

NUMBER OF RIGHT-ANGLE TRIANGLES (PAPER BY PACH–SHARIR)

ABSTRACT.

1. SET UP AND NOTATIONS

- (1) $\mathcal{P} = \{p\}$ denotes a set of finite points in \mathbb{R}^2 . We often write $N := \#\mathcal{P}$. Also, $\mathcal{L} = \{\ell\}$ denotes a set of finite lines in \mathbb{R}^2 .
- (2) Given $p_1, p_2, p_3 \in \mathbb{R}^2$, we denote a triangle spanned by these points by $\triangle(p_1, p_2, p_3)$. Note that $\triangle(p_1, p_2, p_3)$ may be degenerate.
- (3) We are especially interested in a right-angled triangle and

$$\mathcal{T}(\mathcal{P}) := \{(p_1, p_2, p_3) \in (\mathcal{P})^3 : \triangle(p_1, p_2, p_3) \text{ is the right-angle triangle}\}$$

The main result of Pach–Sharir is as follows.

Theorem 1.1 (Pach–Sharir '92). *For any $\mathcal{P} \subset \mathbb{R}^2$,*

e:PachSharir

$$(1.1) \quad \#\mathcal{T}(\mathcal{P}) \leq C(\#\mathcal{P})^2 \log \#\mathcal{P}.$$

We next aim to exhibit the actual estimate, proved by Pach–Sharir, that yields (1.1). The reason of doing this is because it may be interpreted as a certain (discrete) X-ray estimate. For this purpose, we need to introduce the discrete X-ray transform. Suppose we are given a finite points \mathcal{P} .

- (1) For a line $\ell \in \mathbb{R}^2$, define

$$X[\mathcal{P}](\ell) := \#(\mathcal{P} \cap \ell).$$

- (2) Let $\Theta = \Theta(\mathcal{P})$ be a set of directions that spanned by two points of \mathcal{P} : by denoting $\theta_{p,p'} := \frac{p-p'}{|p-p'|}$,

$$\Theta(\mathcal{P}) := \{\theta_{p,p'} : p \neq p' \in \mathcal{P}\}.$$

Note that

e:NumberDirections

$$(1.2) \quad \#\Theta(\mathcal{P}) \leq \binom{\#\mathcal{P}}{2} = \frac{1}{2}\#\mathcal{P}(\#\mathcal{P} - 1) \leq (\#\mathcal{P})^2.$$

- (3) For $\theta \in \mathbb{S}^1$ and $p \in \mathbb{R}^2$, we set

$$\ell^\theta(p) := \{t\theta + p : t \in \mathbb{R}\} = \text{a line in direction } \theta \text{ and passing through } p.$$

We will consider a set of parallel lines in a fixed direction $\theta \in \Theta(\mathcal{P})$ whose centre runs over \mathcal{P} : for each $\theta \in \Theta(\mathcal{P})$,

$$\mathcal{L}^\theta = \mathcal{L}^\theta(\mathcal{P}) := \{\ell^\theta(p) : p \in \mathcal{P}\}.$$

Note that $\ell^\theta(p) = \ell^\theta(p')$ may happen even if $p \neq p'$. Thus,

$$I^\theta = I^\theta(\mathcal{P}) := \#\mathcal{L}^\theta(\mathcal{P}) \leq \#\mathcal{P}.$$

We will often label $\mathcal{L}^\theta(\mathcal{P})$ by

$$\mathcal{L}^\theta(\mathcal{P}) = \{\ell_1^\theta, \dots, \ell_{I^\theta}^\theta\} = \{\ell_i^\theta : i = 1, \dots, I^\theta\}.$$

Similarly, we will also consider a set of vertical lines:

$$\mathcal{L}^{\theta^\perp} = \mathcal{L}^{\theta^\perp}(\mathcal{P}) := \{\ell^{\theta^\perp}(p) : p \in \mathcal{P}\},$$

and label this set by

$$\mathcal{L}^{\theta^\perp}(\mathcal{P}) = \{\ell_1^{\theta^\perp}, \dots, \ell_{J^{\theta^\perp}}^{\theta^\perp}\} = \{\ell_j^{\theta^\perp} : j = 1, \dots, J^{\theta^\perp}\}, \quad J^{\theta^\perp} := \#\mathcal{L}^{\theta^\perp}(\mathcal{P}).$$

(4) Finally, for each $\ell_i^\theta \in \mathcal{L}^\theta(\mathcal{P})$ and $\ell_j^{\theta^\perp} \in \mathcal{L}^{\theta^\perp}(\mathcal{P})$, we denote

$$p_{ij}^\theta := \ell_i^\theta \cap \ell_j^{\theta^\perp},$$

which is a (unique) crossing point of two lines ℓ_i^θ and $\ell_j^{\theta^\perp}$.

