# On measure concentration in graph products 

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Abstract. Bollobás and Leader [1] showed that among the $n$-fold products of connected graphs of order $k$ the one with minimal $t$-boundary is the grid graph. Given any product graph $G$ and a set $A$ of its vertices that contains at least half of $V(G)$, the number of vertices at a distance at least $t$ from $A$ decays (as $t$ grows) at a rate dominated by $\mathbb{P}\left(X_{1}+\ldots+X_{n} \geqslant t\right)$ where $X_{i}$ are some simple i.i.d. random variables. Bollobás and Leader used the moment generating function to get an exponential bound for this probability. We insert a missing factor in the estimate by using a somewhat more subtle technique (cf. [3]).

Keywords: graph product, discrete isoperimetric inequalities, concentration of measure, sums of independent random variables, tail probabilities, large deviations.

## 1. Introduction and theorem

Consider a finite set $[k]$ consisting of $k$ elements: $\{0,1, \ldots, k-1\}$. We may define various metrics (distances) $d$ on $[k]$. One of the ways to do that is to consider a graph $G=(V, E)$ with a vertex set $V=[k]$ and define the distance $d(a, b)$, as the length of the shortest path between $a$ and $b$. In order to have a finite metric, we will, of course, put a restriction that the graph $G$ is connected.

If, for example, we choose $G$ to be a path $P_{k}$, i.e., graph with the edge set $E=$ $\{\{0,1\},\{1,2\}, \ldots,\{k-2, k-1\}\}$ then the resulting metric is the one inherited from the real line with the Euclidean distance. On the other hand, if $G$ is a complete graph $K_{k}$ on $k$ vertices, consisting of all possible pairs of vertices, then $d(a, b)=1$ iff $a \neq b$.

Let us consider a product $[k]^{n}$ of metric spaces $\left([k], d_{1}\right), \ldots,\left([k], d_{n}\right)$ each with the same number of elements but probably distinct metrics $d_{i}$. Let us denote elements of $[k]^{n}$ as $a=\left(a_{1}, \ldots, a_{n}\right)$.

It is easy to see that the $l_{1}$-type metric on $[k]^{n}$ defined as

$$
d(a, b)=d_{1}\left(a_{1}, b_{1}\right)+\cdots+d_{n}\left(a_{n}, b_{n}\right)
$$

is indeed a metric. We choose this way of defining a metric on the product space because we can reconstruct a graph on $[k]^{n}$ by considering a pair $\{a, b\}$ an edge if and only if $d(a, b)=1$.

If metrics $d_{i}$ are induced by graphs $G_{i}$ we shall refer to the graph reconstructed from the metric $d$ as the cartesian product of graphs $G_{i}, i=1, \ldots, n$, denoting it $G=G_{1} \times \ldots \times G_{n}$. We can equivalently define $G$ by saying that a pair $\{a, b\}$ of vertices is an edge whenever there is $i$ such that $\left\{a_{i}, b_{i}\right\}$ is an edge in $G_{i}$ and $a_{j}=b_{j}$ for all $j \neq i$.

Consider the example where $G_{i}=P_{k}$. Multiplying a path by itself we obtain so called $n$-dimensional grid graphs.

Given a subset of vertices $A \subset V$ of a graph $G$ which is not too small (say, has at least $|V| / 2$ elements), how big is its neighbourhood, i.e., vertices having a neighbour in the set $A$ ? More generally, how many vertices are there at a distance from $A$ at most $t$ ?

Let us denote $t$-neighbourhood of $A$ as $A_{t}:=\{a \in V: d(a, b) \leqslant t$ for some $b \in A\}$. Given a graph, we are interested in finding a set that has the smallest $t$-boundary, it is, determining the quantity

$$
\begin{equation*}
\min _{|A| \geqslant|V| / 2}\left|A_{t}\right| \tag{1}
\end{equation*}
$$

It turns out that in the case of product graphs of high dimension a striking phenomenon (known as concentration of measure) is observed: $A_{t}$ is almost all of $V$ whenever $t$ is a small proportion of the diameter of $G$.

We may pose a question from another point of view: given a class of graphs, which one has the slowest growth of $A_{t}$, or, seeking a slightly weaker answer, what is a good lower bound for (1)? This was fully answered by Bollobás and Leader [1] in case when the class consists of all $n$-fold products of graphs on $k$ vertices.

