

Some largest eigenvalue
problems in statistics.

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AGENDA

1. EXAMPLES

- Principal Components Analysis
- Canonical Correlations

2. GENERALITIES

- One & Two Wishart problems
- 'large' $n, p, (q)$ asymptotics

3. LARGEST EIGENVALUE(S) in null cases

- for CCA = Jacobi (\mathbb{R} & \mathbb{C})
[w. P. Forrester, in progress]
- Liouville-Green
- message for stat: 'large' = quite small

4. SOME OPEN QUESTIONS

REVIEW OF PCA : Goal: Dimensionality reduction

E.g: 1. Hotelling (1933)

$n = 140$ cases
 $p = 4$ variables

reading \leftarrow speed
power
arithmetic \leftarrow speed
power

2. Craddock - Flood (1969)

$n = 1095$ Daily data, 500 mb heights
 $p = 130$ Locations

→ Data

Y_{ij} or $Y(t_i, x_j)$

i/t_i cases/times $i = 1, \dots, n$

j/x_j variables/places $j = 1, \dots, p$ ($\leq n$)

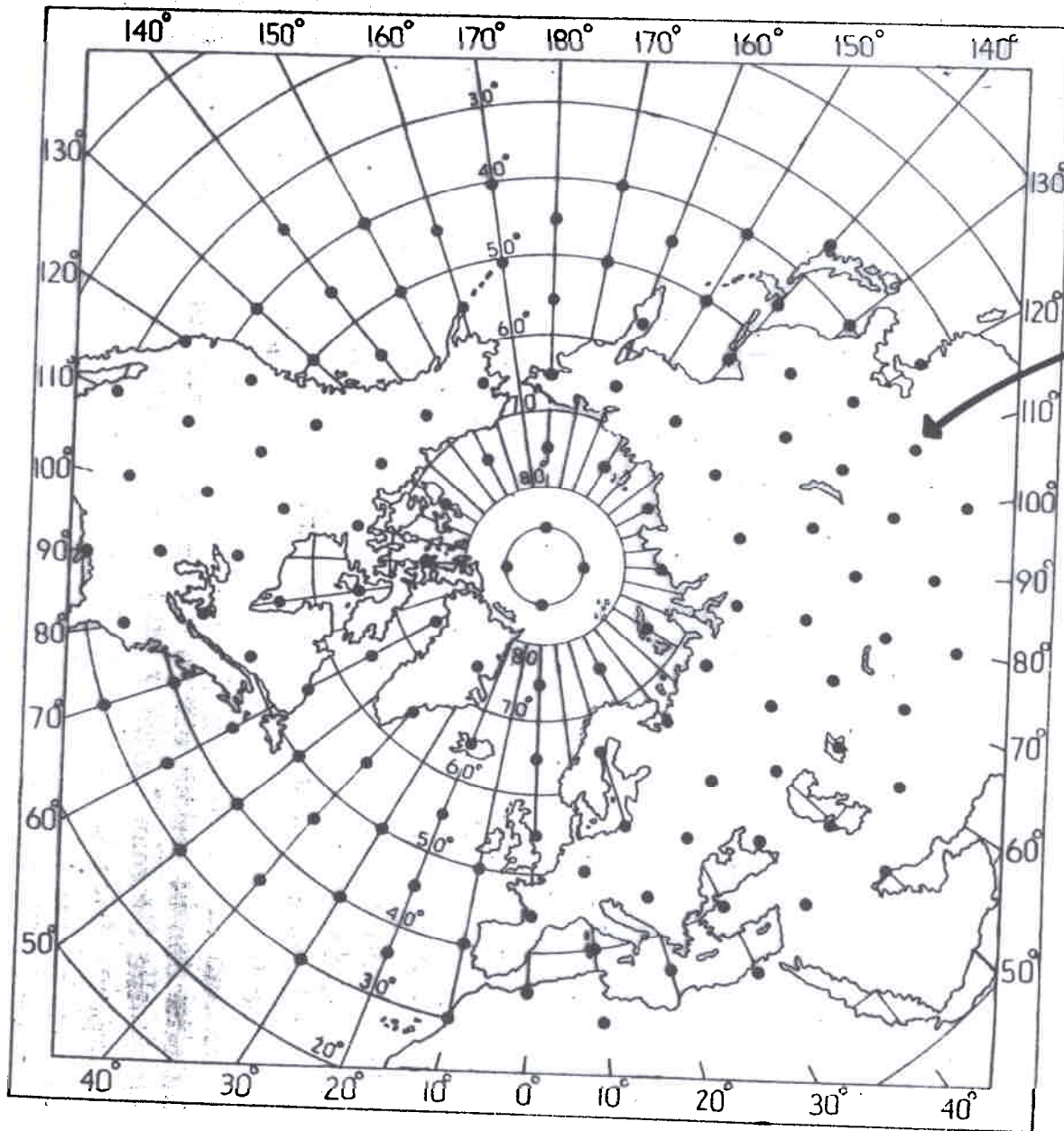
Mean centered $Y_{ij} \leftarrow Y_{ij} - \bar{Y}_{.j}$ $\bar{Y}_{.j} = \frac{1}{n} \sum_{i=1}^n Y_{ij}$

'Covariance' matrix $S = (S_{jj'}) = Y'Y$

$$S_{jj'} = \sum_i Y_{ij} Y_{ij'}$$

Eigenvectors for representing the 500 mb geopotential surface over the Northern Hemisphere

