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# Combinatorial Green's function of a graph and applications to networks

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#### ABSTRACT

Given a finite weighted graph *G* and its Laplacian matrix *L*, the *combinatorial Green's function G* of *G* is defined to be the inverse of L + J, where *J* is the matrix each of whose entries is 1. We prove the following intriguing identities involving the entries in  $\mathcal{G} = (g_{ij})$  whose rows and columns are indexed by the vertices of *G*:  $g_{aa} + g_{bb} - g_{ab} - g_{ba} = \kappa(G_{a*b})/\kappa(G)$ , where  $\kappa(G)$  is the complexity or tree-number of *G*, and  $G_{a*b}$  is obtained from *G* by identifying two vertices *a* and *b*. As an application, we derive a simple combinatorial formula for the resistance between two *arbitrary* nodes in a finite resistor network. Applications to other similar networks are also discussed.

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### 1. Introduction

Given a finite graph *G* with *n* vertices and its Laplacian matrix L = L(G), we define the *augmented* Laplacian matrix of *G* to be  $\mathcal{L} = \mathcal{L}(G) = L + J$ , where *J* denotes the  $n \times n$  matrix each of whose entries is 1. The *tree-number* or *complexity* of *G*, denoted by  $\kappa(G)$ , is the number of spanning trees in *G*. Temperley [7] showed

$$n^2 \cdot \kappa(G) = \det \mathcal{L}(G), \tag{1.1}$$

which is an analog of the Matrix-Tree theorem [3] that states every cofactor of L equals  $\kappa(G)$ .

An important reason for our interest in the augmented Laplacian matrix  $\mathcal{L}$  is that it is invertible when  $\kappa(G)$  is nonzero, unlike the Laplacian matrix L. Moreover,  $\mathcal{L}^{-1}$  acts as an "inverse" of L for solving the Laplace equations  $L\mathbf{x} = \mathbf{y}$  in the sense that  $\mathbf{x} = \mathcal{L}^{-1}\mathbf{y}$  is a desired solution if  $\mathbf{y}$  is in the column space of L (see Section 4). An interesting application of these observations can be found in

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Stephenson and Zelen's work on the information centrality for networks (see Appendix in [6]). Similar methods using Green's functions were applied to compute the resistances in a finite resistor network in terms of the eigenvalues and eigenvectors of the associated Kirchhoff matrix (see e.g. [2,10]).

We define the *combinatorial Green's function*  $\mathcal{G} = \mathcal{G}(G)$  of a connected finite graph G to be the inverse of its augmented Laplacian matrix  $\mathcal{L}(G)$ :

$$\mathcal{G}(G) = \mathcal{L}(G)^{-1}.$$

The main result of this paper is the following intriguing identities involving the entries in  $\mathcal{G}(G) = (g_{ij})$  whose rows and columns are indexed by the vertices of *G*. Let  $G_{a*b}$  denote the *contraction* of *G* obtained by identifying two *arbitrary* vertices *a* and *b* (see Section 2). We will show

$$g_{aa} + g_{bb} - g_{ab} - g_{ba} = \frac{\kappa(G_{a*b})}{\kappa(G)}.$$
 (1.2)

The proof of (1.2) will be based on a generalization of (1.1) and combinatorial analysis of the Laplacian matrix of  $G_{a*b}$ . In subsequent sections, we will see that all of our definitions and results are also valid for a finite weighted graph *G* where the weights are non-negative.

As an application of our main result, we will derive a combinatorial formula for the network resistance  $R_{ab}$  between two *arbitrary* nodes *a* and *b* in a finite resistor network. We will see that our formula for  $R_{ab}$  specializes to that of the effective resistance r(a, b, G) [8] which is valid only for adjacent vertices *a* and *b* in a connected graph *G*. We will also discuss other networks (see e.g. [6]) that are similar to resistor networks.

### 2. Preliminaries

We will assume basic familiarity with standard terminologies from graph theory. One may refer to most textbooks (e.g., [1] or [9]) for their definitions. The graphs that we consider are finite, unoriented, and loopless, but they may have multiple edges. A *complete graph* has one edge between each pair of vertices. An edge connecting two distinct vertices i and j will be denoted ij.

