A probabilistic interpretation of the Macdonald polynomials

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Abstract
The two-parameter Macdonald polynomials are a central object of algebraic combinatorics and representation theory. We give a Markov chain on partitions of $k$ with eigenfunctions the coefficients of the Macdonald polynomials when expanded in the power sum polynomials. The Markov chain has stationary distribution a new two-parameter family of measures on partitions, the inverse of the Macdonald weight (rescaled). The uniform distribution on permutations and the Ewens sampling formula are special cases. The Markov chain is a version of the auxiliary variables algorithm of statistical physics. Properties of the Macdonald polynomials allow a sharp analysis of the running time. In natural cases, a bounded number of steps suffice for arbitrarily large $k$.

Keywords: Macdonald polynomials, random permutations, measures on partitions, auxiliary variables, Markov chain, rates of convergence

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1 Introduction
The Macdonald polynomials $P_{\lambda}(x; q, t)$ are a widely studied family of symmetric polynomials in variables $X = (x_1, x_2, \ldots, x_n)$. Let $\Lambda^k_n$ denote the vector space of homogeneous symmetric polynomials of degree $k$ (with coefficients in $Q$). The Macdonald inner product is determined by setting the inner product between power sum symmetric functions $p_{\lambda}$ as

$$\langle p_{\lambda}, p_{\mu} \rangle = \delta_{\lambda \mu} z_{\lambda}(q, t),$$

with

$$z_{\lambda}(q, t) = z_{\lambda} \prod_i \left( \frac{1 - q^{\lambda_i}}{1 - t^{\lambda_i}} \right) \quad \text{and} \quad z_{\lambda} = \prod_i i^{a_i} a_i!,$$

for $\lambda$ a partition of $k$ with $a_i$ parts of size $i$.

For each $q, t$, as $\lambda$ ranges over partitions of $k$, the $P_{\lambda}(x; q, t)$ are an orthogonal basis for $\Lambda^k_n$. Special values of $q, t$ give classical bases such as Schur functions ($q = t$), Hall–Littlewood functions ($t = 0$), and the Jack symmetric functions (limit as $t \to 1$ with $q^{\alpha} = t$).

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An enormous amount of combinatorics, group theory, and algebraic geometry is coded into these polynomials. A more careful description and literature review is in Section 2.

The original definition of Macdonald constructs $P_\lambda(x; q, t)$ as the eigenfunctions of a somewhat mysterious family of operators $D_{q,t}(z)$. This is used to develop their basic properties in [39]. A main result of the present paper is that the Macdonald polynomials can be understood through a natural Markov chain $M(\lambda, \lambda')$ on the partitions of $k$. For $q, t > 1$, this Markov chain has stationary distribution

$$
\pi_{q,t}(\lambda) = \frac{Z}{z_\lambda(q, t)} \quad \text{with} \quad Z = \frac{(q, q)_k}{(t, q)_k}, \quad (x, y)_k = \prod_{i=0}^{k-1} (1 - xy^i).
$$

Here $z_\lambda(q, t)$ is the Macdonald weight (1.1) and $Z$ is a normalizing constant. The coefficients of the Macdonald polynomials expanded in the power sums give the eigenvectors of $M$, and there is a simple formula for the eigenvalues.

Here is a brief description of $M$. From a current partition $\lambda$, choose some parts to delete: call these $\lambda_J$. This leaves $\lambda_{\lambda_J} = \lambda \setminus \lambda_J$. The choice of $\lambda_{\lambda_J}$ given $\lambda$ is made with probability

$$
w_\lambda(\lambda_{\lambda_J}) = \frac{1}{q^k - 1} \prod_{i=1}^{k} \left( \frac{a_i(\lambda)}{a_i(\lambda_{\lambda_J})} \right) \left( q^i - 1 \right)^{a_i(\lambda) - a_i(\lambda_{\lambda_J})}.
$$

It is shown in Section 2.4 that for each $\lambda$, $w_\lambda(\cdot)$ is a probability distribution with a simple-to-implement interpretation. Having chosen $\lambda_{\lambda_J}$, choose a partition $\mu$ of size $|\lambda| - |\lambda_{\lambda_J}|$ with probability

$$
\pi_{\infty, t}(\mu) = \frac{t}{t - 1} \frac{1}{z_\mu} \prod \left( 1 - \frac{1}{t} \right)^{a_i(\mu)}.
$$

Adding $\mu$ to $\lambda_{\lambda_J}$ gives a final partition $\nu$. These two steps define the Markov chain $M(\lambda, \nu)$ with stationary distribution $\pi_{q,t}$. It will be shown to be a natural extension of basic algorithms of statistical physics: the Swendsen–Wang and auxiliary variables algorithms. Properties of the Macdonald polynomials give a sharp analysis of the running time for $M$.