By J. M. CRADDOCK and C. R. FLOOD
Meteorological Office, Bracknell

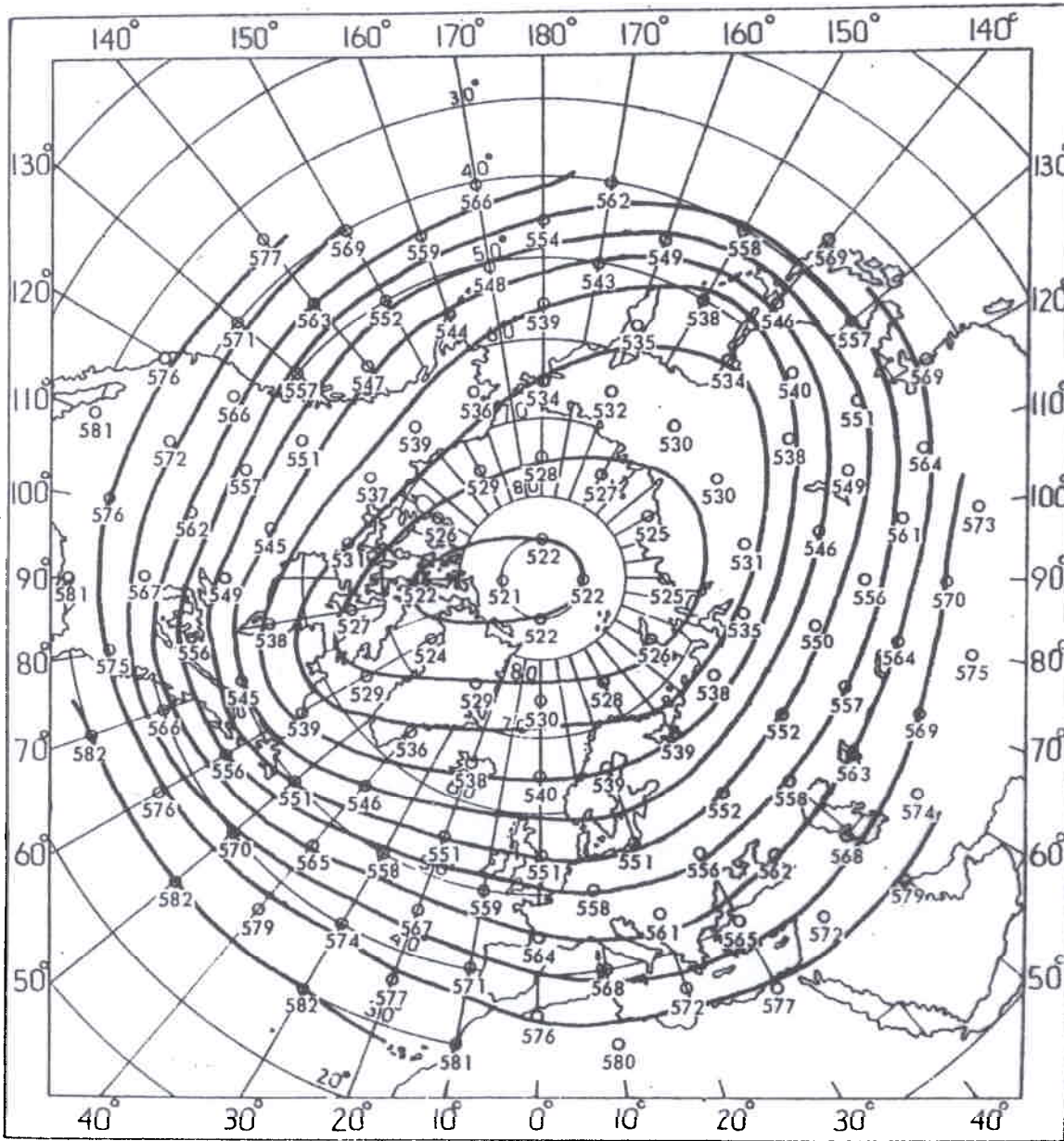


locations
 x_j
 $j=1, \dots, 130$

Mean 500mb field over $t_1 \dots t_{1095}$

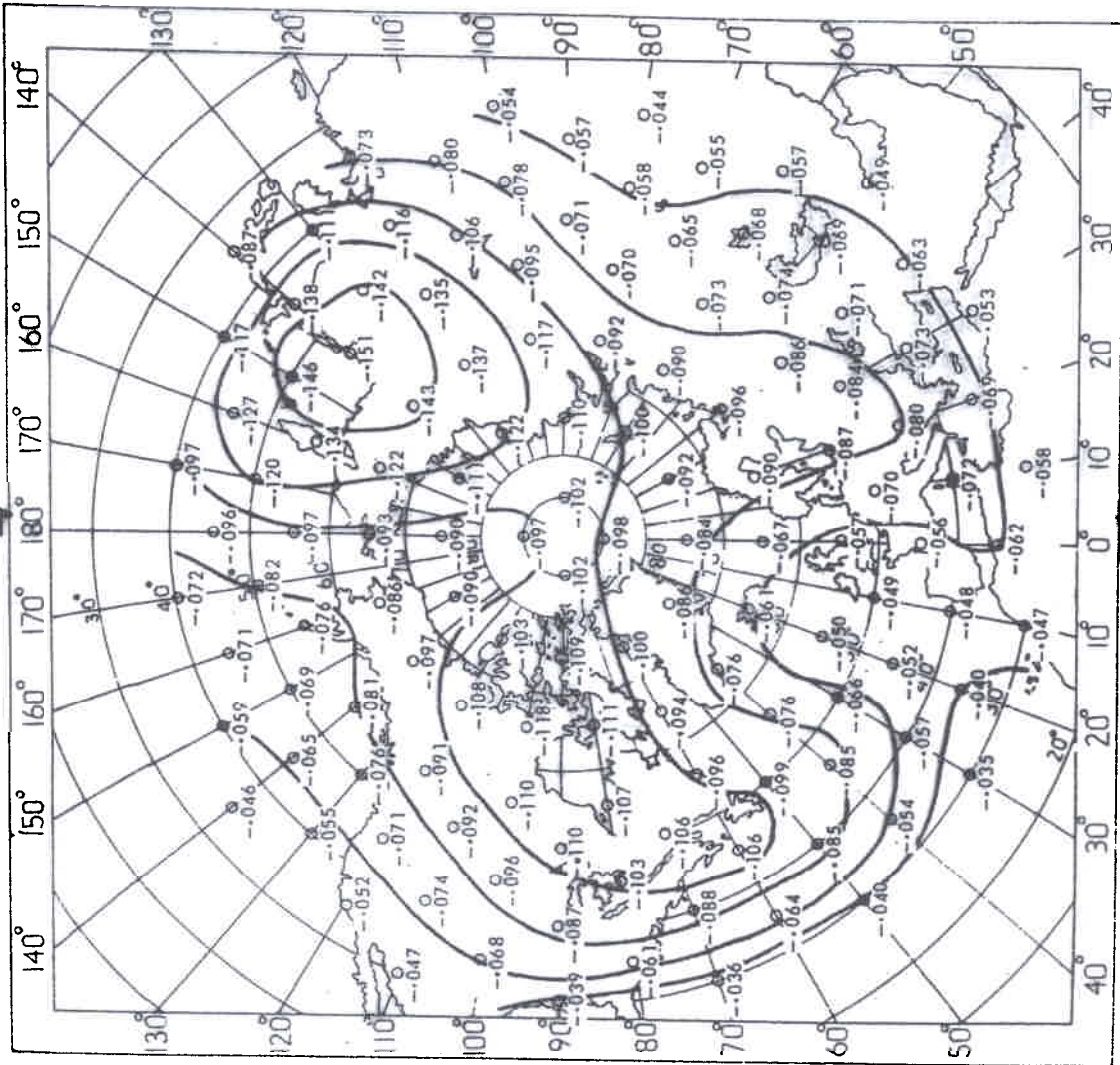
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J. M. CRADDOCK and C. R. FLOOD

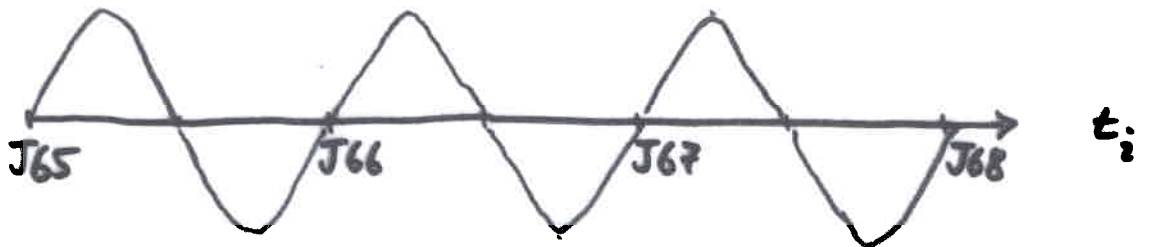


1st
eigenvector
 $v_1(x_j)$
(e.o.f.)

$l_1 = 58.6\%$



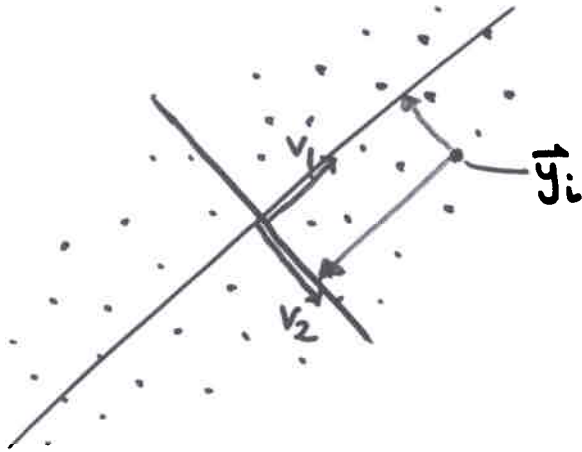
1st p.c. $z_i(t_i) \quad i = 1, \dots, 1095$



MAX VARIANCE DIRECTION

n points in
 p dimensions

$p = 2$



$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

$$\text{Var}\{v' \vec{y}_i\} = v' S v$$

First p.c. variance + eigenvector

$$L_1 = \max \{ v' S v : v' v = 1 \}$$

v_1 = 1st eigenvector / p.c. loadings

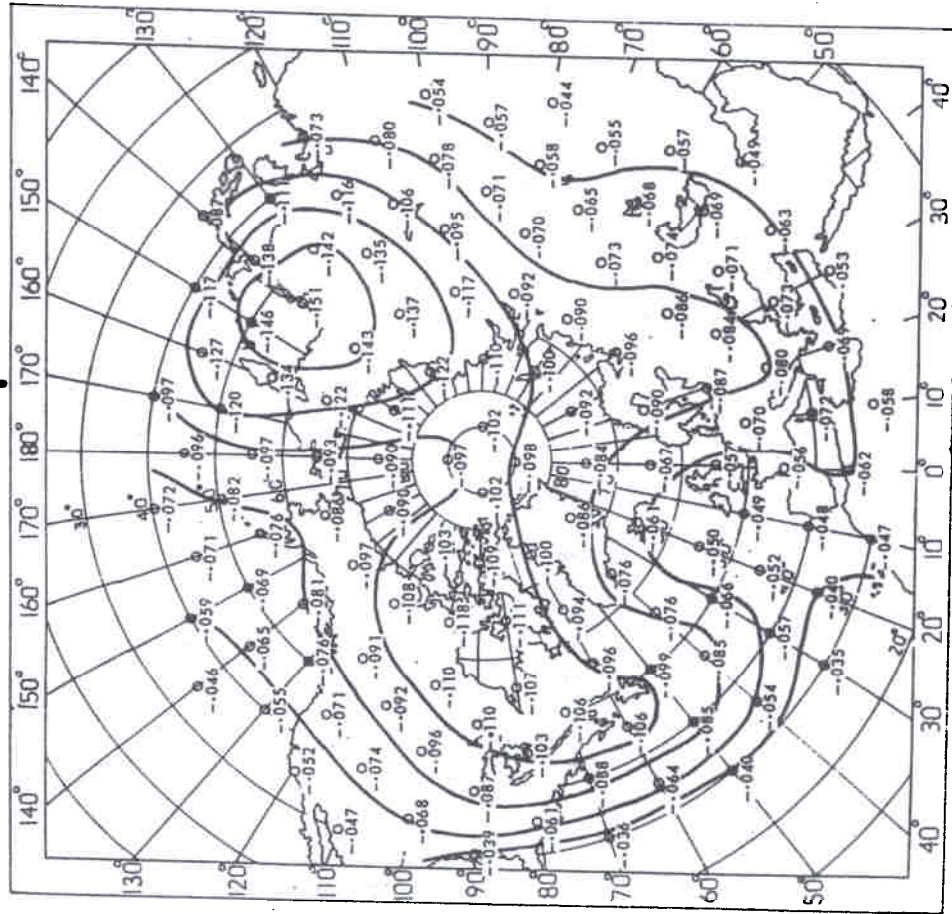
First p.c. :

