime}\right)$-source with $k^{\prime}>\sqrt{m}$, we only need a constant number of sources to extract uniform random bits. Moreover, conditioned on the fixing of all row $j$ 's, for any $l \in S, l \neq j$, all the row $l$ 's are still independent $\left(m, k^{\prime}\right)$-sources. Thus the output of row $l$ is uniform and independent of the output of row $j$. Thus now we obtain an SR-source such that a large fraction of the good rows are pair-wise independent.

However, there is still another problem. The problem is that the non-malleable condenser in [Li12b] has seed length $d=O\left(\log ^{2} n\right)$ which will make the initial $N=n^{O(\log n)}$. Thus this only gives us a quasi-polynomial time algorithm. To fix this, we note that the non-malleable condenser $\mathrm{nmCond}(X, R)$ in [Li12b] uses a seed $R=\left(R_{1}, R_{2}\right)$ and outputs $Z=\left(Y_{1}, Y_{2}\right)$. For a different seed $R^{\prime}=\left(R_{1}^{\prime}, R_{2}^{\prime}\right), Y_{1}$ takes care of the case where $R_{1}=R_{1}^{\prime}$ and $Y_{2}$ takes care of the case where $R_{1} \neq R_{1}^{\prime}$. The reason the seed has length $d=O\left(\log ^{2} n\right)$ is that $Y_{2}$ is an encoding of $R_{1}$ using some random variable produced by $X$ and $R_{2}$ with an alternating extraction protocol, which requires $R_{2}$ to be a uniform string with size at least $\log ^{2} n$. In our case, however, we have the advantage of a supply of independent sources, whereas in the non-malleable condenser case we only have one weak source. Thus, we will use another weak source to provide the entropy used in the alternating extraction protocol. Specifically, we take 4 independent sources ( $X_{1}, X_{2}, X_{3}, X_{4}$ ) and a seed $R=\left(R_{1}, R_{2}\right)$ such that $\left|R_{1}\right|=d=O(\log n)$ and $\left|R_{2}\right|=10 d$. We use $\left(X_{1}, R_{1}, R_{2}\right)$ to produce $Y_{1}$. To produce $Y_{2}$, we first compute $W_{2}=\operatorname{Raz}\left(R_{2}, X_{2}\right)$, where $\operatorname{Raz}$ is a two-source extractor in [Raz05] which works as long as $R_{2}$ has entropy rate $>1 / 2$. This is because in the analysis fixing $R_{1}^{\prime}$ may cause $R_{2}$ to lose entropy, but since $\left|R_{2}\right|=10\left|R_{1}\right|$ conditioned on this fixing $R_{2}$ still has entropy rate roughly $9 / 10$. We then compute $W_{3}=\operatorname{Ext}\left(X_{3}, W_{2}\right)$ so that $W_{3}$ is uniform and has size close to $k$. Now we can use $X_{4}$ and $W_{3}$ to perform the alternating extraction protocol to produce $Y_{2}$. As long as $k>\log ^{2} n$ this will satisfy our requirement, while ensuring that the seed length $|R|=O(\log n)$.

Now we are almost done, except for one remaining small problem. The problem is that in the above analysis we ignored all the error. However, it turns out that the error we achieved in the above process $\epsilon=1 / \operatorname{poly}(n)$ is not small enough for the condenser to work. Note that if the good rows are indeed pair-wise independent then we wouldn't have any cross terms when computing the variance in Chebysev's inequality. However since they are only close to being pair-wise independent we will have roughly $N^{2}=\operatorname{poly}(n)$ cross terms, and each is bounded by roughly $O(\epsilon)$. It turns out the $N$ here is too big for $\epsilon$. Thus we need a smaller error. To fix this, we take several independent sources and from them obtain $c^{\prime}$ independent copies of the SR-sources we described above, each with $N$ rows. We now compute the xor of these sources. Note that the aligned good rows in all these sources still take up a large fraction of $[N]$. On the other hand, since these sources are independent, after the xor a pair of aligned good rows will be $\epsilon^{\epsilon^{c^{\prime}} \text {-close to uniform. We show that we }}$ only need a constant $c^{\prime}$ to achieve a small enough error $\epsilon^{\epsilon^{c^{\prime}}}$ for our condenser, and the error suffices for all subsequent condensing steps.

This gives our whole extractor construction. Thus, we use a constant number of independent sources to prepare the initial SR-source for the condenser. Then we use $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ sources to reduce the number of rows to $k^{5}$, and finally we use another constant number of independent sources to extract random bits. The dominating error comes from the last step where we apply the condenser (the lightest bin protocol), which is $1 / \operatorname{poly}(k)$. By choosing the number of rows where we stop condensing to be $k^{C}$, we can make the error $k^{-C}$ for any constant $C>1$.

By observing that the condenser works for two independent block sources, we can extend our extractor to work for a constant number of independent $(n, k)$ sources (which are used to prepare the initial SR-source) and another 2 independent $k$-block sources with $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ blocks.

### 2.2 Network extractor protocol

In [KLRZ08], the authors showed that if we have a C-source extractor for $(n, k)$ sources with output length $\Omega(k)$ and error $\epsilon$, then there is an explicit $r$-round ( $\left.t, p-1.1(r+1) t, \epsilon+2^{-k^{\Omega(1)}}\right)$ network extractor protocol for $(n, k)$ sources, where $r=\left\lceil\frac{\log C}{\log \log k}\right\rceil+1$. By plugging in our independent source extractor, we obtain the improved network extractor protocol and thus the improved results for distributed computing with weak random sources.

Organization. After some preliminaries, we define alternating extraction in Section 4. We give our independent source extractor in Section 5, and the applications in network extractor protocols in Section 6. Finally we conclude with some open problems in Section 7.

## 3 Preliminaries

We often use capital letters for random variables and corresponding small letters for their instantiations. Let $|S|$ denote the cardinality of the set $S$. All logarithms are to the base 2 .

### 3.1 Probability distributions

Definition 3.1 (statistical distance). Let $W$ and $Z$ be two distributions on a set $S$. Their statistical distance (variation distance) is

$$
\Delta(W, Z) \stackrel{\text { def }}{=} \max _{T \subseteq S}(|W(T)-Z(T)|)=\frac{1}{2} \sum_{s \in S}|W(s)-Z(s)| .
$$

We say $W$ is $\varepsilon$-close to $Z$, denoted $W \approx_{\varepsilon} Z$, if $\Delta(W, Z) \leq \varepsilon$. For a distribution $D$ on a set $S$ and a function $h: S \rightarrow T$, let $h(D)$ denote the distribution on $T$ induced by choosing $x$ according to $D$ and outputting $h(x)$.

### 3.2 Somewhere Random Sources, Extractors and Condensers

Definition 3.2 (Somewhere Random sources). A source $X=\left(X_{1}, \cdots, X_{t}\right)$ is $(t \times r)$ somewhererandom (SR-source for short) if each $X_{i}$ takes values in $\{0,1\}^{r}$ and there is an $i$ such that $X_{i}$ is uniformly distributed.

Definition 3.3. (Block Sources) A distribution $X=X_{1} \circ X_{2} \circ \cdots, \circ X_{t}$ is called a $\left(k_{1}, k_{2}, \cdots, k_{t}\right)$ block source if for all $i=1, \cdots, t$, we have that for all $x_{1} \in \operatorname{Supp}\left(X_{1}\right), \cdots, x_{i-1} \in \operatorname{Supp}\left(X_{i-1}\right)$, $H_{\infty}\left(X_{i} \mid X_{1}=x_{1}, \cdots, X_{i-1}=x_{i-1}\right) \geq k_{i}$, i.e., each block has high min-entropy even conditioned on any fixing of the previous blocks. If $k_{1}=k_{2}=\cdots=k_{t}=k$, we say that $X$ is a $k$ block source.

Definition 3.4. A function TExt: $\{0,1\}^{n_{1}} \times\{0,1\}^{n_{2}} \rightarrow\{0,1\}^{m}$ is a strong two source extractor for min-entropy $k_{1}, k_{2}$ and error $\epsilon$ if for every independent $\left(n_{1}, k_{1}\right)$ source $X$ and $\left(n_{2}, k_{2}\right)$ source $Y$,

$$
\left|(\operatorname{TExt}(X, Y), X)-\left(U_{m}, X\right)\right|<\epsilon
$$

and

$$
\left|(\operatorname{TExt}(X, Y), Y)-\left(U_{m}, Y\right)\right|<\epsilon,
$$

where $U_{m}$ is the uniform distribution on $m$ bits independent of $(X, Y)$.

### 3.3 Average conditional min-entropy

Definition 3.5. The average conditional min-entropy is defined as

$$
\widetilde{H}_{\infty}(X \mid W)=-\log \left(\mathrm{E}_{w \leftarrow W}\left[\max _{x} \operatorname{Pr}[X=x \mid W=w]\right]\right)=-\log \left(\mathrm{E}_{w \leftarrow W}\left[2^{-H_{\infty}(X \mid W=w)}\right]\right) .
$$

Lemma 3.6 ([DORS08]). For any $s>0, \operatorname{Pr}_{w \leftarrow W}\left[H_{\infty}(X \mid W=w) \geq \widetilde{H}_{\infty}(X \mid W)-s\right] \geq 1-2^{-s}$.
Lemma 3.7 ([DORS08]). If a random variable $B$ has at most $2^{\ell}$ possible values, then $\widetilde{H}_{\infty}(A \mid B) \geq$ $H_{\infty}(A)-\ell$.

### 3.4 Prerequisites from previous work

Sometimes it is convenient to talk about average case seeded extractors, where the source $X$ has average conditional min-entropy $\widetilde{H}_{\infty}(X \mid Z) \geq k$ and the output of the extractor should be uniform given $Z$ as well. The following lemma is proved in [DORS08].

Lemma 3.8. [DORS08] For any $\delta>0$, if Ext is a $(k, \epsilon)$ extractor then it is also a $(k+\log (1 / \delta), \epsilon+\delta)$ average case extractor.

For a strong seeded extractor with optimal parameters, we use the following extractor constructed in [GUV09].

