

Determinants of random Cauchy matrices and capacity of wireless networks

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Network information theory: some (recent) history

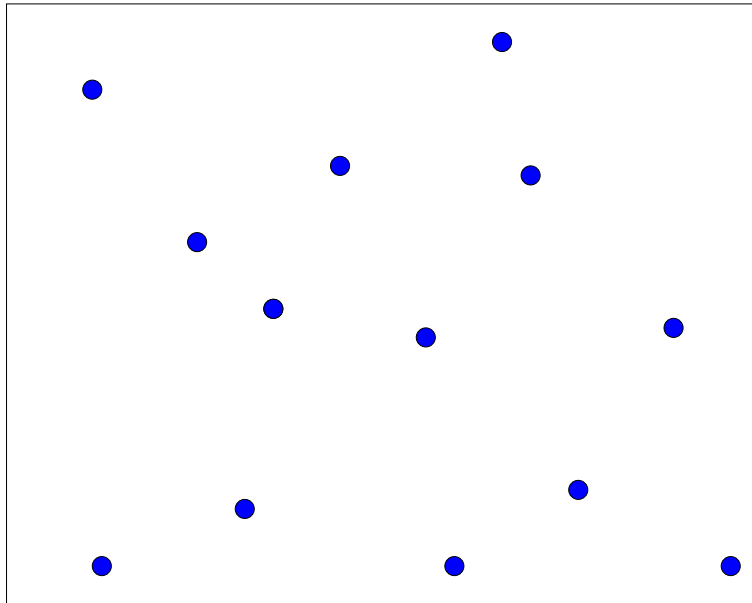
- 70's: classical network information theory
⇒ exact results for “networks” of 3 or 4 users
- 90's: development of self-organized wireless networks with a large number of users (~ 100)
⇒ the focus has changed:

1) exact results → scaling laws

2) entire capacity region → sum capacity, or **transport capacity** (Gupta-Kumar 00):

$$T_c(n) = \sup \sum_{i,j=1}^n R_{ij} r_{ij}$$

Setup



- network composed of n nodes, independently and uniformly distributed in some (square) region of diameter D
- **expanding network**: $D \sim \sqrt{n}$
(\leftrightarrow constant density of nodes)
- no fixed infrastructure (*ad hoc* network)

Further general assumptions

- transmit power constraint P on each node
- additive $\mathcal{N}(0, 1)$ noise at each receiving node
- power attenuation $r^{-2\delta}$ over a distance r
(typically, $\delta \in [1, 2]$)
- **deterministic fading** (the only randomness comes from the random distances between nodes)

Theorem (GK 00)

if $\delta > 1$ and we restrict ourselves to:

- i) point-to-point communications
- ii) interference being treated as noise,

then

$$T_c(n) = O(D\sqrt{n})$$

However:

what about group communication schemes?
or interference cancellation strategies?

⇒ need for information theoretic answers!

First information theoretic results

a) Kumar-Xie (04-05), Jovicic&al (04-05)

if $\delta > 2.25$, then under no specific assumption on the way communication is established, we have

$$T_c(n) = O(D\sqrt{n})$$

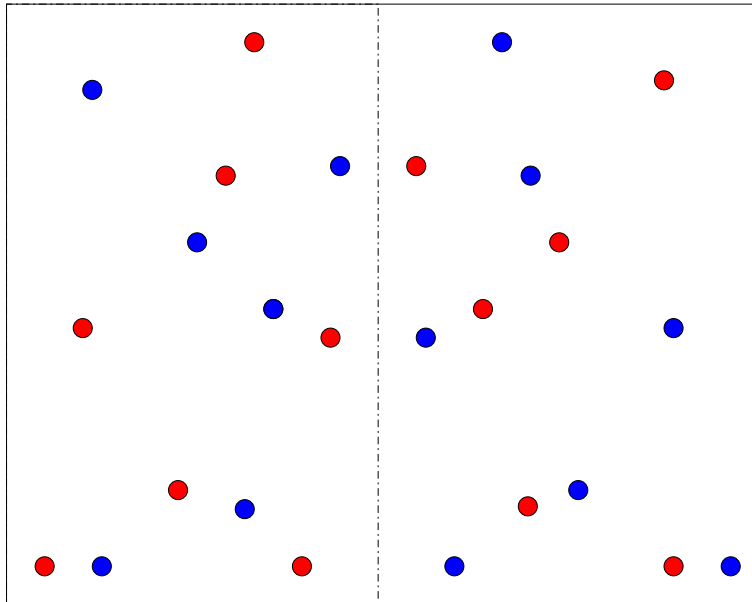
b) Lévêque-Telatar (05)

if $\delta > 1$, then under no specific assumption on the way communication is established, we have

$$T_c(n) = o(Dn)$$

But both these results miss the target, especially if one looks more closely at their proofs!