Section 2 gives background on Macdonald polynomials (Section 2.1), Markov chains (Section 2.2), and auxiliary variables algorithms (Section 2.3). The Markov chain $M$ is shown to be a special case of auxiliary variables and hence is reversible with $\pi_{q,t}(\lambda)$ as stationary distribution. Section 2.4 reviews some of the many different measures used on partitions, showing that $w_\lambda$ and $\pi_{\infty, t}$ above have simple interpretations and efficient sampling algorithms. Section 2.4 also presents simulations of the measure $\pi_{q,t}(\lambda)$ using $M$. This gives an understanding of $\pi_{q,t}$; it also illustrates (numerically) that a few steps of $M$ suffice for large $k$ while classical sampling algorithms (rejection sampling or Metropolis) become impractical.

The main theorems are in Section 3. The Markov chain $M$ is identified as one term of Macdonald operators $D_{q,t}(z)$. The coefficients of the Macdonald polynomials in the power sum basis (suitably scaled) are shown to be the eigenfunctions of $M$ with a simple formula for the eigenvalues. Needed values of the eigenvectors are derived. A heuristic overview of the argument is given (Section 3.2), which may be read now for further motivation.

The main theorem is an extension of earlier work by Hanlon [15, 31] giving a similar interpretation of the coefficients of the family of Jack symmetric functions as eigenfunctions.
of a natural Markov chain: the Metropolis algorithm on the symmetric group for generating from the Ewens sampling formula. Section 4 develops the connection to the present study. Section 5 gives an analysis of the convergence of iterates of \( M \) to the stationary distribution \( \pi_{q,t} \) for natural values of \( q \) and \( t \). Starting from \( (k) \), it is shown that a bounded number of steps suffice for arbitrary \( k \). Starting from \( 1k \), order \( \log k \) steps are necessary and sufficient for convergence.

2 Background and examples

This section contains needed background on four topics: Macdonald polynomials, Markov chains, auxiliary variables algorithms, and measures on partitions and permutations. Each of these has a large literature. We give basic definitions, needed formulae, and pointers to literature. Section 2.3 shows that the Markov chain \( M \) of the introduction is a special case of the auxiliary variables algorithm. Section 2.4 shows that the steps of the algorithm are easy to run, and has numerical examples.

2.1 Macdonald polynomials

Let \( \Lambda_n \) be the algebra of symmetric polynomials in \( n \) variables (coefficients in \( \mathbb{Q} \)). There are many useful bases of \( \Lambda_n \): the monomial \( \{ m_{\lambda} \} \), power sum \( \{ p_{\lambda} \} \), elementary \( \{ e_{\lambda} \} \), homogeneous \( \{ h_{\lambda} \} \), and Schur functions \( \{ s_{\lambda} \} \) are bases whose change of basis formulae contain a lot of basic combinatorics [50, Chap. 7], [39, Chap. I]. More esoteric bases such as the Hall–Littlewood functions \( \{ H_{\lambda}(q) \} \), zonal polynomials \( \{ Z_{\lambda} \} \), and Jack symmetric functions \( \{ J_{\lambda}(\alpha) \} \) occur as the spherical functions of natural homogeneous spaces [39]. In all cases, as \( \lambda \) runs over partitions of \( k \), the associated polynomials form a basis of the vector space \( \Lambda_k \): homogeneous symmetric polynomials of degree \( k \).

Macdonald introduced a two-parameter family of bases \( P_{\lambda}(x; q, t) \) which, specializing \( q, t \) in various ways, gives essentially all the previous bases. The Macdonald polynomials can be succinctly characterized by using the inner product

\[
\langle p_{\lambda}, p_{\mu} \rangle = \delta_{\lambda \mu} z_{\lambda}(q, t)
\]

from (1.1). This is positive definite [39, VI (4.7)] and there is a unique family of symmetric functions \( P_{\lambda} \) such that \( \langle P_{\lambda}, P_{\mu} \rangle_{q, t} = 0 \) if \( \lambda \neq \mu \) and \( P_{\lambda} = \sum_{\mu \subseteq \lambda} u_{\lambda \mu} m_{\mu} \) with \( u_{\lambda \lambda} = 1 \) [39 VI (4.7)]. The properties of \( P_{\lambda} \) are developed by studying \( P_{\lambda} \) as the eigenfunctions of a family of operators \( D_{q, t}(z) \) from \( \Lambda_n \) to \( \Lambda_n \).

