Multidimensional Lambert-Euler inversion and vector-multiplicative coalescent processes

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Lambert-Euler inversion.

In his 1783 work L. Euler considered the following transcendental equation entailed from 1758 work of J. H. Lambert

$$x^{\alpha} - x^{\beta} = (\alpha - \beta)vx^{\alpha + \beta}.$$
 (1)

Letting $\alpha \rightarrow \beta$ in (1), Euler obtained

$$\ln x = v x^{\beta}.$$
 (2)

Next, Euler set $y = x^{\beta}$ and $u = \beta v$ in (2), obtaining

$$\frac{\ln y}{y} = u. \tag{3}$$

Letting $y = e^w$, equation (3) yields

$$we^{-w} = u. \tag{4}$$

Equation (4) gave rise to the Lambert W function, and in particular the function $W_0(x)$ for $-e^{-1} \le x < 0$.

Lambert-Euler inversion.

$$we^{-w} = u$$

Denote $R_0 = (0, 1)$, $\overline{R}_0 = (0, 1]$, and $R_1 = (1, \infty)$.

For $0 < u < e^{-1}$ there are exactly two solutions: one in R_0 and one in R_1 . For $u = e^{-1}$, w = 1 is the only solution.

For $0 < u \leq e^{-1}$ there is exactly one solution w in \overline{R}_0 .



Lambert-Euler inversion yields

 $x(t) := \min\{x > 0 : xe^{-x} = te^{-t}\}, t > 0, \text{ with range } \overline{R}_0 = (0, 1].$

In 1960, x(t) was used by P. Erdős and A. Rényi in random graphs, showing formation of giant cluster.

In 1962, x(t) was used by J. B. McLeod in the analysis of Smoluchowski coagulation equations with multiplicative kernel, observing gelation phenomenon.



Multidimensional Lambert-Euler inversion.

For a given nonnegative irreducible symmetric matrix $V \in \mathbb{R}^{k \times k}$ and a vector $\mathbf{u} \in (0, \infty)^k$, we show that, if the systems

$$y_j \exp\left\{-\mathbf{e}_j^\mathsf{T} V \mathbf{y}\right\} = u_j \qquad j = 1, \dots, k,$$

has at least one solution, it must have a minimal solution y^* , where the minimum is achieved in all coordinates y_j simultaneously.

Moreover, such y^* is the unique solution satisfying $\rho\left(VD[y_j^*]\right) \leq 1$, where $D[y_j^*] = \operatorname{diag}(y_j^*)$ is the diagonal matrix with entries y_j^* and ρ denotes the spectral radius.

Multidimensional Lambert-Euler inversion.

Notations:

- $V \in \mathbb{R}^{k \times k}$ is a nonnegative irreducible symmetric matrix;
- For $\mathbf{x} \in \mathbb{R}^k$ with coordinates x_j , $D[x_j] = diag(x_j)$;
- $\rho(M)$ denotes the spectral radius of matrix M;
- \bullet For a given vector $\mathbf{z} \in (0,\infty)^k$, consider

$$R_0 = \left\{ \mathbf{z} \in (0,\infty)^k : \rho(VD[z_j]) < 1 \right\}$$

$$\overline{R}_0 = \left\{ \mathbf{z} \in (0,\infty)^k : \rho(VD[z_j]) \leq 1 \right\}$$

and

$$R_1 = \left\{ \mathbf{z} \in (0,\infty)^k : \rho(VD[z_j]) > 1 \right\}$$

Multidimensional Lambert-Euler inversion.

$$\overline{R}_0 = \left\{ \mathbf{z} \in (0,\infty)^k : \rho(VD[z_j]) \le 1 \right\}$$
$$R_1 = \left\{ \mathbf{z} \in (0,\infty)^k : \rho(VD[z_j]) > 1 \right\}$$

Theorem (YK and P.T. Otto, 2021). For any given $z \in (0,\infty)^k$, there exists unique $y \in \overline{R}_0$ such that

$$y_j \exp\left\{-\mathbf{e}_j^\mathsf{T} V \mathbf{y}\right\} = z_j \exp\left\{-\mathbf{e}_j^\mathsf{T} V \mathbf{z}\right\} \qquad j = 1, \dots, k.$$

Moreover, if $z \in \overline{R}_0$, then y = z. If $z \in R_1$, then y < z $(y_i < z_i \ \forall i)$, i.e., y is the smallest solution.