Our approach (red dots = added mirror users)



Max flow of information accross the boundary:

$$C_n \leq \sup_{p_X: E(|X_i|^2) \leq P, \forall i} I(X_1, \dots, X_n; Y_1, \dots, Y_n)$$

where

$$\begin{cases} Y_j = \sum_{i=1}^n G_{ij} X_i + Z_j \\ G_{ij} = \frac{1}{\|x_i - y_j\|^\delta} \end{cases}$$

Successive majorizations...

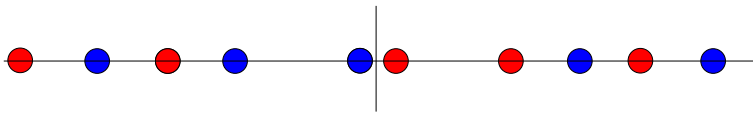
$$\Rightarrow C_n \leq 2 \log \det(I + \sqrt{n} P G)$$

Ultimate hope: show that $C_n = O(\sqrt{n})$
(as this would **imply** $T_c(n) = O(D\sqrt{n})$)

However:

- no simple upper bound on the determinant gives a satisfying answer
- classical random matrix theory is useless in this context

A simpler case: one-dimensional networks



$$\Rightarrow G_{ij} = \frac{1}{(x_i + x_j)^\delta}$$

Theorem (Leveque-Preissmann, IT Trans 05)

if $\delta \in [1, 2]$, then under no specific assumption on the way communication is established,

$$T_c(n) = O(D(\log n)^{3+\varepsilon})$$

Note: in this setting, Gupta-Kumar's scaling law reads:

$$T_c(n) = O(D)$$

Proof idea

1) in order to upperbound $\det(I + G)$, use

$$\begin{aligned}\det(I + G) &= 1 + \text{Tr}(G) + \dots + \det(G) \\ &= \sum_{J \subset \{1, \dots, n\}} \det(G_J)\end{aligned}$$

so one only needs to upperbound $\det G$

2) let $D_\delta = \det G = \det \left(\left\{ \frac{1}{(x_i + x_j)^\delta} \right\} \right)$

integral representation of the determinant
+ Hölder's inequality

$$\Rightarrow D_\delta \leq C_\delta (D_1)^{2-\delta} (D_2)^{\delta-1} \quad \forall \delta \in [1, 2]$$

so one only needs to upperbound D_1 and D_2

Proof idea (cont'd)

3) Cauchy and Borchardt formulas:

$$D_1 = \det \left(\left\{ \frac{1}{x_i + x_j} \right\} \right) = \frac{\prod_{i < j} (x_i - x_j)^2}{\prod_{i, j} (x_i + x_j)}$$

$$D_2 = \det \left(\left\{ \frac{1}{x_i + x_j} \right\} \right) \text{perm} \left(\left\{ \frac{1}{x_i + x_j} \right\} \right)$$

4) key step: a refined analysis of the above expressions gives the following precise estimate:

$$D_1, D_2 \leq \frac{1}{(d_{\min})^n} \exp(-Kn^{3/2})$$

where d_{\min} = minimum distance between any two nodes in the network (typically, $d_{\min} \sim \frac{1}{n}$)

Proof idea (conclusion)

5) gathering all estimates together leads to

$$C_n \leq 2 \log \det(I + \sqrt{n} P G) \leq K (\log n)^{3+\varepsilon}$$

6) implication on transport capacity:

$$\begin{aligned} \sum_{i < j} R_{ij} r_{ij} &= \sum_{i < j} R_{ij} \sum_{k=i}^{j-1} r_{k,k+1} \\ &= \sum_{k=1}^{n-1} r_{k,k+1} \sum_{i \leq k < j} R_{ij} \leq D C_n \end{aligned}$$