Define an operator \( T_{u,x_i} \) on polynomials by

\[
T_{u,x_i} f(x_1, \ldots, x_n) = f(x_1, \ldots, ux_i, \ldots, x_n).
\]

Define \( D_{q,t}(z) \) and \( D_{q,t}^r \) by

\[
D_{q,t}(z) = \sum_{r=0}^{n} D_{q,t}^r z^r = \frac{1}{a_{\delta}} \sum_{w \in S_n} \det(w) x^{\omega_{\delta}} \prod_{i=1}^{n} \left( 1 + z t^{(w_{\delta})_{i}} T_{q,x_i} \right),
\]

where \( \delta = (n-1, n-2, \ldots, 0) \), \( a_{\delta} \) is the Vandermonde determinant and \( x^{\gamma} = x_1^{\gamma_1} \cdots x_n^{\gamma_n} \) for \( \gamma = (\gamma_1, \ldots, \gamma_n) \). For any \( r = 0, 1, \ldots, n \),

\[
D_{q,t}^r = \sum_{I} A_I(x; t) \prod_{i \in I} T_{q,x_i},
\]
where the sum is over all $r$-element subsets $I$ of $\{1,2,\ldots,n\}$ and

$$A_I(x;t) = \frac{1}{a_{I}} \left( \prod_{i \in I} T_{i, x_i} \right) = x^{r(r-1)/2} \prod_{i \in I, j \notin I} \frac{tx_i - x_j}{x_i - x_j} \quad [39 \text{ VI (3.4)}].$$

Macdonald [39 VI (4.15)] shows that the Macdonald polynomials are eigenfunctions of $D_{q,t}(z)$:

$$D_{q,t}(z) P_{\lambda}(x; q, t) = \prod_{i=1}^{n} \left( 1 + z q^{\lambda_i} t^{n-i} \right) P_{\lambda}(x; q, t).$$

This implies that the operators $D_{q,t}^r$ commute, and have the $P_{\lambda}$ as eigenfunctions with eigenvalues the $r$th elementary symmetric function in $\{q^{\lambda_i} t^{n-i}\}$. We will use $D_{q,t}^1$ in our work below. The $D_{q,t}^r$ are self-adjoint in the Macdonald inner product $\langle D_{q,t}^r f, g \rangle = \langle f, D_{q,t}^r g \rangle$. This will translate into having $\pi_{q,t}$ as stationary distribution.

The Macdonald polynomials may be expanded in the power sums [39 VI (8.19)],

$$P_{\lambda}(x; q, t) = \frac{1}{c_{\lambda}(q, t)} \sum_{\rho} \left[ z_{\rho}^{-1} \prod_{i} (1 - t^{\rho_i}) X_{\rho}^\lambda(q, t) \right] p_{\rho}(x)$$

with [39 VI (8.1)] $c_{\lambda}(q, t) = \prod_{s \subseteq \lambda} (1 - q^{a(s) l(s)+1})$ where the product is over the boxes in the shape of $\lambda$, $a(s)$ the arm length and $l(s)$ the leg length of box $s$. The $X_{\rho}^\lambda(q, t)$ are closely related to the two-parameter Kostka numbers $K_{\mu\lambda}(q, t)$ via [39 VI (8.20)],

$$X_{\rho}^\lambda(q, t) = \sum_{\mu} \chi_{\rho}^{\mu} K_{\mu\lambda}(q, t), \quad K_{\mu\lambda}(q, t) = \sum_{\rho} z_{\rho}^{-1} \chi_{\rho}^{\mu} X_{\rho}^\lambda(q, t)$$

with $\chi_{\rho}^{\mu}$ the characters of the symmetric group for the $\lambda$th representation at the $\rho$th conjugacy class. These $K_{\mu\lambda}(q, t)$ have been a central object of study in algebraic combinatorics [7, 23, 26, 27, 28, 29, 30]. The main result of Section 3 shows that $X_{\rho}^\lambda(q, t) \prod_i (1 - q^{\rho_i})$ are the eigenfunctions of the Markov chain $M$.