$$z_1 = \sqrt{L_1} u_1 = Y v_1$$

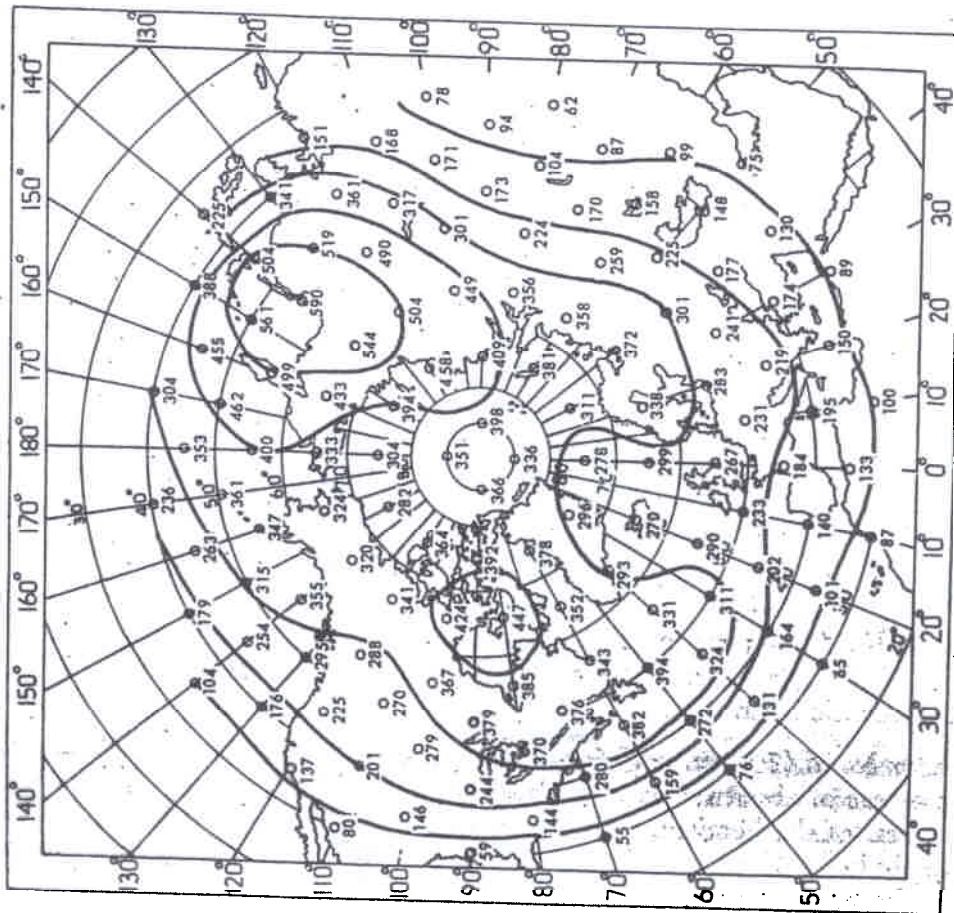
i.e.
$$z_1(t_i) = \sum_j Y(t_i, x_j) v_1(x_j)$$

Seasonal nature of 1st p.c.

1st eigenvector



Variances by location



ORTHOGONAL MAX VARIANCE DIRECTIONS

Iterate on p.c. variances

$$l_k = \max \{ v' S v : v'v = 1, v'v_m = 0 \quad m < k \}$$

→ $v_k = k^{\text{th}}$ eigenvector

$$z_k = \sqrt{l_k} u_k = Y v_k = k^{\text{th}} \text{ p.c.}$$

→ Singular Value Decomposition of data:

$$Y = U L V' = \sum_k \sqrt{l_k} u_k v_k' \quad l_1 \geq l_2 \geq \dots$$

→ Best (linear!) r term approxⁿ to data Y :

$$\hat{Y}_r(t_i, x_j) = \sum_{k=1}^r \sqrt{l_k} u_k(t_i) v_k(x_j)$$

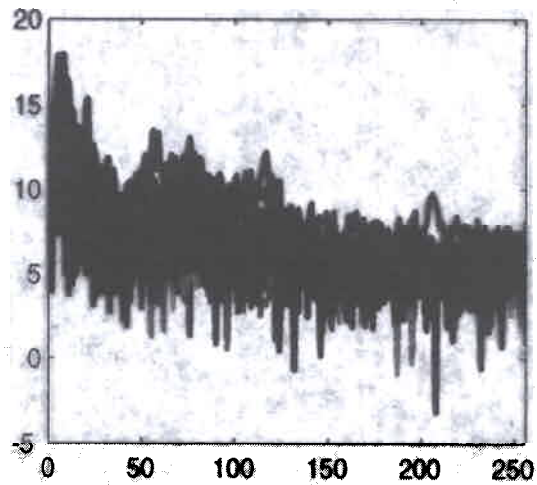
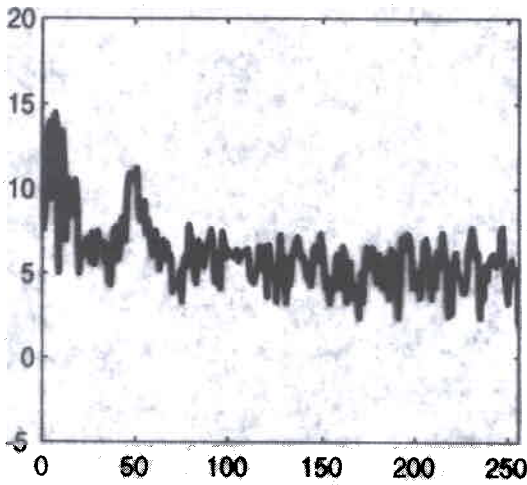
$$\|Y - \hat{Y}_r\|_F^2 = \sum_{k=r+1}^p l_k$$

→ wide use in data reduction/compression

• key role of eigenvalues $\{l_k\}$

Example (via T. Hastie)

Phoneme 'dcl'

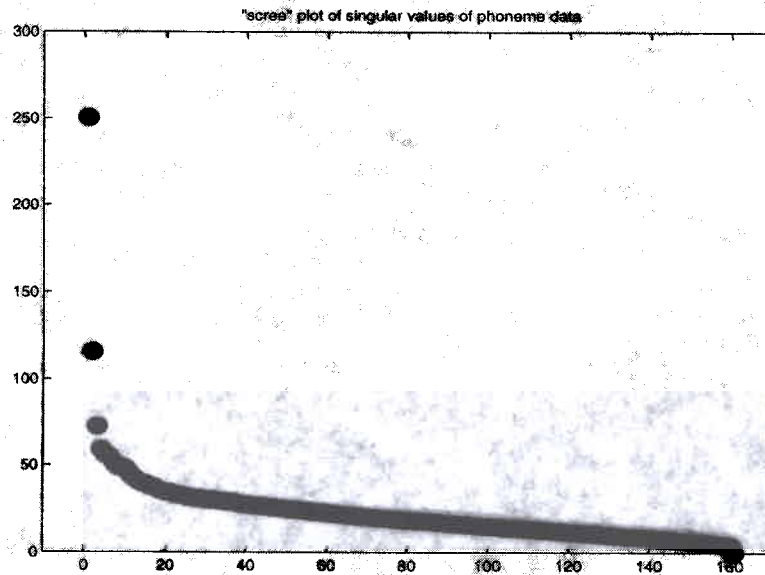


$p = 256$ log periodogram;

$n = 162$ instances (50 spkrs)

GRAPHICAL METHODS : 'SCREE' PLOT

Cattell, 1966



CANONICAL CORRELATIONS ANALYSIS (CCA)

$$X = [x_1 \ x_2 \ \dots \ x_p] \quad Y = [y_1 \ y_2 \ \dots \ y_q]$$

$$\begin{array}{ccccccc} | & | & & | & | & | & | \\ | & | & & | & | & | & | \end{array}$$

Find $a'x$ most correlated with $b'y$

$$\text{Corr}(a'x, b'y) = \frac{a' S_{xy} b}{\sqrt{a' S_{xx} a} \sqrt{b' S_{yy} b}} \quad \begin{array}{l} S_{xy} = X'Y \\ S_{xx} = X'X \\ \vdots \end{array}$$

$$r_k^2 = \max \left\{ a' S_{xy} b : \begin{array}{l} a' S_{xx} a = b' S_{yy} b = 1 \\ a' S_{xx} a_j = b' S_{yy} b_j = 0 \quad j < k \end{array} \right\}$$

→ determinantal equation

$$(*) \quad \det (S_{xy} S_{yy}^{-1} S_{yx} - r^2 S_{xx}) = 0$$

$$\rightarrow r_1^2 \geq r_2^2 \geq \dots \geq r_p^2 \quad \left(\text{and } \begin{array}{l} a_1, \dots, a_p \\ b_1, \dots, b_p \end{array} \right)$$

→ how many r_k^2 are "significant" ?

$$(*) \Leftrightarrow \det (A - r^2 (A+B)) = 0$$

$$A = S_{xy} S_{yy}^{-1} S_{yx} \quad B = S_{xx} - A$$

REGRESSIONS BETWEEN SETS OF VARIABLES

By FREDERICK V. WAUGH, ^{Agricultural Marketing}
Administration, Washington
D.C.

