

Lec 17 Non random fluctuations

$$\text{Since } \lim_{|x| \rightarrow \infty} \frac{T(0, x)}{|x|} = g(z) \quad \text{where } \frac{x}{|x|} \rightarrow z$$

$$\begin{aligned} \text{Fluctuations} &= o(|x|) = T(0, x) - \mathbb{E}[T(0, x)] \\ &\quad + \underbrace{\mathbb{E}[T(0, x)] - g(x)}_{\text{deterministic or nonrandom}} \end{aligned}$$

The first term is controlled by the variance.

$$\sqrt{\mathbb{E}[(T(0, x) - \mathbb{E}[T(0, x)])^2]} = \sqrt{\text{Var}(T(0, x))} \approx |x|^\chi$$

$\chi = \frac{1}{3}$ (conjecturally). But the best bound we

$$\text{have is } \text{Var}(T(0, x)) \leq \frac{|x|}{1 + \log|x|} \Rightarrow \chi \leq \frac{1}{2}$$

It is a major open problem to improve this bound from

$\frac{1}{2}$ (diffusive or Gaussian behavior) to

$\frac{1}{3}$ (Random-matrix subdiffusive behavior)

Let $\boxed{h(x) = T(0, x)}$ for this part of the

lecture (Alexandru's notation)

We wish to control

$$\mathbb{E}[T(0,x)] - g(x) = h(x) - g(x).$$

Exercise: Show $h(x) \geq g(x) \quad \forall x \in \mathbb{Z}^d$

Kesten (1993)

$$g(x) \leq h(x) \leq g(x) + C |x|^{\frac{2}{d}} (\log |x|)^{\frac{1}{d+2}}$$

This is a pretty bad bound and one really ought to

improve the nonrandom fluctuations exponent

(call it γ) to $\gamma \leq \frac{1}{3}$

We don't know this,

1) but Alexander claims Kesten 1993 provides numerical

evidence

2) In last passage percolation with exponential wts

its can be proved.

Kesten's bound is not great, but can we at least

improve it to $\gamma \leq \frac{1}{2}$ like $\alpha \leq \frac{1}{2}$?

Alexander's brilliant argument shows the following:

Thm: (Alexander 93/97):

$$h(x) - g(x) = \mathbb{E} T(0, x) - g(x) \leq C |x|^{1/2} \log |x|$$

average passage time
time constant
#1

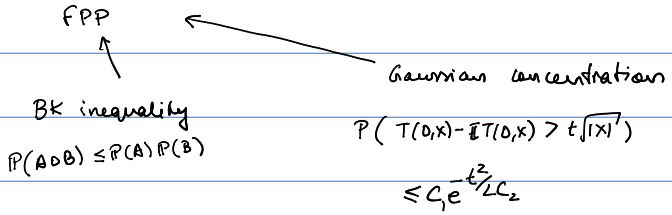
GAP (ν, φ) : h satisfies GAP (ν, φ) if #1 holds $\forall x$.

We will show that $\nu = 1/2$, $\varphi = \log |x|$ for FPP

Ingredients:

1) Alexander's brilliant CHAP / GAP exponent improvement iteration.

2) CHAP (Convex Hull Approximation Property) for



$$\mathbb{E} T(0, x) - g(x) \geq 0$$

deterministic

$$\leq |x|^\nu \varphi(|x|)$$

$$\sqrt{\text{var}(T(0, x))} \leq \frac{|x|^{1/2}}{\sqrt{\log |x|}}$$

$$\nu = \frac{1}{3}, \quad \nu = \frac{1}{2}$$

1) BK inequality.

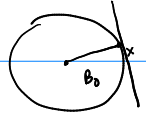
$$2) P(T(0, x) - \mathbb{E} T(0, x) > t \sqrt{|x|}) \leq e^{-Ct^2}$$

Recall $g(x) = \lim_{n \rightarrow \infty} \frac{T(0, nx)}{n}$, $g(x)$ is a norm

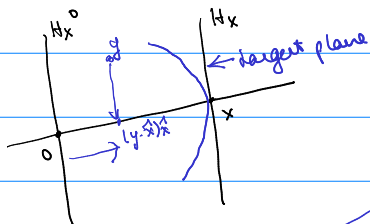
$$C_1 |x|_{B_0} \leq g(x) \leq C_2 |x|$$

$$B_0 = \text{limit shape} = \{x : g(x) \leq 1\}$$

$H_x =$ hyperplane tangent to ∂B_0 at x



$H_x^0 = H_x$ translated to the origin.



$$\{y: g(y) = g(x)\}$$

$$g(\lambda x) = \lambda g(x)$$

\mathbb{H} : homogeneity

linear approximation to the constant.