With these notations, the main estimate of Pach–Sharir may be stated as follows.

Theorem 1.2 (Pach–Sharir '92). *For any $\mathcal{P} \subset \mathbb{R}^2$,*

e:PachSharir-Xray

$$(1.3) \quad \sum_{\theta \in \Theta(\mathcal{P})} \sum_{i=1}^{I^\theta} \sum_{j=1}^{J^{\theta^\perp}} X[\mathcal{P}](\ell_i^\theta) X[\mathcal{P}](\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \leq C(\#\mathcal{P})^2 \log(\#\mathcal{P}).$$

— A continuous analogue to (1.3) —

Let us try to catch a sense of (1.3). Use our familiar notation $Xf(\theta, v) := \int_{\mathbb{R}} f(t\theta + v) dt$. Then the continuous analogue to LHS of (1.3) is as follows:

$$\int_{\mathbb{S}^1} \int_{v_1 \in \langle \theta \rangle^\perp} \int_{v_2 \in \langle \theta \rangle} Xf(\theta, v_1) Xf(\theta^\perp, v_2) K(v_1, v_2; \theta) d\lambda_{\langle \theta \rangle^\perp}(v_1) d\lambda_{\langle \theta \rangle}(v_2) d\sigma(\theta),$$

where $K(v_1, v_2; \theta)$ is some integral kernel^a.

^amaybe something like

$$K(v_1, v_2; \theta) = \mathbf{1}_{\text{supp } f}(\ell^\theta(v_1) \cap \ell^{\theta^\perp}(v_2))???$$

We will see how (1.3) implies their main result (1.1) later.

2. PROOF OF THEOREM OF PACH–SHARIR

Let us give a proof of (1.1). We take arbitrary $\mathcal{P} \subset \mathbb{R}^2$ and fix it below. We thus sometimes abbreviate the dependence of \mathcal{P} .

2.1. Implication of (1.3) \Rightarrow (1.1). In this subsection, we give an interpretation of the problem about the number of right-angle triangles in terms of the X-ray transform. A goal here is to show the following representation:

Claim 2.1. By using above notations,

$$(2.1) \quad \#\mathcal{T}(\mathcal{P}) = \sum_{\theta \in \Theta(\mathcal{P})} \sum_{i=1}^{I^\theta} \sum_{j=1}^{J^{\theta^\perp}} (X[\mathcal{P]}(\ell_i^\theta) - 1)(X[\mathcal{P]}(\ell_j^{\theta^\perp}) - 1) \mathbf{1}_{\mathcal{P}}(\ell_i^\theta \cap \ell_j^{\theta^\perp}).$$

Once one could see this claim, then it in particular follows that

$$(2.2) \quad \#\mathcal{T}(\mathcal{P}) \leq \sum_{\theta \in \Theta(\mathcal{P})} \sum_{i=1}^{I^\theta} \sum_{j=1}^{J^{\theta^\perp}} X[\mathcal{P]}(\ell_i^\theta) X[\mathcal{P]}(\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(\ell_i^\theta \cap \ell_j^{\theta^\perp}).$$

Thus, their main result (1.1) would follow from their X-ray estimate (1.3).

Proof of (2.1). Fix a direction $\theta \in \Theta(\mathcal{P})$ and create a grid

$$\mathcal{L}^\theta \times \mathcal{L}^{\theta^\perp} = \{\ell_1^\theta, \dots, \ell_{I^\theta}^\theta\} \times \{\ell_1^{\theta^\perp}, \dots, \ell_{J^{\theta^\perp}}^{\theta^\perp}\}.$$

We then focus on right-angle triangles with an ‘orientation’ at θ or θ^\perp , (equivalently those created from the grid $\mathcal{L}^\theta \times \mathcal{L}^{\theta^\perp}$). In order to give more precise definition, let us first introduce a subset of \mathcal{T} defined by

$$\mathcal{T}^\theta(p_{ij}^\theta) := \{\Delta(p_{ij}^\theta, p_{i'j}^\theta, p_{ij'}^\theta) : i' \in \{1, \dots, I^\theta\} \setminus \{i\}, j' \in \{1, \dots, J^{\theta^\perp}\} \setminus \{j\} \text{ s.t. } p_{i'j}^\theta, p_{ij'}^\theta \in \mathcal{P}\},$$

for each $(i, j) \in \{1, \dots, I^\theta\} \times \{1, \dots, J^{\theta^\perp}\}$ such that $p_{ij}^\theta := \ell_i^\theta \cap \ell_j^{\theta^\perp} \in \mathcal{P}$. What does this subset mean? In one word, this is a set of all right-angle triangles in \mathcal{T} whose ‘orthogonal vertex’ is at p_{ij}^θ ; see my hand-written picture for more instinct! We then define

$$\mathcal{T}^\theta := \bigcup_{(i,j): p_{ij}^\theta \in \mathcal{P}} \mathcal{T}^\theta(p_{ij}^\theta).$$

