

# Combinatorial Matrix Theory and Majorization

Geir Dahl  
Department of Mathematics  
University of Oslo

including joint work with Richard A. Brualdi

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## Majorization

Let  $x, y \in \mathbb{R}^n$ .  $x_{[j]}$ : the  $j$ th largest component in  $x$ .

Definition:  $x$  is majorized by  $y$ , denoted  $x \preceq y$ , if

$$\sum_{j=1}^k x_{[j]} \leq \sum_{j=1}^k y_{[j]} \quad (k < n)$$

$$\sum_{j=1}^n x_j = \sum_{j=1}^n y_j.$$

Interpretation: " $x$  is less spread out than  $y$ ":  $(7, 5, 3) \preceq (9, 4, 2)$ .

Generalizations: ordering matrices, measure families, group-major. etc.

- Hardy, Littlewood, Pólya, Schur, Muirhead, Dalton,...
- Arnold, Marshall and Olkin: *Inequalities: Theory of Majorization and Its Applications*, (2011) (First ed., 1979)
- Steele: *The Cauchy-Schwarz Master Class: An Introduction to the Art of Mathematical Inequalities*, (2004)

## Basic properties

- permutation invariant:  $x \preceq Px \preceq x$  for every permutation matrix  $P$
- Transitive, reflexive,  $\preceq$  is a **preorder** on  $\mathbb{R}^n$ .
- Majorization is a **partial order** on the (polyhedral) cone

$$\mathcal{D}^n = \{x \in \mathbb{R}^n : x_1 \geq x_2 \geq \cdots \geq x_n\}$$

Actually a lattice (min and max operations).

- Weak majorization:  $x \preceq_w y$

## Characterizations

### Theorem

Let  $x, y \in \mathbb{R}^n$ . Equivalent:

(i)  $x \preceq y$

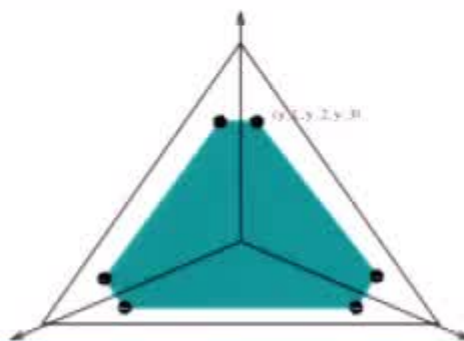
(ii)  $\sum_{i=1}^n g(x_i) \leq \sum_{i=1}^n g(y_i)$  for all convex functions  $g : \mathbb{R} \rightarrow \mathbb{R}$

(iii)  $x = Ay$  for some doubly stochastic matrix  $A$

(iv)  $\sum_i x_i = \sum_i y_i$  and  $\sum_i (x_i - a)^+ \leq \sum_i (y_i - a)^+$  for all  $a \in \mathbb{R}$ .

(v)  $\sum_i |x_i - a| \leq \sum_i |y_i - a|$  for all  $a \in \mathbb{R}$

(vi)  $x$  lies in the convex hull of the orbit of  $y$  under the group of permutation matrices.



## Examples

- Majorization and existence results

### Theorem (Schur-Horn (1923, 1954))

If  $A = [a_{ij}]$  is a Hermitian matrix, with diagonal  $(d_1, d_2, \dots, d_n)$  and eigenvalues  $(\lambda_1, \lambda_2, \dots, \lambda_n)$ , then

$$(d_1, d_2, \dots, d_n) \preceq (\lambda_1, \lambda_2, \dots, \lambda_n).$$

Conversely, if such a majorization holds in  $\mathbb{R}^n$ , then there exists a real symmetric matrix  $A$  with diagonal elements  $d_1, d_2, \dots, d_n$  and eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$ .