Consider, for $r \geqslant 0$, balls around zero $B_{k}^{(n)}(r)=\left\{a \in[k]^{n}: \sum_{i} a_{i} \leqslant r\right\}$.
THEOREM 1 [Bollobás and Leader, [1]]. Let $G_{1}, \ldots, G_{n}$ be connected graphs of order $k$. Let $G=\prod_{i=1}^{n} G_{i}$ be their product. Suppose $r \in\{0,1,2, \ldots\}$, and $A \subset V(G)$ is such that $|A| \geqslant\left|B_{k}^{(n)}(r)\right|$. Then, for $t=0,1,2, \ldots$

$$
\left|A_{t}\right| \geqslant\left|B_{k}^{(n)}(r+t)\right|
$$

The lower bound given by Theorem 1 can be interpreted using probability. Let $X_{1}, \ldots, X_{n}$ be independent copies of a random variable $X$ distributed uniformly over [ $k$ ]:

$$
\begin{equation*}
\mathbb{P}(X=j)=1 / k \quad \text { for all } j \in[k] \tag{2}
\end{equation*}
$$

Now we can estimate $\left|B_{k}^{(n)}(r+t)\right|$ by the means of the following representation:

$$
\begin{equation*}
\left|B_{k}^{(n)}(r+t)\right| / k^{n}=\mathbb{P}\left(X_{1}+\cdots+X_{n} \leqslant r+t\right) \tag{3}
\end{equation*}
$$

Let

$$
\begin{equation*}
Y_{i}=X_{i}-\mathbb{E} X_{i}, \quad i=1,2, \ldots ; \quad S_{n}=Y_{1}+\cdots+Y_{n} \tag{4}
\end{equation*}
$$

Bollobás and Leader [1] estimated the moment generating function $\exp \left\{h S_{n}\right\}$ by calculating moments of $S_{n}$ and then used Chebyshev's inequality

$$
\begin{equation*}
\mathbb{P}\left(S_{n} \geqslant t\right) \leqslant \inf _{h>0} \exp \left\{h\left(S_{n}-t\right)\right\} \tag{5}
\end{equation*}
$$

to obtain the following statement.

THEOREM 2 [Bollobás and Leader [1]]. Let $G_{1}, \ldots, G_{n}$ be connected graphs of order $k$ and let $G=\prod_{i=1}^{n} G_{i}$. Suppose $A \subset V(G)$ is such that $|A| \geqslant|V(G)| / 2$. Then, for $t=0,1,2, \ldots$, we have

$$
\begin{equation*}
1-\left|A_{t}\right| / k^{n} \leqslant \mathbb{P}\left\{S_{n} \geqslant t\right\} \leqslant \exp \left\{-\frac{6 t^{2}}{\left(k^{2}-1\right) n}\right\}=\exp \left\{-\frac{t^{2}}{2 n \sigma^{2}}\right\} \tag{6}
\end{equation*}
$$

where $S_{n}$ is the random variable defined in (4) and $n \sigma^{2}=\operatorname{Var} S_{n}$.
Using the Central Limit Theorem we can see that the constant $6 /\left(k^{2}-1\right)$ in (6) cannot be improved. However, one could expect a bound similar to the right tail of a normal random variable with variance $n \sigma^{2}$. We show that this is indeed the case.

THEOREM 3. For the random variable $S_{n}$ defined in (4) and $t \in \mathbb{R}$ we have

$$
\mathbb{P}\left\{S_{n} \geqslant t\right\} \leqslant c I\left(\frac{t}{\sigma \sqrt{n}}\right) \leqslant \frac{c}{\sqrt{2 \pi}} \frac{\sigma \sqrt{n}}{t} \exp \left\{-\frac{t^{2}}{2 n \sigma^{2}}\right\}
$$

where $I(x)=1-\Phi(x)$ is the survival function of a standard normal random variable, $c=5!e^{5} / 5^{5}=5.699 \ldots$, and $\sigma^{2}=\left(k^{2}-1\right) / 12=\operatorname{Var} S_{n} / n$.