**2.1. Laplacian matrix of a weighted graph.** A weighted graph *G* is a loopless graph such that a nonnegative weight  $w_{ij} = w_{ji}$  is assigned to each edge ij, where *i* and *j* are distinct vertices. A weighted graph may be regarded as a complete graph with non-negative weights assigned to its edges. An unweighted graph may be treated as a weighted graph by letting  $w_{ij}$  equal the number of edges between *i* and *j*. The *adjacency matrix* of *G* with the vertex set  $V(G) = [n] = \{1, 2, ..., n\}$  is the  $n \times n$ symmetric matrix  $A = A(G) = (a_{ij})$  whose entries are given by  $a_{ij} = w_{ij}$  for  $i \neq j$  and  $a_{ii} = 0$  for every *i*. The *degree*  $d_i$  of the vertex *i* is defined by  $d_i = \sum_j w_{ij}$  where  $w_{ii} = 0$  for every *i*. We define D = D(G) to be the  $n \times n$  diagonal matrix whose diagonal entries are  $d_i$ .

The Laplacian matrix of a finite weighted graph *G* is L = L(G) = D - A, which is real symmetric. Since the sum of the entries in every row and every column of *L* is zero, every cofactor of *L* has the same value. We define the *complexity*  $\kappa(G)$  of *G* to be the value of any cofactor of *L*. If *G* is unweighted,  $\kappa(G)$  equals the tree number in *G* by the Matrix-Tree theorem. A weighted graph is defined to be *connected* if  $\kappa(G) \neq 0$ .

**2.2. Contraction of a weighted graph.** An important minor of a graph *G* is the *contraction*  $G_{a*b}$  of *G* that is obtained by shrinking (contracting) the edge *ab* to a point. We may contract *ab* by identifying the vertex *a* with the vertex *b* so that all edges that were incident to *a* and *b* in *G* are incident to *b* in  $G_{a*b}$  (and *a* is no longer a vertex of  $G_{a*b}$ ). As a weighted graph, we define the contraction  $G_{a*b}$  of *G* to be a weighted graph satisfying the following conditions. Let *w* and  $\omega$  denote the weights, and let *d* and  $\delta$  denote the degrees in *G* and  $G_{a*b}$ , respectively.

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$$V(G_{a*b}) = V(G) \setminus \{a\},\$$

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- $\omega_{ib} = w_{ia} + w_{ib}$ , and  $\omega_{ij} = w_{ij}$  if  $i, j \neq b$ ,
- $\delta_b = d_a + d_b 2w_{ab}$ , and  $\delta_i = d_i$  if  $i \neq b$ .

Although the roles of *a* and *b* may be switched in defining  $G_{a*b}$ , we will not do so in order to avoid confusion in what follows. It is important to note that  $G_{a*b}$  is defined as a weighted graph even when  $w_{ab} = 0$  in *G*. Hence, we may have  $\kappa(G_{a*b}) > \kappa(G)$ . For example, if *G* has three vertices *a*, *b*, and *c* and  $w_{ac} = w_{bc} = 1$  and  $w_{ab} = 0$ , then  $\kappa(G_{a*b}) = 2$  and  $\kappa(G) = 1$ .

Since a (weighted) graph can be recovered from its Laplacian matrix, we may also define  $G_{a*b}$  to be the graph whose Laplacian matrix is obtained from L = L(G) by applying the following sequence of operations: ( $R_i(M)$  and  $C_i(M)$  denote row *i* and column *j* of a matrix *M*, respectively)

- (1) replace  $R_b(L)$  by  $R_a(L) + R_b(L)$  (denote the result by  $M_1$ ),
- (2) replace  $C_b(M_1)$  by  $C_a(M_1) + C_b(M_1)$  (denote the result by  $M_2$ ), and
- (3) delete  $R_a(M_2)$  and  $C_a(M_2)$  (denote the result by  $M_3$ ).