Theorem 3.9 ([GUV09]). For every constant $\alpha>0$, and all positive integers $n, k$ and any $\epsilon>0$, there is an explicit construction of a strong $(k, \epsilon)$-extractor Ext : $\{0,1\}^{n} \times\{0,1\}^{d} \rightarrow\{0,1\}^{m}$ with $d=O(\log n+\log (1 / \epsilon))$ and $m \geq(1-\alpha) k$. It is also a strong $(k, \epsilon)$ average case extractor with $m \geq(1-\alpha) k-O(\log n+\log (1 / \epsilon))$.

We need the following construction of strong two-source extractors in [Raz05].
Theorem 3.10 ([Raz05]). For any $n_{1}, n_{2}, k_{1}, k_{2}, m$ and any $0<\delta<1 / 2$ with

- $n_{1} \geq 6 \log n_{1}+2 \log n_{2}$
- $k_{1} \geq(0.5+\delta) n_{1}+3 \log n_{1}+\log n_{2}$
- $k_{2} \geq 5 \log \left(n_{1}-k_{1}\right)$
- $m \leq \delta \min \left[n_{1} / 8, k_{2} / 40\right]-1$

There is a polynomial time computable strong 2-source extractor Raz: $\{0,1\}^{n_{1}} \times\{0,1\}^{n_{2}} \rightarrow$ $\{0,1\}^{m}$ for min-entropy $k_{1}, k_{2}$ with error $2^{-1.5 m}$.

Theorem 3.11 ([Rao06, BRSW06]). There exist constants $c>0$ and $c^{\prime}$ such that for every $n, k$ with $k=k(n)=\Omega\left(\log ^{4} n\right)$ there exists a polynomial time computable function MExt : $\left(\{0,1\}^{n}\right)^{u} \rightarrow$ $\{0,1\}^{m}$ with $m=\Omega(k)$ and $u \leq c^{\prime} \frac{\log n}{\log k}$ s.t. if $X^{1}, X^{2}, \ldots, X^{u}$ are independent $(n, k)$ sources then

$$
\left|\operatorname{MExt}\left(X^{1}, \ldots, X^{u}\right)-U_{m}\right|<2^{-k^{c}}
$$

Moreover, MExt is a strong extractor.
Theorem 3.12 ([BRSW06]). There exist constants $c>0$ and $c^{\prime}$ such that for every $n, k, \ell$ with $k=k(n)>\log ^{10} n$ and $\ell \leq \operatorname{poly}(n)$ there exists a polynomial time computable function SRExt : $\{0,1\}^{\ell k} \times\{0,1\}^{u n} \rightarrow\{0,1\}^{m}$ with $m=\Omega(k)$ and $u \leq c^{\prime} \frac{\log \ell}{\log k}$ s.t. if $X=X^{1} \circ X^{2} \circ \cdots \circ X^{u}$ is a $(k, \cdots, k)$ block sources and $Y$ is an independent $\ell \times k S R$-source then

$$
\left|\operatorname{SRExt}(Y, X)-U_{m}\right|<2^{-k^{c}} .
$$

Moreover, SRExt is a strong extractor.
Theorem 3.13. [DLWZ11, CRS12, Li12a] For every constant $\delta>0$, there exists a constant $\beta>0$ such that for every $n, k \in \mathbb{N}$ with $k \geq(1 / 2+\delta) n$ and $\epsilon>2^{-\beta n}$ there exists an explicit $(k, \epsilon)$ non-malleable extractor with seed length $d=O\left(\log n+\log \epsilon^{-1}\right)$ and output length $m=\Omega(n)$.

The following standard lemma about conditional min-entropy is implicit in [NZ96] and explicit in [MW97].

Lemma 3.14 ([MW97]). Let $X$ and $Y$ be random variables and let $\mathcal{Y}$ denote the range of $Y$. Then for all $\epsilon>0$, one has

$$
\underset{Y}{\operatorname{Pr}}\left[H_{\infty}(X \mid Y=y) \geq H_{\infty}(X)-\log |\mathcal{Y}|-\log \left(\frac{1}{\epsilon}\right)\right] \geq 1-\epsilon .
$$

We also need the following lemma.
Lemma 3.15. [Li12b] Let $X$ and $Y$ be random variables and let $\mathcal{Y}$ denote the range of $Y$. Assume that $X$ is $\epsilon$-close to having min-entropy $k$. Then for any $\epsilon^{\prime}>0$

$$
\underset{Y}{\operatorname{Pr}}\left[(X \mid Y=y) \text { is } \epsilon^{\prime} \text {-close to a source with min-entropy } k-\log |\mathcal{Y}|-\log \left(\frac{1}{\epsilon^{\prime}}\right)\right] \geq 1-\epsilon^{\prime}-\frac{\epsilon}{\epsilon^{\prime}} .
$$

Lemma 3.16. [BIW04] Assume that $Y_{1}, Y_{2}, \cdots, Y_{t}$ are independent random variables over $\{0,1\}^{n}$ such that for any $i, 1 \leq i \leq t$, we have $\left|Y_{i}-U_{n}\right| \leq \epsilon$. Let $Z=\oplus_{i=1}^{t} Y_{i}$. Then $\left|Z-U_{n}\right| \leq \epsilon^{t}$.

## 4 Alternating Extraction

An important ingredient in our construction is the following alternating extraction protocol.
Alternating Extraction. Assume that we have two parties, Quentin and Wendy. Quentin has a source $Q$, Wendy has a source $X$. Also assume that Quentin has a uniform random seed $S_{1}$ (which may be correlated with $Q$ ). Suppose that $\left(Q, S_{1}\right)$ is kept secret from Wendy and $X$ is kept secret from Quentin. Let $\operatorname{Ext}_{q}, \operatorname{Ext}_{w}$ be strong seeded extractors with optimal parameters, such as

| Quentin: $Q, S_{1}$ |  | Wendy: $X$ |
| :---: | :---: | :---: |
| $S_{1}$ | $S_{1}$ | $R_{1}=\operatorname{Ext}_{w}\left(X, S_{1}\right)$ |
|  | $R_{1}$ |  |
| $S_{2}=\operatorname{Ext}_{q}\left(Q, R_{1}\right)$ | $S_{2}$ | $R_{2}=\operatorname{Ext}_{w}\left(X, S_{2}\right)$ |
|  | $R_{2}$ |  |
| $S_{t}=\operatorname{Ext}_{q}\left(Q, R_{t-1}\right)$ | $S_{t}$ |  |
|  |  | $R_{t}=\operatorname{Ext}_{w}\left(X, S_{t}\right)$ |

Figure 1: Alternating Extraction.
that in Theorem 3.9. Let $\ell$ be an integer parameter for the protocol. For some integer parameter $t>0$, the alternating extraction protocol is an interactive process between Quentin and Wendy that runs in $t$ steps.

In the first step, Quentin sends $S_{1}$ to Wendy, Wendy computes $R_{1}=\operatorname{Ext}_{w}\left(X, S_{1}\right)$. She sends $R_{1}$ to Quentin and Quentin computes $S_{2}=\operatorname{Ext}_{q}\left(Q, R_{1}\right)$. In this step $R_{1}, S_{2}$ each outputs $\ell$ bits. In each subsequent step $i$, Quentin sends $S_{i}$ to Wendy, Wendy computes $R_{i}=\operatorname{Ext}_{w}\left(X, S_{i}\right)$. She replies $R_{i}$ to Quentin and Quentin computes $S_{i+1}=\operatorname{Ext}_{q}\left(Q, R_{i}\right)$. In step $i, R_{i}, S_{i+1}$ each outputs $\ell$ bits. Therefore, this process produces the following sequence:

$$
S_{1}, R_{1}=\operatorname{Ext}_{w}\left(X, S_{1}\right), \cdots, S_{t}=\operatorname{Ext}_{q}\left(Q, R_{t-1}\right), R_{t}=\operatorname{Ext}_{w}\left(X, S_{t}\right)
$$

Look-Ahead Extractor. Now we can define our look-ahead extractor. Let $Y=\left(Q, S_{1}\right)$ be a seed, the look-ahead extractor is defined as

$$
\operatorname{la} \operatorname{Ext}(X, Y)=\operatorname{la} \operatorname{Ext}\left(X,\left(Q, S_{1}\right)\right) \stackrel{\text { def }}{=} R_{1}, \cdots, R_{t} .
$$

We first prove the following lemma.
Lemma 4.1. Let $Y=\left(Q, S_{1}\right)$ where $Q$ is an $\left(n_{q}, k_{q}\right)$ source and $S_{1}$ is the uniform distribution over $\ell$ bits. Let $Y^{\prime}=\left(Q^{\prime}, S_{1}^{\prime}\right)$ be another random variable on the same support of $Y$ that is arbitrarily correlated to $Y$. Assume $X$ is an $(n, k)$ source independent of $\left(Y, Y^{\prime}\right)$. Assume that $\mathrm{Ext}_{q}$ and $\mathrm{Ext}_{w}$ are strong seeded extractors that use $\ell$ bits to extract from $\left(n_{q}, k_{q}-2 t \ell\right)$ sources and $(n, k-2 t \ell)$ sources respectively, with error $\epsilon$ and $\ell=O\left(\log \left(\max \left\{n_{q}, n\right\}\right)+\log (1 / \epsilon)\right)$. Let $\left(R_{1}, \cdots, R_{t}\right)=\operatorname{laExt}(X, Y)$ and $\left(R_{1}^{\prime}, \cdots, R_{t}^{\prime}\right)=\operatorname{laExt}\left(X, Y^{\prime}\right)$. Then for any $0 \leq i \leq t-1$, we have

$$
\left(Y, Y^{\prime},\left[R_{1}^{\prime}, \cdots, R_{i}^{\prime}\right],\left[R_{i+1}, \cdots, R_{t}\right]\right) \approx_{\epsilon_{1}}\left(Y, Y^{\prime},\left[R_{1}^{\prime}, \cdots, R_{i}^{\prime}\right], U_{\ell(t-i)}\right),
$$

where $\epsilon_{1}=O\left(t^{2} \epsilon\right)$.
Proof. Let $\left\{S_{i}^{\prime}\right\}$ denote the random variables corresponding to $\left\{S_{i}\right\}$ that are produced in laExt $\left(X, Y^{\prime}\right)$. For any $i, 0 \leq i \leq t-1$, let $\bar{S}_{i}=\left(S_{0}, \cdots, S_{i}\right), \bar{S}_{i}^{\prime}=\left(S_{0}^{\prime}, \cdots, S_{i}^{\prime}\right), \bar{R}_{i}=\left(R_{0}, \cdots, R_{i}\right)$ and $\bar{R}_{i}^{\prime}=\left(R_{0}^{\prime}, \cdots, R_{i}^{\prime}\right)$. We first prove the following claim.

