## $3.1 k$-Wise Independence

Definition 3.1 ( $k$-wise independence) $X_{1}, \ldots, X_{n}$ is $k$-wise independent if $\forall T \subseteq[n],|T|=k,\left\{X_{j}\right\}_{j \in T}$ are independent random variables.

Lemma 3.2 Let $\left\{X_{1}, \ldots, X_{n}\right\}$ be $k$-wise independent random variables in the range $[0,1]$. Assume $k$ is even. Let $X=\sum_{i=1}^{n} X_{i}, \mu=\mathbb{E}[X]$. Then $\forall t>0, \operatorname{Pr}[|X-\mu|>t] \leq\left(O\left(\frac{\sqrt{2 n e}}{t}\right)\right)^{k}$.

## Proof:

With Markov inequility, we have $\operatorname{Pr}\left[(X-\mu)^{k}>t^{k}\right] \leq \frac{\mathbb{E}\left[(X-\mu)^{k}\right]}{t^{k}}$. Moreover, $\mathbb{E}\left[(X-\mu)^{k}\right]=\mathbb{E}\left[\left(\sum_{i=1}^{n}\left(X_{i}-\mu_{i}\right)\right)^{k}\right]$ where $\mu_{i}=\mathbb{E}\left[X_{i}\right]$, as $X_{i}$ 's are $k$-wise independent. Let $Y_{i}=X_{i}-\mu_{i}$. We have $\mathbb{E}\left[Y_{i}\right]=0$. Then the expectation can be written as $\mathbb{E}\left[\left(Y_{1}+Y_{2}+\ldots+Y_{n}\right)^{k}\right]$. Expand it, we have

$$
\mathbb{E}\left[(X-\mu)^{k}\right]=\sum_{j_{1}, \ldots, j_{k} \in[n]} \mathbb{E}\left[\prod_{i=1}^{k} Y_{j_{i}}\right]
$$

where there might be duplicated $j_{i}$. If we assume that $X_{i}$ is binary (or chosen within $[0,1]$ ), each item in the above sum is less than or equal to 1 .

Now we show that some of the items $\mathbb{E}\left[\prod_{i=1}^{k} Y_{j_{i}}\right]$ are zero. Combine all of the duplicated $j_{i}$ 's together and rewrite the expectation as $\mathbb{E}\left[Y_{j_{1}}^{k_{1}} \cdot \ldots \cdot Y_{j_{l}}^{k_{l}}\right]$ where each $j_{i}$ are distinct and the sum of $k_{1}, \ldots, k_{l}$ is $k$. Now we show that if $l>k / 2$,

$$
\begin{array}{rlr}
\mathbb{E}\left[Y_{j_{1}}^{k_{1}} \cdot \ldots \cdot Y_{j_{l}}^{k_{l}}\right] & =\mathbb{E}\left[Y_{j_{1}}^{k_{1}}\right] \cdot \mathbb{E}\left[Y_{j_{2}}^{k_{2}}\right] \cdot \ldots \cdot \mathbb{E}\left[Y_{j_{l}}^{k_{l}}\right] & \left(Y_{i}^{\prime} \text { s are } k \text {-wise independent }\right)  \tag{3.1}\\
\text { if } l>k / 2, & =0 & \left(\exists i \in[l] \text { s.t. } k_{i}=1 \text { and } \mathbb{E}\left[Y_{i}\right]=0 \forall i \in[n]\right)
\end{array}
$$

Thus we need only consider the items with $l \leq k / 2$. The number of items with $l \leq k / 2$ is upper bounded by $\binom{n}{\frac{k}{2}} \cdot k^{\frac{k}{2}}$, which can be considered as the number of choices, choosing $n / 2$ different $j_{i}$ 's from $[n]$, and then choosing $k_{i}$ to be either 0 or $2, \ldots, k$ for all $i \in\left\{1, \ldots, \frac{k}{2}\right\}$. As each item is less than or equal to 1 , we have

$$
\mathbb{E}\left[(X-\mu)^{k}\right] \leq\binom{ n}{\frac{k}{2}} \cdot k^{\frac{k}{2}} \cdot 1 \leq\left(\frac{2 n e}{k}\right)^{\frac{k}{2}} \cdot k^{\frac{k}{2}}=(2 n e)^{\frac{k}{2}}=\sqrt{2 n e}^{k}
$$

Lemma 3.3 (Construction of $k$-wise independent random variables) For any prime $p$ and $k>0$, there is a construction of $k$-wise independent random variables $X_{1}, \ldots, X_{p}$ using $k\lceil\log p\rceil$ bits of randomness.