**Kaftal, Weiss (2009)**: extension to infinite sequences, matrices.

**Atiyah (1982)**: generalization in algebraic geometry.



## Combinatorics:

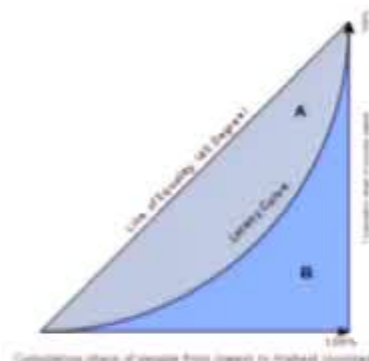
The **Gale-Ryser theorem**: *There exists a  $(0, 1)$ -matrix with row sum vector  $R$  and column sum vector  $S$  if and only  $S \preceq R^*$ .*



**Convexity**: Doubly stochastic matrices, inequalities

**Probability**: Stochastic order/dominance

**Economics**: The Lorenz curve: income distribution, the Gini index:



**Shannon information entropy**:  $E(p) = -\sum_i p_i \ln p_i$

**Quantum physics**: entanglement

- Majorization and min/max of certain symmetric functions

A function  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is **Schur-convex** whenever  $x \preceq y$  implies  $f(x) \leq f(y)$ . So: monotone. Then  $f$  must be symmetric.

**A bounding principle:** Assume  $f$  is Schur-convex on  $S$  and that  $S \subseteq \mathbb{R}^n$  contains a unique *minimal* element  $x^1$  and a unique *maximal* element  $x^2$  in the majorization order. Then

$$\min_{x \in S} f(x) = f(x^1) \quad \text{and} \quad \max_{x \in S} f(x) = f(x^2).$$

Sometimes this gives interesting bounds; the trick is to discover an underlying majorization.

**Examples:** Arithmetic-geometric mean ineq., Kantorovich ineq.

**And:** next eigenvalues of certain Laplacian matrices ...

## Laplacian energy

Discretizing the Laplace equation (a PDE)

$$\Delta u = \frac{\partial^2 u}{\partial x_1^2} + \frac{\partial^2 u}{\partial x_2^2} = 0$$

gives a linear system with variables on a grid. More generally, we can consider heat flow in a graph.

Let  $G$  be a simple undirected graph with  $n$  vertices,  $m$  edges.

Laplacian matrix:

$$L(G) = D(G) - A(G)$$

where  $A(G)$ : adjacency matrix,  $D(G)$ : diagonal matrix with vertex degrees. So:  $(L(G))_{ij} = -1$  when vertices  $i \neq j$  are adjacent, otherwise 0, and degrees on the diagonal. Studied in Spectral graph theory.

$L(G)$ : real, symmetric, positive semidefinite, with eigenvalues

$$\mu_1 \geq \mu_2 \geq \dots \geq \mu_n = 0.$$



- **Dahl**, The Laplacian energy of threshold graphs and majorization (LAA, 2015). See also **Helmberg, Trevisan**, Threshold graphs of maximal Laplacian energy (Disc. Math, 2015). Different approaches.

Laplacian energy:  $LE(G) = \sum_{i=1}^n |\mu_i - 2m/n|$ ; distance of L. eigenvalues from average degree.

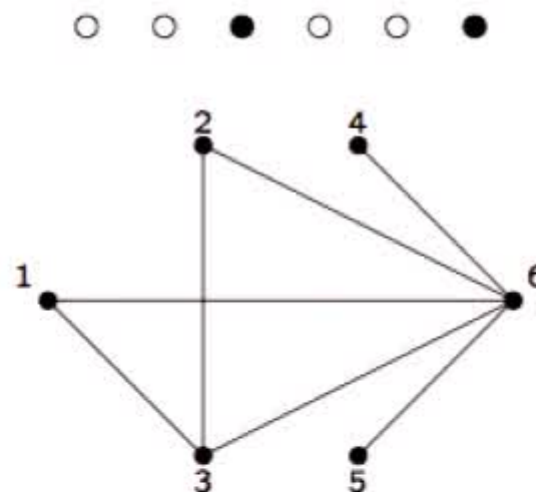
- Then  $LE(G)$  is a **Schur-convex function** of  $\mu = (\mu_1, \mu_2, \dots, \mu_n)$ , i.e., increasing w.r.t. the majorization order.
- **Grone-Merris conjecture**, proved by **Bai**:  $\mu \preceq d^*$ , where  $d^*$  is the conjugate sequence of degree vector  $d$ ;  $d_k^* = |\{i : d_i \geq k\}|$ .
- So:  $LE(G) \leq \sum_{i=1}^n |d_i^* - 2m/n|$ .
- Combining Grone-Merris-Bai with Schur-Horn gives:

$$d \preceq \mu \preceq d^*.$$

Equality:  $\mu = d^*$  if and only if  $G$  is a **threshold graph**. So: **integral!!!**

- Goal: Find a threshold graph which maximizes the Laplacian energy
- A main message: finding underlying majorization gives nice analysis

**Threshold graph:** repeatedly add either an **isolated** vertex or a **dominating** vertex, which is a vertex that is connected to all vertices previously added.