Clearly, the entries in  $M_2$  except those in  $R_a(M_2)$  and  $C_a(M_2)$  are the weights and degrees for  $G_{a*b}$  as described above. The last operation (3) corresponds to eliminating the vertex *a* from V(G). It is clear that we have  $M_3 = L(G_{a*b})$ .

Note that the above three operations may be applied to any square matrix M, and we will denote the resulting matrix by  $M_{a*b}$ , called a *contraction* of M. With this notation, we have

$$L(G_{a*b}) = L(G)_{a*b}.$$
 (2.1)

We note the following useful properties of contractions. If *M* has the zero sum property for its rows and columns, then so does any contraction of *M*. If *M* has rank  $\leq 1$ , then so does any contraction of *M*. The sum of all entries of *M* equals that of any contraction of *M*. We also have

$$(M+N)_{a*b} = M_{a*b} + N_{a*b}.$$
 (2.2)

**Example.** This example will be discussed again in Section 4. Let *G* be a weighted graph with the vertex set  $\{1, 2, 3, 4\}$  with the weights  $w_{13} = 0$ ,  $w_{24} = 2$ , and  $w_{ij} = 1$  otherwise. Then

$$L(G) = \begin{pmatrix} 2 & -1 & 0 & -1 \\ -1 & 4 & -1 & -2 \\ 0 & -1 & 2 & -1 \\ -1 & -2 & -1 & 4 \end{pmatrix}.$$

The following are the Laplacian matrices for various contractions of G:

$$L(G_{1*3}) = \begin{pmatrix} 4 & -2 & -2 \\ -2 & 4 & -2 \\ -2 & -2 & 4 \end{pmatrix} \quad L(G_{2*4}) = \begin{pmatrix} 2 & 0 & -2 \\ 0 & 2 & -2 \\ -2 & -2 & 4 \end{pmatrix} \quad L(G_{1*2}) = \begin{pmatrix} 4 & -1 & -3 \\ -1 & 2 & -1 \\ -3 & -1 & 4 \end{pmatrix}.$$

**Lemma 1.** Let  $M = (m_{ij})$  be an  $n \times n$  matrix, and let  $\mu_{ij}$  be the (i, j)-cofactor of M, i.e.,  $\mu_{ij} = (-1)^{i+j} \det M_{ij}$ , where  $M_{ij}$  is obtained from M by removing  $R_i(M)$  and  $C_j(M)$ . Then the following identity holds for all i and j:

$$\det M_{i*i} = \mu_{ii} + \mu_{jj} - \mu_{ij} - \mu_{ji}.$$

**Proof.** First, we will prove the case i = 1 and j = 2. Note that  $M_{11}$  and  $M_{12}$  differ only in their first columns. Also,  $M_{22}$  and  $M_{21}$  differ only in their first columns. By the linearity of determinant on columns, we have

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 $\mu_{11} - \mu_{12} = \det M_{11} + \det M_{12} = \det M'$  and  $\mu_{22} - \mu_{21} = \det M_{22} + \det M_{21} = \det M''$ ,

where

$$M' = \begin{pmatrix} m_{22} + m_{21} & m_{23} & \cdots & m_{2n} \\ m_{32} + m_{31} & m_{33} & \cdots & m_{3n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n2} + m_{n1} & m_{n3} & \cdots & m_{nn} \end{pmatrix} \qquad M'' = \begin{pmatrix} m_{11} + m_{12} & m_{13} & \cdots & m_{1n} \\ m_{31} + m_{32} & m_{33} & \cdots & m_{3n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} + m_{n2} & m_{n3} & \cdots & m_{nn} \end{pmatrix}.$$

Note that M' and M'' differ only in their first rows. It is now clear by the linearity of determinant on rows that det  $M' + \det M'' = \det M_{1*2}$ .