This is a collection of all right-angle triangles whose shortest edge is oriented at either θ or θ^\perp . Thus, \mathcal{T} , all right-angle triangles, may be decomposed into

$$\mathcal{T} = \bigcup_{\theta \in \Theta} \mathcal{T}^\theta = \bigcup_{\theta \in \Theta} \bigcup_{(i,j): p_{ij}^\theta \in \mathcal{P}} \mathcal{T}^\theta(p_{ij}^\theta).$$

As an important remark, we note that $\mathcal{T}^\theta(p_{ij}^\theta)$ and $\mathcal{T}^{\theta'}(p_{i'j'}^{\theta'})$ are ‘independent’ in the sense that

$$\mathcal{T}^\theta(p_{ij}^\theta) \cap \mathcal{T}^{\theta'}(p_{i'j'}^{\theta'}) = \emptyset$$

e: NumberRightangle-Xray

berRightangle-Xray(Ineq)

whenever $(\theta, i, j) \neq (\theta', i', j')$ (that is, either one of the following holds true: $\theta \neq \theta'$, $i \neq i'$, or $j \neq j'$). Therefore, we have that

$$\#\mathcal{T} = \sum_{\theta \in \Theta} \sum_{i=1}^{I^\theta} \sum_{j=1}^{J^{\theta^\perp}} \#\mathcal{T}^\theta(p_{ij}^\theta) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta).$$

Finally, for fixed (i, j) such that $p_{ij}^\theta \in \mathcal{P}$, we notice from the definition of $\mathcal{T}^\theta(p_{ij}^\theta)$ that

$$\begin{aligned} \#\mathcal{T}^\theta(p_{ij}^\theta) &= \#\{i' \in \{1, \dots, I^\theta\} \setminus \{i\} : p_{i'j}^\theta \in \mathcal{P}\} \times \#\{j' \in \{1, \dots, J^{\theta^\perp}\} \setminus \{j\} : p_{ij'}^\theta \in \mathcal{P}\} \\ &= (X[\mathcal{P}](\ell_j^{\theta^\perp}) - 1)(X[\mathcal{P}](\ell_i^\theta) - 1). \end{aligned}$$

This concludes the proof of (2.1). \square

2.2. Szemerédi–Trotter in X-ray language.

Theorem 2.2 (Szemerédi–Trotter for lines). *Let \mathcal{L} be a finite collection of lines in \mathbb{R}^2 , and $k \in \mathbb{N}$. Then*

$$\begin{aligned} \#\{k\text{-rich points of } \mathcal{L}\} &:= \#\{p \in \mathbb{R}^2 : \exists \ell_1, \dots, \ell_k \in \mathcal{L} \text{ s.t. } x \in \ell_1 \cap \dots \cap \ell_k\} \\ \text{e:ST-Line} \quad (2.3) \quad &\leq C \max\left\{\frac{(\#\mathcal{L})^2}{k^3}, \frac{\#\mathcal{L}}{k}\right\}. \end{aligned}$$

According to the well-known point-line duality, (2.3) is equivalent to the following:

Theorem 2.3 (Szemerédi–Trotter for points). *Let \mathcal{L} be a finite collection of lines in \mathbb{R}^2 , \mathcal{P} be a finite collection of points in \mathbb{R}^2 , and $k \in \mathbb{N}$. Then*

$$\text{e:ST-Point} \quad (2.4) \quad \#\{\ell \in \mathcal{L} : \exists p_1, \dots, p_k \in \mathcal{P} \cap \ell\} \leq C \max\left\{\frac{(\#\mathcal{P})^2}{k^3}, \frac{\#\mathcal{P}}{k}\right\}.$$

The inequality (2.4) may be described in terms of the X-ray transform as follows:

Corollary 2.4 (Szemerédi–Trotter in terms of X-ray transform). *Let \mathcal{L} be a finite collection of lines in \mathbb{R}^2 , \mathcal{P} be a finite collection of points in \mathbb{R}^2 , and $k \in \mathbb{N}$. Then*

$$\text{e:ST-X-ray} \quad (2.5) \quad \#\{\ell \in \mathcal{L} : X[\mathcal{P}](\ell) \geq k\} \leq C \max\left\{\frac{(\#\mathcal{P})^2}{k^3}, \frac{\#\mathcal{P}}{k}\right\}.$$

Proof. Clearly, $\exists p_1, \dots, p_k \in \mathcal{P} \cap \ell$ is equivalent to $X[\mathcal{P}](\ell) \geq k$. \square

Szemerédi–Trotter = weak-type estimate of the X-ray transform

The threshold of k in (2.5) is given by $k = \sqrt{\#\mathcal{P}}$.