The author conjectures that the constant $c=5.699 \ldots$ can be replaced by a constant $c=3!e^{3} / 3^{3}=4.463 \ldots$

Theorem 3 gives an improvement upon the bound (6) whenever $t$ is of order larger than $\sigma \sqrt{n}$ which is the case when we set $t$ to be a 'small fixed proportion' of the diameter of the grid graph, namely $t=\varepsilon \operatorname{diam}\left(P_{k}^{n}\right)=\varepsilon n(k-1)$. with an arbitrarily small $\varepsilon>0$.

Proof of Theorem 3. Consider, for any $h<t$, a function $x \mapsto(x-h)_{+}^{5}$. As $\mathbb{I}\{x \geqslant t\} \leqslant(x-h)_{+}^{5} /(t-h)^{5}$, we get

$$
\begin{equation*}
\mathbb{P}\left\{S_{n} \geqslant t\right\}=\mathbb{E} \mathbb{I}\left\{S_{n} \geqslant t\right\} \leqslant \inf _{h<t} \frac{\mathbb{E}\left(S_{n}-h\right)_{+}^{5}}{(t-h)^{5}} \tag{7}
\end{equation*}
$$

Applying Lemma 3 and Lemma 1.1 of [2] we conclude the proof.

## 2. Lemmas and their proofs

Consider a random variable $\tau=\tau\left(b, \sigma^{2}\right)$ which assumes values $\{-b, 0, b\}$, with probabilities

$$
\mathbb{P}(\tau=-b)=\mathbb{P}(\tau=b)=\frac{\sigma^{2}}{2 b^{2}} \quad \text { and } \quad \mathbb{P}(\tau=0)=1-\frac{\sigma^{2}}{b^{2}}
$$

Lemma 1. For any $h \in \mathbb{R}$ we have

$$
\begin{equation*}
\mathbb{E}(Y-h)_{+}^{5} \leqslant \mathbb{E}(\tau-h)_{+}^{5} \tag{8}
\end{equation*}
$$

where $Y$ is a centered discrete uniform random variable on $[k]$ as defined in (4) and $\tau=\tau(\max Y, \operatorname{Var} Y)$.

Proof. Note that $Y$ is symmetric and so satisfies the conditions of Lemma 3 of [5] with $b=\max Y$ and $\sigma^{2}=\operatorname{Var} Y$. Therefore we get that for $h \in \mathbb{R}$

$$
\begin{equation*}
\mathbb{E}(Y-h)_{+}^{3} \leqslant \mathbb{E}(\tau-h)_{+}^{3} \tag{9}
\end{equation*}
$$

To prove (8) it suffices to show that $f(h)=\mathbb{E}(\tau-h)_{+}^{5}-\mathbb{E}(Y-h)_{+}^{5} \geqslant 0$. The function $h \mapsto(x-h)_{+}^{5}$ has the second continuous derivative. Therefore we can differentiate $f$ under the integral to obtain

$$
f^{\prime}(h)=-5 \mathbb{E}(\tau-h)_{+}^{4}+5 \mathbb{E}(Y-h)_{+}^{4}, \quad f^{\prime \prime}(h)=20 \mathbb{E}(\tau-h)_{+}^{3}-20 \mathbb{E}(Y-h)_{+}^{3}
$$

It is obvious that $f\left(b_{1}\right)=f^{\prime}\left(b_{1}\right)=0$. Moreover, $f$ is convex because from (9) we have $f^{\prime \prime} \geqslant 0$. Therefore $f \geqslant 0$.

The following result is probably the essence of the paper.
LEMMA 2. Let $\tau=\tau\left(b, \sigma^{2}\right)$ with $b$ and $\sigma$ satisfying $\sigma^{2} / b^{2} \geqslant 1 / 3$. Then for all $h \in \mathbb{R}$ we have

$$
\mathbb{E}(\tau-h)_{+}^{5} \leqslant \mathbb{E}(\eta-h)_{+}^{5}
$$

where $\eta$ is a normal random variable with mean zero and variance $\sigma^{2}$.
Proof. For simplicity and without loss of generality we may assume that $b=1$, because the general case follows by rescaling. Under this assumption we have that $\sigma^{2} \geqslant 1 / 3$. To prove the lemma it suffices to show that $\mathbb{E}(\eta-h)_{+}^{5}-\mathbb{E}(\tau-h)_{+}^{5}=$ : $f(h) \geqslant 0$.