Claim 4.2. For any $i$, we have that

$$
\left(R_{i}, S_{i-1}^{-}, S_{i-1}^{-}, R_{i-1}^{-}, R_{i-1}^{\prime}, S_{i}, S_{i}^{\prime}, Y, Y^{\prime}\right) \approx_{(2 i-1) \epsilon}\left(U_{\ell}, S_{i-1}^{-}, S_{i-1}^{\prime}, R_{i-1}^{-}, R_{i-1}^{-}, S_{i}, S_{i}^{\prime}, Y, Y^{\prime}\right)
$$

and

$$
\left(S_{i+1}, \bar{S}_{i}, \bar{S}_{i}^{\prime}, \bar{R}_{i}, \bar{R}_{i}^{\prime}\right) \approx_{(2 i) \epsilon}\left(U_{\ell}, \bar{S}_{i}, \bar{S}_{i}^{\prime}, \bar{R}_{i}, \bar{R}_{i}^{\prime}\right)
$$

Moreover, conditioned on $\left(S_{i-1}^{-}, S_{i-1}^{-}, R_{i-1}^{-}, R_{i-1}^{\prime}, S_{i}, S_{i}^{\prime}\right),\left(R_{i}, R_{i}^{\prime}\right)$ are both deterministic functions of $X$ and the average conditional min-entropy of $Q$ is at least $k_{q}-2 i \ell$; conditioned on $\left(\bar{S}_{i}, \bar{S}_{i}^{\prime}, \bar{R}_{i}, \bar{R}_{i}^{\prime}\right)$, $\left(Q, Q^{\prime}, S_{i+1}, S_{i+1}^{\prime}\right)$ is independent of $X$ and the average conditional min-entropy of $X$ is at least $k-2 i \ell$.

We prove the claim by induction on $i$. When $i=0$, the statement is trivially true. Now we assume that the statements hold for $i=j$ and we prove them for $i=j+1$.

We first fix $\left(\bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}\right)$. Note that now $\left(Q, Q^{\prime}, S_{j+1}, S_{j+1}^{\prime}\right)$ is independent of $X$. Moreover $S_{j+1}$ is $(2 j) \epsilon$-close to uniform. Since the average conditional min-entropy of $X$ is at least $k-2 j \ell \geq$ $k-2 t \ell$, By Theorem 3.9 we have that

$$
\left(R_{j+1}, \bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}\right) \approx_{(2 j+1) \epsilon}\left(U_{\ell}, \bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}\right)
$$

Since $\left(Q, Q^{\prime}, S_{j+1}, S_{j+1}^{\prime}\right)$ is independent of $X$, we also have

$$
\left(R_{j+1}, \bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}, Y, Y^{\prime}\right) \approx_{(2 j+1) \epsilon}\left(U_{\ell}, \bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}, Y, Y^{\prime}\right)
$$

Moreover, conditioned on $\left(\bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}\right),\left(R_{j+1}, R_{j+1}^{\prime}\right)$ are both deterministic functions of $X$, and the average conditional min-entropy of $Q$ is at least $k_{q}-2 j \ell-2 \ell=k_{q}-2(j+1) \ell$.

Next, since conditioned on $\left(\bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}\right),\left(R_{j+1}, R_{j+1}^{\prime}\right)$ are both deterministic functions of $X$, they are independent of $\left(Q, Q^{\prime}\right)$. Moreover $R_{j+1}$ is $(2 j+1) \epsilon$-close to uniform. Since the average conditional min-entropy of $Q$ is at least $k_{q}-2(j+1) \ell \geq k_{q}-2 t \ell$, By Theorem 3.9 we have that

$$
\begin{aligned}
&\left(S_{j+2}, \bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}, R_{j+1}, R_{j+1}^{\prime}\right) \\
& \approx_{(2 j+2) \epsilon}\left(U_{\ell}, \bar{S}_{j}, \bar{S}_{j}^{\prime}, \bar{R}_{j}, \bar{R}_{j}^{\prime}, S_{j+1}, S_{j+1}^{\prime}, R_{j+1}, R_{j+1}^{\prime}\right)
\end{aligned}
$$

Namely,

$$
\left(S_{j+2}, \overline{S_{j+1}}, \overline{S_{j+1}^{\prime}}, \overline{R_{j+1}}, \overline{R_{j+1}^{\prime}}\right) \approx_{(2(j+1)) \epsilon}\left(U_{\ell}, \overline{S_{j+1}}, \overline{S_{j+1}^{\prime}}, \overline{R_{j+1}}, \overline{R_{j+1}^{\prime}}\right)
$$

Moreover, conditioned on $\left(\overline{S_{j+1}}, \overline{S_{j+1}^{\prime}}, \overline{R_{j+1}}, \overline{R_{j+1}^{\prime}}\right),\left(Q, Q^{\prime}, S_{j+2}, S_{j+2}^{\prime}\right)$ is independent of $X$ since $S_{j+2}$ and $S_{j+2}^{\prime}$ are deterministic functions of $Q$ and $Q^{\prime}$ respectively. Also note that now the average conditional min-entropy of $X$ is at least $k-2 j \ell-2 \ell=k-2(j+1) \ell$.

Therefore, we have that for any $i$,

$$
\left(R_{i}, R_{i-1}^{-}, R_{i-1}^{\prime}, Y, Y^{\prime}\right) \approx_{(2 i-1) \epsilon}\left(U_{\ell}, R_{i-1}^{-}, R_{i-1}^{\prime}, Y, Y^{\prime}\right)
$$

Thus for any $i$,

$$
\left(Y, Y^{\prime},\left[R_{1}^{\prime}, \cdots, R_{i}^{\prime}\right],\left[R_{i+1}, \cdots, R_{t}\right]\right) \approx_{\epsilon_{1}}\left(Y, Y^{\prime},\left[R_{1}^{\prime}, \cdots, R_{i}^{\prime}\right], U_{\ell(t-i)}\right),
$$

where $\epsilon_{1}=\sum_{j=i+1}^{t}((2 j-1) \epsilon)=O\left(t^{2} \epsilon\right)$.
Next, we need the following definitions and constructions from [DW09].
Definition 4.3. [DW09] Given $S_{1}, S_{2} \subseteq\{1, \cdots, t\}$, we say that the ordered pair ( $S_{1}, S_{2}$ ) is topheavy if there is some integer $j$ such that $\left|S_{1}^{\geq j}\right|>\left|S_{2}^{\geq j}\right|$, where $S \geq j \stackrel{\text { def }}{=}\{s \in S \mid s \geq j\}$. Note that it is possible that $\left(S_{1}, S_{2}\right)$ and $\left(S_{2}, S_{1}\right)$ are both top-heavy. For a collection $\Psi$ of sets $S_{i} \subseteq\{1, \cdots, t\}$, we say that $\Psi$ is pairwise top-heavy if every ordered pair $\left(S_{i}, S_{j}\right)$ of sets $S_{i}, S_{j} \in \Psi$ with $i \neq j$, is top-heavy.

Now, for any $m$-bit message $\mu=\left(b_{1}, \cdots, b_{m}\right)$, consider the following mapping of $\mu$ to a subset $S \subseteq\{1, \cdots, 4 m\}:$

$$
f(\mu)=f\left(b_{1}, \cdots, b_{m}\right)=\left\{4 i-3+b_{i}, 4 i-b_{i} \mid i=1, \cdots, m\right\}
$$

i.e., each bit $b_{i}$ decides if to include $\{4 i-3,4 i\}$ (if $b_{i}=0$ ) or $\{4 i-2,4 i-1\}$ (if $b_{i}=1$ ) in $S$. We now have the following lemma.

Lemma 4.4. [DW09] The above construction gives a pairwise top-heavy collection $\Psi$ of $2^{m}$ sets $S \subseteq\{1, \cdots, t\}$ where $t=4 \mathrm{~m}$. Furthermore, the function $f$ is an efficient mapping of $\mu \in\{0,1\}^{m}$ to $S_{\mu}$.

Now we have the following construction.
Let $r \in\left(\{0,1\}^{\ell}\right)^{t}$ be the output of the look-ahead extractor defined above, i.e., $r=\left(r_{1}, \cdots, r_{t}\right)=$ laExt $\left(X,\left(Q, S_{1}\right)\right)$. Let $\Psi=\left\{S_{1}, \cdots, S_{2^{m}}\right\}$ be the pairwise top-heavy collection of sets constructed above. For any string $\mu \in\{0,1\}^{m}$, define the function $\operatorname{laMAC}_{r}(\mu) \stackrel{\text { def }}{=}\left[r_{i} \mid i \in S_{\mu}\right]$, indexed by $r$.

## 5 Independent Source Extractor

In this section we present our construction of independent source extractor. Let Ext, nmExt, Raz, MExt be the extractors in theorem 3.9, theorem 3.13, theorem 3.10 and theorem 3.11 respectively. Let laExt and laMAC be the look-ahead extractor and the function defined above. We first show how to use a constant number of independent $(n, k)$ sources with $k \geq \log ^{4} n$ to obtain a somewhere random source such that there exists a large fraction of rows where each pair is close to being independent and uniform.

Let $X_{1}, X_{2}, X_{3}, X_{4}$ be 4 independent $(n, k)$ sources. Let $r=\left(r_{1}, r_{2}\right)$ be a string such that $r_{1}$ has length $d$ and $r_{2}$ has length $20 d$ where $d=O(\log n)$ is the seed length that guarantees error $\epsilon=1 / \operatorname{poly}(n)$ in theorem 3.9. For every $r \in\{0,1\}^{21 d}$, do the following and obtain a source $Y^{r}$.

