## **Research Update for MURI Project**

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1. Random matrices with heavy-tails (big *n* big *p*): (joint work with Thomas Mikosch and Oliver Pfaffel)

- Large dimensional data sets appear in many quantitative fields like finance, environmental sciences, wireless communications, fMRI, and genetics.
- Structure in this data can often be analyzed via sample covariances.
  PCA is used to transform data to a new set of variables, the principal components, ordered such that the first few retain most of the variation of the data.

Goal: In this work, we study the asymptotic properties of the largest eigenvalues from the sample covariance matrix.

Setup (simplified version for this talk):

Let {**X**<sub>*t*</sub>} be an iid sequence of random vectors of length p with Pareto tails and index  $\alpha \in (2,4)$ . That is,

$$P(X_{t,i} > x) \sim \frac{C}{x^{\alpha}}, \quad as \ x \to \infty.$$

Assume the rv's have mean 0, so that the covariance matrix is given by

 $\Gamma = E(\mathbf{X}_{\mathsf{t}}\mathbf{X}_{\mathsf{t}}^T).$ 

Estimate  $\Gamma$  by the sample covariance matrix

$$\widehat{\Gamma} = \frac{1}{n} \sum_{t=1}^{n} \mathbf{X}_{t} \mathbf{X}_{t}^{T}$$

Classical results: Assume the vector consists of IID N(0,1) rvs.

• For  $n \to \infty$  and p fixed, Anderson (1963) proved that

$$\left(\frac{n}{2}\right)^{-1/2} (\hat{\lambda}_{(1)}/n - 1) \xrightarrow{d} N(0,1),$$

where  $\hat{\lambda}_{(1)}$  is the largest eigenvalue of the empirical covariance matrix  $n\hat{\Gamma}$ .

• Johnstone [2001] showed that for  $p, n \to \infty, \frac{p}{n} \to \gamma \in (0,2)$ , then

$$\frac{\sqrt{n} + \sqrt{p}}{\sqrt[3]{\frac{1}{\sqrt{n}} + \frac{1}{\sqrt{p}}}} \left( \frac{(\hat{\lambda}_{(1)})}{(\sqrt{n} + \sqrt{p})^2} - 1 \right) \xrightarrow{d} \text{Tracy-Widom distribution.}$$

**Theorem:** Let  $\{X_t\}$  be an iid sequence of random vectors of length p w/

$$X_{t,j} = \sum_{i=0}^{\infty} \theta_{iZ_{j-i}},$$

where  $\{Z_i\}$  is an iid sequence of rvs satisfying  $P(|Z_i| > x) \sim \frac{1}{x^{\alpha}}$ , as  $x \to \infty$ . Let  $\hat{\lambda}_{(1)} > \cdots > \hat{\lambda}_{(p)}$  be the decreasing eigenvalues of the empirical covariance matrix  $n\hat{\Gamma} = \sum_{t=1}^{n} \mathbf{X}_t \mathbf{X}_t^T$ . Then for almost **any** sequence  $p_n \to \infty$  (limsup\_n  $\frac{p_n}{\exp\{cn\}} < \infty$ ), then with  $c = \theta_0^2 + \theta_1^2 + \cdots$ ,  $(np)^{-\frac{2}{\alpha}} \hat{\lambda}_{(i)} \stackrel{d}{\to} c\Gamma_i^{-\frac{2}{\alpha}}, \qquad if \alpha \in (0,2)$ 

$$(np)^{-\frac{2}{\alpha}}(\widehat{\lambda}_{(i)} - n\lambda_i) \xrightarrow{d} c\Gamma_i^{-\frac{2}{\alpha}}, \quad if \; \alpha \in (2,4),$$

where  $\Gamma_i = E_1 + \dots + E_i$ ,  $E_1, E_2, \dots$ , are iid unit exponentials,  $\lambda_i$  is the  $i^{th}$  largest eigenvalue of  $\Gamma$ .

$$(np)^{-\frac{2}{\alpha}}\hat{\lambda}_{(i)} \xrightarrow{d} c\Gamma_{i}^{-\frac{2}{\alpha}}, \qquad if \ \alpha \in (0,2)$$
$$(np)^{-\frac{2}{\alpha}}(\hat{\lambda}_{(i)} - n\lambda_{i}) \xrightarrow{d} c\Gamma_{i}^{-\frac{2}{\alpha}}, \qquad if \ \alpha \in (2,4),$$

#### Remarks:

- Limits only depend on dependence between the rows via the constant *c*.
- In the first case,  $\hat{\lambda}_{(1)}/\hat{\lambda}_{(2)} \xrightarrow{d} \Gamma_2^{\frac{2}{\alpha}}/\Gamma_1^{\frac{2}{\alpha}}$ , which is the same regardless of the dependence between the rows!
- Results generalize to linear dependence between columns.
- Looking at problems where dependence is more than linear between rows.

