

## Hardness Of Approximation

### Lecture 5: Finishing NP-hardness of $gap3Lin(\frac{1}{2} + \delta, 1 - \delta)$

Instructor: Irit Dinur and Amey Bhangale

Scribe: Roie Salama

## 1 Reminder from Last Week

Last week we described a reduction to  $gap-3Lin$ . The sketch is as follows:

1. Start with an instance  $I_1$  of  $gap-3Lin(0.99, 1 - \epsilon)$ .
2. Construct a "Smooth linear Label Cover" by doing smooth parallel repetition on  $I_1$ .
3. Construct the final instance  $I_2$  of  $gap-3Lin$ .

Check the previous lecture notes for more details. In this lecture, we prove the completeness and soundness of the reduction, thereby finishing the proof of NP-hardness of  $gap-3Lin(\frac{1}{2} + \delta, 1 - \delta)$  for every constant  $\delta > 0$ .

## 2 Completeness and Soundness

### 2.1 Completeness

**Claim 2.1.** *If  $val(I_1) = 1 - \epsilon \Rightarrow val(I_2) \geq 1 - k\epsilon$*

*Proof.* In this case, the instance  $I_1$  is  $(1 - \epsilon)$  satisfiable. We fix this assignment  $\sigma$  to the variables and set  $f_u$  to be the Hadamard encoding of  $\sigma$  restricted to the variables in  $u$ . Clearly, this assignment satisfies the folding property as it is coming from one fixed global assignment. Now, by union bound for at least  $1 - k\epsilon$  fraction of  $U$ , all the constraints are satisfied by  $\sigma$ . Thus, for these  $f_u$ 's, the  $3Lin$  test passes with probability 1. Hence, overall the acceptance probability is  $1 - k\epsilon$  and thus  $val(I_2) \geq 1 - k\epsilon$ .  $\square$

### 2.2 Soundness

**Claim 2.2.** *Assume  $\delta \gg O(\beta\sqrt{k})$ . If  $Val(I_2) \geq \frac{1}{2} + \delta \Rightarrow$  the value of the Label Cover instance  $\geq \frac{\delta^4}{128}$*

*Proof.* By averaging, for at least  $\frac{\delta}{2}$  of the  $u$ 's,  $f_u$  passes the test with probability greater than  $\frac{1}{2} + \frac{\delta}{2}$ . Now, using Claim 4.1 from the previous lecture, for every such  $u$  we have  $|\hat{f}_u(S)| \geq \delta$  for some  $S \subseteq [3k]$  such that the vector  $1_S$  satisfies the clauses  $C_1^u, C_2^u, \dots, C_k^u$  (constraints corresponding to  $u$ ). Call these  $u$ 's "good", and also these  $S$ 's "good".

Note that good  $S$ 's are "rare", in the sense that for every function  $f_u$ , at most  $\frac{1}{\delta^2}$  of its coefficients are greater than  $\delta$ , that follows from the fact that  $\sum_S \hat{f}_u(S)^2 = 1$ .

For by the sub-code covering property, we have

$$\begin{aligned} \hat{f}_u(S) &:= \mathbb{E}_{x \in \{0,1\}^{3k}} [f_u(x) \chi_S(x)] \\ (\text{Claim 3.2, lecture 4}) &= \mathbb{E}_{v \in N(u)} \mathbb{E}_{y \in \{0,1\}^{3k-2\beta k}} [f_u(y^{\uparrow uv}) \chi_S(y^{\uparrow uv})] \pm O(\beta\sqrt{k}) \\ &= \mathbb{E}_{v \in N(u)} [\hat{f}_v(S^{\downarrow uv})] \pm O(\beta\sqrt{k}) \end{aligned}$$

Here,  $S^{\downarrow uv}$  is an operation which takes a string from the domain of  $f_u$  to the domain of  $f_v$  in a natural way by deleting the extra coordinates. Thus, for a good  $S$ , we have

$$\mathbb{E}_{v \in N(u)}[\hat{f}_v(S^{\downarrow uv})] \geq \delta - O(\beta\sqrt{k}) \geq \frac{\delta}{2},$$

assuming  $\delta \gg O(\beta\sqrt{k})$ . Note that for an edge  $(u, v)$  the label pair  $(1_S, 1_{S^{\downarrow uv}})$  satisfies the constraint on the edge  $(u, v)$  for every good  $S$ . Thus, the above inequality says that for a typical neighbor of a good  $u$ , the Fourier coefficient corresponding to the projected label is also heavy. More formally, by averaging argument, at least  $\frac{\delta}{4}$  fraction of  $v \in N(u)$ ,  $|\hat{f}_v(S^{\downarrow uv})| \geq \frac{\delta}{4}$ .