1. Let $W_{1}=\operatorname{Ext}\left(X_{1}, r_{1}\right)$ and $Y_{1}=\operatorname{nmExt}\left(W_{1}, r_{2}\right)$ such that $Y_{1}$ has $2 d \sqrt{k}$ bits.
2. Let $W_{2}=\operatorname{Raz}\left(r_{2}, X_{2}\right), W_{3}=\operatorname{Ext}\left(X_{3}, W_{2}\right)$ and $W_{4}=\operatorname{laExt}\left(X_{4}, W_{3}\right)$ with $t=4 d$ and $\ell=2 \sqrt{k}$, where $W_{3}$ is viewed as $Q$ and $S_{1}$ is the prefix of $W_{3}$ with $d$ bits.
3. Let $Y_{2}=\operatorname{laMAC}_{W_{4}}\left(r_{1}\right)$ and $Y^{r}=Y_{1} \circ Y_{2}$.

Now assume that $R \in\{0,1\}^{21 d}$ is a uniform random seed independent of $X_{1}, X_{2}, X_{3}, X_{4}$. Let $\mathcal{A}:\{0,1\}^{21 d} \rightarrow\{0,1\}^{21 d}$ be any deterministic function such that $\forall r \in\{0,1\}^{21 d}, \mathcal{A}(r) \neq r$. Let $Y^{r}$ be the source obtained with $r$ and $Y^{\mathcal{A}(r)}$ be the source obtained with $\mathcal{A}(r)$. We have the following lemma.

Lemma 5.1. For some $\epsilon=1 / \operatorname{poly}(n)$, with probability $1-\epsilon$ over the fixing of $R=r$, we have

$$
\operatorname{Pr}_{y^{\prime} \leftarrow Y_{\mathcal{A}(r)}}\left[\left.Y^{r}\right|_{Y \mathcal{A}(r)=y^{\prime}} \text { is } \epsilon-\text { close to } a(10 d \sqrt{k}, \sqrt{k}) \text { source }\right] \geq 1-\epsilon .
$$

Proof. Let $r^{\prime}=\mathcal{A}(r)=\left(r_{1}^{\prime}, r_{2}^{\prime}\right)$. Since $r^{\prime} \neq r$, we have two cases: $r_{1}^{\prime}=r_{1}$ or $r_{1}^{\prime} \neq r_{1}$. We call a string $r \in\{0,1\}^{21 d}$ bad if conditioned on $R=r$,

$$
\operatorname{Pr}_{y^{\prime} \leftarrow Y_{\mathcal{A}(r)}}\left[\left.Y^{r}\right|_{Y \mathcal{A}(r)=y^{\prime}} \text { is } \epsilon-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right]<1-\epsilon \text {. }
$$

Now we consider two other deterministic functions $\mathcal{A}_{1}:\{0,1\}^{21 d} \rightarrow\{0,1\}^{21 d}$ and $\mathcal{A}_{2}:\{0,1\}^{21 d} \rightarrow$ $\{0,1\}^{21 d}$. For all the $r$ 's such that $r_{1}^{\prime}=r_{1}$, we let $\mathcal{A}_{1}(r)=r^{\prime}$. For all the other $r$ 's we let $\mathcal{A}_{1}(r)_{1}=r_{1}$ and choose $\mathcal{A}_{1}(r)_{2}$ arbitrarily but such that $\mathcal{A}_{1}(r)_{2} \neq r_{2}$. For all the $r$ 's such that $r_{1}^{\prime} \neq r_{1}$, we let $\mathcal{A}_{2}(r)=r^{\prime}$. For all the other $r$ 's we choose $\mathcal{A}_{2}(r)$ arbitrarily but such that $\mathcal{A}_{2}(r)_{1} \neq r_{1}$. Thus for any $r$, we have $\mathcal{A}_{1}(r)_{1}=r_{1}$ and $\mathcal{A}_{2}(r)_{1} \neq r_{1}$. Note that any bad $r$ in $\mathcal{A}$ is either a bad $r$ in $\mathcal{A}_{1}$ or $\mathcal{A}_{2}$. Thus the number of bad $r$ 's in $\mathcal{A}$ is at most the sum of the numbers of bad $r$ 's in $\mathcal{A}_{1}$ and $\mathcal{A}_{2}$.

First consider $\mathcal{A}_{1}$. We slightly abuse notation and let $R^{\prime}=\mathcal{A}_{1}(R)=\left(R_{1}^{\prime}, R_{2}^{\prime}\right)$. Note that $R_{1}^{\prime}=$ $R_{1}$. We now fix $R_{1}=r_{1}$. By theorem 3.9 , with probability $1-\epsilon_{1}$ over this fixing, $W_{1}=\operatorname{Ext}\left(X_{1}, r_{1}\right)$ is $\epsilon_{1}$-close to uniform, where $\epsilon_{1}=1 / \operatorname{poly}(n)$. Note that after we fix $R_{1}=r_{1}, R_{2}$ is still uniform and $R_{2}^{\prime}$ is now a deterministic function of $R_{2}$ with $R_{2}^{\prime} \neq R_{2}$. Thus when $W_{1}$ is $\epsilon_{1}$-close to uniform, by theorem 3.13,

$$
\left(Y_{1}, Y_{1}^{\prime}, R_{2}\right) \approx_{\epsilon_{1}+1 / \operatorname{poly}(n)}\left(U_{2 d \sqrt{k}}, Y_{1}^{\prime}, R_{2}\right)
$$

where $Y_{1}^{\prime}=\operatorname{nmExt}\left(W_{1}, R_{2}^{\prime}\right)$.
Thus with probability $1-\epsilon_{2}$ over the further fixing of $R_{2}=r_{2}$, we have

$$
\operatorname{Pr}_{y^{\prime} \leftarrow Y_{1}^{\prime}}\left[\left.Y_{1}\right|_{Y_{1}^{\prime}=y^{\prime}} \approx_{\epsilon_{2}} U_{2 d \sqrt{k}}\right] \geq 1-\epsilon_{2},
$$

where $\epsilon_{2}=1 / \operatorname{poly}(n)$. Note that once $r$ is fixed, $\left(Y_{2}, Y_{2}^{\prime}\right)$ is a deterministic function of $\left(X_{2}, X_{3}, X_{4}\right)$ and thus is independent of $Y_{1}$. Therefore we can further condition on $Y_{2}^{\prime}$ and $Y_{1}$ is still close to uniform, and thus $Y^{r}$ is close to a source with min-entropy $2 d \sqrt{k}>\sqrt{k}$ conditioned on $Y^{r^{\prime}}$. Thus the fraction of bad $r$ 's in $\mathcal{A}_{1}$ is at most $\epsilon_{1}+\epsilon_{2}=1 / \operatorname{poly}(n)$.

Next, consider $\mathcal{A}_{2}$. We slightly abuse notation and let $R^{\prime}=\mathcal{A}_{2}(R)=\left(R_{1}^{\prime}, R_{2}^{\prime}\right)$. We will use letters with prime to denote the random variables produced with $R^{\prime}$. Now we have $R_{1}^{\prime} \neq R_{1}$. We first fix $R_{1}=r_{1}$ and $R_{1}^{\prime}=r_{1}^{\prime}$. After $R_{1}$ is fixed, $R_{2}$ is still uniform. However, fixing $R_{1}^{\prime}$ may cause $R_{2}$ to lose entropy. By lemma 3.14 , with probability $1-\epsilon_{3}$ over this fixing, $R_{2}$ has min-entropy $20 d-d-d=18 d$, where $\epsilon_{3}=1 / 2^{d}=1 / \operatorname{poly}(n)$. Note that after this fixing, $R_{2}^{\prime}$ is a deterministic function of $R_{2}$. Thus by theorem 3.10 we can output $d$ bits in $W_{2}$ and we have that

$$
\left(W_{2}, R_{2}, R_{2}^{\prime}\right) \approx_{1 / \operatorname{poly}(n)}\left(U_{d}, R_{2}, R_{2}^{\prime}\right)
$$

Thus we can further fix $R_{2}=r_{2}$ (and also $R_{2}^{\prime}=r_{2}^{\prime}$ ) and with probability $1-\epsilon_{4}=1-1 / \operatorname{poly}(n)$ over this fixing, $W_{2}$ is $1 / \operatorname{poly}(n)$-close to uniform. Note that now we have fixed $R$ and $R^{\prime}$, and $W_{2}$ is a deterministic function of $X_{2}$. Note also that $W_{2}^{\prime}$ is correlated with $W_{2}$. When $W_{2}$ is $1 / \operatorname{poly}(n)$-close to uniform, by theorem 3.9 we can output 0.9 k bits in $W_{3}$ and we have that $W_{3}$ is $1 / \operatorname{poly}(n)$-close to uniform. Note that $W_{3}^{\prime}$ is correlated with $W_{3}$. However, $\left(W_{3}, W_{3}^{\prime}\right)$ is independent of $X_{4}$. Let $W_{4}=\operatorname{laExt}\left(X_{4}, W_{3}\right)=\left(V_{1}, \cdots, V_{t}\right)$ and $W_{4}^{\prime}=\operatorname{laExt}\left(X_{4}, W_{3}^{\prime}\right)=\left(V_{1}^{\prime}, \cdots, V_{t}^{\prime}\right)$. By lemma 4.1 (and notice that $2 t \sqrt{k} \ll k, d \ll k)$, we have that for any $0 \leq i \leq t-1$,

$$
\left(\left[V_{1}^{\prime}, \cdots, V_{i}^{\prime}\right],\left[V_{i+1}, \cdots, V_{t}\right]\right) \approx_{\epsilon_{5}}\left(\left[V_{1}^{\prime}, \cdots, V_{i}^{\prime}\right], U_{2(t-i) \sqrt{k}}\right)
$$

where $\epsilon_{5}=1 / \operatorname{poly}(n)+O\left(t^{2} 2^{-\Omega(\sqrt{k})} \operatorname{poly}(n)\right)=1 / \operatorname{poly}(n)$.
Now note that $Y_{2}=\operatorname{IrMAC}_{W_{4}}\left(r_{1}\right)$ and $Y_{2}^{\prime}=\operatorname{IrMAC}_{W_{4}^{\prime}}\left(r_{1}^{\prime}\right)$. Let the two sets in Lemma 4.4 that correspond to $r_{1}$ and $r_{1}^{\prime}$ be $H$ and $H^{\prime}$ respectively. Since $r_{1} \neq r_{1}^{\prime}$, by Lemma 4.4 there exists $j \in[4 d]$ such that $\left|H^{\geq j}\right|>\left|H^{\prime \geq j}\right|$. Let $l=\left|H^{\geq j}\right|$. Thus $l \leq t=4 d$ and $\left|H^{\prime \geq j}\right| \leq l-1$. Let $V_{H}$ be the concatenation of $\left\{V_{i}, i \in H^{\geq j}\right\}$ and $V_{H^{\prime}}^{\prime}$ be the concatenation of $\left\{V_{i}^{\prime}, i \in H^{\prime \geq j}\right\}$. By the above equation we have that

$$
\left(\left[V_{1}^{\prime}, \cdots, V_{j-1}^{\prime}\right], V_{H}\right) \approx_{\epsilon_{5}}\left(\left[V_{1}^{\prime}, \cdots, V_{j-1}^{\prime}\right], U_{2 l \sqrt{k}}\right)
$$