Proof: Fix a finite field $\mathbb{F}_{p}$ where $p$ is a prime. Sample a uniform vector $\vec{\alpha}=\left\{\alpha_{0}, \alpha_{1}, \ldots, \alpha_{k-1}\right\} \in \mathbb{F}_{p}^{k}$. Let $h_{\vec{\alpha}}(y):=\sum_{i=0}^{k-1} \alpha_{i} \cdot y^{i}$. We can construct a set of $p$ random variables $\left\{X_{i}=h_{\vec{\alpha}}(i)\right\}_{i=0}^{p-1}$.
First we observe that $X_{i}$ for all $i \in\{0, \ldots, p-1\}$ is uniform over $\mathbb{F}_{p}$. Now we prove that the random variables $\left\{X_{i}\right\}$ are $k$-wise independent. In other words, we need to prove the following claim:

Claim 3.4 For any $T \subseteq\{0, \ldots, p-1\},|T|=k$, denote $T=\left\{i_{0}, \ldots, i_{k-1}\right\}$, for any $\vec{\beta}=\left(\beta_{0}, \ldots, \beta_{k-1}\right)$,

$$
\operatorname{Pr}\left[X_{i_{j}}=\beta_{j} \forall j \in\{0, \ldots, k-1\}\right]=\frac{1}{p^{k}}
$$

Proof: We can write the event in the following way,

$$
\operatorname{Pr}\left[X_{i_{j}}=\beta_{j} \forall j \in\{0, \ldots, k-1\}\right]=\operatorname{Pr}\left[\left(\begin{array}{ccccc}
1 & i_{0} & i_{0}^{2} & \ldots & i_{0}^{k-1} \\
1 & i_{1} & i_{1}^{2} & \ldots & i_{1}^{k-1} \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
1 & i_{k-1} & i_{k-1}^{2} & \ldots & i_{k-1}^{k-1}
\end{array}\right) \vec{\alpha}=\vec{\beta}\right]
$$

The matrix (denoted with $M$ ) in the equation above is a Vandermonde's matrix the determinant of which is non-zero. Thus $M \vec{\alpha}=\vec{\beta}$ has single solution.

As the sampling of vector $\vec{a}$ uses $k \cdot\lceil\log p\rceil$ random bits, the lemma is proven.

Error Reduction Comparison Assume that some algorithm $\mathcal{A}$ uses $R$ bits of randomness with running time $T$ has success probability $\frac{2}{3}$. The table shows running time overhead and number of random bits needed with different kinds of random variables to amplify the success probability of $\mathcal{A}$ to $1-\epsilon$,

|  | Running Time | Random bits |
| ---: | :---: | :---: |
| Independent r.v.s | $O\left(T \cdot \log \left(\frac{1}{\epsilon}\right)\right)$ | $O\left(R \cdot \log \left(\frac{1}{\epsilon}\right)\right)$ |
| 2-wise independent r.v.s | $O\left(T \cdot \frac{1}{\epsilon}\right)$ | $2 R+2 \log \left(\frac{1}{\epsilon}\right)+O(1)$ |
| $k$-wise independent r.v.s | $O\left(\left(\frac{1}{\epsilon}\right)^{\frac{2}{k}} \cdot T\right)$ | $k R+2 \cdot \log \left(\frac{1}{\epsilon}\right)+O(k)$ |

### 3.2 Probabilistic Method

This is a general technique to show the existence of objects using probabilistic arguments. As an example, we prove the existence of Ramsey graphs using this technique.

Definition 3.5 ( $k$-Ramsey Graphs) $G=(V, E)$ is a $k$-Ramsey Graph if it is an undirected graph on $n$ vertices (i.e., $|V|=n$ ) and the largest independent set and the largest clique in $G$ are of size not larger than $k$.

Claim 3.6 (Erdös 1947) There exists $(2 \log n+O(1))$-Ramsey graphs on $n$ vertices.

Proof: Pick a random graph $G\left(n, \frac{1}{2}\right)$, i.e., there are $n$ vertices and each edge is presented with probability $\frac{1}{2}$. Let $k$ be a parameter which will be determined later. Let $T \subseteq[n]$ be any set of indices such that $|T|=k$. Then we have

$$
\operatorname{Pr}\left[G_{T} \text { is a clique or an independent set }\right] \leq 2 \cdot 2^{-\binom{k}{2}}
$$

where $G_{T}$ denotes the induced subgraph in $G$ by $T$. For succinctness, we denote the event " $G_{T}$ is a clique or an independent set" with $\mathcal{E}_{T}$. Then

$$
\begin{align*}
\operatorname{Pr}[G \text { is not } k-\text { Ramsey }] & \leq \operatorname{Pr}\left[\bigcup_{T \subseteq[n],|T|=k} \mathcal{E}_{T}\right] \\
\text { (union bound) } & \leq \sum_{T \subseteq[n],|T|=k} \operatorname{Pr}\left[\mathcal{E}_{T}\right] \leq\binom{ n}{k} \cdot 2 \cdot 2^{-\binom{k}{2}}  \tag{3.2}\\
& \leq\left(\frac{n e}{k}\right)^{k} \cdot 2^{-\frac{k(k-1)}{2}} \cdot 2
\end{align*}
$$

Pick $k=2 \log n+O(1)$ such that

$$
\begin{equation*}
\left(\frac{n e}{k}\right)^{k} \cdot 2^{-\frac{k(k-1)}{2}} \cdot 2<1 \tag{3.3}
\end{equation*}
$$

which means there must exist some graph $G$ that is $k$-Ramsey.

