

Binomial Formulas, Interpolation Polynomials, and Symmetric Function Inequalities

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GSCC 2025, USC
March 17, 2025

Joint work with Siddhartha Sahi. [arXiv:2403.02490](https://arxiv.org/abs/2403.02490)
Slides: <https://sites.math.rutgers.edu/~hc813/>

For non-negative integers m, n , and an indeterminate x ,

$$(x+1)^n = \sum_m \binom{n}{m} x^m.$$

Newton: n could be any real number, and x is a real number in a neighborhood of 0.

Cauchy: q -binomial formula

$$\prod_{i=1}^n (1 + xq^i) = \sum_m \binom{n}{m}_q q^{m(m+1)/2} x^m.$$

Question

How to generalize this to symmetric polynomials?

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Let $\lambda = (\lambda_1 \geq \dots \geq \lambda_n) \in \mathbb{Z}_{\geq 0}^n$ be an integer partition. Schur polynomial in $x = (x_1, \dots, x_n)$ is defined by

$$s_\lambda = \frac{\det(x_i^{\lambda_j + n - j})}{\det(x_i^{n - j})}.$$

In 1978, A. Lascoux (see [Macdonald, P. 47]) showed that

$$s_\lambda(x + \mathbf{1}) = \sum_{\mu \subseteq \lambda} d_{\lambda\mu} s_\mu(x),$$

where $\mathbf{1} = (1, \dots, 1)$ and

$$d_{\lambda\mu} = \det \left(\binom{\lambda_i + n - i}{\mu_j + n - j} \right)_{1 \leq i, j \leq n}.$$

Zonal polynomials C_λ are polynomials that statisticians care about. They are closely related to Wishart distribution, which is a distribution of random symmetric and positive-definite matrices. In the '60s, the following binomial expansion

$$\frac{C_\lambda(x+1)}{C_\lambda(x)} = \sum_{\mu} \binom{\lambda}{\mu} \frac{C_\mu(x)}{C_\mu(1)}.$$

was studied by A. Constantine, A. James, R. Muirhead.

Jack polynomials $P_\lambda(x; \tau)$ are a deformation of Schur and Zonal polynomials, depending on a parameter $\tau (= 1/\alpha)$:

$\tau = 1$: Schur; $\tau = \frac{1}{2}$: Zonal;

$\tau = 0$: monomial; $\tau = \infty$: elementary (conjugate).

In the '90s, Lassalle, Kaneko, Okounkov–Olshanski studied binomial formula in the Jack case.

$$\frac{P_\lambda(x + \mathbf{1}; \tau)}{P_\lambda(\mathbf{1}; \tau)} = \sum_{\mu} \binom{\lambda}{\mu}_{\tau} \frac{P_{\mu}(x; \tau)}{P_{\mu}(\mathbf{1}; \tau)},$$

where the binomial coefficient is the evaluation of the **interpolation Jack polynomial** h_{μ} :

$$\binom{\lambda}{\mu}_{\tau} = h_{\mu}(\bar{\lambda}; \tau)$$

Macdonald polynomial $P_\lambda(x; q, t)$ depends on two parameters q, t :
 $q = t$: Schur; $t = 1$: monomial; $q = 1$: elementary (conjugate);
 $q = 0$: Hall–Littlewood; $t = 0$: q -Whittaker.
 In 1998, Okounkov and Lassalle proved:

$$\frac{P_\lambda(x; q, t)}{P_\lambda(t^\delta; q, t)} = \sum_{\mu} \binom{\lambda}{\mu}_{q, t} \frac{h_{\mu}^{\text{monic}}(x; \tau)}{P_{\mu}(t^\delta; \tau)},$$

where the binomial coefficient is the evaluation of the **interpolation Macdonald polynomial** h_{μ} :

$$\binom{\lambda}{\mu}_{q, t} = h_{\mu}(\bar{\lambda}; q, t)$$

Definition

The *unital interpolation polynomial*, denoted by h_μ , is the unique symmetric polynomial that satisfies the following interpolation condition and degree condition:

$$h_\mu(\bar{\lambda}) = \delta_{\lambda\mu}, \quad |\lambda| \leq |\mu|,$$

$$\deg h_\mu = |\mu|,$$

where $\bar{\lambda}_i = \lambda_i + (n - i)\tau$ in the Jack case, and $\bar{\lambda}_i = q^{\lambda_i} t^{n-i}$ in the Macdonald case.