PROFESSOR HOTELLING'S PAPER, "Relations between Two Sets of Variables,"¹ should be widely known and his method used by practical statisticians. Yet, few practical statisticians seem to know of the paper, and

$X =$ "wheat characteristics" (raw)

$x_1 =$ kernel texture

$x_2 =$ test weight

$x_3 =$ damaged kernels

$x_4 =$ foreign material

$x_5 =$ crude protein in wheat

$Y =$ "flour characteristics" (finished)

$y_1 =$ wheat per bbl. of flour

$y_2 =$ ash in flour

$y_3 =$ crude protein in flour

$y_4 =$ gluten quality index

$a_i x$ index of wheat quality

$b_i y$... flour ...

GOAL: highly correlated grading of raw + finished products

$$p = 5$$

$$q = 4$$

$$n = 138$$

Monthly Weather Review

Origins and Levels of Monthly and Seasonal Forecast Skill for United States Surface Air Temperatures Determined by Canonical Correlation Analysis

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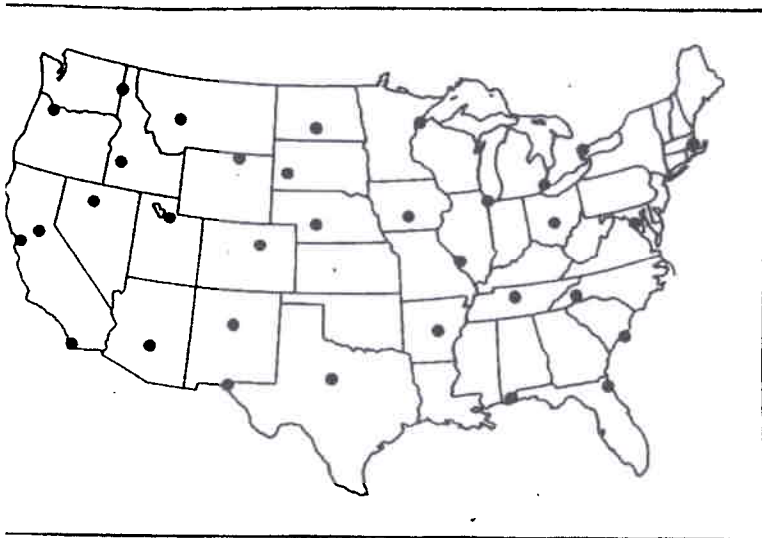


FIG. 1. Locations of stations/districts providing surface air temperature predictand data.

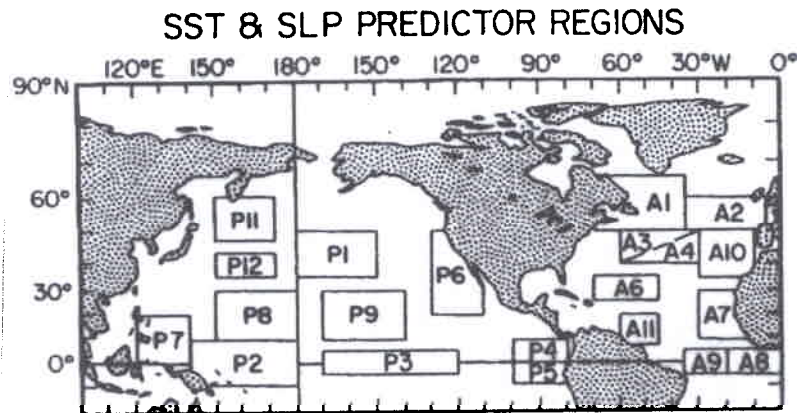


FIG. 2. SST from the large averaging areas shown above were used as predictor information. SLP predictor data came from the region 20°-70°N, 140°E to the Greenwich Meridian.

Y vars : surface air temps at 33 U.S. locations
monthly data, 1931-1980

X vars : sea surface temp (SST) in 21 regions
for 3 prior months in 2 seasons

$p = 126$

$(21 \times 3 \times 2)$

$q = 33$

$n = 600$

(50×12)

ROOTS OF A DETERMINANTAL EQUATION

$$|A - r^2(A+B)| = 0$$

where

$$A = X' P X$$

$$P = Y(Y'Y)^{-1} Y'$$

$$B = X' P^\perp X$$

$$P^\perp = I - P$$

Introduce probability: $[X: Y] \sim N(0, I_n \otimes \Sigma)$ $\Sigma = \begin{cases} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{cases}$
 $n \times (p+q)$

Null distribution $\Sigma_{xy} = 0 \iff e_1 = \dots = e_p = 0$

(and transform to $\Sigma_{xx} = I$)

BASIC SETTING: 2 INDEPENDENT WISHARTS

$$A \sim W_p(q, I) \quad \text{indep. , Wishart}$$

$$B \sim W_p(n-q, I)$$

Multivariate Beta roots := $(u_i)_{i=1}^p$

$$|u(A+B) - A| = 0$$

\Leftrightarrow Multivariate F roots := $(w_i)_{i=1}^p$ $w = u/(1-u)$

$$|wB - A| = 0$$

MULTIVARIATE LINEAR MODEL

$$Y = X \beta + E \quad E \sim N(0, I_n \otimes \Sigma)$$

$n \times p$ $n \times q$ $q \times p$ $n \times p$

q predictors p responses

Let P = orthoprojection on column span of X

$$\begin{array}{ll} A = Y' P Y & \text{model SS} \sim W_p(q, \Sigma, \beta) \\ B = Y' (I - P) Y & \text{error SS} \sim W_p(n - q, \Sigma) \end{array} \left. \vphantom{\begin{array}{l} A \\ B \end{array}} \right\} \text{indep}$$

Invariant tests of $H_0: \beta = 0$ ($p \leq q, p \leq n - q$)
use latent roots of AB^{-1}

E.g. Chemometrics (Skagerberg 92 in Breiman 91
et.al. Friedman)

$p = 6$ output characteristics of polymers
(correlated)

$q = 22$ predictors: temps, feed rate

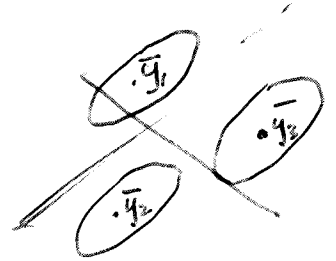
$n = 56$ observations

MULTIPLE DISCRIMINANT ANALYSIS

$i = 1, \dots, q$ populations

n_i observations / pop'n on p variables

$$\vec{y}_{i1}, \dots, \vec{y}_{in_i} \sim N_p(\mu_i, \Sigma)$$



Between class:

$$A = \sum_i n_i (\bar{y}_i - \bar{y})(\bar{y}_i - \bar{y})' \sim W_p(q-1, \Sigma, \mathcal{R})$$

Within class:

$$B = \sum_{i,j} (y_{ij} - \bar{y}_i)(y_{ij} - \bar{y}_i)' \sim W_p(n-q, \Sigma)$$

Discriminant functions l_i solve

$$(A - w_i B) l_i = 0$$

- How many l_i are useful ($\leftrightarrow w_i$ signif)
- under H_0 , roots of AB^{-1}

2. GENERALITIES:

(non-central) WISHART

$$Y = \begin{bmatrix} \vec{y}_1 + z\vec{y}'_1 \\ \vdots \\ \vec{y}_n + z\vec{y}'_n \end{bmatrix}$$

$$\vec{y}_i + z\vec{y}'_i \stackrel{\text{ind}}{\sim} \text{CN}_p(\vec{\mu}_i, \Sigma)$$

$$M = \begin{bmatrix} \vec{\mu}_1 \\ \vdots \\ \vec{\mu}_n \end{bmatrix}$$

$$A = Y^T Y \sim \text{CW}_p(n, \Sigma; \Omega)$$

$$\Omega = \Sigma^{-1} M^T M$$

• $M = 0 \rightarrow$ central Wishart

• $p = 1 \rightarrow \chi^2_n(\omega) \quad \omega = M^T M / \sigma^2$

Roots of determinantal equations

"Wishart"

$$\det[A - lI] = 0$$

- principal components, MDS

$B \sim W_p(n', \Sigma')$ independent of A :

"M. Beta"

$$\det[A - u(A+B)] = 0$$

- canonical correlations

"M. F"

$$\det[A - wB] = 0$$

- multivariate linear model

- mult discriminant; equality of covariances

Role of Eigenvalues in Some classical questions

Hypothesis testing: e.g. $H_0: \Sigma = I$ or $\Sigma_X = \Sigma_Y$
 $H_0: M = 0$
 $H_0: \text{Cov}(X, Y) = 0$

→ group invariant tests based on (l_i) , (u_i) , (w_i)

Estimation: e.g. of Σ , using

'mle': $\hat{\Sigma} = n^{-1}A = ULU^T$ $U \in O(p)$, $L = \text{diag}(l_i)$

Need to shrink (l_i) :

e.g. $n = p = 10$ BUT $(l_i) = \begin{matrix} \underline{3.07} & 1.40 & 1.12 & 0.78 & 0.51 \\ & 0.30 & 0.16 & .095 & .036 & \underline{.00} \end{matrix}$
 $\Sigma = I$ (one sample!)

⇒ $\hat{\Sigma} = U \varphi(L) U^T$ Stein, Perlman-Lin, Haff, Berger, Loh, ...