(1) In the case of $k \geq \sqrt{\#\mathcal{P}}$, (2.5) becomes

$$\#\{\ell \in \mathcal{L} : X[\mathcal{P]}(\ell) \geq k\} \leq C \frac{\#\mathcal{P}}{k}.$$

This may be manifestly read as

$$\|X[\mathbf{1}_{\mathcal{P}}]\|_{L^{1,\infty}(\mathcal{L})} \leq C \|\mathbf{1}_{\mathcal{P}}\|_{L^1}.$$

(2) In the case of $k \leq \sqrt{\#\mathcal{P}}$, (2.5) becomes

$$\#\{\ell \in \mathcal{L} : X[\mathcal{P]}(\ell) \geq k\} \leq C \frac{(\#\mathcal{P})^2}{k^3}.$$

This may be manifestly read as

$$(2.6) \quad \|X[\mathbf{1}_{\mathcal{P}}]\|_{L^{3,\infty}(\mathcal{L})}^3 \leq C \|\mathbf{1}_{\mathcal{P}}\|_{L^{\frac{3}{2}}}^3.$$

e:ST-L3/2-weakL3

In particular, (2.6) suggests a strong type estimate of $X[\mathcal{P}]$ by loosing some logarithmic factor. This is indeed the case as follows:

Corollary 2.5 (Strong $L^{\frac{3}{2}}$ - L^3 bound of the X-ray transform). *Let \mathcal{L} be a finite collection of lines in \mathbb{R}^2 , \mathcal{P} be a finite collection of points in \mathbb{R}^2 , and $N := \#\mathcal{P}$. Then*

e:ST-StrongX-ray

$$(2.7) \quad \|\mathbf{1}_{\{X[\mathcal{P]} \leq \sqrt{N}\}} X[\mathcal{P}]\|_{L^3(\mathcal{L})}^3 \leq C \log N \|\mathbf{1}_{\mathcal{P}}\|_{L^{\frac{3}{2}}}^3 = C(\#\mathcal{P})^2 \log \#\mathcal{P}.$$

Proof. This is perhaps standard argument to upgrade some weak-type estimate to the strong one by allowing logarithmic loss.

$$\begin{aligned} \|\mathbf{1}_{\{X[\mathcal{P]} \leq \sqrt{N}\}} X[\mathcal{P}]\|_{L^3(\mathcal{L})}^3 &= \sum_{\ell \in \mathcal{L} : X[\mathcal{P]}(\ell) \leq \sqrt{N}} X[\mathcal{P]}(\ell)^3 \\ &= \sum_{k=0}^{\sqrt{N}} \sum_{\ell \in \mathcal{L} : X[\mathcal{P]}(\ell) = k} X[\mathcal{P]}(\ell)^3 \\ &= \sum_{k=0}^{\sqrt{N}} k^3 L_{=k}, \end{aligned}$$

where

$$L_{=k} := \#\{\ell \in \mathcal{L} : X[\mathcal{P]}(\ell) = k\}.$$

By introducing

$$L_{\geq k} := \#\{\ell \in \mathcal{L} : X[\mathcal{P]}(\ell) \geq k\},$$

we readily see that

$$L_{=k} = L_{\geq k} - L_{\geq k+1}.$$

Thus,

$$\begin{aligned}
\|\mathbf{1}_{\{X[\mathcal{P}] \leq \sqrt{N}\}} X[\mathcal{P}]\|_{L^3(\mathcal{L})}^3 &= \sum_{k=0}^{\sqrt{N}} k^3 (L_{\geq k} - L_{\geq k+1}) \\
&= 0 + \sum_{k=1}^{\sqrt{N}} k^3 L_{\geq k} - \sum_{k=1}^{\sqrt{N}} (k-1)^3 L_{\geq k} - (\sqrt{N})^3 L_{\geq \sqrt{N}+1} \\
&= \sum_{k=1}^{\sqrt{N}} (3k^2 - 3k + 1) L_{\geq k} - (\sqrt{N})^3 L_{\geq \sqrt{N}+1} \\
&\leq 4 \sum_{k=1}^{\sqrt{N}} k^2 L_{\geq k}.
\end{aligned}$$