This normalization is called *unital* as $\binom{\mu}{\mu} = h_\mu(\bar{\mu}) = 1$.

The *monic* normalization h_μ^{monic} is defined so that the coefficient of m_μ is 1. $h_\mu^{\text{monic}} = P_\mu + \text{lower degree terms}$.

The above is type *A* interpolation polynomials, introduced by Knop–Sahi in the '90s. Okounkov also introduced a type *BC* analogue, defined by setting $\bar{\lambda}_i = \lambda_i + (n - i)\tau + \alpha$ and $aq^{\lambda_i} t^{n-i}$.

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Okounkov–Olshanski proved the following combinatorial formulas:

$$P_{\lambda}^{\text{monic}, J}(x; \tau) = \sum_T \psi_T(\tau) \prod_{s \in \lambda} x_{T(s)},$$

$$h_{\lambda}^{\text{monic}, AJ}(x; \tau) = \sum_T \psi_T(\tau) \prod_{s \in \lambda} \left(x_{T(s)} - \left(a'_{\lambda}(s) + (n - T(s) - l'_{\lambda}(s))\tau \right) \right),$$

$$P_{\lambda}^{\text{monic}, M}(x; q, t) = \sum_T \psi_T(q, t) \prod_{s \in \lambda} x_{T(s)},$$

$$h_{\lambda}^{\text{monic}, AM}(x; q, t) = \sum_T \psi_T(q, t) \prod_{s \in \lambda} \left(x_{T(s)} - q^{a'_{\lambda}(s)} t^{n - T(s) - l'_{\lambda}(s)} \right),$$

where all the sums are over column-strict semi-standard reverse tableaux $T: \lambda \rightarrow [n]$, i.e., weakly decreasing along the rows and strictly decreasing along the columns.

Let $n = 2$, $\mu = (3, 2)$, there are two such tableaux:

2	2	1
1	1	

,

2	2	2
1	1	

.

$$\text{Hence } s_\mu = P_\mu^J = P_\mu^M = m_\mu = x_1^3 x_2^2 + x_1^2 x_2^3,$$

$$\begin{aligned} h_\mu^{\text{monic}, AJ} &= x_2 x_1 (x_2 - 1)(x_1 - 1)(x_1 - 2 - \tau) \\ &\quad + x_2 x_1 (x_2 - 1)(x_1 - 1)(x_2 - 2) \\ &= x_1 x_2 (x_1 - 1)(x_2 - 1)(x_1 + x_2 - \tau - 4) \end{aligned}$$

$$\begin{aligned} h_\mu^{\text{monic}, AM} &= (x_2 - 1)(x_1 - 1)(x_2 - q)(x_1 - q)(x_1 - q^2 t) \\ &\quad + (x_2 - 1)(x_1 - 1)(x_2 - q)(x_1 - q)(x_2 - q^2) \\ &= (x_1 - 1)(x_2 - 1)(x_1 - q)(x_2 - q)(x_1 + x_2 - q^2 t - q^2) \end{aligned}$$

The defining condition involves the following 12 partitions:

$(0, 0), (1, 0), (1, 1), (2, 0), (2, 1), (3, 0), (2, 2), (3, 1), (4, 0), (3, 2), (4, 1), (5, 0)$.

Note that $\overline{(\lambda_1, \lambda_2)} = (\lambda_1 + \tau, \lambda_2), (q^{\lambda_1} t, q^{\lambda_2})$. One can easily see that h_μ vanishes at all but $\overline{(3, 2)}$.

Moreover, h_μ also vanishes at $\overline{(m, 0)}$ and $\overline{(m-1, 1)}$, $\forall m \geq 6$.