In general, assume  $1 \le i < j \le n$ . Let *P* be the matrix obtained from *M* by switching row *i* with row 1, row *j* with row 2, column *i* with column 1, and column *j* with column 2. Let  $\pi_{ij}$  be the (i, j)-cofactor of *P*. Then  $\pi_{11} = \mu_{ii}$  because  $P_{11}$  and  $M_{ii}$  differ by an even permutation of rows and columns. Similarly, we have  $\pi_{22} = \mu_{jj}$ ,  $\pi_{12} = \mu_{ij}$ , and  $\pi_{21} = \mu_{ji}$ . Also it is easily checked that  $M_{i*j}$  and  $P_{1*2}$  differ by an even permutation of rows and columns. Therefore, det  $M_{i*j} = \det P_{1*2}$ , and the result follows.  $\Box$ 

### 3. Main theorems

If an  $n \times n$  matrix M satisfies the zero sum condition for its rows and columns, then it is easily checked that every cofactor of M has the same value (see e.g. [4, Lemma 5.6.5] for a proof). For example, we've already seen that every cofactor of the Laplacian matrix L(G) of a finite graph G is  $\kappa(G)$ . The following is a generalization of Temperley's tree-number formula (1.1).

**Theorem 2.** Let *M* be an  $n \times n$  matrix such that the sum of entries in every row and every column is zero, and let  $\mu$  denote the value of any cofactor of *M*. Let *U* be an  $n \times n$  rank 1 matrix, and let  $\sigma$  denote the sum of all of its entries. Then the following identity holds:

$$\mu \cdot \sigma = \det(M + U).$$

**Proof.** Let  $M + U = (C_1 + D_1, C_2 + D_2, ..., C_n + D_n)$ , where  $C_i$ 's and  $D_i$ 's are the columns of M and U, respectively. Given any subset  $S \subset [n]$ , define  $\Delta_S = (X_1, X_2, ..., X_n)$ , where  $X_i = D_i$  if  $i \in S$  and  $X_i = C_i$  if  $i \notin S$ . For example,  $\Delta_{\emptyset} = M$  and  $\Delta_{[n]} = U$ . By the multilinearity of determinant on columns, we have

$$\det(M+U) = \sum_{S \subset [n]} \det \Delta_S$$

where the sum is over all subsets *S* of [*n*]. Clearly, we have det  $\Delta_{\emptyset} = \det M = 0$ . Also, if |S| > 1, then det  $\Delta_S = 0$  because *U* has rank 1 and every column of *U* is a multiple of a single column. Furthermore, if we let  $\sigma_i$  be the sum of all entries in  $D_i$ , then det  $\Delta_{\{i\}} = \mu \cdot \sigma_i$  for every  $i \in [n]$ . Therefore, we have

$$\det(M+U) = \sum_{0 \leqslant i \leqslant n} \det \Delta_{\{i\}} = \sum_{0 \leqslant i \leqslant n} \mu \cdot \sigma_i = \mu \cdot \sigma. \quad \Box$$

Recall that for a finite weighted graph *G*, we *defined*  $\kappa(G)$  to be the value of any cofactor of *L*(*G*). Let  $\mathcal{L}(G) = L(G) + J$ . The following is the weighted version of Temperley's tree-number formula (1.1).

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**Corollary 3.** For a finite weighted graph *G* with *n* vertices, we have

$$n^2 \cdot \kappa(G) = \det \mathcal{L}(G).$$

It follows that  $\mathcal{L} = \mathcal{L}(G)$  is non-singular if  $\kappa(G) \neq 0$ . As in the case of unweighted graphs, we define the combinatorial Green's function of a finite weighted graph *G* to be  $\mathcal{G} = \mathcal{G}(G) = \mathcal{L}^{-1}$ . Assume that the rows and columns of  $\mathcal{G}$  are indexed by the vertices of *G*. The following is the main theorem of the paper.

**Theorem 4.** Let *G* be a finite weighted graph with n (> 1) vertices and  $\kappa(G) \neq 0$ . The entries in  $\mathcal{G} = (g_{ij})$  satisfy the following identities:

$$g_{aa} + g_{bb} - g_{ab} - g_{ba} = \frac{\kappa(G_{a*b})}{\kappa(G)}$$

for any arbitrary pair of distinct vertices a and b of G.