We now then apply Szemerédi–Trotter in terms of the X-ray transform (2.5) to conclude that

$$\|\mathbf{1}_{\{X[\mathcal{P}] \leq \sqrt{N}\}} X[\mathcal{P}]\|_{L^3(\mathcal{L})}^3 \leq C \sum_{k=1}^{\sqrt{N}} k^2 \frac{(\#\mathcal{P})^2}{k^3} = C(\#\mathcal{P})^2 \log(\#\mathcal{P}).$$

□

2.3. Conclude the proof of (1.3). Given above preparation, we are now at the stage of doing something trivial, that is Cauchy–Schwarz. First, we separate three cases

e: Bilinear Xray

$$\begin{aligned}
&\sum_{\theta \in \Theta} \sum_{i=1}^{I^\theta} \sum_{j=1}^{J^{\theta^\perp}} X[\mathcal{P}](\ell_i^\theta) X[\mathcal{P}](\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \\
(2.8) \quad &= \sum_{\theta \in \Theta} \sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta) \sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \\
&\quad + \text{term involving } \sum_{i: X[\mathcal{P}](\ell_i^\theta) > \sqrt{N}} \quad + \text{term involving } \sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) > \sqrt{N}}.
\end{aligned}$$

As we will see in the end, the main contribution comes from the first term. So, we will focus on how to deal with the first term. We fix $\theta \in \Theta$ and estimate

e: CS1

$$\begin{aligned}
&\sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} \sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta) X[\mathcal{P}](\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \\
(2.9) \quad &\leq \left(\sum_{i,j} \mathbf{1}_{\{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}\}} X[\mathcal{P}](\ell_i^\theta)^2 \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \right)^{\frac{1}{2}} \left(\sum_{i,j} \mathbf{1}_{\{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}\}} X[\mathcal{P}](\ell_j^{\theta^\perp})^2 \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \right)^{\frac{1}{2}} \\
&= \left(\sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta)^2 \sum_j \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \right)^{\frac{1}{2}} \left(\sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_j^{\theta^\perp})^2 \sum_i \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \right)^{\frac{1}{2}}.
\end{aligned}$$

Notice that

$$\sum_j \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) = \#\{j \in \{1, \dots, J^{\theta^\perp}\} : \ell_i^\theta \cap \ell_j^{\theta^\perp} \in \mathcal{P}\} = X[\mathcal{P}](\ell_i^\theta),$$

and similarly

$$\sum_i \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) = X[\mathcal{P}](\ell_j^{\theta^\perp}).$$

Therefore,

$$\begin{aligned} & \sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} \sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta) X[\mathcal{P}](\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \\ & \leq \left(\sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta)^3 \right)^{\frac{1}{2}} \left(\sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_j^{\theta^\perp})^3 \right)^{\frac{1}{2}}. \end{aligned}$$

By taking a summation in θ and applying CS again,

First term

$$\begin{aligned} & = \sum_{\theta \in \Theta} \sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} \sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta) X[\mathcal{P}](\ell_j^{\theta^\perp}) \mathbf{1}_{\mathcal{P}}(p_{ij}^\theta) \\ & \leq \sum_{\theta \in \Theta} \left(\sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta)^3 \right)^{\frac{1}{2}} \left(\sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_j^{\theta^\perp})^3 \right)^{\frac{1}{2}} \\ \boxed{\text{e: CS2}} \quad (2.10) \quad & \leq \left(\sum_{\theta} \sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta)^3 \right)^{\frac{1}{2}} \left(\sum_{\theta} \sum_{j: X[\mathcal{P}](\ell_j^{\theta^\perp}) \leq \sqrt{N}} X[\mathcal{P}](\ell_j^{\theta^\perp})^3 \right)^{\frac{1}{2}} \\ & = \sum_{\theta} \sum_{i: X[\mathcal{P}](\ell_i^\theta) \leq \sqrt{N}} X[\mathcal{P}](\ell_i^\theta)^3 = \|\mathbf{1}_{\{X[\mathcal{P}](\ell) \leq \sqrt{N}\}} X[\mathcal{P}]\|_{L^3(\mathcal{L})}^3, \end{aligned}$$

where \mathcal{L} denotes all lines spanned by two points of \mathcal{P} . We conclude the desired estimate for the first term of (2.8) from $L^{\frac{3}{2}}-L^3(\mathcal{L})$ boundedness of $X[\mathcal{P}]$ (2.7).

We are left to handle other terms in (2.8). However, these terms will be bounded by $\#\mathcal{P} \log \#\mathcal{P}$, and thus it is an error term; see original paper by Pach–Sharir for details.