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Proposition (Knop–Sahi, Okounkov '90s, Extra Vanishing Property)

$$\binom{\lambda}{\mu} := h_{\mu}(\bar{\lambda}) = 0, \quad \text{unless } \lambda \supseteq \mu. \quad \binom{m}{n} = 0, \quad \text{unless } m \geq n.$$

Theorem (Sahi '11, C–Sahi '24)

The binomial coefficient is positive and monotone:

$$\begin{aligned} \binom{\lambda}{\mu} \in \mathbb{F}_{>0} &\iff \lambda \supseteq \mu. & \binom{m}{n} > 0 &\iff m \geq n. \\ \binom{\lambda}{\nu} - \binom{\mu}{\nu} \in \mathbb{F}_{\geq 0} &\text{ if } \lambda \supseteq \mu. & \binom{m}{k} - \binom{n}{k} \geq 0 &\text{ if } m > n. \end{aligned}$$

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For Jack polynomials

$$\frac{P_\lambda(x+1; \tau)}{P_\lambda(1; \tau)} = \sum_{\nu \subseteq \lambda} \binom{\lambda}{\nu} \frac{P_\nu(x; \tau)}{P_\nu(1; \tau)}$$

Theorem (C–Sahi '24)

TFAE:

- $\lambda \supseteq \mu$, i.e., $\lambda_i \geq \mu_i$ for each i .
- $\frac{s_\lambda(x+1)}{s_\lambda(1)} - \frac{s_\mu(x+1)}{s_\mu(1)}$ is Schur positive.
- $\frac{m_\lambda(x+1)}{m_\lambda(1)} - \frac{m_\mu(x+1)}{m_\mu(1)}$ is monomial positive.
- $\frac{e_\lambda(x+1)}{e_\lambda(1)} - \frac{e_\mu(x+1)}{e_\mu(1)}$ is elementary positive.
- $\frac{P_\lambda(x+1; \tau)}{P_\lambda(1; \tau)} - \frac{P_\mu(x+1; \tau)}{P_\mu(1; \tau)}$ is Jack positive over $\mathbb{F}_{\geq 0}$.

Write $S_\lambda(x) = \frac{s_\lambda(x)}{s_\lambda(1)}$ and $\tilde{S}_\lambda(x) = S_\lambda(x+1)$, and similarly for M and $\tilde{M}$, E and $\tilde{E}$, P^* and $\tilde{P}^*$, then

$$\begin{aligned}\tilde{S}_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} - \tilde{S}_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} &= S_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} + \frac{4}{3}S_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} + \frac{8}{3}S_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 3S_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 2S_{\begin{smallmatrix} \square \\ \square \end{smallmatrix}} + 2S_{\square}; \\ \tilde{M}_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} - \tilde{M}_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} &= M_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} + M_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} + 3M_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 2M_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 3M_{\begin{smallmatrix} \square \\ \square \end{smallmatrix}} + 2M_{\square}; \\ \tilde{E}_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} - \tilde{E}_{\begin{smallmatrix} \square \\ \square \end{smallmatrix}} &= E_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 2E_{\begin{smallmatrix} \square \\ \square \end{smallmatrix}} + 2E_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 4E_{\begin{smallmatrix} \square \\ \square \end{smallmatrix}} + E_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + 2E_{\square}; \\ \tilde{P}^*_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} - \tilde{P}^*_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} &= P^*_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} + \frac{2\tau+2}{\tau+2}P^*_{\begin{smallmatrix} \square & \square & \square \\ \square & & \end{smallmatrix}} + \frac{2\tau+6}{\tau+2}P^*_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + \frac{4\tau+2}{\tau+1}P^*_{\begin{smallmatrix} \square & \square \\ \square & \end{smallmatrix}} + \frac{\tau+3}{\tau+1}P^*_{\begin{smallmatrix} \square \\ \square \end{smallmatrix}} + 2P^*_{\square}.\end{aligned}$$

Recall that when $\tau = 1, 0, \infty$, Jack specializes to Schur, monomial and elementary (conjugated) respectively.

$\mathbb{F} = \mathbb{Q}(\tau)$, let $\mathbb{F}_{\geq 0} := \{f/g \mid f, g \in \mathbb{Z}_{\geq 0}[\tau], g \neq 0\}$ and $\mathbb{F}_{> 0} := \mathbb{F}_{\geq 0} \setminus \{0\}$. In particular, $f(\tau_0) > 0$ for $f \in \mathbb{F}_{> 0}$ and $\tau_0 \in (0, \infty)$.