This gives a randomized strategy to get a non trivial satisfying assignment to the Label Cover instance. For every good  $u$ , assign a random label from the following set

$$\mathcal{L}_u := \{1_S \mid \hat{f}_u(S) \geq \delta \text{ and } 1_S \text{ satisfies } C_1^u, C_2^u, \dots, C_k^u\}.$$

Also, for  $v \in V$ , assign a random label from the following list

$$\mathcal{L}_v := \left\{ 1_T \mid \hat{f}_v(T) \geq \frac{\delta}{4} \right\}.$$

(Here  $f_v$  is embedded in  $f_u$  and it does not matter which  $u$  one chooses, as we get the same function because of the folding.) We know  $|\mathcal{L}_v|$  is of size at most  $\frac{16}{\delta^2}$ . For a good  $u$ ,  $|\mathcal{L}_u| \geq 1$  and suppose we pick a label  $1_S$ . Using the above argument, for at least  $\frac{\delta}{4}$  fraction of  $v \in N(u)$ , the label  $1_{S^{\downarrow uv}}$  is present in  $\mathcal{L}_v$ . For such neighbors, the probability that the constraint on  $(u, v)$  is satisfied by the randomized labeling is at least  $\frac{\delta^2}{16}$  (this is because we have to pick the correct label from a list of size at most  $\frac{16}{\delta^2}$ ). Thus in expectation, for at least  $\frac{\delta}{2}$  fraction of  $u$  (these are the good  $u$ 's), for at least  $\frac{\delta}{4}$  fraction of the neighbors of  $u$ , the constraint is satisfied with probability at least  $\frac{\delta^2}{16}$ . Overall, at least  $\frac{\delta^4}{128}$  fractions of the constraints are satisfied by the randomized labeling in expectation.  $\square$

Recall that we are setting  $k = \frac{1}{\sqrt{\epsilon}}$  and  $\beta = \frac{1}{k^{0.6}}$ . Thus, the in the soundness case, the value of the Label Cover instance is at most  $2^{-\Omega(\beta k)} = 2^{-\Omega(k^{0.4})}$  and hence from the above claim  $\text{val}(I_2)$  is at most  $\frac{1}{2} + O(\beta\sqrt{k})$  in the soundness case for large enough  $k$ . Therefore we get that  $\text{gap-3Lin}(\frac{1}{2} + O(\frac{1}{k^{0.1}}), 1 - \frac{1}{k^2})$  is NP-hard. Setting  $k$  a large enough constant proves NP-hardness of  $\text{gap-3Lin}(\frac{1}{2} + \delta, 1 - \delta)$  for every constant  $\delta > 0$ .

### 3 Boolean functions and influence

**Definition 3.1.** for  $f : \{-1, +1\}^n \rightarrow \{-1, +1\}$  define its  $i^{\text{th}}$  influence by

$$\text{Inf}_i(f) = \Pr_{x \sim \{-1, +1\}^n} [f(x) \neq f(x^{(i)})],$$

where  $x^{(i)}$  means flipping the  $i$ -th bit of  $x$ .

For example, for the parity function

$$\text{Parity}(x_1, \dots, x_n) = \prod_{i=1}^n x_i$$

$$\forall i : \text{Inf}_i(\text{Parity}) = 1$$

It is easy to see that the  $i^{th}$  influence is precisely the following:

$$Inf_i(f) = \sum_{i \in S} \hat{f}(S)^2$$

Next, we define

$$Inf_i^{(1-\delta)}(f) = \sum_{i \in S} (1 - \delta)^{|S|-1} \hat{f}(S)^2$$

called the  $\delta$ -attenuated influence. While there can be as many as  $n$  coordinates of a Boolean function whose influence is large (eg. Parity has all the influences 1), it is bounded in case of  $\delta$ -attenuated influences of *any* Boolean function.

**Claim 3.2.** *for every  $f : \{-1, +1\}^n \rightarrow \{-1, +1\}$*

$$|\{i \in [n] \mid Inf_i^{(1-\delta)}(f) \geq \epsilon\}| \leq \frac{1}{\epsilon \delta}$$

*Proof.*  $\sum_i Inf_i^{(1-\delta)}(f) = \sum_{i \in S} (1 - \delta)^{|S|-1} \hat{f}(S)^2 = \sum_{S \subset [n]} |S| (1 - \delta)^{|S|-1} \hat{f}(S)^2 \leq \sum_S \frac{1}{\delta} \hat{f}(S)^2 \leq \frac{1}{\delta}$   
and the result follows (because otherwise the sum on the  $\epsilon$ -heavy influences alone would exceed  $\frac{1}{\delta}$ ).  $\square$

## References