Case 1. If $h \geqslant 1$, then $(\tau-h)_{+} \equiv 0$ so $f \geqslant 0$ holds trivially.
Case 2. If $h \leqslant-1$, then

$$
\begin{aligned}
f(h) & =\mathbb{E}(\eta-h)_{+}^{5}-\mathbb{E}(\tau-h)^{5} \geqslant \mathbb{E}(\eta-h)^{5}-\mathbb{E}(\tau-h)^{5} \\
& =\left(-5 h \mathbb{E} \eta^{4}-10 h^{3} \mathbb{E} \eta^{2}-h^{5}\right)-\left(-5 h \mathbb{E} \tau^{4}-10 h^{3} \mathbb{E} \tau^{2}-h^{5}\right) \\
& =5 h\left(-3 \sigma^{4}+2 \cdot 1^{4} \cdot \sigma^{2} / 2\right) \geqslant 0
\end{aligned}
$$

since $\sigma^{2} \geqslant 1 / 3$ and odd moments of symmetric random variables vanish.
Case 3. $h \in[-1,0]$. We may reduce this case to the Case 4 as soon as we show that $f(-t) \geqslant f(t)$ for all $t \in[0,1]$. Since $(\eta-t)_{+}=(-\eta+t)_{-}$is equal in distribution to $(\eta+t)_{-}\left(\right.$here $\left.(x)_{-}=\max \{-x, 0\}\right)$, and $\sigma^{2} \geqslant 1 / 3$, we have

$$
\begin{aligned}
f(-t)-f(t) & =\mathbb{E}(\eta+t)_{+}^{5}-\mathbb{E}(\eta-t)_{+}^{5}-\mathbb{E}(\tau+t)_{+}^{5}+\mathbb{E}(\tau-t)_{+}^{5} \\
& =\mathbb{E}(\eta+t)^{5}-(1+t)^{5} \frac{\sigma^{2}}{2}-t^{5}\left(1-\sigma^{2}\right)+(1-t)^{5} \frac{\sigma^{2}}{2} \\
& =5 t \mathbb{E} \eta^{4}+10 t^{3} \mathbb{E} \eta^{2}+t^{5}-5 t \sigma^{2}-10 t^{3} \sigma^{2}-t^{5} \\
& =5 t \cdot 3 \sigma^{4}-5 t \sigma^{2}=5 t\left(3 \sigma^{4}-\sigma^{2}\right) \geqslant 0
\end{aligned}
$$

Case 4. $h \in[0,1]$. It is easy to check that function $f$ restricted to the interval $[0,1]$ is five times differentiable and its $k$-th derivative is

$$
f^{(k)}(h)=(-1)^{k} c_{k}\left(\mathbb{E}(\eta-h)_{+}^{5-k}-\frac{\sigma^{2}}{2}(1-h)^{5-k}\right), \quad k=1,2, \ldots, 5
$$

where $c_{k}$ are positive constants, and we make a convention $0^{0}=1$.
The following argument is clear if one looks at the graphs of $f^{(k)}$.
Note that $f^{(5)}(h)=c_{5} \sigma^{2} / 2-c_{5} \mathbb{P}(\eta>h)$, so $f^{(5)}$ is increasing. By Chebyshev's inequality we have $\mathbb{P}(\eta>1) \leqslant \sigma^{2} / 2$, so $f^{(5)}(1) \geqslant 0$. Consequently, there is a number $x \in[0,1]$ such that $f^{(5)} \leqslant 0$ on $[0, x]$ and $f^{(5)} \geqslant 0$ on $[x, 1]$.á Therefore $f^{(3)}$ is concave on $[0, x]$ and $f^{(3)}$ is convex on $[x, 1]$.

In order to see how the sign of $f^{(3)}$ varies, we observe that

$$
f^{(3)}(0)=-c_{3}\left(\mathbb{E}\left(\eta_{+}\right)^{2}-\sigma^{2} / 2\right)=0, \quad \text { and } \quad f^{(3)}(1)=-c_{3}\left(\mathbb{E}\left((\eta-1)_{+}\right)^{2}\right)<0
$$

Consequently, there is some number $y \in[0,1]$ such that $f^{(3)} \geqslant 0$ on $[0, y]$ and $f^{(3)} \leqslant 0$ on $[y, 1]$. Therefore, $f^{\prime}$ is convex on $[0, y]$ and $f^{\prime}$ is concave on $[y, 1]$.

