### 9.1 Introduction

In this lecture, we talked about zig-zag product of graphs, and introduced how to make use of products we covered so far to construct mildly and strongly explicit expanders. Zig-zag product could also be used in the proof for PCP theorem.

### 9.2 Zig-zag Product

Definition 9.1 Let $G$ be a $\left(N_{1}, D_{1}\right)$-graph, i.e., a $D_{1}$-regular graph with $N_{1}$ nodes, and $H$ be $a\left(D_{1}, D_{2}\right)$ graph. The zig-zag product of $G$ and $H$ is a $\left(N_{1} \times D_{1}, D_{2}^{2}\right)$-regular graph, which is denoted by $G(2) H$. Let $(v, i)$ where $v \in V(G), i \in\left[D_{1}\right]$ denote a node in $G$ (2) $H$, and the $(a, b)$-th neighbor of $(v, i)$ in $G$ (2) $H$ where $a, b \in\left[D_{2}\right]$ denote the $\left(a D_{2}+b\right)$-th neighbor of $(v, i)$ in $G(2) H$. For each node $(v, i) \in G(2) H$, it has $D_{2}^{2}$ neighbors, and the $(a, b)$-th neighbor is $(u, j)$ computed as follow:

- Let $i^{\prime}$ be the $a$-th neighbor of node $i$ in $H$.
- Let $u$ be the $i^{\prime}$-th neighbor of $v$ in $G$. Thus, $(v, u)$ is the $i^{\prime}$-th edge leaving $v$.
- For $u, v$ is also a neighbor of $u$. Suppose $v$ is the $j^{\prime}$-th neighbor of $u$.
- Let $j$ be the $b$-th neighbor of $j^{\prime}$ in $H$.

Informally, zig-zag product decreases the degree without hurting expansion too much. In particular, we choose $D_{2}^{2} \ll D_{1}$. We can consider $G$ as the "large graph" and $H$ as the "small graph". The intuition behind this construction is that we want that a random step on $G(2) H$ corresponds to a step on $G$, but using a random step on $H$ to choose which neighbor to go. For each $v \in V(G)$, we replace it by a cloud of $D_{1}$ nodes, with $i$ th node corresponding to the $i$ th edge that is incident on $v$. Consider a random step on $G$ (2) $H$, starting from $(v, i)$. It will first jump into a random node in this cloud, i.e., $\left(v, i^{\prime}\right)$, since $a$ is randomly chosen. After $i^{\prime}$ is determined, we will jump to a deterministic node $\left(u, j^{\prime}\right)$ in the cloud of $u$. Then we will pick up $b$ randomly, which pushes us to a random node $(u, j)$ in that cloud.

An example of zig-zag product is shown in Fig 9.1. The figure was borrowed from lecture note of last semester.

Lemma 9.2 If $H$ is a complete graph, $G(\mathbb{Z}) H=G \otimes H$.

Theorem 9.3 $G(2) H$ is a $D_{2}^{2}$-regular graph on $N_{1} D_{1}$ nodes where $\lambda(G(Z) H) \leq \lambda(G)+\lambda(H)$.

This theorem was proved in the paper by Reimgold, Vadhan, and Wigderson, in which they presented the zig-zag product. We will prove a slightly simpler version in this lecture, and a further simpler proof can be found in the textbook.


Figure 9.1: An example of zig-zag product.

Lemma 9.4 $G$ (2) $H$ is a $D_{2}^{2}$-regular graph on $N_{1} D_{1}$ nodes where $\lambda(G$ (2) $H) \leq \lambda(G)+2 \lambda(H)$.
The proof for this lemma is in the textbook, in which the authors use the Matrix-Decomposition approach.

Lemma 9.5 $G(2) H$ is a $D_{2}^{2}$-regular graph on $N_{1} D_{1}$ nodes where $\lambda(G(2) H) \leq \lambda(G)+\lambda(H)+\lambda(H)^{2}$.

Proof: We use Vector-Decomposition to prove this lemma. Let

$$
\widetilde{A_{H}}=I_{N_{1}} \otimes A_{H}
$$

be a matrix in $\mathbb{R}^{N_{1} D_{1} \times N_{1} D_{1}}$ with its diagonal containing several blocks of $A_{H}$, corresponding to vertex replacement. Let $P \in \mathbb{R}^{N_{1} D_{1} \times N_{1} D_{1}}$ be a permutation matrix s.t.

$$
P_{(v, i),(u, j)}=1,
$$

iff $e=(u, v) \in E(G)$ where $e$ is the $i$-th edge incident on $v$ and $e$ is also the $j$-th edge incident on $u$. Other entries in $P$ wil be 0 .