□

Remark

following the steps of the preceding proof, one sees that the scaling law

$$T_c(n) = O(D(\log n)^{3+\varepsilon})$$

still holds for both

- **dense** randomly distributed networks (D cst)
- networks with an **arbitrary placement of nodes** separated by a minimum distance d_{\min}

Back to two-dimensional networks

in this setting, we have

$$G_{ij} = \frac{1}{((x_i + x_j)^2 + (y_i - y_j)^2)^{\delta/2}}$$

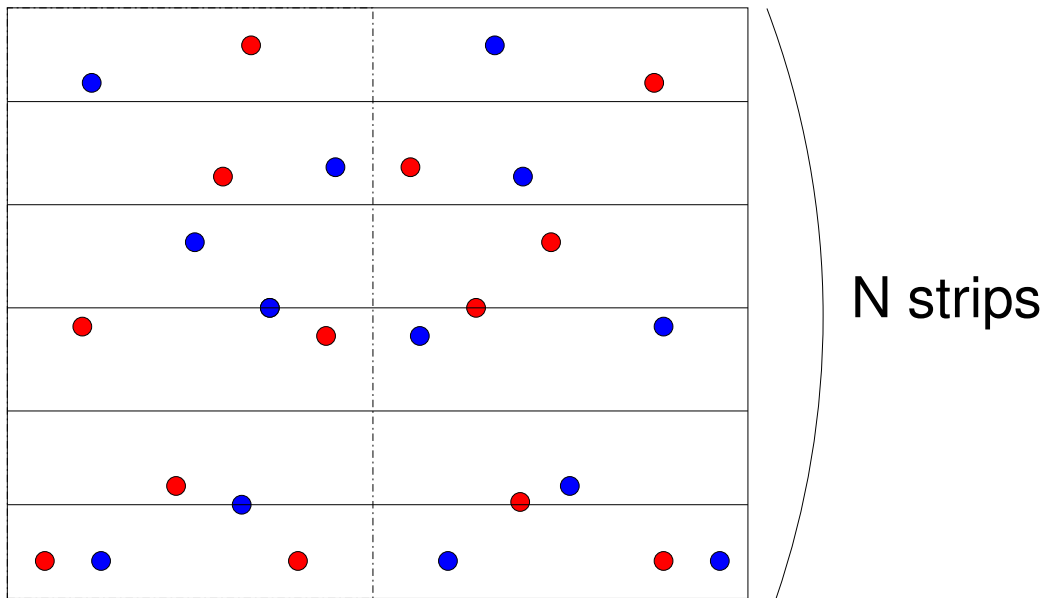
computing the determinant of such matrices is harder... nevertheless, we have the following:

Theorem (Özgür-Lévêque, IZS 06)

if $\delta \in [1, 2]$, then under no specific assumption on the way communication is established,

$$T_c(n) = O\left(D n^{\frac{1}{2} + \frac{1}{2(\delta+4)} + \varepsilon}\right)$$

Proof idea: get back to the 1D case!



$$C_n \leq 2 \log \det(I + \sqrt{nP} G)$$

$$\leq 2 \sum_{l=1}^N \log \det(I + \sqrt{nP} G^{(l)})$$

with $G^{(l)}$ the diagonal block of the matrix G corresponding to the strip l .

Proof idea (cont'd)

1) averaging:

$$\begin{aligned} & E_{X,Y}(\log \det(I + \sqrt{nPG})) \\ & \leq E_X \left(\sum_{l=1}^N \log \det(I + \sqrt{nP} E_Y(G^{(l)})) \right) \end{aligned}$$

this quantity turns out to be an $O(N(\log n)^{3+\varepsilon})$
for $N \geq n^{\frac{1}{2} + \frac{1}{2(\delta+4)}}$

2) concentration (use a theorem of McDiarmid and the interlacing property of eigenvalues):

$$\begin{aligned} & |\log \det(I + \sqrt{nPG}) - E_{X,Y}(\log \det(I + \sqrt{nPG}))| \\ & = O(n^{\frac{1}{2} + \varepsilon}) \end{aligned}$$

□

Conclusion

in the main regime of interest ($\delta \in [1, 2]$), we have recovered Gupta-Kumar's square root law from an information theoretic point of view (up to a small polynomial factor)

The following improvements are expected:

- general result for $\delta \geq 1$
- exact scaling law up to $\log n$ factors
- results for dense or arbitrarily placed 2D networks