**Trace** of  $G$ : the number of dominating vertices. Here 2.

**Degree vector** of a graph  $G$  with  $n$  vertices,  $m$  edges:  $d = (d_1, d_2, \dots, d_n)$  is a monotone, nonnegative and integral vector with  $\sum_i d_i = 2m$ . Let  $\kappa(d) = \max\{i : d_i \geq i\}$ .

From graph theory (Ruch and Gutman):  $d$  is the degree sequence of a graph if and only if

$$\sum_{i=1}^k d_i \leq \sum_{i=1}^k (d_i^* - 1) \quad (k \leq \kappa(d)).$$

**Threshold graphs:** Equality here, so  $d_i = d_i^* - 1$  ( $i \leq \kappa(d)$ ).  
*This makes it easy to construct all threshold graphs, and see Laplacian eigenvalues.*



**Example:** Let  $n = 6$  and  $m = 7$ .

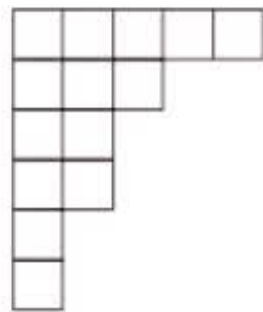
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Here the Laplacian eigenvalue vector is  $\mu = (6, 4, 2, 1, 1, 0)$ .

We fix  $n$ ,  $m$  and  $\kappa(G)$ . Remember:  $LE(G) = \sum_{i=1}^n |d_i^* - 2m/n|$ .

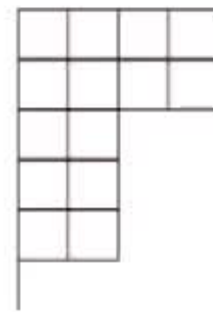
**Lemma:**  $LE(G) = 2 \sum_{i=1}^n (d_i^* - \alpha)^+$  where  $\alpha = 2m/n$ .

**Example:**  $n = 6$ ,  $m = 7$  and  $\alpha = 2m/n = 7/3$ . Move the blocks!



$$\mu(G) = (6, 4, 2, 1, 1, 0)$$

$$LE(G) = 32/3$$



$$\mu(G') = (5, 5, 2, 2, 0, 0)$$

$$LE(G') = 32/3$$

Connection to majorization: **integer partitions**.

Let  $p, q > 0$  and  $N \geq 0$  be three integers with  $N \leq pq$ .

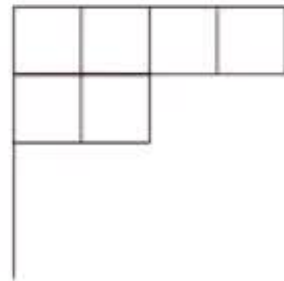
Let  $\mathcal{P}_{p,q}^N$  be the set of all integer partitions of  $N$  where each part  $x_i$  is bounded by  $q$ , i.e., nonincreasing integral vectors  $x = (x_1, x_2, \dots, x_p) \in \mathbb{R}^p$  satisfying

$$\sum_{i=1}^p x_i = N \text{ and } 0 \leq x_i \leq q \text{ (} i \leq p \text{)}.$$

Majorization on  $\mathcal{P}_{p,q}^N$ ; poset:  $x \preceq y$  means that  $\sum_{i=1}^k x_i \leq \sum_{i=1}^k y_i$  for  $k \leq p$ . Define:

- $\hat{x} = (q, q, \dots, q, r, 0, \dots, 0)$  where the number of  $q$ 's is  $\lfloor N/q \rfloor$  and  $r = N - \lfloor N/q \rfloor q$ .
- $\tilde{x} = (v+1, \dots, v+1, v, \dots, v)$ , where  $v = \lfloor N/p \rfloor$  and the number of components being  $v+1$  is  $N - pv$ .