Theorem (Cuttler–Greene–Skandera '11, Sra '16)

Let $|\lambda| = |\mu|$. TFAE:

- λ dominates μ , i.e., $\lambda_1 + \cdots + \lambda_i \geq \mu_1 + \cdots + \mu_i$, for each i .
- (Muirhead's inequality) $\frac{m_\lambda(x)}{m_\lambda(\mathbf{1})} - \frac{m_\mu(x)}{m_\mu(\mathbf{1})} \geq 0, \quad \forall x \in [0, \infty)^n.$
- (Newton's inequality) $\frac{e_{\lambda'}(x)}{e_{\lambda'}(\mathbf{1})} - \frac{e_{\mu'}(x)}{e_{\mu'}(\mathbf{1})} \geq 0, \quad \forall x \in [0, \infty)^n.$
- (Gantmacher's inequality) $\frac{p_\lambda(x)}{p_\lambda(\mathbf{1})} - \frac{p_\mu(x)}{p_\mu(\mathbf{1})} \geq 0, \quad \forall x \in [0, \infty)^n.$
- (Sra's inequality) $\frac{s_\lambda(x)}{s_\lambda(\mathbf{1})} - \frac{s_\mu(x)}{s_\mu(\mathbf{1})} \geq 0, \quad \forall x \in [0, \infty)^n.$

Theorem (Khare–Tao '18)

λ weakly dominates $\mu \iff \frac{s_\lambda(x+1)}{s_\lambda(\mathbf{1})} - \frac{s_\mu(x+1)}{s_\mu(\mathbf{1})} \geq 0, \forall x \in [0, \infty)^n.$

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$$\lambda \text{ weakly dominates } \mu \iff \frac{s_\lambda(x+1)}{s_\lambda(\mathbf{1})} - \frac{s_\mu(x+1)}{s_\mu(\mathbf{1})} \geq 0, \forall x \in [0, \infty)^n.$$

Conjecture (C-Sahi '24)

For $\tau \in (0, \infty)$,

- (CGS Conjecture for Jack polynomials) Let $|\lambda| = |\mu|$. λ dominates μ if and only if

$$\frac{P_\lambda(x, \tau)}{P_\lambda(\mathbf{1})} - \frac{P_\mu(x, \tau)}{P_\mu(\mathbf{1})} \geq 0, \quad \forall x \in [0, \infty)^n.$$

- (KT Conjecture for Jack polynomials) λ weakly dominates μ if and only if

$$\frac{P_\lambda(x + \mathbf{1}; \tau)}{P_\lambda(\mathbf{1})} - \frac{P_\mu(x + \mathbf{1}; \tau)}{P_\mu(\mathbf{1})} \geq 0, \quad \forall x \in [0, \infty)^n.$$

Note that the CGS conjecture, together with our theorem, implies the KT conjecture; also, the “if” direction of the CGS conjecture is easily seen to be true by some degree consideration.

In two variables,

$$S_{\begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \end{array}} - S_{\begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & & \end{array}} = \frac{1}{15}(x_1 - x_2)^2(3x_1^2 + 4x_1x_2 + 3x_2^2)$$

$$S_{\begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & & \end{array}} - S_{\begin{array}{|c|c|} \hline \square & \square \\ \hline \square & \square \\ \hline \end{array}} = \frac{1}{3}(x_1 - x_2)^2x_1x_2$$

$$P^*_{\begin{array}{|c|c|c|c|} \hline \square & \square & \square & \square \\ \hline \end{array}} - P^*_{\begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & & \end{array}} = \frac{(\tau + 3)(x_1 - x_2)^2}{4(2\tau + 1)(2\tau + 3)} \left(\tau(x_1 + x_2)^2 + 2(x_1^2 + x_1x_2 + x_2^2) \right)$$

$$P^*_{\begin{array}{|c|c|c|} \hline \square & \square & \square \\ \hline \square & & \end{array}} - P^*_{\begin{array}{|c|c|} \hline \square & \square \\ \hline \square & \square \\ \hline \end{array}} = \frac{(\tau + 1)}{2(2\tau + 1)}(x_1 - x_2)^2x_1x_2$$

Thank you!

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arXiv:2403.02490

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