Thus with probability $1-\sqrt[3]{\epsilon_{5}}$ over the fixings of $\left(V_{1}^{\prime}, \cdots, V_{j-1}^{\prime}\right)$, $V_{H}$ is $\sqrt[3]{\epsilon_{5}^{2}}$-close to $U_{2 l \sqrt{k}}$.
Since the size of $V_{H^{\prime}}^{\prime}$ is at most $2(l-1) \sqrt{k}$, we can further fix $V_{H^{\prime}}^{\prime}$ and by lemma 3.15 we have that with probability $1-2 \sqrt[3]{\epsilon_{5}}$ over this fixing, $V_{H}$ is $\sqrt[3]{\epsilon_{5}}$-close to a source with min-entropy $2 \sqrt{k}-O(\log n)>\sqrt{k}$. Note that $Y_{2}^{\prime}$ is fixed when both $\left(V_{1}^{\prime}, \cdots, V_{j-1}^{\prime}\right)$ and $V_{H^{\prime}}^{\prime}$ are fixed. Thus we have shown that

$$
\operatorname{Pr}_{y^{\prime} \leftarrow Y_{2}^{\prime}}\left[\left.Y_{2}\right|_{Y_{2}^{\prime}=y^{\prime}} \text { is } \sqrt[3]{\epsilon_{5}}-\text { close to a } \sqrt{k} \text {-source }\right] \geq 1-3 \sqrt[3]{\epsilon_{5}} \text {. }
$$

Finally, note that we have already fixed $\left(R, R^{\prime}\right)$ before. After this fixing, $\left(Y_{2}, Y_{2}^{\prime}\right)$ is a deterministic function of $\left(X_{2}, X_{3}, X_{4}\right)$, while $\left(Y_{1}, Y_{1}^{\prime}\right)$ is a deterministic function of $X_{1}$. Thus $\left(Y_{2}, Y_{2}^{\prime}\right)$ is independent of $\left(Y_{1}, Y_{1}^{\prime}\right)$. Therefore we can further fix $Y_{1}^{\prime}$ and $Y_{2}$ is still close to a source with min-entropy $\sqrt{k}$. Thus $Y^{r}$ is close to a source with min-entropy $\sqrt{k}$ conditioned on $Y^{r^{\prime}}$. Note the fraction of bad $r$ 's in $\mathcal{A}_{2}$ is at most $\epsilon_{3}+\epsilon_{4}=1 / \operatorname{poly}(n)$. Now choose $\epsilon=\max \left\{\epsilon_{1}+\epsilon_{2}+\epsilon_{3}+\epsilon_{4}, 3 \sqrt[3]{\epsilon_{5}}\right\}=1 / \operatorname{poly}(n)$ and the lemma is proved.

We now have the following lemma.
Lemma 5.2. For some $\epsilon=1 / \operatorname{poly}(n)$ there exists a subset $S \subset\{0,1\}^{21 d}$ with $|S| \geq(1-\epsilon) 2^{21 d}$ such that for any $i, j \in S, i \neq j$, we have

$$
\operatorname{Pr}_{y \leftarrow Y^{j}}\left[\left.Y^{i}\right|_{Y^{j}=y} \text { is } \epsilon-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right] \geq 1-\epsilon \text {. }
$$

Proof. Let $\epsilon$ be the same as in lemma 5.1. For any $i, j \in\{0,1\}^{21 d}, i \neq j$, we say that $j$ is bad for $i$ if

$$
\operatorname{Pr}_{y \leftarrow Y^{j}}\left[\left.Y^{i}\right|_{Y^{j}=y} \text { is } \epsilon-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right]<1-\epsilon \text {. }
$$

Let $B=\left\{i \in\{0,1\}^{21 d}: \exists j \in\{0,1\}^{21 d}, j \neq i\right.$ and $j$ is bad for $\left.i\right\}$. We claim that $|B| \leq \epsilon 2^{21 d}$. Otherwise, we can construct a deterministic function $\mathcal{A}:\{0,1\}^{21 d} \rightarrow\{0,1\}^{21 d}$ as follows. For all $i \in B$, let $\mathcal{A}(i)$ be a bad $j$ for $i$; for all the other $i \in\{0,1\}^{21 d}$, define $\mathcal{A}(i)$ to be any $j \in\{0,1\}^{21 d}$ such that $j \neq i$. Thus when $R$ is uniformly sampled from $\{0,1\}^{21 d}$, we have that with probability at least $\epsilon$ over the fixing of $R=r$,

$$
\operatorname{Pr}_{y^{\prime} \leftarrow Y^{\mathcal{A}(r)}}\left[\left.Y^{r}\right|_{Y \mathcal{A}(r)=y^{\prime}} \text { is } \epsilon-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right]<1-\epsilon,
$$

which contradicts lemma 5.1.
Now let $S=\{0,1\}^{21 d} \backslash B$. We have that $|S| \geq(1-\epsilon) 2^{21 d}$ and for any $i, j \in S, i \neq j$,

$$
\operatorname{Pr}_{y \leftarrow Y^{j}}\left[\left.Y^{i}\right|_{Y^{j}=y} \text { is } \epsilon-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right] \geq 1-\epsilon .
$$

Now let $c$ be the number of independent $(10 d \sqrt{k}, \sqrt{k})$ sources that are needed to extract $m=\Omega(\sqrt{k})$ bits with error $\epsilon^{\prime}=2^{-k^{\Omega(1)}} \leq 1 / \operatorname{poly}(n)$, as in theorem 3.11. Note that since $k \geq \log ^{4} n$ we have $\sqrt{k}=\Omega\left(d^{2}\right)$. Thus $c=O(\log (\operatorname{lod} \sqrt{k}) / \log (\sqrt{k}))$ is an absolute constant. We now take $4 c$ independent $(n, k)$ sources $X_{1}, X_{2}, \cdots, X_{4 c}$ and divide them equally into $c$ sets $\left\{X_{1}, X_{2}, X_{3}, X_{4}\right\}, \cdots,\left\{X_{4 c-3}, X_{4 c-2}, X_{4 c-1}, X_{4 c}\right\}$. For each set we use the procedure described above to get $2^{21 d}=\operatorname{poly}(n)$ number of sources $\left\{Y_{i}^{r}\right\}$, for $r \in\{0,1\}^{21 d}$ and $i \in[c]$. Now for any $r \in\{0,1\}^{21 d}$, let $Z^{r}=\operatorname{MExt}\left(Y_{1}^{r}, \cdots, Y_{c}^{r}\right)$. Thus we obtain $2^{21 d}=\operatorname{poly}(n)$ number of sources $\left\{Z^{r}\right\}$, for $r \in\{0,1\}^{21 d}$. We now have the following lemma.
Lemma 5.3. For some $\epsilon=1 / \operatorname{poly}(n)$ there exists a subset $S \subset\{0,1\}^{21 d}$ with $|S| \geq(1-\epsilon) 2^{21 d}$ such that for any $i, j \in S, i \neq j$, we have

$$
\left(Z^{i}, Z^{j}\right) \approx_{\epsilon} U_{2 m},
$$

where $m=\Omega(\sqrt{k})$.
Proof. Let $\epsilon_{1}$ be the error in lemma 5.2. By lemma 5.2, for each $t \in[c]$, there exists a subset $S_{t} \subset\{0,1\}^{21 d}$ with $\left|S_{t}\right| \geq\left(1-\epsilon_{1}\right) 2^{21 d}$ such that for any $i, j \in S_{t}, i \neq j$, we have

$$
\operatorname{Pr}_{y \leftarrow Y_{t}^{j}}\left[\left.Y_{t}^{i}\right|_{Y_{t}^{j}=y} \text { is } \epsilon_{1}-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right] \geq 1-\epsilon_{1} \text {. }
$$

Let $S=\cap_{t} S_{t}$. Then we have $|S| \geq\left(1-c \epsilon_{1}\right) 2^{21 d}$ and for any $i, j \in S, i \neq j$, we have that for any $t \in[c]$,

$$
\operatorname{Pr}_{y \leftarrow Y_{t}^{j}}\left[\left.Y_{t}^{i}\right|_{Y_{t}^{j}=y} \text { is } \epsilon_{1}-\text { close to a }(10 d \sqrt{k}, \sqrt{k}) \text { source }\right] \geq 1-\epsilon_{1} \text {. }
$$

By the above we know that $\forall t \in[c], Y_{t}^{j}$ is $2 \epsilon_{1}$-close to a $(10 d \sqrt{k}, \sqrt{k})$ source. Thus by theorem 3.11 we have

$$
Z^{j} \approx_{2 c \epsilon_{1}+\epsilon^{\prime}} U_{m}
$$

Next, we fix all $Y_{t}^{j}, t \in[c]$, and we have that with probability $1-c \epsilon_{1}$ over this fixing, for any $t$, $Y_{t}^{i}$ is $\epsilon_{1}$-close to a $(10 d \sqrt{k}, \sqrt{k})$ source. Note that after this fixing $Y_{t}^{i}$ are still independent, thus by theorem 3.11 we have

$$
Z^{i} \approx_{c \epsilon_{1}+\epsilon^{\prime}} U_{m}
$$

Since we already fixed all $Y_{t}^{j}, t \in[c]$, this implies that

$$
\left(Z^{i}, Z^{j}\right) \approx_{2 c \epsilon_{1}+\epsilon^{\prime}}\left(U_{m}, Z^{j}\right) .
$$

Thus we have

$$
\left(Z^{i}, Z^{j}\right) \approx_{4 c \epsilon_{1}+2 \epsilon^{\prime}} U_{2 m}
$$