Vector-Multiplicative Coalescent Process.

Consider k types of particles, $1, \ldots, k$.

Let $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \dots, \alpha_k)^T$ be a column vector, where $\alpha_i \ge 0$ are reals satisfying $\sum_{i=1}^k \alpha_i > 0$.

Let matrix $V = (v_{i,j})$ be nonnegative, irreducible, and symmetric.

Vector-multiplicative coalescent process:

• The process begins with $\sum_{i=1}^{k} \alpha_i n + o(\sqrt{n})$ singletons distributed between the k types so that for each $i = 1, \ldots, k$, there are $\alpha_i n + o(\sqrt{n})$ particles of type i.

• A particle of type *i* **bonds** with a particle of type *j* with the intensity (rate) $v_{i,j}/n$. The bonds are formed independently.

Vector-Multiplicative Coalescent Process.

• Each cluster of weight x bonds together x_1, \ldots, x_k particles of corresponding types $1, \ldots, k$.

• Clusters with weight vectors \mathbf{x} and \mathbf{y} would coalesce into a cluster of weight $\mathbf{x} + \mathbf{y}$ with rate $K(\mathbf{x}, \mathbf{y})/n$, where

 $K(\mathbf{x},\mathbf{y}) = \mathbf{x}^{\mathsf{T}} V \mathbf{y}.$

Hydrodynamic limit as $n \to \infty$:

For $\mathbf{x} = (x_1, x_2, \dots, x_k)^{\mathsf{T}}$ let $\zeta_{\mathbf{x}}(t)$ denote the relative (to *n*) number of clusters bonding together particles into a cluster with x_i particles of type *i* for all *i*.

$$\frac{d}{dt}\zeta_{\mathbf{x}}(t) = -\zeta_{\mathbf{x}}(t) \left(\mathbf{x}^{\mathsf{T}} V \boldsymbol{\alpha}\right) + \frac{1}{2} \sum_{\mathbf{y}, \mathbf{z} : \mathbf{y} + \mathbf{z} = \mathbf{x}} \left(\mathbf{y}^{\mathsf{T}} V \mathbf{z}\right) \zeta_{\mathbf{y}}(t) \zeta_{\mathbf{z}}(t), \quad \zeta_{\mathbf{x}}(0) = \sum_{i=1}^{k} \alpha_{i} \delta_{\mathbf{e}_{i}, \mathbf{x}}$$

Abel's binomial theorem: a variation.

$$y^{-1}(x+y+n)^n = \sum_{k=0}^n \binom{n}{k} (x+k)^k (y+n-k)^{n-k-1}$$

Swap x with y, and k with n - k. Then,

$$x^{-1} (x + y + n)^n = \sum_{k=0}^n \binom{n}{k} (x + k)^{k-1} (y + n - k)^{n-k}$$

Add the two formulas together:

$$(x^{-1} + y^{-1})(x + y + n)^n = \sum_{k=0}^n \binom{n}{k} (x + k)^{k-1} (y + n - k)^{n-k-1} (x + y + n)$$

Thus,

$$(x^{-1} + y^{-1})(x + y + n)^{n-1} = \sum_{k=0}^{n} {n \choose k} (x + k)^{k-1} (y + n - k)^{n-k-1}$$

Abel's binomial theorem: a variation.

$$(x^{-1} + y^{-1})(x + y + n)^{n-1} = \sum_{k=0}^{n} \binom{n}{k} (x + k)^{k-1} (y + n - k)^{n-k-1}$$

Therefore,

$$(x^{-1} + y^{-1})(x + y + n)^{n-1} - x^{-1}(y + n)^{n-1} - y^{-1}(x + n)^{n-1}$$

$$=\sum_{k=1}^{n-1} \binom{n}{k} (x+k)^{k-1} (y+n-k)^{n-k-1}$$

Hence,

$$\sum_{k=1}^{n-1} \binom{n}{k} k^{k-1} (n-k)^{n-k-1} = \lim_{\substack{x \to 0 \\ y \to 0}} \sum_{k=1}^{n-1} \binom{n}{k} (x+k)^{k-1} (y+n-k)^{n-k-1}$$
$$= \lim_{\substack{x \to 0 \\ y \to 0}} \frac{(x+y+n)^{n-1} - (y+n)^{n-1}}{x} + \lim_{\substack{x \to 0 \\ y \to 0}} \frac{(x+y+n)^{n-1} - (x+n)^{n-1}}{y}$$