Define $g_x(y) = g\left(y \cdot \frac{x}{|x|} \cdot \frac{x}{|x|}\right)$

That is $g_x(y)$ is the unique linear functional

that is 1) $g_x(y) = 0$ on H_x^0

2) $g_x(x) = g(x)$

POLL.

would you be willing to meet on Friday night

YES

NO

Exercise: Show $|g_x(y)| \leq g(x)$ using the symmetries of g and convexity.

$$Q_x(\psi, \varphi) = \{y \in \mathbb{Z}^d: |y| \leq K|x|, g_x(y) \leq g(x),$$

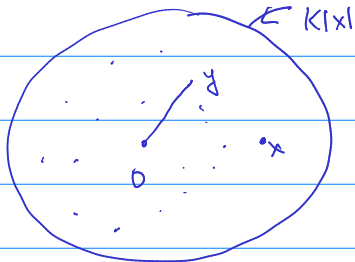
$$h(y) \leq g_x(y) + C|x|^\psi \varphi(|x|)\}$$

← GAP

So K and C are constants, but we will suppress them

$\varphi: [1, \infty) \rightarrow \mathbb{R}$ is a nonnegative increasing fn.

Q_x is the set of good increments y (good for $h(y)$)



$$h(y) = \mathbb{E}T(0, y)$$

$$h(y) - g_x(y) \leq C|x|^\psi \varphi(|x|)$$

$\psi < 1$

That help id make good progress towards $g(x)$

1) $g_x(y) \leq g(x)$ makes sure we're making

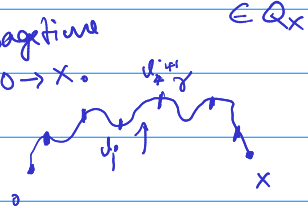
"progress towards $g(x)$ "

2) $h(y) \leq g_x(y) + C|x|^d \log |x|$ makes sure
 $\hookrightarrow \leq g(x)$
 the increments are GOOD.

error on these increments is small
 and there are not too many increments.
 $\exists v_{i+1} - v_i \in \text{"good increments"}$

Idea: How would one try to prove gap?

Follows from considerations of the paragonetina
 an a geodesic from $0 \rightarrow x$.



Suppose \exists m good increments in $Q_x(v, \varphi)$

st $x = \sum_{i=1}^m y_i$

Then $h(x) \leq \sum_{i=1}^m h(y_i) \leq \sum_{i=1}^m g_x(y_i) + C|y_i|^d \varphi(|y_i|)$
 (Note: g_x is linear, $C|y_i|^d \varphi(|y_i|)$ is error by GAP)

$\leq g_x(x) + C(m^d |x|^d) \varphi(K|x|)$
 (Note: φ is subadditive)

$|y_i| \leq K|x|$

- 1) \exists m good increments in each path
- 2) m is not too large,

So if we can show that m is not too large, then we're in business. BUT THIS IS HARD TO SHOW

(Alexander says that this does not seem natural)

GAP \equiv General Approximation Property

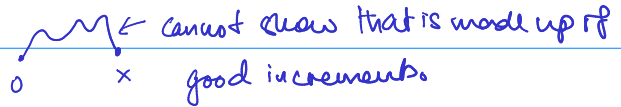
What do we replace this by? Property called CHAP

CHAP \equiv Convex Hull Approximation Property.

Lemma: Suppose for each $x \in \mathbb{Q}^d$ st $|x| \geq M \exists n \geq 1$

and γ from 0 to nx with a sequence $0 = v_0, v_1, \dots, v_m = nx$

st $m \leq a \cdot n$, $v_i - v_{i-1} \in Q_x$ for all $1 \leq i \leq m$
 (Note: a is a constant)



Then h satisfies something called CHAP (Convex Hull Approximation Property)

The difference is that here we have $\exists n$ st...

(One would expect to see some sort of Borel-Cantelli to say ALL n cannot be bad)

Consider the increments $\{v_i - v_{i-1}\}$. They may repeat,

so let $\beta_n(y, \delta)$ be the # of times $v_i - v_{i-1} = y$

Then write $nx = \sum_{y \in \mathbb{Q}_x} \beta_n(y, \delta) y$ ← (#0)
 ↖ can sum over all \mathbb{Q}_x by allowing $\beta_n = 0$

By the assumption $\sum \beta_n(y, \delta) \leq an$ ($m = \#$ of increments)
 ↘ by assumption in the lemma

let $\alpha = \sum \beta_n(y, \delta) \cdot \frac{a(y, \delta)}{a(y, \delta)}$
 ↘ convex combination in \mathbb{Q}_x