Let $\epsilon=4 c \epsilon_{1}+2 \epsilon^{\prime}=1 / \operatorname{poly}(n)$, and the lemma is proved.
We now describe the lightest bin protocol.
Lightest bin protocol: Assume there are $N$ strings $\left\{z^{i}, i \in[N]\right\}$ where each $z_{i} \in\{0,1\}^{m}$ with $m>\log N$. The output of a lightest bin protocol with $r<N$ bins is a subset $T \subset[N]$ that is obtained as follows. Image that each string $z^{i}$ is associated with a player $P_{i}$. Now, for each $i, P_{i}$ uses the first $\log r$ bits of $z_{i}$ to select a bin $j$, i.e., if the first $\log r$ bits of $z_{i}$ is the binary expression of $j-1$, then $P_{i}$ selects bin $j$. Now let bin $l$ be the bin that is selected by the fewest number of players. Then

$$
T=\left\{i \in[N]: P_{i} \text { selects bin } l .\right\}
$$

We now have the following lemma.
Lemma 5.4. Assume that we have $N$ sources $Z_{1}^{i}, i \in[N]$ over $m>10 \log (1 / \epsilon)$ bits and a subset $S \subset[N]$ with $|S| \geq \alpha N$ for some constant $\alpha>0$ such that for any $i, j \in S, i \neq j$,

$$
\left(Z_{1}^{i}, Z_{1}^{j}\right) \approx_{\epsilon} U_{2 m}
$$

with $\epsilon<1 / N^{12}$.
Let $Z_{1}=Z_{1}^{1} \circ \cdots \circ Z_{1}^{N}$. Run the lightest bin protocol with $N^{1 / 4}$ bins and let the output contain $N_{2}$ elements $\left\{i_{1}, i_{2}, \cdots, i_{N_{2}} \in[N]\right\}$. Assume that $X$ is an $(n, k)$ source independent of $Z_{1}$ with $k>40 \log (1 / \epsilon)$. For any $j \in\left[N_{2}\right]$, let $Z_{2}^{j}=\operatorname{Ext}\left(X, Z_{1}^{i_{j}}\right)$ where $\operatorname{Ext}$ is the strong seeded extractor in theorem 3.9 and output $m_{2}=k / 4$ bits. Then for any $\delta>N^{-1 / 2}$, with probability at least $1-3 N^{1 / 2} /\left(\delta^{2} s\right)-4 N^{-1 / 2}$ over the fixing of $Z_{1}$, there exists a subset $S_{2} \subset\left[N_{2}\right]$ with $\left|S_{2}\right| \geq \alpha(1-\delta) N_{2}$ such that for any $i, j \in S_{2}, i \neq j$,

$$
\left(Z_{2}^{i}, Z_{2}^{j}\right) \approx_{\epsilon_{2}} U_{2 m_{2}}
$$

with $\epsilon_{2}<1 / N_{2}^{12}$ and $m_{2}>10 \log \left(1 / \epsilon_{2}\right)$.
Proof. Note that the lightest bin contains at most $N^{3 / 4}$ elements. We first show that in the lightest bin protocol, with high probability every bin contains at least $(\alpha-\delta) N^{3 / 4}$ elements in $S$.

Consider a particular bin and consider the choices of the $Z_{1}^{i}$ 's with $i \in S$. Let $s=|S|$. Let $V_{i}$ be the indicator variable of whether $Z_{1}^{i}$ chooses this bin and let $V=\sum_{i \in S} V_{i}$. Let $p_{i}=\operatorname{Pr}\left[V_{i}=1\right]$ and $q_{i}=\operatorname{Pr}\left[V_{i}=0\right]$. Then we have

$$
E[V]=\sum_{i \in S} E\left[V_{i}\right]=\sum_{i \in S} p_{i} .
$$

We know for any $i \in S, Z_{1}^{i}$ is $\epsilon$-close to uniform. Thus $\operatorname{Pr}\left[V_{i}=1\right] \geq N^{-1 / 4}-\epsilon$. Therefore

$$
E[V] \geq\left(N^{-1 / 4}-\epsilon\right) s
$$

Note that

$$
\begin{aligned}
\operatorname{Pr}\left[V<N^{-1 / 4}(1-\delta) s\right] & \leq \operatorname{Pr}\left[|V-E[V]|>\delta N^{-1 / 4} s-\epsilon s\right] \\
& \leq \operatorname{Pr}\left[|V-E[V]|>0.9 \delta N^{-1 / 4} s\right],
\end{aligned}
$$

since $\epsilon s<1$ and $\delta>N^{-1 / 2}$.
Thus by Chebysev's inequality we have

$$
\operatorname{Pr}\left[V<N^{-1 / 4}(1-\delta) s\right] \leq \operatorname{Var}[V] /\left(0.81 \delta^{2} N^{-1 / 2} s^{2}\right)<2 N^{1 / 2} \operatorname{Var}[V] /\left(\delta^{2} s^{2}\right)
$$

We now compute $\operatorname{Var}[V]$. By definition

$$
\begin{aligned}
\operatorname{Var}[V] & =E(V-E[V])^{2}=E\left(\sum_{i \in S}\left(V_{i}-E\left[V_{i}\right]\right)\right)^{2} \\
& =\sum_{i \in S} \operatorname{Var}\left[V_{i}\right]+\sum_{i, j \in[S], i \neq j} E\left[\left(V_{i}-E\left[V_{i}\right]\right)\left(V_{j}-E\left[V_{j}\right)\right] .\right.
\end{aligned}
$$

For each $i \in S$, we have

$$
\operatorname{Var}\left[V_{i}\right]=p_{i} q_{i}<p_{i} \leq N^{-1 / 4}+\epsilon
$$

Next, note that

$$
E\left[\left(V_{i}-E\left[V_{i}\right]\right)\left(V_{j}-E\left[V_{j}\right)\right]=E\left[V_{i} V_{j}\right]-E\left[V_{i}\right] E\left[V_{j}\right] .\right.
$$

Since $\left(Z_{1}^{i}, Z_{1}^{j}\right) \approx_{\epsilon} U_{2 m}$, we have $E\left[V_{i} V_{j}\right]=\operatorname{Pr}\left[V_{i}=1, V_{j}=1\right] \leq N^{-1 / 2}+\epsilon, E\left[V_{i}\right] \geq N^{-1 / 4}-\epsilon$ and $E\left[V_{j}\right] \geq N^{-1 / 4}-\epsilon$. Thus

$$
E\left[V_{i} V_{j}\right]-E\left[V_{i}\right] E\left[V_{j}\right] \leq N^{-1 / 2}+\epsilon-\left(N^{-1 / 4}-\epsilon\right)^{2}<\left(2 N^{-1 / 4}+1\right) \epsilon<2 \epsilon
$$

Thus

$$
\operatorname{Var}[V]<\left(N^{-1 / 4}+\epsilon\right) s+2 s^{2} \epsilon<N^{-1 / 4} s+3,
$$

since $\epsilon<1 / N^{12}$. Therefore we have

$$
\operatorname{Pr}\left[V<N^{-1 / 4}(1-\delta) s\right]<2 N^{1 / 2}\left(N^{-1 / 4} s+3\right) /\left(\delta^{2} s^{2}\right)<3 N^{1 / 4} /\left(\delta^{2} s\right)
$$

Thus by the union bound, we have that the probability that every bin contains at least $N^{-1 / 4}(1-$ $\delta) s$ elements in $S$ is at least $1-3 N^{1 / 2} /\left(\delta^{2} s\right)$. When this happens, let $S_{2}$ be the set of elements in $S$ in the lightest bin. Then we have $\left|S_{2}\right| \geq N^{-1 / 4}(1-\delta) s \geq \alpha(1-\delta) N^{3 / 4} \geq \alpha(1-\delta) N_{2}$.

Next, we show that with high probability the new sources with index in $S_{2}$ are pair-wise close to uniform. For this, consider any $i, j \in[S], i \neq j$. Let $W^{i}=\operatorname{Ext}\left(X, Z_{1}^{i}\right)$ and $W^{j}=\operatorname{Ext}\left(X, Z_{1}^{j}\right)$. Note that $\left(Z_{1}^{i}, Z_{1}^{j}\right) \approx_{\epsilon} U_{2 m}$. First assume that $\left(Z_{1}^{i}, Z_{1}^{j}\right)$ is indeed uniform, then by theorem 3.9 we have

$$
\left(W^{i}, Z_{1}^{i}\right) \approx_{\epsilon}\left(U_{m_{2}}, Z_{1}^{i}\right)
$$

Now we fix $Z_{1}^{i}$ and $W^{i}$. Note that after fixing $Z_{1}^{i}, W^{i}$ is a deterministic function of $X$. Thus by lemma 3.14, with probability $1-2^{-k / 4}>1-\epsilon$ over this fixing, $X$ is an $(n, k-k / 4-k / 4=k / 2)$ source. After this fixing, $Z_{1}^{j}$ is still uniform and independent of $X$, thus again by theorem 3.9 we have

$$
\left(W^{j}, Z_{1}^{j}\right) \approx_{\epsilon}\left(U_{m_{2}}, Z_{1}^{j}\right)
$$

Therefore

$$
\left(W^{i}, W^{j}, Z_{1}^{i}, Z_{1}^{j}\right) \approx_{3 \epsilon}\left(U_{2 m_{2}}, Z_{1}^{i}, Z_{1}^{j}\right)
$$

Adding back the error where $\left(Z_{1}^{i}, Z_{1}^{j}\right) \approx_{\epsilon} U_{2 m}$, we have

$$
\left(W^{i}, W^{j}, Z_{1}^{i}, Z_{1}^{j}\right) \approx_{4 \epsilon}\left(U_{2 m_{2}}, Z_{1}^{i}, Z_{1}^{j}\right) .
$$

Therefore, with probability $1-4 N^{-2.5}$ over the fixing of $\left(Z_{1}^{i}, Z_{1}^{j}\right),\left(W^{i}, W^{j}\right)$ is $N^{2.5} \epsilon$-close to uniform. Thus by the union bound (and noticing that $s \leq N$ ), we have that with probability at least $1-4 N^{-1 / 2}$ over the fixing of $Z_{1}$, for any $i, j \in[S], i \neq j,\left(W^{i}, W^{j}\right)$ is $N^{2.5} \epsilon$-close to uniform. In particular, this implies that the new sources with index in $S_{2}$ are pair-wise close to uniform. Note that $N_{2} \leq N^{3 / 4}$ and $\epsilon<1 / N^{12}$, thus $N^{2.5} \epsilon<1 / N_{2}^{12}$. Also note that $m_{2}=k / 4>10 \log (1 / \epsilon)>$ $10 \log \left(1 / \epsilon_{2}\right)$. By the union bound, the lemma is proved.

