Can algebraic graph theory help to find good block designs for experiments?



3rd Workshop on Algebraic Graph Theory and its Applications, Mathematical Center in Akademgorodok, Novosibirsk, 8 November 2020

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In his talk on 4 November, Misha Muzychuk asked

"What insights or problems can algebraic graph theorists gain from work in statistics?"











We have 6 varieties of cabbage to compare in this field. How do we avoid bias?



Partition the experimental units into homogeneous blocks and plant each variety on one plot in each block.

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Algebraic graph theory and block designs

I have *v* treatments that I want to compare. I have *b* blocks, with *k* experimental units in each block. (These are physical objects, that exist before I decide where to put the treatments.) (In the field example, the experimental units were plots.) I have *v* treatments that I want to compare. I have *b* blocks, with *k* experimental units in each block. (These are physcial objects, that exist before I decide where to put the treatments.)

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contiguous plots	4	6	cabbage varieties	6
wine tasters	12	4	wines	16

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How should I choose a block design?

What makes a block design good?











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This is always true when there are no blocks, but may not be otherwise.

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Algebraic graph theory and block designs





Statisticians know that it is best to use all treatments as equally as possible.

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Biologists know that they should compare all treatments with the same thing.

They should not test treatment 6 now and compare the results with testing treatment 1 ten

Algebraic graph theory and block designs

Conventions: columns are blocks (sometimes rows, but the boxes should make it clear); order of treatments within each block is irrelevant; order of blocks is irrelevant.

1	1	1	1	2	2	2
2	3	3	4	3	3	4
3	4	5	5	4	5	5

1	1	1	1	2	2	2
1	3	3	4	3	3	4
2	4	5	5	4	5	5

binary

non-binary

A design is **binary** if no treatment occurs more than once in any block.

1	1	2	3	4	5	6
2	4	5	6	10	11	12
3	7	8	9	13	14	15

1	1	1	1	1	1	1
2	4	6	8	10	12	14
3	5	7	9	11	13	15

replications differ by ≤ 1

queen-bee design

The replication of a treatment is its number of occurrences.

A design is a **queen-bee** design if there is a treatment that occurs in every block.

1	2	3	4	5	6	7
2	3	4	5	6	7	1
4	5	6	7	1	2	3



balanced (2-design)

non-balanced

A binary design is **balanced** if every pair of distinct treaments occurs together in the same number of blocks.

There are *bk* experimental units.

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If ω is an experimental unit, put

$$\begin{array}{lll} f(\omega) &=& {\rm treatment} \ {\rm on} \ \omega \\ g(\omega) &=& {\rm block} \ {\rm containing} \ \omega. \end{array}$$

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For $i = 1, \ldots, v$ put

$$r_i = |\{\omega : f(\omega) = i\}|$$
 = replication of treatment *i*.

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 $r_i = |\{\omega : f(\omega) = i\}|$ = replication of treatment *i*.

For i = 1, ..., v and j = 1, ..., b, let

$$n_{ij} = |\{\omega : f(\omega) = i \text{ and } g(\omega) = j\}|$$

= number of experimental units in block j which have treatment i.

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The $v \times b$ incidence matrix N has entries n_{ij} .

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Algebraic graph theory and block designs

Levi graph (also called incidence graph)

one vertex for each treatment,

- one vertex for each treatment,
- one vertex for each block,

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- one edge for each experimental unit, with edge ω joining vertex f(ω) (the treatment on ω) to vertex g(ω) (the block containing ω).

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- one edge for each experimental unit, with edge ω joining vertex f(ω) (the treatment on ω) to vertex g(ω) (the block containing ω).

It is a bipartite graph,

with n_{ij} edges between treatment-vertex *i* and block-vertex *j*.