Claim 9.6 $A_{G(2) H}=\widetilde{A_{H}} P \widetilde{A_{H}}$, where $A_{G(Z) H}$ is the random walk matrix for $G(2) H$.
To prove the above lemma, we should bound the following spectral norm:

$$
\begin{equation*}
\max _{x \in \mathbb{R}^{N_{1} D_{1}},\|x\|_{2}=1, x \perp 1_{N_{1} D_{1}}}\left|x^{T} \widetilde{A_{H}} P \widetilde{A_{H}} x\right| . \tag{9.1}
\end{equation*}
$$

We then use Vector-Decomposition to rewrite

$$
x=\left(x_{1}, x_{2}, \ldots, x_{N_{1}}\right)=\left(x_{1}^{\|}, x_{2}^{\|}, \ldots, x_{N_{1}}^{\|}\right)+\left(x_{1}^{\perp}, x_{2}^{\perp}, \ldots, x_{N_{1}}^{\perp}\right)=x^{\|}+x^{\perp}
$$

where $x_{i}^{\|} \| 1_{D_{1}}, x_{i}^{\perp} \perp 1_{D_{1}}$ for all $i \in\left[N_{1}\right]$. Each $x_{i}^{\|}, x_{i}^{\perp}$ is the vector decomposition restricted on $i$-th cloud.
We make the following two useful observations: 1) $\widetilde{A_{H}} x^{\|}=x^{\|}$since for each $\left.i, A_{H} x_{i}^{\|}=x_{i}^{\|} ; 2\right)\left\|\widetilde{A_{H}} x \perp\right\|_{2} \leq$ $\lambda(H)\left\|x^{\perp}\right\|_{2}$ since it holds for each $i$. After substituting $x=x^{\|}+x^{\perp}$ into equation 9.1 , the remaining thing is to show that:

$$
\left|\left(x^{\|} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\|}+2\left(x^{\|} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\perp}+\left(x^{\perp} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\perp}\right| \leq \lambda(G)+\lambda(H)+\lambda(H)^{2} .
$$

We will deal with each of three terms separately and by triangle inequality, we will get our result.

1. $\left|\left(x^{\|} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\|}\right| \leq \lambda(G)$.

We define $y \in \mathbb{R}^{N_{1}}$ s.t. $y_{i}=\sqrt{D_{1}} x_{i, 1}^{\|}$. If we collapse $x^{\|}$by shrinking each cloud, and normalizing the result, we will get $y$. We have

$$
\begin{aligned}
\left|\left(x^{\|} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\|}\right| & \left.=\left|x^{\|^{T}} P x^{\|}\right| \quad \text { (by observation } 1\right) \\
& =\left|y^{T} A_{G} y\right| \quad \text { (by cancel out } 2 \sqrt{D_{1}} \text { factors) } \\
& \leq \lambda(G) \quad(\text { by expansion of } G)
\end{aligned}
$$

2. $\left|2\left(x^{\|} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\perp}\right| \leq \lambda(H)$.

$$
\begin{aligned}
\left|2\left(x^{\|} \widetilde{A_{H}}\right)^{T} P \widetilde{P A_{H}} x^{\perp}\right| & =\left|2\left(x^{\|}\right)^{T} P \widetilde{A_{H}} x^{\perp}\right| \quad \text { (by observation 1) } \\
& \leq 2\left\|\left(x^{\|}\right)^{T} P\right\|_{2}\left\|\widetilde{A_{H}} x^{\perp}\right\|_{2} \quad \text { (by Cauchy-Schwartz) } \\
& \leq 2\left\|x^{\|}\right\|_{2} \lambda(H)\left\|x^{\perp}\right\|_{2} \quad \text { (by permuting in the same cloud, and observation 2) } \\
& \leq 2 \lambda(H) \frac{\left\|x^{\|}\right\|_{2}^{2}+\left\|x^{\perp}\right\|_{2}^{2}}{2} \quad \text { (by AM-GM ineq) } \\
& \leq \lambda(H)
\end{aligned}
$$

3. $\left|\left(x^{\perp} \widetilde{A_{H}}\right)^{T} \widetilde{P} \widetilde{A_{H}} x^{\perp}\right| \leq \lambda(H)^{2}$.

$$
\begin{aligned}
\left|\left(x^{\perp} \widetilde{A_{H}}\right)^{T} P \widetilde{A_{H}} x^{\perp}\right| & \leq\left\|\widetilde{A_{H}} x^{\perp}\right\|_{2}\|P\|_{2}\left\|\widetilde{A_{H}} x^{\perp}\right\|_{2} \quad \text { (by Cauchy-Schwartz) } \\
& \leq \lambda(H)^{2}\left\|x^{\perp}\right\|_{2}^{2} \quad\left(\text { since }\|P\|_{2} \text { is at most 1, and observation } 2\right) \\
& \leq \lambda(H)^{2}
\end{aligned}
$$

### 9.3 Constructing Explicit Expanders

### 9.3.1 Mildly Explicit

Let $G_{1}=H$ be a $\left(D^{4}, D, 1 / 4\right)$ expander constructed by brute-force. Let $G_{i+1}=G_{i}^{2}\left(\mathbb{Z} G_{1}\right.$.
Claim 9.7 $G_{n}$ is a $\left(D^{4 n}, D^{2}, 1 / 2\right)$ expander.
Proof: By induction. $G_{n}^{2}:\left(D^{4 n}, D^{4}, 1 / 4\right) . G_{1}:\left(D^{4}, D, 1 / 4\right), G_{n}^{2}$ (Z) $G_{1}:\left(D^{4(n+1)}, D^{2}, 1 / 2\right)$.

### 9.3.2 Strongly Explicit

Let $G_{1}=H$ be a $\left(D^{4}, D, 1 / 4\right)$ expander constructed by brute-force. Let $G_{i+1}=\left(G_{i} \otimes G_{i}\right)^{2}$ (2) $G_{1}$.