→ difficult to analyze for fixed n, p .

Classification, Regression, Clustering, ...

Non-null densities

E.g. (l_i) from $A \sim W_p(n, \Sigma)$

$$f(L) = c |\Sigma|^{-\frac{n}{2}} \hat{F}_0(-\frac{1}{2}\Sigma^{-1}, A) \prod_i l_i^{\frac{n-m-1}{2}} \prod_{i < j} (l_i - l_j)^{2-1}$$

$$F_0(-\Sigma^{-1}, A) = \int_{\substack{U(p) \\ O(p)}} \text{etr}\{-\Sigma^{-1} U A U^*\} dU$$

$$[\Sigma = I \rightarrow \text{Laguerre}\{U, 0\}E]$$

James, 1964 Hypergeom. functions of matrix argument

F_0 exponential χ^2 , Wishart, $\lambda(A)$

F_1 binomial F , $\lambda(AB^{-1})$

F_0 Bessel non-central χ^2 , Wishart, mea

F_1 confluent hyper. non-central F , $\lambda(AB^{-1})$

F_2 Gaussian hyper. multiple R^2 , CCA

• influence on practice?

• useful approximations via RMT?

TRADITIONAL ASYMPTOTICS

p fixed, $n \rightarrow \infty$

$$A = X^T X = U L U^T \sim W_p(n, \Sigma) \quad \Sigma = \text{diag}(\lambda_1, \dots, \lambda_r, 1, \dots, 1) \quad (\lambda_1 > \dots > \lambda_r > 1 = \lambda_{r+1} = \dots = \lambda_p)$$

$$\sqrt{\frac{n}{2}} \left(\frac{L}{n} - \lambda \right) \xrightarrow{\mathcal{D}} D$$

Girshick, 39 \rightarrow Anderson, 63

$$\begin{cases} D_1, \dots, D_r \stackrel{\text{ind}}{\sim} N(0, \lambda_i^2) \\ D' = (D_{r+1}, \dots, D_p) \sim \text{GOE}(p-r) \end{cases}$$

$$f_{D'}(d) = c e^{-\frac{1}{2} \sum_{j=1}^p d_j^2} \prod_{r < j < k \leq p} |d_j - d_k|$$

Null case: $r=0$; \rightarrow not (traditionally) useful.

Large n, p (+ q) asymptotics:

	Craddock Flood	Phoneme	Barnett- Preßendorfer	Wough	Chemo- metrics
n	1095	161	600	137	56
p	130	256	126	4	6
q			33	5	22

First try: $p/n \rightarrow c_1 > 0$, $q/n \rightarrow c_2 > 0$

3. 'CASE STUDY' : Largest eigenvalues in null cases:

[PCA]
etc.] $A = X^T X \sim CW_p(n, I) \rightarrow l_1 \geq l_2 \geq \dots \geq l_p$

$$f(l) = c \prod_i e^{-\frac{1}{2} l_i} l_i^{\frac{n-p-1}{2}} \prod_{i < j} (l_i - l_j)^{2^{-1}} \quad \text{Laguerre } \{U, 0\} E$$

Empirical spectrum: Marčenko-Pastur + ...

Strong law for l_1 : Geman, + ... Bai (99)

Tracy-Widom limit for rescaled l_1 : Johansson 2000 \mathbb{C}
IMJ 2001 \mathbb{R} .

[CCA]
etc.] $A \sim W_p(q, I)$ $>$ indep, $p \leq q, n-q$
 $B \sim W_p(n-q, I)$

$u_1 \geq u_2 \geq \dots \geq u_p$ solve $\det[A - u(A+B)] = 0$

$$f(u) = c \prod_i u_i^{\frac{1}{2}(q-p-1)} (1-u_i)^{\frac{1}{2}(n-q-p-1)} \prod_{i < j} (u_i - u_j)^{2^{-1}}$$

Jacobi $\{U, 0\} E$

Fisher, Girschick, Hsu, Mood, Roy 1939

LIMITING EMPIRICAL SPECTRUM

Wachter 1980

$$A \sim W_p(q, I) \perp B \sim W_p(n-q, I) \quad p \leq q, n-q$$

$$|A - u_i(A+B)| = 0 \quad u_1 \geq u_2 \geq \dots \geq u_p \geq 0$$

NOTE: $u_i = r_i^2$ squared correlation scale

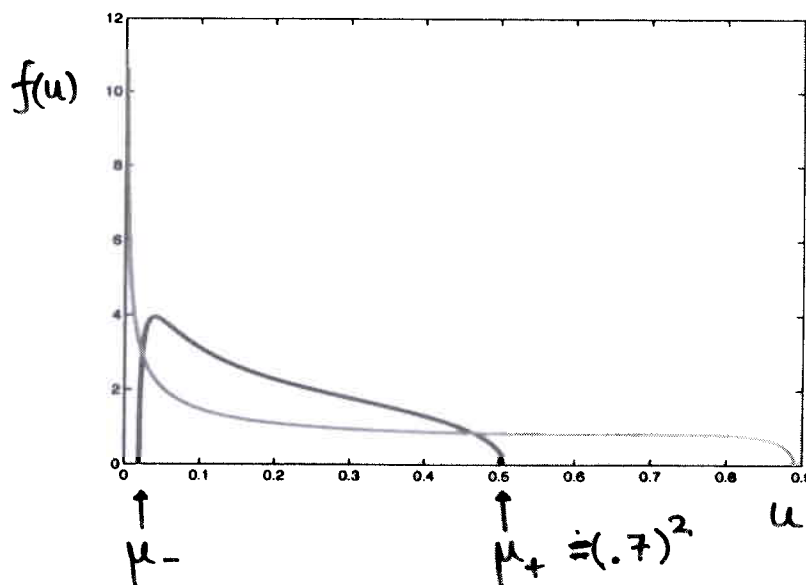
ASSUME: $0 < \sin^2 \frac{\gamma_0}{2} \leftarrow \frac{p-1/2}{n-1} \leq \frac{q-1/2}{n-1} \rightarrow \sin^2 \frac{\phi_0}{2}$

THEN: $F_p(u) = p^{-1} \# \{i : u_i \leq u\} \rightarrow \int_0^u f(u') du'$

$$f(u) = c_u \frac{\sqrt{(\mu_+ - u)(u - \mu_-)}}{u(1-u)} \quad c_u = 2\pi \sin^2 \frac{\gamma_0}{2}$$

where

$$\mu_{\pm} = \cos^2 \left(\frac{\pi}{2} - \frac{\phi_0 \pm \gamma_0}{2} \right)$$



c.f. also

Bai - Yin - Krishnaiah

Silverstein ('85)

Bai (99)

$n = 200, p = 20$
 $q = 40$

"evil RA"

LIMITING DISTRIBUTION FOR u_i

$$A \sim W_p(q, I) \perp\!\!\!\perp B \sim W_p(n-q, I) \quad (\text{resp complex})$$

Wishart

$$|A - u_i(A+B)| = 0 \quad u_1 \geq u_2 \geq \dots \geq u_p \quad p \leq q, n-q$$

Let $p, q(p), n(p) \rightarrow \infty$

Set $\sin^2 \frac{\gamma_p}{2} = \frac{p-1/2}{n-1} \quad \sin^2 \frac{\varphi_p}{2} = \frac{q-1/2}{n-1}$

$$\mu_{p+} = \cos^2 \left(\frac{\pi}{2} - \frac{\varphi_p + \gamma_p}{2} \right)$$

$$\sigma_{p+}^3 = \frac{1}{(2n-2)^2} \frac{\sin^4(\varphi_p + \gamma_p)}{\sin \varphi_p \cdot \sin \gamma_p}$$

Assume $(\gamma_p, \varphi_p) \rightarrow (\gamma_0, \varphi_0)$ with $0 < \gamma_0 \leq \varphi_0$