Example 1: v = 4, b = k = 3

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1	2	1
3	3	2
4	4	2



Example 1: v = 4, b = k = 3












Example 2: v = 8, b = 4, k = 3

1	2	3	4
2	3	4	1
5	6	7	8

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1	2	3	4
2	3	4	1
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Algebraic graph theory and block designs

one vertex for each treatment,

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- one edge for each unordered pair α , ω , with $\alpha \neq \omega$, $g(\alpha) = g(\omega)$ (in the same block) and $f(\alpha) \neq f(\omega)$: this edge joins vertices $f(\alpha)$ and $f(\omega)$.

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If $i \neq j$ then the number of edges between vertices *i* and *j* is

$$\lambda_{ij} = \sum_{s=1}^{b} n_{is} n_{js};$$

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There are no loops.

If $i \neq j$ then the number of edges between vertices *i* and *j* is

$$\lambda_{ij} = \sum_{s=1}^{b} n_{is} n_{js};$$

this is called the **concurrence** of *i* and *j*, and is the (i, j)-entry of $\Lambda = NN^{\top}$.

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Algebraic graph theory and block designs

1	2	1
3	3	2
4	4	2





Levi graph

concurrence graph





Levi graph can recover design concurrence graph may have more symmetry





Levi graph can recover design more vertices concurrence graph may have more symmetry

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Levi graph can recover design more vertices more edges if k = 2 concurrence graph may have more symmetry

more edges if $k \ge 4$

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Example 2: v = 8, b = 4, k = 3

1	2	3	4
2	3	4	1
5	6	7	8

Example 2: v = 8, b = 4, k = 3

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2	3	4	1
5	6	7	8



Example 3: v = 15, b = 7, k = 3









Algebraic graph theory and block designs

The Laplacian matrix *L* of the concurrence graph *G* is a $v \times v$ matrix with (i, j)-entry as follows:

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The Laplacian matrix L of the concurrence graph G is a $v \times v$ matrix with (i, j)-entry as follows:

The Laplacian matrix \tilde{L} of the Levi graph \tilde{G} is a $(v+b) \times (v+b)$ matrix with (i, j)-entry as follows: \blacktriangleright \tilde{L}_{ii} = valency of *i* $= \begin{cases} k & \text{if } i \text{ is a block} \\ \text{replication } r_i \text{ of } i & \text{if } i \text{ is a treatment} \end{cases}$ • if $i \neq j$ then $L_{ij} = -($ number of edges between *i* and *j*)

 $= \begin{cases} 0 & \text{if } i \text{ and } j \text{ are both treatments} \\ 0 & \text{if } i \text{ and } j \text{ are both blocks} \\ -n_{ij} & \text{if } i \text{ is a treatment and } j \text{ is a block, or vice versa.} \end{cases}$ Algebraic graph theory and block designs

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All row-sums of *L* and of \tilde{L} are zero, so both matrices have 0 as eigenvalue on the appropriate all-1 vector.

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Theorem

The following are equivalent.

- 1. 0 is a simple eigenvalue of L;
- 2. *G* is a connected graph;
- 3. \tilde{G} is a connected graph;
- 4. 0 is a simple eigenvalue of \tilde{L} ;
- 5. the design Δ is connected in the sense that all differences between treatments can be estimated.

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From now on, assume connectivity.

Call the remaining eigenvalues *non-trivial*. They are all non-negative. Under the assumption of connectivity, the Moore–Penrose generalized inverse L^- of L is defined by

$$L^{-} = \left(L + \frac{1}{v}J_{v}\right)^{-1} - \frac{1}{v}J_{v},$$

where J_v is the $v \times v$ all-1 matrix.

(The matrix $\frac{1}{v}J_v$ is the orthogonal projector onto the null space of *L*.)

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The Moore–Penrose generalized inverse \tilde{L}^- of \tilde{L} is defined similarly.

Electrical networks

We can consider the concurrence graph *G* as an electrical network with a 1-ohm resistance in each edge. Connect a 1-volt battery between vertices *i* and *j*. Current flows in the network, according to these rules.

1. Ohm's Law:

In every edge, voltage drop = current \times resistance = current.

2. Kirchhoff's Voltage Law:

The total voltage drop from one vertex to any other vertex is the same no matter which path we take from one to the other.