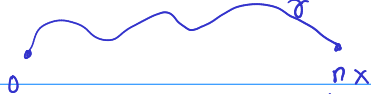
and $\frac{x}{\alpha} = \sum_{y \in \mathbb{Q}_x} \frac{\beta_n(y, \delta)}{\alpha} y$
 Now these coefficients sum to 1.

and thus $\frac{x}{\alpha} \in \overbrace{\text{Convex Hull}(\mathbb{Q}_x)}^{\text{CHAP}}$

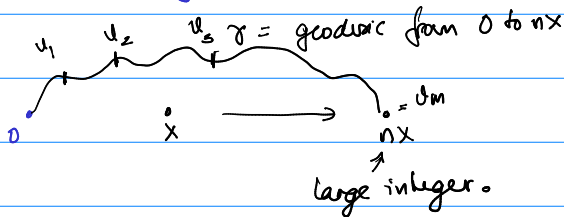
and $g_x(nx) = ng_x(x) = \sum \beta_n(y, \delta) g_x(y)$
 $ng(x) \leq g(x) \sum_{y \in \mathbb{Q}} \beta_n(y, \delta) = g(x) na$

$\Rightarrow \alpha \geq 1$
 $g_x(y) = g\left(\left(\frac{y \cdot x}{nx}\right) \frac{x}{\frac{x}{nx}}\right)$

But I can show that for some n

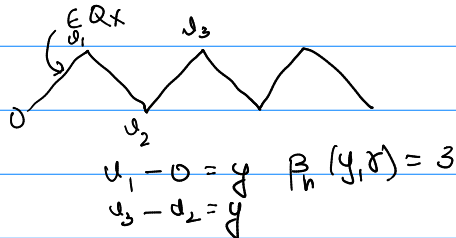


↗ rescale then I can show $\exists m \leq an$ many good increments.



$nx = \sum_{y \in \mathbb{Q}_x} \beta_n(v_i, \delta) y$
 ↘ fixed set of points in \mathbb{Z}^d

fix a seq v_1, \dots, v_m . Then you see



If we can show that \exists a bunch of good increments on δ from 0 to nx then we have CHAP.

$$\text{GAP: } h(x) - g(x) \leq |x|^p \varphi(|x|)$$

\uparrow
 $\mathbb{E}T(0, x)$

CHAP: h satisfies CHAP(ν, φ) if $\exists a$ st for $a \geq x \geq 1$

$$\frac{x}{a} \in \text{Co}(Q_x(\nu, \varphi)) \quad \forall x \in Q^d, |x| > 1$$

\uparrow
 GOOD INCREMENTS.

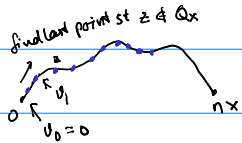
← ignore the constants

Exercise: In d dimensions if $z \in \text{Co}(A)$, then \exists

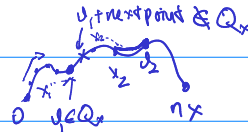
$$\{y_i\}_{i=1}^{d+1} \text{ st } z = \sum_{i=1}^{d+1} \alpha_i y_i \text{ with } |\alpha_i| \geq 0, \sum_{i=1}^{d+1} \alpha_i = 1$$

any point in the convex hull can be written as a convex combination of $d+1$ increments.

How to construct good increments:



So you're trying to find good increments that are as far apart as possible



Find a Q_x skeleton deterministic set

$x_2 - x_1$ is in Q_x
 $\hookrightarrow v_2 - v_1$ is in Q_x as well.

Theorem 1.8: Suppose h is subadditive and $h(x) \leq c|x|$

$$h(x) = \mathbb{E}T(0, x)$$

$$h(x) \leq c|x|$$

POLL:

For our $h(x) = \mathbb{E}T(0, x)$, a good constant c is:

A	B	C	D
1	$\mathbb{E}[T_e^2]$	$\mathbb{E}[T_e]$	$\mathbb{E}[e^{\lambda T_e}]$

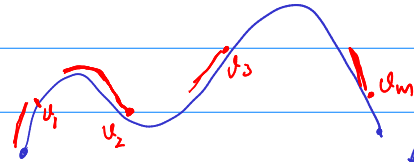
If h satisfies GAP(1, φ) and

If h satisfies CHAP(ν, φ) THEN h satisfies GAP(1, φ)

GAP is what we wanted to prove.

improve this exposed

This is Alexander's main theorem.



$$\varphi(x) = x$$

$$(\mathbb{E}[T_e])^2 \leq \mathbb{E}[T_e^2]$$

$$h(x) \leq C|x| \quad g(x) = \lim_{n \rightarrow \infty} \frac{h(nx)}{n} \leq C|x|$$

$$h(x) - g(x) \geq 0$$

$$\Rightarrow h(x) - g(x) \leq C|x|$$

h already satisfies $GAP(1, \varphi)$

Note: sublinear $h \Rightarrow h(x) \leq C|x| \Rightarrow I^+$ satisfies

$GAP(1, \varphi)$ ^{exponent 1.}

I^+ relies on iterating the following result.