**Example:**  $p = q = 4$  and  $N = 6$ . Then  $\hat{x} = (4, 2, 0, 0)$  and  $\tilde{x} = (2, 2, 1, 1)$  and their Ferrers diagrams are



### Lemma

$\hat{x}$  is the unique maximal element and  $\tilde{x}$  is the unique minimal element in the poset  $(\mathcal{P}_{p,q}^N, \preceq)$ . Therefore,

$$\tilde{x} \preceq x \preceq \hat{x} \quad \text{for all } x \in \mathcal{P}_{p,q}^N.$$

Minimal and maximal threshold degree vectors. Let  $n = 7$ ,  $m = 8$ . So  $2 \leq k \leq 3$ .

$$\hat{F}^{(2)} = \left[ \begin{array}{cc|cccc} 1 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right], \quad \tilde{F}^{(2)} = \left[ \begin{array}{cc|cccc} 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right],$$

and

$$\hat{F}^{(3)} = \left[ \begin{array}{ccc|cccc} 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ \hline 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right], \quad \tilde{F}^{(3)} = \left[ \begin{array}{ccc|cccc} 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ \hline 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array} \right].$$

Moreover

$$\begin{aligned} \hat{d}^{(2)} &= (6, 3, 2, 2, 1, 1, 1), & \tilde{d}^{(2)} &= (5, 4, 2, 2, 2, 1, 0), \\ \hat{d}^{(3)} &= (5, 3, 3, 3, 1, 1, 0), & \tilde{d}^{(3)} &= (4, 4, 3, 3, 2, 0, 0), \\ \hline \hat{\mu}^{(2)} &= (7, 4, 2, 1, 1, 1, 0), & \tilde{\mu}^{(2)} &= (6, 5, 2, 2, 1, 0, 0), \\ \hat{\mu}^{(3)} &= (6, 4, 4, 1, 1, 0, 0), & \tilde{\mu}^{(3)} &= (5, 5, 4, 2, 0, 0, 0). \end{aligned}$$

Inequalities for Laplacian energy for minimal/maximal threshold graphs:

$$\begin{aligned}
 L(\hat{d}^{(k_1)}) &\geq L(\hat{d}^{(k_1+1)}) \geq \dots \geq L(\hat{d}^{(\lfloor \alpha \rfloor)}) \leq L(\hat{d}^{(\lceil \alpha \rceil)}) \leq \dots \leq L(\hat{d}^{(k_2)}), \\
 L(\tilde{d}^{(k_1)}) &\geq L(\tilde{d}^{(k_1+1)}) \geq \dots \geq L(\tilde{d}^{(\lfloor \alpha \rfloor)}) \leq L(\tilde{d}^{(\lceil \alpha \rceil)}) \leq \dots \leq L(\tilde{d}^{(k_2)}), \\
 L(\hat{d}^{(k)}) &\geq L(\tilde{d}^{(k)}) && (k_1 \leq k \leq \lfloor \alpha \rfloor), \\
 L(\hat{d}^{(k)}) &\leq L(\tilde{d}^{(k)}) && (\lceil \alpha \rceil \leq k \leq k_2).
 \end{aligned}$$

### Theorem

Let  $n$  and  $m$  be positive integers. Then

$$\Delta_{n,m}^{LE} = 2 \max\{L(\hat{d}^{(k_1)}), L(\tilde{d}^{(k_2)})\},$$

so the Laplacian energy in  $\mathcal{T}_{n,m}$  is maximized by one of the two  $(n, m)$ -extreme threshold degree vectors  $\hat{d}^{(k_1)}$  and  $\tilde{d}^{(k_2)}$ .

**Extensions:** minimize, or min/max among connected threshold graphs



**Qualitative matrix theory** deals with matrix properties that only depend on the signs on the entries of the matrix. Motivation from economic models (P. Samuelson). See **Brualdi and Shader**: *Matrices of Sign-Solvable Linear Systems*, (1995).

The qualitative class of a matrix  $A$  consists of those matrices with same signs on its entries as  $A$ .

- **Brualdi and Dahl**, Strict sign-central matrices, *SIAM Matrix Analysis Appl.* (2015).

Let  $A$  be a real matrix. Define:

- $A$  is **strict central**:  $A$  has a positive vector in its null space.
- $A$  is **strict sign-central** (SSC-matrix): each matrix in the qualitative class of  $A$  is strict central.

Related work:

- **Ando and Brualdi**, Sign-central matrices, (1994).
- **Lee and Shader**, Sign-consistency and solvability of constrained linear systems, (1998).