3. Kirchhoff's Current Law:

At every vertex which is not connected to the battery, the total current coming in is equal to the total current going out.

Find the total current *I* from *i* to *j*, then use Ohm's Law to define the effective resistance R_{ij} between *i* and *j* as 1/I.

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Theorem

The effective resistance R_{ij} between vertices i and j in G is

$$R_{ij} = \left(L_{ii}^{-} + L_{jj}^{-} - 2L_{ij}^{-}\right).$$

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Effective resistances are easy to calculate without matrix inversion if the graph is sparse.

Example 2 calculation: v = 8, b = 4, k = 3



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Theorem

If i and j are treatment vertices in the Levi graph \tilde{G} and \tilde{R}_{ij} is the effective resistance between them in \tilde{G} then

$$\tilde{R}_{ij} = kR_{ij}.$$





















$$V = 23 \quad I = 8 \quad \tilde{R} = \frac{23}{8} \qquad \begin{vmatrix} 1 & 2 & 3 & 4 \\ 2 & 3 & 4 & 1 \\ 5 & 6 & 7 & 8 \end{vmatrix}$$



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Theorem (Gaffke, 1982)

Let G and \tilde{G} be the concurrence graph and Levi graph for a connected incomplete-block design for v treatments in b blocks of size k. Then the number of spanning trees for \tilde{G} is equal to k^{b-v+1} times the number of spanning trees for G.

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- —equivalently, it maximizes the number of spanning trees for the concurrence graph *G*;
- —equivalently, it maximizes the number of spanning trees for the Levi graph \tilde{G} ;
- over all block designs with block size *k* and the given *v* and *b*.

Theorem (Kshirsagar, 1958; Kiefer, 1975) If there is a balanced incomplete-block design (BIBD) (2-design) for v treatments in b blocks of size k, then it is A- and D-optimal. Moreover, no non-BIBD is A- or D-optimal. For decades, it was assumed that, for given values of v, b and k,

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Minimal connectivity

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so all connected designs are equally good under the D-criterion.

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The Levi graph is a tree, so effective resistance = graph distance, so the only A-optimal designs are the queen-bee designs.

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- If the block design is connected and b(k-1) = v then the Levi graph has a single cycle.

Each spanning tree is made by removing a single edge from the cycle, so the D-optimal designs are those in which the maximum number of edges are in the cycle.

A-optimal designs when k = 2 and b = v



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A-optimal designs when k = 2 and b = v



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A-optimal designs when k = 2 and b = v



For $v \ge 13$ the A-optimal design is a triangle with all other edges adjacent to a single vertex of the triangle. For v = 12, the cycle can be either a triangle or a square.

Suppose that
$$\bar{r} = \frac{\sum_i r_i}{v} < 2$$
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Blocks are rows, treatments with single replication are drones.



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$$n \ge n_0 = \left\lfloor \frac{2v - bk}{b} \right\rfloor \qquad k' \le k_0 = k - n_0$$
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The drones contribute nothing to the number of spanning trees.

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The drones contribute nothing to the number of spanning trees. $\tilde{R}_{A_1C_1} = 1 + \tilde{R}_{AC} + 1_{\text{Algebraic graph theory and block designs}}$

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Theorem (cf. Herzberg and Jarrett, 2007) If there are n drones in each block of Δ , and the core design Γ has v' treatments in b blocks of size k' then the sum of the treatment resistances in Δ

$$= bn(bn + v' - 1) + R_T(\Gamma) + nR_{BT}(\Gamma) + n^2R_B(\Gamma),$$

where

 $R_T(\Gamma) = the sum of the treatment resistances in \Gamma$ $R_B(\Gamma) = the sum of the block resistances in \Gamma$ $R_{BT}(\Gamma) = the sum of the treatment-block$ resistances in Γ .

1. For D-optimality, have as few drones as possible.

- 1. For D-optimality, have as few drones as possible.
- If *v* is large then *n* is large, so we need to focus on reducing *R*_B(Γ), so it may be best to increase the number of drones and decrease *k'* (the size of blocks in the core design Γ), so that average replication within Γ is more than 2.