Prop: Suppose $n \leq C|x|$, h satisfies both $GAP(\beta, \varphi)$ and

$CHAP(\nu, \varphi)$ then h satisfies $GAP(\beta', \varphi)$ where

$$\beta' = \frac{\beta}{1 + \beta - \nu} < \beta$$

fixed point of this iteration is:

$$\beta = f(\beta) \quad \beta = \frac{\beta}{1 + \beta - \nu}$$

$$1 + \beta - \nu = 1$$

what is the fixed point of this iteration?

POLL

A	B	C
β	ν	$\frac{1}{2}$

Pf: Start with x , and pick a parameter q , ^{a free parameter}

We assume $GAP(\beta, \varphi)$

$0 < q \leq |x|$ and we will optimize over q . Assume $|x|$ is large, and q is st

Assume $CHAP(\nu, \varphi) \Rightarrow GAP(\beta', \varphi)$

by $CHAP$, $\frac{x}{q} \in Co(Q_x)$

$$\frac{x}{q} = \sum_{i=1}^{d+1} \alpha_i y_i \quad \text{and of course } \sum_{i=1}^{d+1} \alpha_i \leq \alpha$$

is the same α in the definition of $CHAP$

These α_i are the $\beta_n(y)$ we considered

Thus $x = \underbrace{x^*}_{\substack{\mathbb{Z}^d \\ \text{Essentially } x/q}} + x - x^* \rightarrow \text{CHAP control the error}$

where $x^* = \sum \alpha_i y_{q_i}$ grad increments.

We can use subadditivity to bound $\overline{h(x^*) - g_x(x^*)} \leftarrow \text{Error 1}$

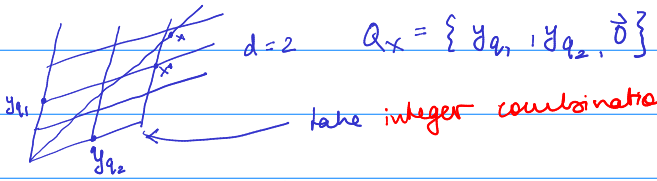
and then $\overline{\text{GAP}(\beta, \varphi)}$ to bound $h(x - x^*) - g_x(x - x^*) \leftarrow \text{Error 2}$

Then we optimize over q to improve the error!

THIS IS THE MAIN IDEA OF THE ITERATION:

break up the error and control part of it with CHAP

and the rest with GAP. This improved the EXPONENT!



$\frac{x}{q} = \sum_{i=1}^{d+1} \alpha_{q_i} y_{q_i}$ with $\alpha_{q_i} \geq 0$
 and $\sum_{i=1}^{d+1} \alpha_{q_i} \in [1, a]$
 Then set $x^* = \sum_{i=1}^d \lfloor q \alpha_{q_i} \rfloor y_{q_i}$ multiply by q and get integer part.

$\frac{x}{\alpha q} \in \text{Co}(Q_x)$

α_{q_i} may not be integers. I want to pick integer combinations of $\frac{1}{q} y_{q_i}$

$h = \text{ET}(0, x) : \mathbb{Z}^d \rightarrow \mathbb{R}$

and $x - x^* = \sum_{i=1}^{d+1} \beta_{q_i} y_{q_i}$

$\beta_{q_i} = q \alpha_{q_i} - \lfloor q \alpha_{q_i} \rfloor \in [0, 1)$
 integer approximation error.