Abel's binomial theorem: a variation.

$$\sum_{k=1}^{n-1} \binom{n}{k} k^{k-1} (n-k)^{n-k-1} = \lim_{\substack{x \to 0 \\ y \to 0}} \frac{(x+y+n)^{n-1} - (y+n)^{n-1}}{x}$$
$$+ \lim_{\substack{x \to 0 \\ y \to 0}} \frac{(x+y+n)^{n-1} - (x+n)^{n-1}}{y}$$
$$= 2 \lim_{h \to 0} \frac{(h+n)^{n-1} - n^{n-1}}{h} = 2 \frac{d}{dx} x^{n-1} \Big|_{x=n} = 2(n-1)n^{n-2}.$$
Identity
$$\sum_{k=1}^{n-1} \binom{n}{k} k^{k-1} (n-k)^{n-k-1} = 2(n-1)n^{n-2} \text{ rewrites as}$$
$$n^{n-2} = \frac{1}{2(n-1)} \sum_{k=1}^{n-1} \binom{n}{k} k(n-k) k^{k-2} (n-k)^{n-k-2} \text{ which} \dots$$

Identity $\sum_{k=1}^{n-1} {n \choose k} k^{k-1} (n-k)^{n-k-1} = 2(n-1)n^{n-2}$ rewrites as

$$n^{n-2} = \frac{1}{2(n-1)} \sum_{k=1}^{n-1} {n \choose k} k(n-k) k^{k-2} (n-k)^{n-k-2}$$

which has everything to do with spanning trees!

In particular,

 T_n = the number of spanning trees in a complete graph K_n satisfies the following recursion

$$T_n = \frac{1}{2(n-1)} \sum_{k=1}^{n-1} {n \choose k} k(n-k) T_k T_{n-k}$$

Thus, $T_n = n^{n-2}$



Abel's binomial theorem yields

$$n^{n-2} = \frac{1}{2(n-1)} \sum_{k=1}^{n-1} {n \choose k} k(n-k) k^{k-2} (n-k)^{n-k-2}$$

Equivalently,

 T_n = the number of spanning trees in a complete graph K_n satisfies

$$T_n = \frac{1}{2(n-1)} \sum_{k=1}^{n-1} {n \choose k} k(n-k) T_k T_{n-k}$$

implying $T_n = n^{n-2}$.

Question: Is there a useful generalization?

Let
$$\mathbf{x} = (x_1, x_2, \dots, x_k)^T$$
 be a column vector, where $x_i \ge 0$ are integers satisfying $\sum_{i=1}^k x_i > 0$.

Consider a graph $K_{\mathbf{x}}(V)$ equipped with edge weights:

- $K_{\mathbf{x}}(V)$ is a complete graph with $\sum_{i=1}^{k} x_i$ vertices partitioned into k kinds;
- For each i = 1, ..., k, $K_x(V)$ has x_i vertices of kind i;

• Let $v_{i,j} = v_{j,i}$ be the weight of each edge connecting a vertex *i*-th kind to a vertex of *j*-th kind, and let $V = (v_{i,j})$ be the $k \times k$ matrix of weights.

Consider a graph $K_{\mathbf{x}}(V)$ equipped with edge weights $V = (v_{i,j})$.

If \mathcal{T} is a spanning tree of $K_{\mathbf{x}}(V)$, then the weight of \mathcal{T} is the **product** of the weights of all of its edges.

Let T_x denote the weighted spanning tree enumerator of $K_x(V)$, i.e., T_x is the sum of weights of all spanning trees of $K_x(V)$.

Theorem (YK and P. T. Otto, 2021).

$$T_{\mathbf{x}} = \frac{1}{2\left(\sum_{i=1}^{k} x_{i} - 1\right)} \sum_{\mathbf{y}, \mathbf{z}: \mathbf{y} + \mathbf{z} = \mathbf{x}} {\binom{x_{1}}{y_{1}} \binom{x_{2}}{y_{2}} \dots \binom{x_{k}}{y_{k}} \left(\mathbf{y}^{\mathsf{T}} V \mathbf{z}\right) T_{\mathbf{y}} T_{\mathbf{z}}}$$

Consider a graph $K_{\mathbf{x}}(V)$ equipped with edge weights $V = (v_{i,j})$. Let $T_{\mathbf{x}}$ denote the weighted spanning tree enumerator of $K_{\mathbf{x}}(V)$.