A matrix  $A$  is **central** whenever it has a nonzero nonnegative vector in its null space.

Geometrically: **the origin is in the convex hull of the columns of  $A$ .**

**Sign-central**: each matrix in the qualitative class of  $A$  is central.

## Motivation: discrete financial market

- a matrix  $P = [p_{ij}]$ : rows correspond to scenarios, columns to assets.
- $p_{ij}$ : rel. change in the value of asset  $j$  for scenario  $i$  (one time step).
- **portfolio**: a vector  $x \in \mathbb{R}^n$  where  $x_j$  is the quantity of asset  $j$  an investor holds from time  $t_0$  to  $t_1$ .
- $Px$  the payoff of  $x$  for each of the scenarios.
- **arbitrage**:  $Px$  is nonnegative, but nonzero.
- **The fundamental theorem of asset pricing/mathematical finance**:  
*there is no arbitrage if and only if there is a probability measure on the set of scenarios which makes each asset price process a martingale.*  
This means that there is a positive vector in the null space of  $P^T$ , i.e.,  $P^T$  is **strict central**.

So:

- $P^T$  is a **strict central** matrix iff the market is arbitrage-free
- $P^T$  is **strict sign-central** iff all markets in the qualitative class of  $P$  are arbitrage-free.

This is a robustness question, motivated by uncertainty in the data  $p_{ij}$ .

**Example:** An SSC matrix:

$$F_m = \begin{bmatrix} 1 & -1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & -1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & -1 \end{bmatrix}.$$

Farkas' lemma/duality gives:

### Theorem

Let  $A \in M_{m,n}$ . Then the following statements are equivalent:

- (i)  $A$  is a *strict central matrix*.
- (ii) The only nonnegative vector in the row space of  $A$  is the zero vector.

A diagonal matrix  $D$  is called a *strict signing* if its diagonal entries are  $\pm 1$ .

### Theorem (Ando and Brualdi (94))

For every  $m \times n$   $(0, \pm 1)$ -matrix  $A$ , the following are equivalent:

- (i)  $A$  is a *sign-central matrix*.
- (ii) For every strict signing  $D$  of order  $m$ , the matrix  $DA$  contains a nonnegative column.

The next theorem contains a characterization of the SSC property, see also [Lee and Shader](#).

A diagonal matrix  $D$  is called a **signing** if its diagonal entries are  $0, -1, 1$ .

### Theorem

*Let  $A$  be an  $m \times n$   $(0, \pm 1)$ -matrix with no zero rows or columns.*

*Then the following are equivalent:*

*(i)  $A$  is an **SSC-matrix**.*

*(ii) For every signing  $D \neq O$ , the matrix  $DA$  contains a nonzero nonnegative column.*

This may be interpreted in the model of a financial market: For each simple nonzero portfolio  $x$  there is a scenario  $i \leq m$  such that its payoff vector is nonpositive and nonzero.



The next result gives an upper bound on the number of columns of a **minimal SSC matrix**, i.e., an SSC matrix where no column can be deleted without destroying the SSC property.

### Theorem

*Let  $A$  be an  $m \times n$   $(0, \pm 1)$ -matrix which is minimal SSC.*

*Then  $n \leq 2^m$ .*

*If  $n = 2^m$ , then  $A$  equals (up to column permutations) the matrix  $E_m$ .*

## Majorization for partially ordered sets

**Brualdi and Dahl**, Majorization for partially ordered sets, *Discrete Math.*, 2013



## Majorization extensions:

- **Choquet ordering:**  $\mu, \nu$  probability measures on a topological vector space  $X$ :  $\nu$  is a **dilation** of  $\mu$  if  $\int \phi d\mu \leq \int \phi d\nu$  for all cont. convex functions on  $X$ . **Phelps (1966), Meyer (1966), Alfsen (1971, 2008)**
- **Majorization for measure families:** **Blackwell (1951), Karlin, Rinott (1983), Torgersen (1968, 1985, 1991)**
- **Majorization induced by convex cones and groups:** **Marshall, Walkup, Wets (1977), Niezgodá (1998, 2007), Eaton (1984), Eaton, Perlman (1977), Lewis (1996), Tam (2000)**
- **Matrix majorization, polytopes etc:** **Hwang, Pyo (2001), Brualdi (1984), Brualdi, Hwang (1996), Dahl (1999, 2001, 2008)**