Subadditivity by

$$h(x^*) \leq \sum_{i=1}^{d+1} \alpha_i |g(y_{q_i}) - g_x(y_{q_i})|$$

↓ goodness of increment (d+1) their errors are small

$$\leq \sum_{i=1}^{d+1} \alpha_i |g(y_{q_i}) - g_x(y_{q_i})| \leq \sum_{i=1}^{d+1} \alpha_i \left[g_x(y_{q_i}) + C \left| \frac{x}{q} \right|^p \varphi\left(\left| \frac{x}{q} \right|\right) \right]$$

linearity

$$\leq g_x(x^*) + C \alpha^{-(d+1)} |x|^p \varphi(|x|)$$

↑ see parameter ↑ monotonicity and q ↑

- (#2)

To bound $h(x-x^*)$ assume first that $|x-x^*| \geq H$ and

$$g(y_{q_i}) - g_x(y_{q_i}) \leq h(y_{q_i}) - g_x(y_{q_i}) \leq C \left| \frac{x}{q} \right|^p \varphi\left(\left| \frac{x}{q} \right|\right)$$

$$\Rightarrow \sum_{i=1}^{d+1} \alpha_i [g(y_{q_i}) - g_x(y_{q_i})] \leq C(d+1) \left| \frac{x}{q} \right|^p \varphi(|x|)$$

Since $x - x^* = \sum \alpha_i y_{q_i}$

$$|x - x^*| \leq \sum_{i=1}^{d+1} |y_{q_i}| \leq C(d+1) \frac{|x|}{q} \quad \text{--- (#2a)}$$

Thus $h(x-x^*) \leq g(x-x^*) + C|x-x^*|^p \varphi(|x-x^*|)$

↑ GAP ↓ subadditivity

$$\leq g_x(x-x^*) + \sum_{i=1}^{d+1} \alpha_i (g(y_{q_i}) - g_x(y_{q_i}))$$

↑ add and subtract

$$+ C \frac{|x|^p}{q^p} \varphi\left(\frac{C|x|}{q}\right)$$

(#2a)

(#3)

| Assumption of GAP(β, φ)

Combining (#2) and (#3)

$$h(x) \leq h(x^+) + h(x-x^+)$$

$$\leq g(x) + C_1 q^{-\nu} |x|^{\beta} \varphi(|x|)$$

$$+ g(x-x^+) + C_2 \frac{|x|}{q^{\nu}} \varphi(|x|) + C_3 \frac{|x|^{\beta}}{q^{\beta}} \varphi(|x|)$$

$g(x) = g(x^+)$

$$\leq g(x) + \underbrace{\left(C_1 q^{-\nu} |x|^{\beta} \right)}_{\text{Error 1}} + \underbrace{C_2 |x| q^{-\nu}}_{\text{Error 2}} \varphi(|x|)$$

So simply choose q st

$$q^{-\nu} |x|^{\beta} = |x|^{\beta} q^{-\beta} \Rightarrow q^{-\nu + \beta} = |x|^{\beta - \nu}$$

$$\Rightarrow q = |x|^{\frac{\beta - \nu}{1 + \beta - \nu}}$$

$$\Rightarrow |x|^{\beta} q^{-\beta} = |x|^{\beta - \frac{\beta(\beta - \nu)}{1 + \beta - \nu}} = |x|^{\frac{\beta}{1 + \beta - \nu}}$$

$\frac{\beta}{1 + \beta - \nu} \rightarrow$ A better error!

$$h(x) - g(x) \leq C |x|^{\frac{\beta}{1 + \beta - \nu}}$$

Amazing, right?

Lesson: Strange scaling, relaxing and playing terms

off against each other improved inequalities.

Too

Lesson: Terry ^{Tao} talks about this in a blog post about

Cauchy-Schwarz / Hölder.

$$ab \leq \frac{a^p}{p} + \frac{b^q}{q}$$

Introduce parameter λ $a, b > 0$

Young's inequality.

$$\rightarrow \underbrace{\lambda a}_{\text{new parameter } \lambda} |b| \leq \frac{\lambda^p a^p}{p} + \frac{b^q}{q}$$

Integrate to get $\frac{|a|^p |b|^q}{p}$

$$\int ab \leq \frac{\lambda^p}{p} |a|^p + \frac{1}{\lambda^q} \frac{|b|^q}{q}$$

Let $\lambda^p |a|^p = \frac{1}{\lambda^q} |b|^q$

$\Rightarrow \lambda^{p+q} = \frac{|b|^q}{|a|^p}$

$\frac{1}{p} + \frac{1}{q} = 1 \Rightarrow p+q = pq$

$$\Rightarrow \lambda^p = \frac{|b|^q}{|a|^{\frac{pq}{p}}} \left(\frac{p}{q}\right)^{\frac{1}{q}}$$

$\Rightarrow \frac{\lambda^p |a|^p}{p} = \frac{|b|^q |a|^p}{p}$

$p(1 - \frac{1}{q}) = 1$

$\Rightarrow \int ab \leq |a|^p |b|^q$

Extremely powerful idea in inequalities.

You introduced a parameter λ and optimized over it.

There's a bunch of technical stuff to ensure that constants don't mess things up terribly under iteration.