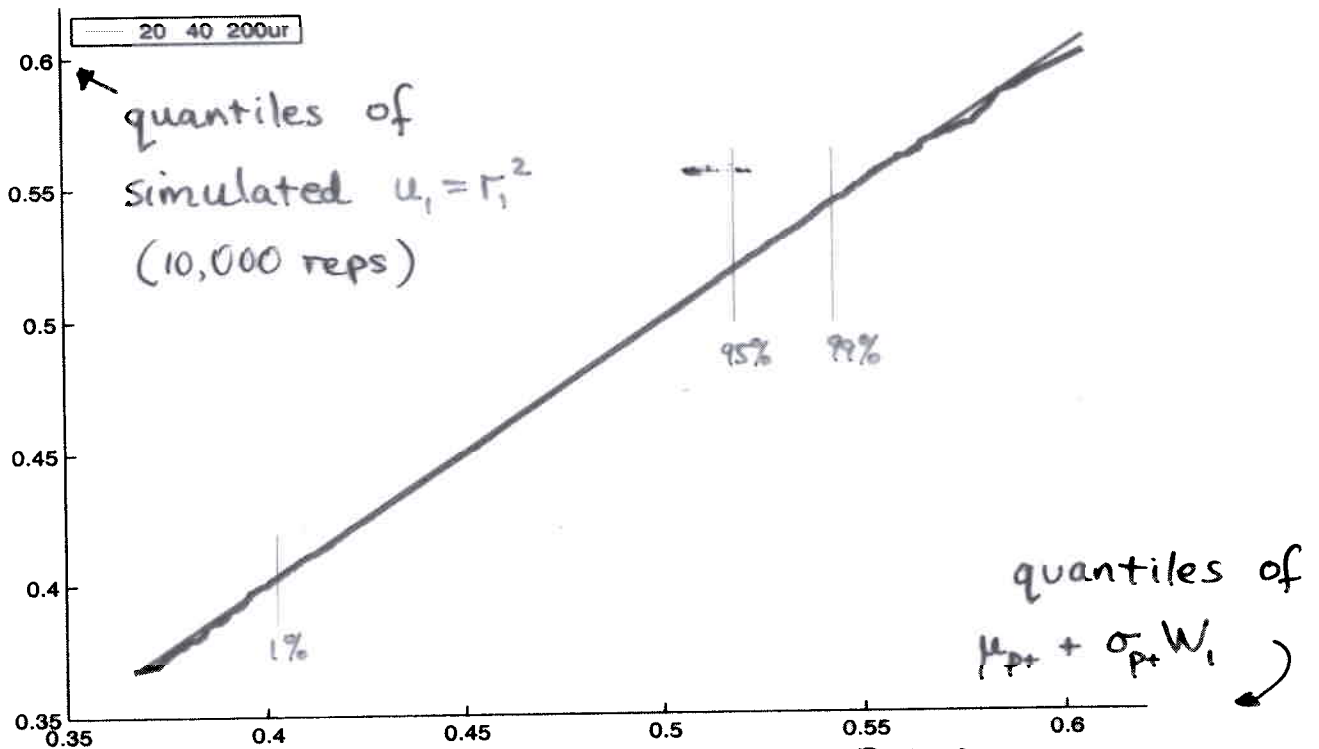
Theorem $\frac{u_i - \mu_{p+}}{\sigma_{p+}} \xrightarrow{-\infty} W_1$ (resp W_2)
(Tracy-Widom laws)

|| Real case: $p^{-1/2}, q^{-1/2}, n-1$ v. important for numerics

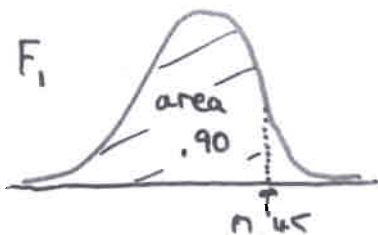
- reduces error from $O(p^{-1/3})$ to $O(p^{-2/3})$

Complex case: tweak $\mu_{p+}^c, \sigma_{p+}^c$ to get $O(p^{-2/3})$

Finite (p,q,n) simulations of $u_1 = r_1^2$



Percentile for W_1	TW (μ, σ)	20,40,200 (.494, .024)	5,10,50 (.478, .061)	2,4,20 (.442, .117)	2 * SE
-3.90	.01	.010	.008	.000	(.002)
-3.18	.05	.052	.049	.009	(.004)
-2.78	.10	.104	.099	.046	(.006)
-1.91	.30	.311	.304	.267	(.009)
-1.27	.50	.507	.506	.498	(.010)
-0.59	.70	.706	.705	.711	(.009)
<u>0.45</u>	.90	<u>.904</u>	.910	.911	(.006)
0.98	.95	.950	.955	.958	(.004)
2.02	.99	.990	.992	.995	(.002)



$$\hat{P} \left[\frac{u_1 - \mu_p}{\sigma_p} \leq 0.45 \mid (n, p, q) = (20, 40, 200) \right]$$

REMARKS

- $p^{-2/3}$ scale of variability for u_i
- 95 % tile $\doteq \mu_{p+} + \sigma_{p+}$
- 99 % tile $\doteq \mu_{p+} + 2\sigma_{p+}$
- if $\mu_{p+} > .8$ better approx on logit scale:

$$v_i = \log u_i / (1 - u_i)$$

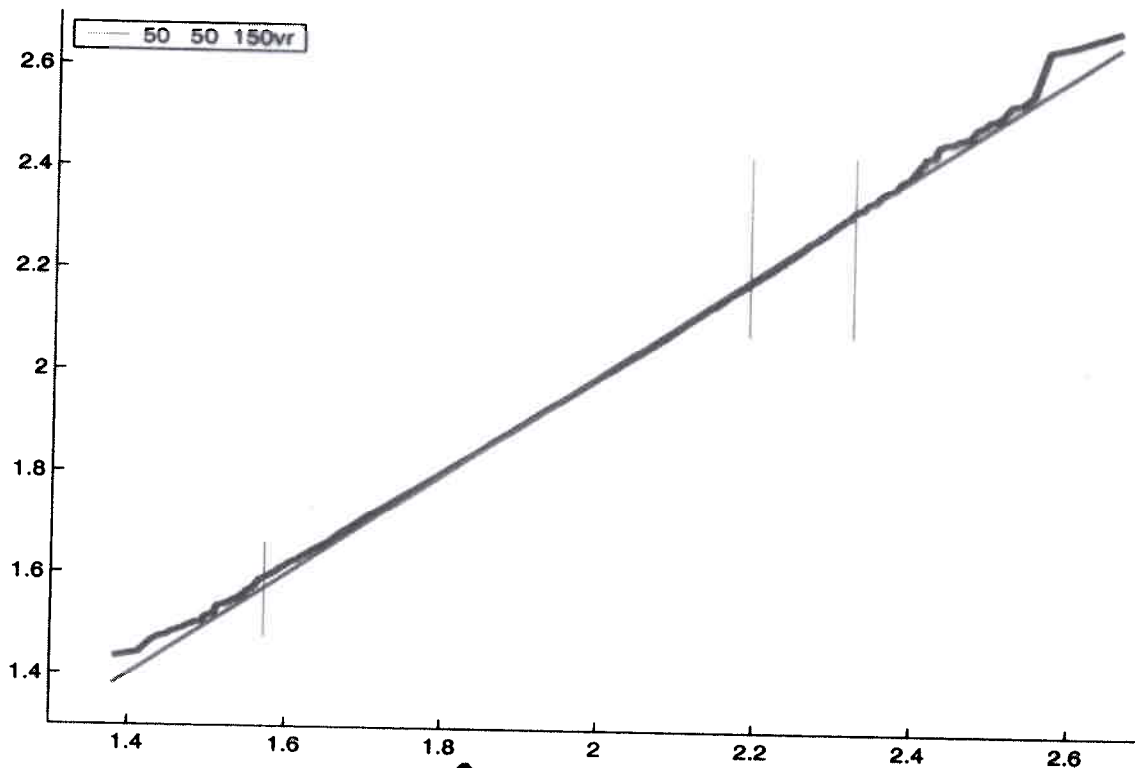
$$\mu_{v+} = \log \frac{\mu_{p+}}{1 - \mu_{p+}} \quad \sigma_{v+} = v'(\mu_{p+}) \sigma_{p+} = \frac{\sigma_{p+}}{\mu_{p+}(1 - \mu_{p+})}$$

- Smallest eigenvalue : previous assumptions
and $\gamma_0 < \varphi_0$

$$\sigma_{p-}^3 = \frac{1}{(2n-2)^2} \frac{\sin^4(\varphi_p - \gamma_p)}{\sin \varphi_p \cdot \sin \gamma_p}$$

then $\frac{\mu_{p-} - u_p}{\sigma_{p-}} \xrightarrow{D} W_1 \quad (W_2)$

- Corresponding limit dist^{ns} for $u_2 \geq \dots \geq u_k$
 $u_{p-k} \geq \dots \geq u_{p-1}$
 k fixed.



Percentile	TW (μ, σ)	50,50,150 (2.06, .127)	5,5,15 (1.93, .594)	P. q. n. 2,2,6 (1.69, 1.11)	2 * SE
-3.90	.01	.007	.002	.010	(.002)
-3.18	.05	.042	.023	.037	(.004)
-2.78	.10	.084	.062	.074	(.006)
-1.91	.30	.289	.262	.264	(.009)
-1.27	.50	.499	.495	.500	(.010)
-0.59	.70	.708	.725	.730	(.009)
0.45	.90	.905	.919	.931	(.006)
0.98	.95	.953	.959	.966	(.004)
2.02	.99	.990	.991	.993	(.002)

QUALITY OF APPROXIMATION: AN ANALOGY

t -statistic $\sqrt{n}\bar{x}/s$

largest root L_1 of S

Model $X_i \stackrel{\text{ind}}{\sim} N(\mu, \sigma^2)$
 $H_0: \mu = 0$

$\vec{X}_i \sim N(0, \Sigma)$
 $H_0: \Sigma = I$

Exact Law $t \sim t_{n-1}$

$L_1 \sim \text{LOE}(p, n-p)$

Approx Law $\Phi(x) = \int_{-\infty}^x \phi(s) ds$

$F_1(x) = \exp\left\{-\frac{1}{2} \int_x^{\infty} q(s) + (x-s)^2 q(s) ds\right\}$

Second-Order Accuracy

'Correlation' functions

$$P\{t_{(n-1)} \leq x\} = \Phi(x) + O\left(\frac{1}{\sqrt{n}}\right)^2$$

$$\sigma_{np} S_p(\mu_{np} + \sigma_{np} x, \mu_{np} + \sigma_{np} y)$$

$$\rightarrow S(x, y) + O(p^{-2/3})$$

Conj: $P\{L_1 \leq \mu_{np} + \sigma_{np} x\}$
 $= F_1(x) + O(p^{-2/3})$

Robustness to Model

- analogous issues
- Soshnikov (2001)