2. Indegree/outdegree analysis for growth networks

Collaborators(?): Sid, Bo Jiang, and Don

Krapivsky et al 2001 model:

The model is recursively defined. If  $V_n$  represents the nodes at *time* n, then

• with prob *p*, a new node attaches to existing node *v* WP

$$\frac{in(v)+\lambda}{\sum_{v \in V_n}(in(v)+\lambda)}$$

(indegree of v goes up by 1.)

 with prob 1-p, a new edge u → v is created between two existing nodes u and v with prob

$$\frac{(in(v)+\lambda)(out(u)+\mu)}{\sum_{u\neq v\in V_n}(in(v)+\lambda)(out(u)+\mu)}$$

Results from Krapivsky:

Let

 $N_{i,j} = number of nodes with indegree i and outdegree j$   $N_{i,\cdot} = number of nodes with ind i;$  $N_{\cdot,j} = number of nodes with out j;$ 

Defining the relative frequencies (assuming they exist) via,

$$f_{i,j} = \lim_{n \to \infty} \frac{N_{i,j}}{n}$$

Marginal distributions:

•  $f_{i,\cdot} \sim i^{-v_{in}}$ ,  $v_{in} = 2 + p\lambda$  and  $f_{\cdot,j} \sim j^{-v_{out}}$ ,  $v_{out} = 2 + p(1+\mu)/(1-p)$ 

Joint distributions:

• If 
$$v_{in} = v_{out}$$
, then  $f_{i,j} \sim C \frac{i^{\lambda-1}j^{\mu}}{(i+j)^{2\lambda+1}}$ 

Similar results for reciprocity models (Bo and Don): At each step, new node v is added such that

• with prob 1-*p*, it has an outgoing edge  $v \rightarrow u$  WP

 $\frac{(in(u)+\lambda)}{\sum_{u\in V_n}(in(u)+\lambda)}$ 

with prob p, an edge v → u is created and a reciprocal edge
 u → v between two existing nodes u and v is created with
 prob

 $\frac{(in(u)+\lambda)}{\sum_{u\in V_n}(in(u)+\lambda)}$ 

Similar results for reciprocity models (Bo and Don):

Let

 $N_{i,j}$  = number of nodes with indegree *i* and outdegree *j*  $N_{i,\cdot}$  = number of nodes with ind *i*;  $N_{\cdot,j}$  = number of nodes with out *j*;

Defining the relative frequencies (assuming they exist) via,

$$f_{i,j} = \lim_{n \to \infty} \frac{N_{i,j}}{n}$$

Marginal distributions:

•  $f_{i,\cdot} \sim (A+B)i^{-\nu_{in}}, v_{in} = 2 + p + \lambda$  and  $f_{\cdot,j} \sim Ci^{-\nu_{out}}, v_{out} = ?$ 

Two views:

1. Double limit--empirical process:

$$F_{n}(\cdot) = \frac{1}{n} \sum_{t=1}^{n} \epsilon_{inv(v_{t}),out(v_{t})}(\cdot)$$
  
So for  $g: \mathbb{N}^{+} \times \mathbb{N}^{+} \to \mathbb{R}$ ,  
$$F_{n}(g) = \frac{1}{n} \sum_{\substack{t=1\\n}}^{n} g(inv(v_{t}),out(v_{t}))$$
$$= \sum_{\substack{i,j=1\\n}}^{n} n^{-1} N_{i,j}g(i,j)$$
$$\to \sum_{\substack{i,j=1\\n}}^{\infty} f_{i,j}g(i,j)$$
  
*i.e.*, 
$$F_{n}(\cdot) \to \sum_{\substack{i,j=1\\n}}^{\infty} f_{i,j}\epsilon_{i,j}(\cdot)$$