**Proof.** Let  $l_{ij}$  be the (i, j)-cofactor of  $\mathcal{L}$ . Note that we have  $g_{ij} = l_{ij} / \det \mathcal{L}$  because  $\mathcal{G} = \mathcal{L}^{-1}$ . We also have  $\det \mathcal{L} = n^2 \kappa(G)$  by Corollary 3. Therefore,

$$g_{aa} + g_{bb} - g_{ab} - g_{ba} = \frac{1}{n^2 \kappa(G)} (l_{aa} + l_{bb} - l_{ab} - l_{ba})$$
  
=  $\frac{1}{n^2 \kappa(G)} \det(\mathcal{L}_{a*b})$  (by Lemma 1)  
=  $\frac{1}{n^2 \kappa(G)} \det(L(G)_{a*b} + J_{a*b})$  (by (2.2)).

Since J has rank 1 and the sum of its entries is  $n^2$ , the same is true for  $J_{a*b}$ . Also we have  $L(G)_{a*b} = L(G_{a*b})$  by (2.1), and every cofactor of  $L(G_{a*b})$  equals  $\kappa(G_{a*b})$ . Therefore, by Theorem 2, we have

$$\det(L(G)_{a*b} + J_{a*b}) = n^2 \kappa(G_{a*b}),$$

and the theorem follows.  $\hfill \Box$ 

#### 4. Applications to networks

In this section, an (undirected) network is represented by a finite connected weighted graph *G* with *n* vertices. Its Laplacian matrix *L* may be regarded as a symmetric linear transformation on  $\mathbb{R}^n$  equipped with the standard inner product. Let **1** be the column vector each of whose entry is 1, and **0** the zero vector in  $\mathbb{R}^n$ . Since  $\mathcal{L} = L + J$  is invertible, let  $\mathcal{G} = \mathcal{L}^{-1}$ .

**Lemma 5.** Suppose  $\mathbf{y} \perp \mathbf{1}$ . Then,  $\mathbf{x} = \mathcal{G}\mathbf{y}$  is a solution to  $L\mathbf{x} = \mathbf{y}$ .

**Proof.** Let  $\mathbf{x} = \mathcal{G}\mathbf{y}$ . Then we have  $\mathcal{L}\mathbf{x} = \mathbf{y}$ . Multiplying this equation by J, we get  $JL\mathbf{x} + J^2\mathbf{x} = J\mathbf{y}$ . Since  $JL\mathbf{x} = J\mathbf{y} = \mathbf{0}$  and  $J^2 = nJ$ , we see that  $J\mathbf{x} = \mathbf{0}$ . Therefore  $L\mathbf{x} = (L + J)\mathbf{x} = \mathcal{L}\mathbf{x} = \mathbf{y}$ .  $\Box$ 

In what follows, one may refer to [5] for relevant definitions and laws concerning electrical circuits. Our background discussion of a resistor network will follow [10]. Let *G* represent a finite resistor network consisting of  $[n] = \{1, 2, ..., n\}$  as nodes and a resistor for each pair  $i, j \in [n]$  with the resistance  $r_{ij} = r_{ji}$ . Let the weight of the edge ij in *G* be the conductance  $c_{ij} = c_{ji} = r_{ij}^{-1}$ . If i and j are not

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connected by a resistor, then  $r_{ij} = \infty$  and  $c_{ij} = 0$ . Let  $\mathcal{G} = (g_{ij})$  be the combinatorial Green's function of *G*.