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Example. Let k = 1, $x = x_1 = n$, and $V = v_{1,1} = 1$. Then,

 T_n = the number of spanning trees in a complete graph K_n and

$$T_n = \frac{1}{2(n-1)} \sum_{m=1}^{n-1} {n \choose m} m(n-m) T_m T_{n-m}$$

Question: Is there a general expression for $T_x = T_x(V)$?

Consider a complete graph K_k consisting of vertices $\{1, \ldots, k\}$ with weights $w_{i,j} = w_{j,i} \ge 0$ assigned to its edges [i, j], let the weight $W(\mathcal{T})$ of a spanning tree \mathcal{T} be the product of the weights of all of its edges.

Denote $\tau(K_k, w_{i,j}) = \sum_{\mathcal{T}} W(\mathcal{T})$ denote the weighted spanning tree enumerator, i.e., the sum of weights of all spanning trees in K_k .

Theorem (YK and P. T. Otto, 2021).

$$T_{\mathbf{x}}(V) = \frac{\tau(K_k, x_i x_j v_{i,j})}{\mathbf{x}^1} (V \mathbf{x})^{\mathbf{x}-1}$$

Notation: for vectors \mathbf{a}, \mathbf{b} in \mathbb{R}^k let $\mathbf{a}^{\mathbf{b}} = a_1^{b_1} a_2^{b_2} \dots a_k^{b_k}$ Also, $\mathbf{1} = (1, \dots, 1)^T$ and $\mathbf{x}^1 = \prod_{i=1}^k x_i$.

Vector-Multiplicative Coalescent Process.

$$\frac{d}{dt}\zeta_{\mathbf{x}}(t) = -\zeta_{\mathbf{x}}(t) \left(\mathbf{x}^{\mathsf{T}} V \boldsymbol{\alpha}\right) + \frac{1}{2} \sum_{\mathbf{y}, \mathbf{z} : \mathbf{y} + \mathbf{z} = \mathbf{x}} \left(\mathbf{y}^{\mathsf{T}} V \mathbf{z}\right) \zeta_{\mathbf{y}}(t) \zeta_{\mathbf{z}}(t), \quad \zeta_{\mathbf{x}}(0) = \sum_{i=1}^{k} \alpha_{i} \delta_{\mathbf{e}_{i}, \mathbf{x}}$$

Solution: Plug in

$$\zeta_{\mathbf{x}}(t) = \boldsymbol{\alpha}^{\mathbf{x}} \frac{T_{\mathbf{x}}}{\mathbf{x}!} e^{-(\mathbf{x}^{\mathsf{T}} V \boldsymbol{\alpha})t} t^{x_1 + \dots + x_k - 1}, \quad \text{where } \mathbf{x}! = \prod_{i=1}^k x_i!$$

obtaining

$$T_{\mathbf{x}} = \frac{1}{2\left(\sum_{i=1}^{k} x_{i} - 1\right)} \sum_{\mathbf{y}, \mathbf{z}: \mathbf{y} + \mathbf{z} = \mathbf{x}} {\binom{x_{1}}{y_{1}} \binom{x_{2}}{y_{2}} \dots \binom{x_{k}}{y_{k}} \left(\mathbf{y}^{\mathsf{T}} V \mathbf{z}\right) T_{\mathbf{y}} T_{\mathbf{z}}}$$

Thus,

$$T_{\mathbf{x}}(V) = \frac{\tau(K_k, x_i x_j v_{i,j})}{\mathbf{x}^1} (V \mathbf{x})^{\mathbf{x}-1}$$

Vector-Multiplicative Coalescent Process.