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2. Single sequence limit–point process:

$$T_n(\cdot) = \sum_{t=1}^n \epsilon_{\{\frac{inv(v_t)}{a_n}, \frac{out(v_t)}{b_n}\}}(\cdot)$$

so that for  $g: \mathbb{R}^+ \times \mathbb{R}^+ \to \mathbb{R}$ , bounded with support on  $[x, \infty) \times [y, \infty)$ .

$$T_{n}(g) = \sum_{t=1}^{n} g\left(\frac{inv(v_{t})}{a_{n}}, \frac{out(v_{t})}{b_{n}}\right) = \sum_{i \ge a_{n}x, j \ge b_{n}y} n^{-1} N_{i,j} n g\left(\frac{i}{a_{n}}, \frac{j}{b_{n}}\right)$$
$$\sim \iint_{a_{n}x, b_{n}y}^{\infty \infty} f(u, v) n g\left(\frac{u}{a_{n}}, \frac{v}{b_{n}}\right) du dv$$
$$= \iint_{x y}^{\infty \infty} n f(ua_{n}, vb_{n}) na_{n} b_{n} g(u, v) du dv$$

2. Single sequence limit-point process (cont):

$$= \iint_{x y}^{\infty \infty} nf(ua_n, vb_n)na_nb_ng(u, v)dudv$$
$$\rightarrow \iint_{\infty}^{\infty \infty} c(u, v)g(u, v)dudv$$

$$\rightarrow \iint_{x y} c(u, v)g(u, v)dudv$$

provided we can choose  $a_n$  and  $b_n$  such that  $na_nb_nf(ua_n, vb_n) \rightarrow c(u, v).$ 

In particular,

$$T_n(du, dv) \xrightarrow{v} c(u, v) du dv \quad a.s.$$

Krapivsky's example:

Assume  $v_{in} = v_{out}$ , in which case

$$f(i,j) \sim C \frac{i^{\lambda-1} j^{\mu}}{(i+j)^{2\lambda+1}}$$
  
Take  $a_n = b_n = n^{1/(1+p\lambda)}$ , and since  $\mu - \lambda = -(1+p\lambda)$ ,

$$na_n^2 f(a_n u, a_n v) \sim C \frac{na_n^2 a_n^{\lambda - 1} a_n^{\mu} u^{\lambda - 1} v^{\mu}}{a_n^{2\lambda + 1} (u + v)^{(2\lambda + 1)}} = C \frac{na_n^{\mu - \lambda} u^{\lambda - 1} v^{\mu}}{(u + v)^{(2\lambda + 1)}}$$
$$= C \frac{u^{\lambda - 1} v^{\mu}}{(u + v)^{(2\lambda + 1)}} =: c(u, v).$$

Observe that

$$c(au,av) = a^{-2}a^{\mu-\lambda}c(u,v)$$

so that the corresponding bivariate regularly measure is homogeneous with index  $-(1 + p\lambda)$ , i.e., regularly varying with index  $\alpha = 1 + p\lambda$ .

Summary:

$$T_n(\cdot) = \sum_{t=1}^n \epsilon_{\{\underbrace{inv(v_t)}{a_n}, \underbrace{out(v_t)}{b_n}\}}(\cdot) \xrightarrow{v} c(u, v) du dv \quad a.s.$$

where 
$$a_n = b_n = n^{1/(1+p\lambda)}$$
.

Note that the marginals have similar behavior, i.e.,

$$\sum_{t=1}^{n} \epsilon_{\{\underline{inv(v_t)}\\a_n\}}(\cdot) \xrightarrow{v} Cu^{-(1+p\lambda)-1} du \quad a.s.$$

i.e., regularly varying with the same index  $1 + p\lambda$ .

#### What do I intend to work on?

Attachment models:

- Develop the theory to establish the convergences (double limit or single sequence limit (see Sid)
- Attempt to understand the genesis of the power laws for the indegree/outdegrees using methods outside of solutions for recurrence equations (see Sid).
- Establish CLTs associated with the empirical and point process convergences.
- Estimation procedure (MLE) for estimating parameters of the model (p, λ, μ)
- Develop procedures for checking goodness of fit.

# How can MURI team members provide support and expertise?

• Data!

Where do I need help?

• Data