Now we have the following construction.

## Construction 5.5. Independent Source Extractor.

Let $\epsilon$ be the error in lemma 5.3 and let $N_{1}=2^{21 d}$. Let $c_{1}$ be an integer constant such that $\epsilon^{c_{1}}<1 / N_{1}^{12}$. We first take $C=4 c c_{1}$ independent $(n, k)$ sources and from them obtain $c_{1}$ SRsources $Z_{1}^{\prime}, \cdots, Z_{c_{1}}^{\prime}$ where each $Z_{i}^{\prime}=Z_{i}^{\prime 1} \circ Z_{i}^{\prime 2} \circ \cdots \circ Z_{i}^{\prime N_{1}}$ contains $N_{1}$ rows, as in lemma 5.3. Let $Z_{1}=\bigoplus_{i=1}^{c_{1}} Z_{i}^{\prime}$. Set $t=1$. While the number of rows in $Z_{t}$ is bigger than $\ell=k^{5}$ we do the following:

1. Run the lightest bin protocol with $Z_{t}$ and $r_{t}=N_{t}^{1 / 4}$ bins and let the output contain $N_{t+1}$ elements $\left\{i_{1}, i_{2}, \cdots, i_{N_{t+1}} \in\left[N_{t}\right]\right\}$.
2. Take a fresh independent $(n, k)$ source $X_{C+t}$ and for any $j \in\left[N_{t+1}\right]$, let $Z_{t+1}^{j}=\operatorname{Ext}\left(X_{C+t}, Z_{t}^{i_{j}}\right)$ where Ext is the strong seeded extractor in theorem 3.9 and output $m_{2}=k / 4$ bits.
3. Let $Z_{t+1}=Z_{t+1}^{1} \circ \cdots \circ Z_{t+1}^{N_{t+1}}$. Set $t=t+1$.

At the end of the iteration we get a source $Z_{t}$ with at most $\ell=k^{5}$ rows. Let SRExt be the extractor in theorem 3.12, set up to extract from an $\ell \times \frac{k}{4}$ source and $c_{2}$ independent $(n, k)$ sources $X_{C+t+1}, \cdots, X_{C+t+c_{2}}$ (note that independent sources are a special case of block sources). The final output is $W=\operatorname{SRExt}\left(Z_{t}, X_{C+t+1}, \cdots, X_{C+t+c_{2}}\right)$.

Theorem 5.6. The above construction is an extractor for $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ independent sources with error $1 / \operatorname{poly}(k)$.

Proof. We first show that the number of independent sources we use is $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$. To see this, note that to obtain one $Z_{i}^{\prime}$ we use a constant $4 c$ number of independent sources, and the error is $\epsilon=1 / \operatorname{poly}(n)$ as in lemma 5.3. Note that $N_{1}=2^{21 d}=\operatorname{poly}(n)$, thus it suffices to take $c_{1}$ to be a constant. Next note that in the lightest bin protocol each time the number of rows decreases from $N$ to at most $N^{3 / 4}$, thus it takes $t=O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ number of independent sources to get the number of rows down to $k^{5}$. Finally note that $c_{2}=O\left(\log \left(k^{5}\right) / \log k\right)=O(1)$. Thus the total number of independent sources used is $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$.

Next, by lemma 5.3 we know that for each $Z_{i}^{\prime}$ there exists a subset $S_{i} \subset\left[N_{1}\right]$ with $\left|S_{i}\right| \geq(1-\epsilon) N_{1}$ such that any pair of rows in $S_{i}$ is $\epsilon$-close to uniform. Now let $S=\cap_{i=1}^{c_{1}} S_{i}$. Then we have that $|S| \geq\left(1-c_{1} \epsilon\right) N_{1}$ and by lemma 3.16, for any $i, j \in S, i \neq j$,

$$
\left(Z_{1}^{i}, Z_{1}^{j}\right) \approx_{\epsilon^{c_{1}}} U_{2 m}
$$

where $m=\Omega(\sqrt{k})$.
Note that $\epsilon^{c_{1}}<1 / N_{1}^{12}$ and $k>\log ^{4} n$. Thus $Z_{1}$ satisfies the conditions in lemma 5.4 with $\alpha=1-c_{1} \epsilon=1-1 / \operatorname{poly}(n)$. Now let $\delta=1 /(3 t)$ in lemma 5.4 and consider the lightest bin protocol where we get $Z_{1}, \cdots, Z_{t}$ with each $Z_{i}$ having $N_{i}$ rows. By lemma 5.4 if the "good" event in the lemma always happens, then the "good" set $S_{i}$ in each $Z_{i}$ has size at least $s_{i} \geq$ $\alpha(1-\delta)^{t} N_{i}>\alpha(1-\delta t) N_{i}>N_{i} / 2$. Thus the probability of the "bad" event in lemma 5.4 is at $\operatorname{most} 3 N_{i}^{1 / 2} /\left(\delta^{2} s_{i}\right)+4 N_{i}^{-1 / 2}=O\left(t^{2} N_{i}^{-1 / 2}\right)$. Note that for any $i \leq t-1, N_{i}>k^{5}$. Thus the total error is at most

$$
t O\left(t^{2} k^{-5 / 2}\right)=O\left(t^{3} k^{-5 / 2}\right)<1 /\left(10 k^{2}\right)
$$

Thus we have that with probability $1-1 /\left(10 k^{2}\right)$ over the fixings of all previous independent sources, $Z_{t}$ is $k^{-40}$-close to (note that $N_{t} \geq s_{t} \geq\left(k^{5}\right)^{3 / 4} / 2$ ) an SR-source with at most $k^{5}$ rows. Now by theorem $3.12, W$ is $2^{-k^{\Omega(1)}}$-close to uniform. Therefore, the total error of the output is at most $1 /\left(10 k^{2}\right)+2^{-k^{\Omega(1)}}<1 / k^{2}$.

Remark 5.7. The error in the extractor can be made $1 / k^{C}$ for any constant $C>1$, just by setting the number of rows in the final source $Z_{t}$ to be an appropriate poly $(k)$. The time of the algorithm can be larger (but still polynomial in $n$ ), and the number of sources needed is still $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$.

Remark 5.8. When the entropy $k$ is smaller, we can get better error dependence on $k$. Specifically, we can set the number of rows in the final source $Z_{t}$ to be $k^{\Omega\left(\log \left(\frac{\log n}{\log k}\right)+1\right)}$. In this way the number of sources needed is still $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$, but the error is $k^{-\Omega\left(\log \left(\frac{\log n}{\log k}\right)+1\right)}$. As an example, when $k$ is at most $2^{\log ^{\alpha} n}$ for some constant $0<\alpha<1$, the error is $k^{-\Omega(\log \log n)}$.

Now we show that we can actually give an extractor for a constant number of independent $(n, k)$ sources, plus two independent $(n, k)$-block sources, each with $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ blocks. The extractor is very similar to the extractor for independent sources.

Theorem 5.9. There exists an absolute constant $c>0$ and a polynomial time computable function BExt : $\{0,1\}^{c n} \times\{0,1\}^{\text {tn }} \times\{0,1\}^{\text {tn }} \rightarrow\{0,1\}^{m}$ such that for any $n, k \in \mathbb{N}$ with $k>\log ^{10} n$ and $t=O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$, if $X=\left(X_{1}, \cdots, X_{c}\right)$ are $c$ independent $(n, k)$ sources and $Y=\left(Y_{1} \circ \cdots \circ\right.$ $\left.Y_{t}\right), W=\left(W_{1} \circ \cdots \circ W_{t}\right)$ are 2 independent $(k, \cdots, k)$ block sources such that $X$ is independent of $(Y, W)$, then

$$
\operatorname{BExt}(X, Y, W) \approx_{\epsilon} U_{m},
$$

where $m=\Omega(k)$ and $\epsilon=1 / \operatorname{poly}(k)$.
Proof sketch. As before, we first use a constant number of independent sources $X=\left(X_{1}, \cdots, X_{c}\right)$ to obtain a somewhere random source $Z$ with $N=\operatorname{poly}(n)$ rows such that there exists $S \subset[N]$ with $|S| \geq(1-\epsilon) N$ such that any pair of rows in $S$ is $\epsilon$-close to uniform, for some $\epsilon=1 / \operatorname{poly}(n)$. Next, we want to use the lightest bin protocol to reduce the number of rows in the somewhere random source. In the extractor for independent sources, each time we use an independent $(n, k)$ source to reduce the number of rows from $N$ to roughly $N^{3 / 4}$. Here, however, each time we will use one block from either $Y$ or $W$. If at one time we use a block from $Y$, then the next time we will use a block from $W$. More specifically, first we run the lightest bin protocol on $Z$, and use the strings in the lightest bin as seeds to apply a strong extractor Ext to $Y_{1}$. Thus we obtain a somewhere random source $Z_{1}$. Next we run the lightest bin protocol on $Z_{1}$, and use the strings in the lightest bin as seeds to apply a strong extractor Ext to $W_{1}$. Thus we obtain a somewhere random source $Z_{2}$. We then run the lightest bin protocol on $Z_{2}$, and use the strings in the lightest bin as seeds to apply a strong extractor Ext to $Y_{2}$. Thus we obtain a somewhere random source $Z_{3}$. We keep on doing this until the rows in the somewhere random source $Z_{t}$ reduces to say $k^{5}$. Assume $Z_{t}$ is obtained from $Y$, finally we can use the extractor BExt from theorem 3.12 to extract from $Z_{t}$ and another $O(1)$ blocks of $W$.