$$\frac{d}{dt}\zeta_{\mathbf{x}}(t) = -\zeta_{\mathbf{x}}(t) \left(\mathbf{x}^{\mathsf{T}} V \boldsymbol{\alpha}\right) + \frac{1}{2} \sum_{\mathbf{y}, \mathbf{z} : \mathbf{y} + \mathbf{z} = \mathbf{x}} \left(\mathbf{y}^{\mathsf{T}} V \mathbf{z}\right) \zeta_{\mathbf{y}}(t) \zeta_{\mathbf{z}}(t), \quad \zeta_{\mathbf{x}}(0) = \sum_{i=1}^{k} \alpha_{i} \delta_{\mathbf{e}_{i}, \mathbf{x}}$$

Theorem (YK and P. T. Otto, 2021).

$$\zeta_{\mathbf{x}}(t) = \frac{1}{\mathbf{x}!} \alpha^{\mathbf{x}} \frac{\tau(K_k, x_i x_j v_{i,j})}{\mathbf{x}^1} (V \mathbf{x})^{\mathbf{x}-1} e^{-(\mathbf{x}^{\mathsf{T}} V \alpha)t} t^{x_1 + \dots + x_k - 1},$$

where $\mathbf{x}! = \prod_{i=1}^k x_i!$ and $\mathbf{a}^{\mathbf{b}} = a_1^{b_1} a_2^{b_2} \dots a_k^{b_k}.$

• $\tau(K_k, w_{i,j})$ is computed via Kirchhoff's Weighted Matrix-Tree Theorem.

Gelation.

Consider the hydrodynamic limit $\zeta_{\mathbf{x}}(t)$.

Initial total mass: $\sum_{x} \zeta_{x}(0)x = \alpha$.

The gelation time T_{gel} is the time after which the total mass

$$\sum_{\mathbf{x}} \zeta_{\mathbf{x}}(t) \mathbf{x}$$

begins to dissipate, i.e.,

$$T_{gel} = \inf \Big\{ t > 0 : \sum_{\mathbf{x}} \zeta_{\mathbf{x}}(t) \mathbf{x} < \alpha \Big\}.$$

Multidimensional Lambert-Euler inversion is used for establishing gelation and finding the value of the gelation time

$$T_{gel} = \frac{1}{\rho(VD[\alpha_i])}.$$

Application in minimal spanning trees.

Let matrix $V = (v_{i,j})$ and vector $\boldsymbol{\alpha}$ be as before.

Let $K_{\alpha[n]}$ denote a graph with vertices divided into k partitions of respective sizes

 $\alpha_1[n] = \alpha_1 n + o(\sqrt{n}), \quad \dots, \quad \alpha_k[n] = \alpha_k n + o(\sqrt{n}),$

where, each vertex in the *i*-th partition is connected with each vertex in the *j*-th partition by an edge if and only if $v_{i,j} = v_{j,i} > 0$. Even within an *i*-th partition.

We equip $K_{\alpha[n]}$ with edge lengths: each edge e connecting a vertex in the *i*-th partition with a vertex in the *j*-th partition has an associated random variable $\ell_e \sim \text{Beta}(1, v_{i,j})$, distributed on (0, 1) via the beta probability density function

$$f_{i,j}(x) = v_{i,j}(1-x)^{v_{i,j}-1}, \qquad 0 < x < 1.$$

Random variables ℓ_e are sampled independently.

Application in minimal spanning trees.

Let random variable L_n denote the length of the minimal spanning tree of $K_{\alpha[n]}$.

Theorem (YK, P. T. Otto, and A. Yambartsev).

$$\lim_{n\to\infty}\mathbb{E}[L_n]=\sum_{\mathbf{x}}\int_0^\infty\zeta_{\mathbf{x}}(t)\,dt.$$

Theorem (YK and P. T. Otto, 2021).

$$\lim_{n \to \infty} \mathbb{E}[L_n] = \sum_{\mathbf{x}} \frac{(\mathbf{x}^{\mathsf{T}} \mathbf{1} - \mathbf{1})!}{\mathbf{x}!} \, \boldsymbol{\alpha}^{\mathbf{x}} \frac{\tau(K_k, x_i x_j v_{i,j})}{\mathbf{x}^{\mathsf{1}}} (V \mathbf{x})^{\mathbf{x} - 1} \left(\mathbf{x}^{\mathsf{T}} V \boldsymbol{\alpha} \right)^{-\mathbf{x}^{\mathsf{T}} \mathbf{1}}$$

The time of formation of a giant component in G(n, p)

$$p_c \sim rac{1}{n \,
ho(VD[lpha_i])}$$