The *network resistance*  $R_{ij}$  between *i* and *j* is what an ohm meter would read if it is connected to *i* and *j*. The electrical potential at the node *i* is denoted by  $V_i$  and the net current flowing *into* the network at the node *i* by  $I_i$  with the constraint  $\sum_{i=1}^{n} I_i = 0$ . The Kirchhoff's law states  $\sum_{i=1}^{n} c_{ij}(V_i - V_j) = I_i$  for each *i*, which is equivalent to

$$L\vec{V} = \vec{I},\tag{4.1}$$

where  $\vec{V}$  and  $\vec{I}$  are vectors in  $\mathbb{R}^n$  whose components are  $V_i$  and  $I_i$ , respectively. In order to compute the resistance  $R_{ab}$  between two nodes a and b, an external current source with current I is connected to a and b so that  $I_a = I$ ,  $I_b = -I$  and  $I_i = 0$  for  $i \neq a, b$ . Then, the network resistance is given by

$$R_{ab} = \frac{V_a - V_b}{I}.\tag{4.2}$$

Since we have  $\vec{l} \perp \mathbf{1}$ , Lemma 5 implies that  $\vec{V} = \mathcal{G}\vec{l}$  is a solution to (4.1). Therefore, we have  $V_a = (g_{aa} - g_{ab})I$  and  $V_b = (g_{ba} - g_{bb})I$ . Now the following theorem is immediate from (4.2) and Theorem 4.

**Theorem 6.** The network resistance between two arbitrary nodes a and b in a finite resistor network G is the ratio

$$R_{ab}(G) = \frac{\kappa(G_{a*b})}{\kappa(G)}.$$

**Examples.** 1. Let *G* be the complete graph  $K_n$  with every weight equal to 1. Then  $\kappa(G_{a*b})$  equals the number of the spanning trees in *G* that contain the edge *ab*. Since a spanning tree in *G* has n - 1 edges, one obtains the identity  $\binom{n}{2}\kappa(G_{a*b}) = (n-1)\kappa(G)$ . Hence,  $R_{ab} = \kappa(G_{a*b})/\kappa(G) = (n-1)/\binom{n}{2} = 2/n$ .

2. Let *G* be a cycle  $C_n$  of length *n* with every weight equal to a constant *w*. Given two nodes *a* and *b*, suppose  $G_{a*b}$  is a one point union of two cycles one of length *m* and the other of length (n-m). Clearly, we have  $\kappa(G) = nw^{n-1}$  and  $\kappa(G_{a*b}) = m(n-m)w^{n-2}$ . Hence,  $R_{ab} = m(n-m)/nw$ .

3. Theorem 6 enables relative ranking among  $R_{ab}$ 's without knowing their exact values. Referring back to the example in Section 2, we have  $\kappa(G_{1*3}) = 12$ ,  $\kappa(G_{2*4}) = 4$ , and  $\kappa(G_{a*b}) = 6$  for all other pairs *a* and *b*. So the network resistances can be ranked in the order of  $R_{13}$ ,  $R_{ab}$ , and  $R_{24}$ .

4. If *G* is a finite graph (unweighted), and if *a* and *b* are required to be adjacent in *G*, then Theorem 6 specializes to the formula for the *effective resistances* r(a, b, G) by Thomassen [8]. It is shown that  $r(a, b, G) = \tau_{ab}(G)/\tau(G)$ , where  $\tau_{ab}(G)$  is the number of spanning trees in *G* containing the edge *ab* and  $\tau(G) = \kappa(G)$ , the tree-number of *G*. Since  $\kappa(G_{a*b}) = \tau_{ab}(G)$  when *a* and *b* are adjacent in *G*, we see that  $r(a, b, G) = R_{ab}(G)$  in this case.

5. The network conductance between two arbitrary nodes *a* and *b* in a resistor network is defined  $C_{ab} = R_{ab}^{-1} = \kappa(G)/\kappa(G_{a*b})$ . It is interesting to note that this exact formula appeared in the computation of the amount of information  $I_{ab}$  contained in *all* possible paths between two arbitrary nodes *a* and *b* in a network [6]. Here, a network is represented by a finite weighted graph *G* whose weights correspond to, e.g., the frequency of communication. Based on the theory of statistical estimation, it was shown that  $I_{ab} = (g_{aa} + g_{bb} - 2g_{ab})^{-1}$ , where  $g_{ij}$  are the entries in  $\mathcal{G}(G)$ . Hence, it follows from Theorem 4 that  $I_{ab} = \kappa(G)/\kappa(G_{a*b})$ .

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