If there are 4(2 + n) varieties in 4 blocks of size 4 + n, the design on the left is A-better than the design on the right if and only if n < 50.

1	2	3	4	<i>n</i> drones	1 2 3	n+1 drones
1	2	5	6	<i>n</i> drones	1 2 4	n+1 drones
3	6	7	8	<i>n</i> drones	1 3 4	n+1 drones
4	5	7	8	<i>n</i> drones	2 3 4	n+1 drones

Conjecture (Underpinned by theoretical work by C.-S. Cheng) *If the connectivity is more than minimal, then all D-optimal designs have (almost) equal replication.*

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If $\bar{r} > 3.5$ *then designs optimal under one criterion are (almost) optimal under the other criteria.*

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Most other people designing experiments do not have that knowledge, so they ask the computer to find a good design. To cut down the amount of work needed, they typically make some assumptions about conditions that good designs must satisfy. When I am asked to help in the design of a real experiment, I typically use all sorts of knowledge about nice structures like orthogonal Latin squares, distance-regular graphs, and association schemes.

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Within the last nine months, three collaborators contacted me by email to say something like

You might be interested in this optimal design that my computer found.

Here is a better design than yours. It is not equi-replicate.

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In another, I sent the correspondent a better design, taken from a published paper of mine. She replied

I am surprised. Two blocks in your design have the same set of core treatments. I had assumed that that would not be good, so did not allow my program to look for things like that.

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If someone can find a function f(v, b, k) and a criterion on its value such that, when the criterion is satisfied, programs should relax their usual assumptions in their search for good experimental designs, it would be immensely useful.

References I: Surveys

- R. A. Bailey and Peter J. Cameron: Combinatorics of optimal designs. In *Surveys in Combinatorics 2009* (eds. S. Huczynska, J. D. Mitchell and C. M. Roney-Dougal), London Mathematical Society Lecture Note Series, 365, Cambridge University Press, Cambridge, 2009, pp. 19–73.
- R. A. Bailey and Peter J. Cameron: Using graphs to find the best block designs. In *Topics in Structural Graph Theory* (eds. L. W. Beineke and R. J. Wilson), Cambridge University Press, Cambridge, 2013, pp. 282–317.

References II: Optimality

A. M. Kshirsagar:

A note on incomplete block designs. Annals of Mathematical Statistics **29** (1958), 907–910.

▶ J. Kiefer:

Construction and optimality of generalized Youden designs.

In *A Survey of Statistical Design and Linear Models* (ed. J. N. Srivastava), North-Holland, Amsterdam, 1975,

pp. 333–353.

 Kirti R. Shah and Bikhas K. Sinha: *Theory of Optimal Designs*. Lecture Notes in Statistics 54, 1989, Springer-Verlag, New York.

References III: D-optimality

C.-S. Chêng:

Maximizing the total number of spanning trees in a graph: two related problems in graph theory and optimum design theory.

Journal of Combinatorial Theory Series B 31 (1981), 240–248.

N. Gaffke:

Optimale Versuchsplanung für linear Zwei-Faktor Modelle. PhD thesis, Rheinisch-Westfälische Technische Hochschule, Aachen, 1978.

N. Gaffke:

Connected graphs with a minimal number of spanning trees.

Journal of Combinatorial Theory Series B 30 (1981), 166–183.

N. Gaffke:

D-optimal block designs with at most six varieties. *Journal of Statistical Planning and Inference* **6** (1982), 183–200. Agnes M. Herzberg and Richard G. Jarrett: A-optimal block designs with additional singly replicated treatments.

Journal of Applied Statistics 34 (2007), 61–70.

Tue Tjur: Block designs and electrical networks. Annals of Statistics 19 (1991), 1010–1027.

▶ R. A. Bailey:

Designs for two-colour microarray experiments. *Applied Statistics* **56** (2007), 356–394.