Convergence Strategy for Extreme Eigenvalues

$$f(x_1, \dots, x_N) = \frac{1}{N!} (q) \det [K_{N(i)}(x_i, x_j)]$$

Correlation functions:

$$e_{N,k}(x_1, \dots, x_k) = (q) \det [K_{N(i)}(x_i, x_j)]$$

[Soshnikov] Convergence of moments $\int_{I_k} e_{N,k} \rightarrow \int_{I_k} e_k \quad \forall I$

(+...) implies, for determinantal point fields F_N, F

$$\mathbb{L}\{x_{(1)}, \dots, x_{(k)} | F_N\} \xrightarrow[N \rightarrow \infty]{} \mathbb{L}\{x_{(1)}, \dots, x_{(k)} | F\} \quad k \text{ fixed}$$

so, need (uniform) convergence of rescaled kernel

$$\sigma_N K_N(\mu_N + \sigma_N s, \mu_N + \sigma_N t) \rightarrow K_A(s, t)$$

AND to reduce error from $O(N^{-1/3})$ to $O(N^{-2/3})$

need good approx^{ns} to center μ_N
scale σ_N

JACOBI \rightarrow AIRY

To show

$$\sigma_N K_N(\mu_N + \sigma_N s, \mu_N + \sigma_N t) \rightarrow K_A(s, t) = \frac{1}{s-t} \begin{vmatrix} Ai(s) & Ai(t) \\ Ai'(s) & Ai'(t) \end{vmatrix}$$

use Christoffel - Darboux property

$$K_N(x, y) = \sum_{k=0}^{N-1} \phi_k(x) \phi_k(y) = \frac{a_N}{x-y} \begin{vmatrix} \phi_N(x) & \phi_N(y) \\ \phi_{N-1}(x) & \phi_{N-1}(y) \end{vmatrix}$$

So, need to show

$$\boxed{\delta N^{-1/6} \phi_N(\mu_N + \sigma_N s) \approx Ai(s)} + O(N^{-2/3})$$

where

$$\phi_N(x) = h_N^{-1/2} (1-x)^{\alpha/2} (1+x)^{\beta/2} P_N^{\alpha, \beta}(x),$$

and, treble asymptotics:

$$\begin{pmatrix} \alpha \\ \beta \\ N \end{pmatrix} = \begin{pmatrix} n-p-q \\ q-p \\ p \end{pmatrix} \rightarrow \infty$$

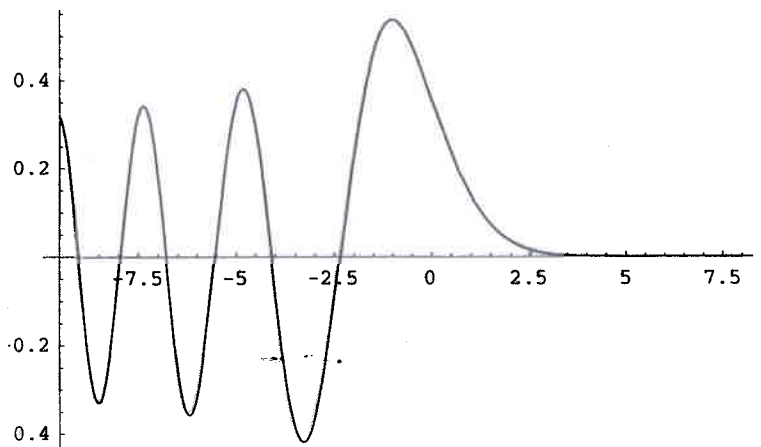
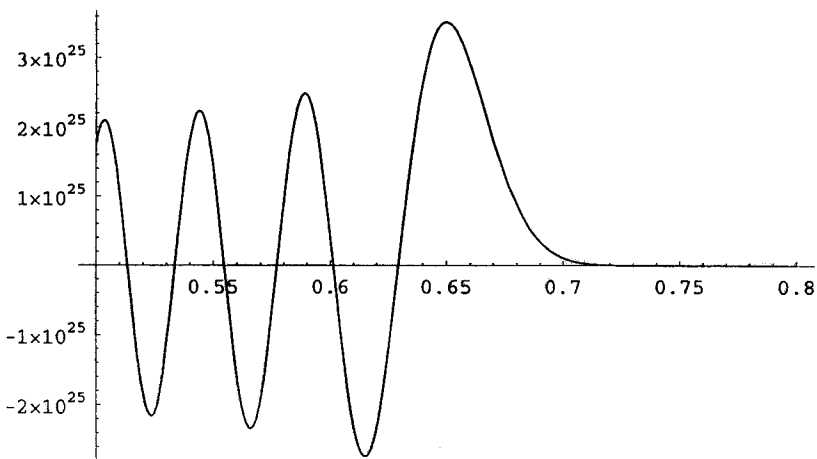
Example:

$$(\alpha, \beta, N) = (200, 100, 100)$$

$$\Leftrightarrow (p, q, n) = (100, 200, 500)$$

$$(1-x)^{\alpha/2} (1+x)^{\beta/2} P_N^{\alpha, \beta}(x)$$

$$Ai(s)$$



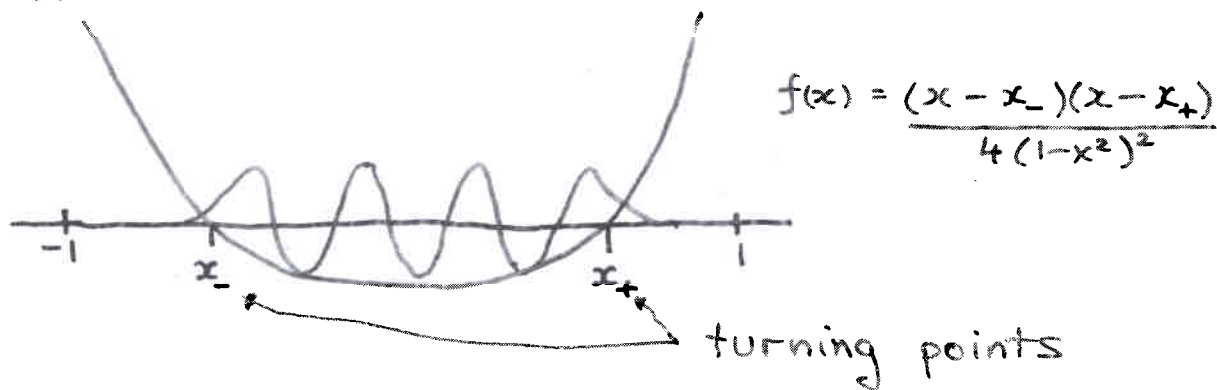
$$\boxed{Ai''(s) = s Ai(s)}$$

LIIOUVILLE - GREEN asymptotics for ortho polynomials

e.g. Laguerre $L_N^\alpha(x)$, Jacobi $P_N^{\alpha, \beta}(x)$ α, β, N large

Satisfy 2nd order o.d.e.

(*)
$$\frac{d^2 w}{dx^2} = \{ \kappa^2 f(x) + g(x) \} w(x) \quad \kappa = \kappa(N) \text{ large}$$



Transform
$$\frac{d^2 W}{d^2 \zeta} = [\kappa^2 \zeta + \psi(\zeta)] W(\zeta)$$

$$\zeta^{3/2}(x) = \int_{x_+}^x \sqrt{f(y)} dy$$

ERROR BOUND (Olver, 74) \exists solution of (*) with

$$w(x, \kappa) = \hat{f}^{-1/4}(x) \{ A_2(\kappa^{2/3} \zeta) + \varepsilon(x, \kappa) \} \quad \hat{f}(x) = \frac{f(x)}{\zeta}$$

$$|\varepsilon(x, \kappa)| \leq |A_2|(\kappa^{2/3} \zeta) \left\{ \exp\left[\frac{c_0}{\kappa} V(\zeta)\right] - 1 \right\}$$

so long as
$$V(\zeta) = \int_{\zeta}^{\infty} |\psi(v)| v^{-1/2} dv < \infty$$

Virtues of Error Bound

• constrains approxⁿ: $V(\gamma)$ convergent

$$\Rightarrow g(x) \sim \frac{-1/4}{(1-x)^2} \quad \Rightarrow \quad k_N = 2N + \alpha + \beta + 1$$

\Rightarrow uniform error bounds in x : $|E(x, k)| = O(1/N)$

Centering + Scaling constants: $x_N = x_+$

σ_N by matching: $k^{2/3} J(x_N + \sigma_N s) \approx s$ s small

$$\Rightarrow \sigma_N = \frac{1}{k^{2/3} J(x_N)} \quad \Rightarrow \quad \sigma_N^3 = \frac{2 \sin^4(\varphi + \gamma)}{k^2 \sin \varphi \sin \gamma}$$

\Rightarrow Jacobi \rightarrow Airy approxⁿ: with $x = x_N + \sigma_N s$

$$\phi_N(x) = \left(\frac{\sigma_N k_N}{1-x^2} \right)^{1/2} [\text{Ai}(s) + O(N^{-2/3})]$$