In order to see how the sign of $f^{\prime}$ varies we check that

$$
\begin{aligned}
& f^{\prime}(0)=-5\left(\mathbb{E}\left(\eta_{+}\right)^{4}-\sigma^{2} / 2\right)=-5\left(3 \sigma^{4} / 2-\sigma^{2} / 2\right) \leqslant 0 \\
& f^{\prime}(1)=-5\left(\mathbb{E}\left(\eta_{+}\right)^{4}\right)<0, \quad \text { and } \quad f^{\prime \prime}(1)=20\left(\mathbb{E}\left(\eta_{+}\right)^{3}\right)>0
\end{aligned}
$$

so we see that $f^{\prime}$ is negative on $[0,1]$. Finally, since $f(1)=\mathbb{E}(\eta-1)_{+}^{5}>0$, we get that $f>0$ on $[0,1]$.

LEMMA 3. Let the random variable $S_{n}$ be defined as in 4. Then for any $h<t$ we have

$$
\begin{equation*}
\mathbb{E}\left(S_{n}-h\right)_{+}^{5} \leqslant \mathbb{E}\left(Z_{n}-h\right)_{+}^{5} \tag{10}
\end{equation*}
$$

where $\eta$ is a centered normal random variable such that $\operatorname{Var} Z_{n}=\operatorname{Var} S_{n}=n \sigma^{2}$.
Proof. We can write $Z$ as a sum $\eta_{1}+\cdots+\eta_{n}$ of i.i.d normal random variables each with mean zero and variance $\sigma^{2}$. We will now use induction on $n$ to prove (10). For $n=1$ it is equivalent to the combination of Lemmas 1 and 2 . Now suppose (10) holds for $1, \ldots, n-1$. Using the induction hypothesis twice (for $n-1$ and 1 ), we get

$$
\begin{aligned}
\mathbb{E}\left(S_{n}-h\right)_{+}^{5} & =\mathbb{E}\left[\mathbb{E}\left(\left(Y_{1}+Y_{2}+\cdots+Y_{n}-h\right)_{+}^{5} \mid Y_{1}\right)\right] \\
& \leqslant \mathbb{E}\left[\mathbb{E}\left(\left(Y_{1}+\eta_{2}+\cdots+\eta_{n}-h\right)_{+}^{5} \mid Y_{1}\right)\right] \\
& =\mathbb{E}\left[\mathbb{E}\left(\left(Y_{1}+\eta_{2}+\cdots+\eta_{n}-h\right)_{+}^{5} \mid \eta_{2}, \ldots, \eta_{n}\right)\right] \\
& \leqslant \mathbb{E}\left[\mathbb{E}\left(\left(\eta_{1}+\eta_{2}+\cdots+\eta_{n}-h\right)_{+}^{5} \mid \eta_{2}, \ldots, \eta_{n}\right)\right]=\mathbb{E}\left(Z_{n}-h\right)_{+}^{5}
\end{aligned}
$$

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## REZIUME

## M. Šileikis. Apie mato koncentracija grafu sandaugoje

Bollobás ir Leader [1] parodè, jog tarp $n$ jungių $k$-osios eilės grafų sandaugų didžiausią mato koncentraciją turi $n$-matès gardelės grafas. Jei aibė $A$ turi pusę grafų sandaugos viršūnių, tai viršūniư, esančių nuo $A$ ne arčiau kaip per $t$, skaičius yra aprěžtas tikimybe $\mathbb{P}\left(X_{1}+\cdots+X_{n} \geqslant t\right)$, kur $X_{i}-$ tam tikri paprasti n.v.p. atsitiktiniai dydžiai. Bollobás ir Leader naudodami momentų generuojančią funkciją gavo eksponentinị ívertị. Naudodami kiek subtilesnę techniką (plg. [3]), mes pagerinome íverčio eilę, itterpdami trūkstamą daugiklị.

Raktiniai žodžiai: grafų sandauga, diskrečios izoperimetrinės nelygybės, mato koncentracija, nepriklausomų atsitiktinių dydžių sumos, uodegų tikimybės, didieji nuokrypiai.