For the analysis, notice that by lemma 5.4, when we are computing $Z_{i+1}$ we can fix all previous $Z, Z_{1}, \cdots, Z_{i-1}$ and with high probability over this fixing, $Z_{i}$ is a somewhere random source such that there exists a large fraction of rows where any pair of the rows is close to uniform. By induction one can show that after all these fixings, $Z_{i}$ is a deterministic function of either $Y_{j}$ or $W_{j}$, for some block $j$. Without loss of generality assume that $Z_{i}$ is a deterministic function of $Y_{j}$. Thus $Z_{i}$ is independent of $W_{j}$. The property of a block source guarantees that after the fixings, $W_{j}$ is still a $k$-source. Thus we can use $Z_{i}$ and $W_{j}$ to compute $Z_{i+1}$. Note that if we now further fix $Z_{i}$, then indeed $Z_{i+1}$ is a deterministic function of $W_{j}$. Moreover, $Y_{j+1}$ is still a $k$-source. Finally, we can use the extractor BExt from theorem 3.12 to obtain the final output.

## 6 Applications in Network Extractor Protocol

We now apply our independent source extractors to network extractor protocols. The following theorem is proved in [KLRZ08].

Theorem 6.1. For every $n, k, p, t \in \mathbb{N}$ assume that there is an explicit C -source extractor for $(n, k)$ sources with output length $\Omega(k)$ and error $\epsilon$, then there is an explicit $r$-round $(t, p-1.1(r+1) t, \epsilon+$ $\left.2^{-k^{\Omega(1)}}\right)$ network extractor protocol for $(n, k)$ sources, where $r=\left\lceil\frac{\log C}{\log \log k}\right\rceil+1$.

Remark 6.2. The constant 1.1 can be replaced by $1+\alpha$ for any constant $\alpha>0$.

Plugging our extractor for independent sources which takes $O\left(\log \left(\frac{\log n}{\log k}\right)\right)+O(1)$ sources with error $1 / \operatorname{poly}(k)$, we obtain the following theorem.

Theorem 6.3. There exists a constant $c>1$ such that for every $n, k, p, t \in \mathbb{N}$ with $k>\log ^{c} n$, there is an explicit 2 -round $(t, p-3.1 t, 1 / \operatorname{poly}(k))$ network extractor protocol for $(n, k)$ sources.
Remark 6.4. The constant 3.1 can be replaced by $3+\alpha$ for any constant $\alpha>0$.
In the definition of a network extractor, let $\mathcal{G}=\left\{i_{1}, \ldots, i_{g}\right\}$ denote the set of players with private, random outputs: $\left|\left(B, Z_{i}\right)-\left(B, U_{m}\right)\right|<\epsilon$. Because each $Z_{i}$ depends only on $X_{i}$ and $B$, the above condition implies that

$$
\left|\left(B,\left(X_{i}\right)_{i \notin \mathcal{G}},\left(Z_{i}\right)_{i \in \mathcal{G}}\right)-\left(B,\left(X_{i}\right)_{i \notin \mathcal{G}}, U_{g m}\right)\right|<g \epsilon .
$$

In other words, after running the network extractor protocol, the joint distribution of the outputs of all the players in $\mathcal{G}$ is close to being independent and uniform, even after seeing all communication and all the sources of the rest of the players. Since $g<p$ and our independent source extractor can be made to have error $1 / k^{C}$ for any constant $C>1$, as long as $p / k^{C}$ is small enough, we can run any existing distributed computing protocols using the output of our network extractor protocol. For example, we can obtain the following theorems.

Theorem 6.5 (Synchronous Byzantine Agreement). There exists a constant $c_{1}>1$ such that for any constants $\alpha>0$ and $c_{2}>1$ the following holds. Assume $p$ players each has access to an independent $(n, k)$-source with $k>\log ^{c_{1}} n$ and $k>p^{1 / c_{2}}$, then there exist explicit (in $n$ ) synchronous $O(\log p)$ expected round protocols for Byzantine Agreement in the full information model that tolerates $(1 / 5-\alpha) p$ faulty players.
Theorem 6.6 (Leader Election). There exists a constant $c_{1}>1$ such that for any constants $\alpha>0$ and $c_{2}>1$ the following holds. Assume $p$ players each has access to an independent $(n, k)$-source with $k>\log ^{c_{1}} n$ and $k>p^{1 / c_{2}}$, then there exist explicit (in $n$ ) synchronous $\log ^{*} p+O(1)$ round protocols for leader election that tolerates $(1 / 4-\alpha) p$ faulty players.

## 7 Conclusions and Open Problems

In this paper we give new explicit extractors for independent weak random sources that improve previous best results exponentially. We then apply our extractor to network extractor protocols and obtain distributed computing protocols that can tolerate a nearly optimal fraction of faulty players even for weak sources with entropy as small as polylog $(n)$. This dramatically improves previous results.

Several natural interesting open problems remain. The first is to reduce the error of our extractor. Currently we only achieve error $1 / \operatorname{poly}(k)$ (or slightly better). It would be nice to improve the error to $2^{-k^{\Omega(1)}}$, as in [BRSW06]. Second and more importantly, our techniques seem promising for further improvement. For example, instead of just using pair-wise independence in the SR-source, we can try to use $r$-wise independence for larger $r$. This may reduce the number of rows in the SR-source faster, and thus resulting in extractors that need fewer sources. However, if $r$ gets larger then correspondingly we need the error $\epsilon$ to be smaller, which may need more independent sources to achieve. Thus, there is some trade-off and it would be nice to see what is the limit of our techniques. Finally, it is an open problem to see if our techniques can be applied to constructing extractors or dispersers for other classes of sources.

## References

[BIW04] Boaz Barak, R. Impagliazzo, and Avi Wigderson. Extracting randomness using few independent sources. In Proceedings of the 45th Annual IEEE Symposium on Foundations of Computer Science, pages 384-393, 2004.
[BKS $\left.{ }^{+} 05\right]$ Boaz Barak, Guy Kindler, Ronen Shaltiel, Benny Sudakov, and Avi Wigderson. Simulating independence: New constructions of condensers, Ramsey graphs, dispersers, and extractors. In Proceedings of the 37th Annual ACM Symposium on Theory of Computing, pages 1-10, 2005.
[Bou05] Jean Bourgain. More on the sum-product phenomenon in prime fields and its applications. International Journal of Number Theory, 1:1-32, 2005.
[BRSW06] Boaz Barak, Anup Rao, Ronen Shaltiel, and Avi Wigderson. 2 source dispersers for $n^{o(1)}$ entropy and Ramsey graphs beating the Frankl-Wilson construction. In Proceedings of the 38th Annual ACM Symposium on Theory of Computing, 2006.
[CG88] Benny Chor and Oded Goldreich. Unbiased bits from sources of weak randomness and probabilistic communication complexity. SIAM Journal on Computing, 17(2):230-261, 1988.
[CRS12] Gil Cohen, Ran Raz, and Gil Segev. Non-malleable extractors with short seeds and applications to privacy amplification. In Proceedings of the 27th Annual IEEE Conference on Computational Complexity, 2012.
[DLWZ11] Yevgeniy Dodis, Xin Li, Trevor D. Wooley, and David Zuckerman. Privacy amplification and non-malleable extractors via character sums. In Proceedings of the 52nd Annual IEEE Symposium on Foundations of Computer Science, 2011.
[DORS08] Y. Dodis, R. Ostrovsky, L. Reyzin, and A. Smith. Fuzzy extractors: How to generate strong keys from biometrics and other noisy data. SIAM Journal on Computing, 38:97139, 2008.
[DW09] Yevgeniy Dodis and Daniel Wichs. Non-malleable extractors and symmetric key cryptography from weak secrets. In Proceedings of the 41st Annual ACM Symposium on Theory of Computing, pages 601-610, 2009.
[Fei99] Uriel Feige. Noncryptographic selection protocols. In IEEE, editor, Proceedings of the 40th Annual IEEE Symposium on Foundations of Computer Science, pages 142-152. IEEE Computer Society Press, 1999.
[GSV05] Shafi Goldwasser, Madhu Sudan, and Vinod Vaikuntanathan. Distributed computing with imperfect randomness. In DISC 2005, 2005.
[GUV09] Venkatesan Guruswami, Christopher Umans, and Salil Vadhan. Unbalanced expanders and randomness extractors from Parvaresh-Vardy codes. Journal of the ACM, 56(4), 2009.
[KLR09] Yael Kalai, Xin Li, and Anup Rao. 2-source extractors under computational assumptions and cryptography with defective randomness. In Proceedings of the 50th Annual IEEE Symposium on Foundations of Computer Science, 2009.
[KLRZ08] Yael Tauman Kalai, Xin Li, Anup Rao, and David Zuckerman. Network extractor protocols. In Proceedings of the 49th Annual IEEE Symposium on Foundations of Computer Science, 2008.
[Li11] Xin Li. Improved constructions of three source extractors. In Proceedings of the 26th Annual IEEE Conference on Computational Complexity, 2011.
[Li12a] Xin Li. Design extractors, non-malleable condensers and privacy amplification. In Proceedings of the 44th Annual ACM Symposium on Theory of Computing, 2012.
[Li12b] Xin Li. Non-malleable condensers for arbitrary min-entropy, and almost optimal protocols for privacy amplification. Technical report, Arxiv, 2012. arXiv:1211.0651.
[Li12c] Xin Li. Non-malleable extractors, two-source extractors and privacy amplification. In Proceedings of the 53nd Annual IEEE Symposium on Foundations of Computer Science, 2012.
[MW97] Ueli M. Maurer and Stefan Wolf. Privacy amplification secure against active adversaries. In CRYPTO '97, 1997.
[NZ96] Noam Nisan and David Zuckerman. Randomness is linear in space. Journal of Computer and System Sciences, 52(1):43-52, 1996.
[Rao06] Anup Rao. Extractors for a constant number of polynomially small min-entropy independent sources. In Proceedings of the 38th Annual ACM Symposium on Theory of Computing, 2006.
[Raz05] Ran Raz. Extractors with weak random seeds. In Proceedings of the 37th Annual ACM Symposium on Theory of Computing, pages 11-20, 2005.
[RZ01] Alexander Russell and David Zuckerman. Perfect information leader election in $\log ^{*} n+$ $O(1)$ rounds. Journal of Computer and System Sciences, 63(4):612-626, 2001.


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[^1]:    ${ }^{1}$ A $k$-block source is a source with several blocks such that conditioned on any fixing of previous blocks, every block has min-entropy $k$.