Similarly for ϕ_{N-1} :

$$\begin{aligned} x_{N-1} &= x(N-1, \alpha, \beta) \\ \sigma_{N-1} &= \sigma(N-1, \alpha, \beta) \end{aligned}$$

Lazy Higher Order Approximation Seek good μ, σ with

$$\sigma K_N(\mu + s\sigma, \mu + t\sigma) = K_A(s, t) + R_N \quad (†)$$

From Christoffel-Darboux,

$$K_N(x, y) = a_N \frac{\phi_N(x)\phi_{N-1}(y) - \phi_N(y)\phi_{N-1}(x)}{x - y}, \quad \text{with}$$

$$\phi_N(x) = \left(\frac{\sigma_N K_N}{1-x^2} \right)^{1/2} [Ai(s_N) + O(N^{-2/3})], \quad s_N = \frac{x - x_N}{\sigma_N}$$

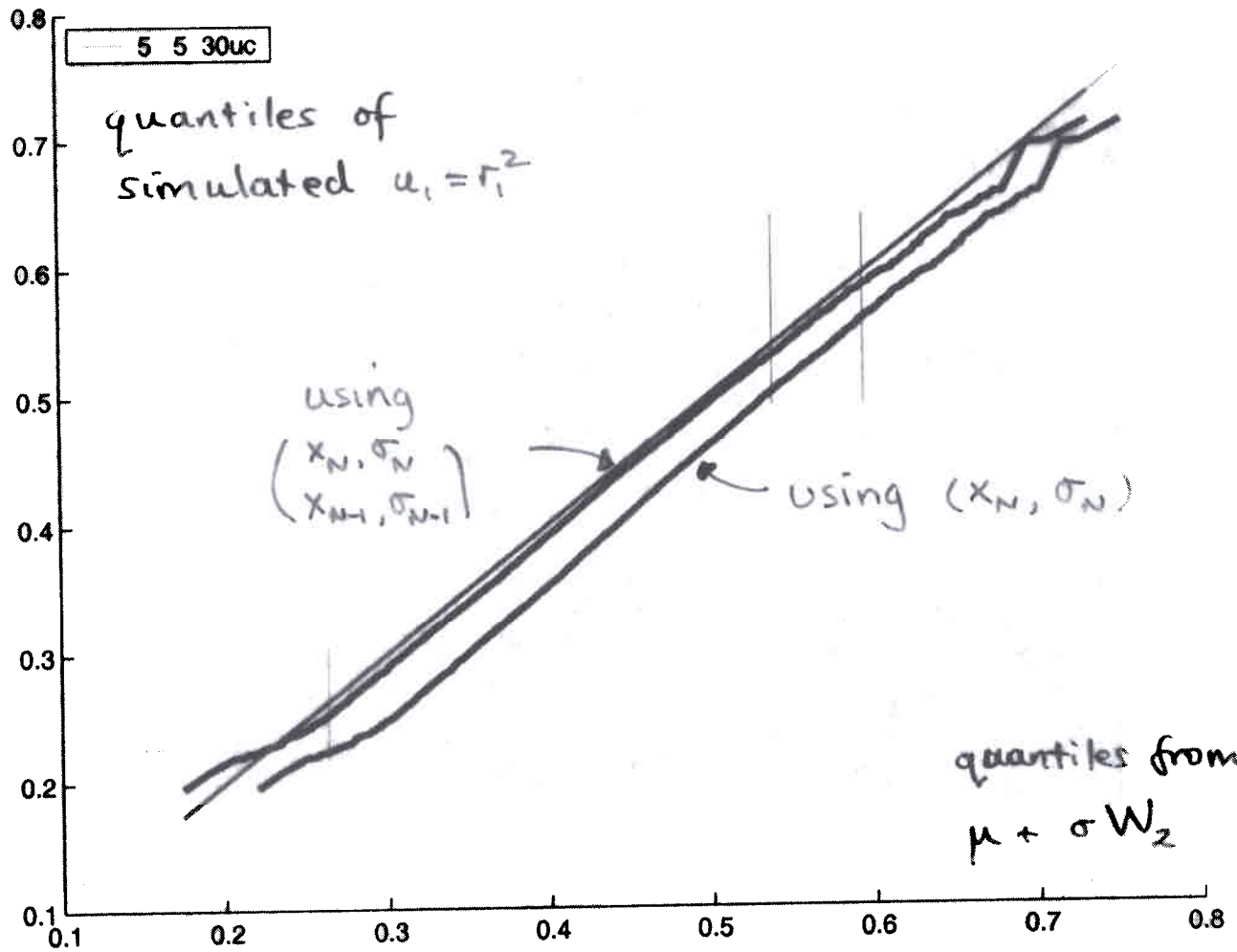
For ϕ_N use center x_N , scale σ_N ,

but using (x_N, σ_N) in (†) $\Rightarrow R_N = O(N^{-1/3})$

For ϕ_{N-1} use center x_{N-1} scale σ_{N-1} $s_{N-1} = \frac{x - x_{N-1}}{\sigma_{N-1}}$

and with $s = \frac{s_N + s_{N-1}}{2}, \dots \Rightarrow \boxed{R_N = O(N^{-2/3})}$

$$\Rightarrow \mu = \frac{x_N/\sigma_N + x_{N-1}/\sigma_{N-1}}{1/\sigma_N + 1/\sigma_{N-1}}, \quad \frac{1}{\sigma} = \frac{1}{2} \left(\frac{1}{\sigma_N} + \frac{1}{\sigma_{N-1}} \right)$$



THE REAL CASE + higher order approximation

$$P_{N,k}(x_1, \dots, x_k) = q \det \left[f_{N,i}(x_i, x_j) \right]_{1 \leq i, j \leq k}$$

$$f_{N,i}(x, y) = \begin{bmatrix} K_{N,i}(x, y) & I_{N,i}(x, y) \\ D_{N,i}(x, y) & S_{N,i}(x, y) \end{bmatrix}$$

Laguerre OE: closed form representation in Widom, 99

Jacobi OE: use Adler - Forrester - Nagao - van Mierbeke, 00

$$K_{N,i}^{\alpha-1, \beta-1}(x, y) = \underbrace{\sqrt{\frac{1-x^2}{1-y^2}} K_{N-1,2}^{\alpha, \beta}(x, y)}_{\text{Laguerre OE}} + \underbrace{a_{N-1} \frac{K_{N-1}}{2} \psi_{N-1}(y) (\epsilon * \psi_{N-2})(x)}_{\text{Jacobi OE}}$$

$$\begin{aligned} x &= x_{N-1} + s \sigma_{N-1} \\ y &= \dots + t \dots \end{aligned}$$

$$\psi_N(x) = \phi_N(x) / \sqrt{1-x^2}$$

$$\epsilon(x) = \frac{1}{2} \operatorname{sgn} x$$

$$\begin{aligned} K_A(s, t) &= \frac{\Delta}{2} A_i(s) A_i(t) \\ &+ O(N^{-2/3}) \end{aligned}$$

$$\begin{aligned} \frac{1}{2} A_i(t) \int_{-\infty}^s A_i(u) du &+ \frac{\Delta}{2} A_i(s) A_i(t) \\ &+ O(N^{-2/3}) \end{aligned}$$

• 'miraculous' cancellation of $O(N^{-1/3})$ terms

⇒ much improved small (n, p, q) approxⁿ.

SOME OPEN QUESTIONS

E.g. 'Non-white' Wishart

$$A \sim \mathbb{C}W_p(n, \Sigma)$$

$$f(L; \Sigma) = c |\Sigma|^{-n} \prod_i L_i^{n-p} \int_{U(p)} \text{etr}(-\Sigma^{-1} U A U^*) dU \Delta^2(L) \quad (\text{James})$$

$$= c \prod_i \lambda_i \prod_i L_i^{n-p} \frac{\det[e^{-L_k/\lambda_j}]}{\Delta(\lambda_j^{-1})} \Delta(L) \quad (\text{HCIZ})$$

→ determinantal correlation functions

Distribution of L_1 (or L_2, \dots) as $n/p \rightarrow \gamma$?

E.g. a) $\Sigma = (\lambda_1, \dots, \lambda_\eta > 1 = \lambda_{\eta+1} = \dots = \lambda_p)$ η FIXED

$$\lambda_\eta \approx n^{-1} (\sqrt{n} + \sqrt{p})^2$$

b) power law $\lambda_k = c k^{-\beta}$

Progress : • Junho Baik on (a)

• S. Peché + G. Ben Arous

A Vaguer List:

- Extreme eigenvalues:
 - 'Bootstrap' C.I.'s + validity as $n/p \rightarrow \gamma$?
 - strong law behavior for general Σ
- Eigenvectors:
 - Consistency, asymptotic distⁿ as $n/p \rightarrow \gamma$
 - Effect of regularization (FDA)
 - 'Sparse' versions of PCA (Lu)
- Empirical distⁿ of eigenvalues
 - (further) statistical uses of Marcenko-Pastur
 - use of CLT for $\Sigma h(l_i)$
- Estimation of Large covariance matrices
 - sparsity for non-unit variances
 - Bayes estimates (Guionnet)
- Classification / Clustering
 - models for large covariance structures (Bickel-Levine)
- Issues from application domains
 - climate studies, face recognition, document retrieval ...