The Macdonald polynomials used here are associated to the root system $A_n$. Macdonald [40] has defined analogous functions for the other root systems using similar operators. In a major step forward, Cherednik [13] gives an independent development in all types, using the double affine Hecke algebra. See [39, 41] for a comprehensive treatment. Using this language, Ram and Yip [48] give a “formula” for the Macdonald polynomials in general type. In general type the double affine Hecke is a powerful tool for understanding actions. We believe that our Markov chain can be developed in general type if a suitable analogue of the power sum basis is established.

2.2 Markov chains

Let $\mathcal{X}$ be a finite set. A Markov chain on $\mathcal{X}$ may be specified by a matrix $M(x, y) \geq 0$, $\sum_y M(x, y) = 1$. The interpretation being that $M(x, y)$ is the chance of moving from $x$ to $y$ in one step. Then $M^2(x, y) = \sum_z M(x, z) M(z, y)$ is the chance of moving from $x$ to $y$ in two steps, and $M^\ell(x, y)$ is the chance of moving from $x$ to $y$ in $\ell$ steps. Under mild conditions, always met in our examples, there is a unique stationary distribution
\[ \pi(x) \geq 0, \sum_x \pi(x) = 1. \] This satisfies \( \sum_x \pi(x)M(x,y) = \pi(y) \). Hence, the (row) vector \( \pi \) is a left eigenvector of \( M \) with eigenvalue 1. Probabilistically, picking \( x \) from \( \pi \) and taking one further step in the chain leads to the chance \( \pi(y) \) of being at \( y \).

All of the Markov chains used here are reversible, satisfying the detailed balance condition \( \pi(x)M(x,y) = \pi(y)M(y,x) \), for all \( x, y \) in \( \mathcal{X} \). Set \( L^2(\mathcal{X}) \) to be \( \{ f : \mathcal{X} \to \mathbb{R} \} \) with 

\[
(f_1, f_2) = \sum_x \pi(x)f_1(x)f_2(x) \].

Then \( M \) acts as a contraction on \( L^2(\mathcal{X}) \) by \( Mf(x) = \sum_y M(x,y)f(y) \). Reversibility is equivalent to \( M \) being self-adjoint. In this case, there is an orthogonal basis of (right) eigenfunctions \( f_i \) and real eigenvalues \( \beta_i \), \( 1 = \beta_0 \geq \beta_1 \geq \cdots \geq \beta_{|\mathcal{X}|-1} \geq -1 \) with \( Mf_i = \beta_if_i \). For reversible chains, if \( f_i(x) \) is a left eigenvector, then \( f_i(x)/\pi(x) \) is a right eigenvector with the same eigenvalue.

A basic theorem of Markov chain theory shows that \( M_\ell^x(y) = M_\ell^x(x,y) \xrightarrow{\ell} \pi(y) \). (Again, there are mild conditions, met in our examples.) The distance to stationarity can be measured in \( L^1 \) by the total variation distance:

\[
\| M_\ell^x - \pi \|_{TV} = \max_{A \subseteq \mathcal{X}} | M_\ell^x(x,A) - \pi(A) | = \frac{1}{2} \sum_y | M_\ell^x(x,y) - \pi(y) |.
\]

Distance is measured in \( L^2 \) by the chi-squared distance:

\[
\| M_\ell^x - \pi \|_2^2 = \sum_y \frac{(M_\ell^x(x,y) - \pi(y))^2}{\pi(y)} = \sum_{i=1}^{|\mathcal{X}|-1} \frac{\beta_i^2}{|\mathcal{X}|},
\]

where \( \bar{f}_i \) is the eigenvector \( f_i \), normalized to have \( L^2 \)-norm 1. The Cauchy–Schwarz inequality shows

\[
4 \| M_\ell^x - \pi \|_{TV}^2 \leq \| M_\ell^x - \pi \|_2^2.
\]

Using these bounds calls for getting one’s hands on eigenvalues and eigenvectors. This can be hard work, but has been done in many cases. A central question is this: given \( M, \epsilon > 0 \), and a starting state \( x \), how large must \( \ell \) be so that \( \| M_\ell^x - \pi \|_{TV} < \epsilon \)?

Background on the quantitative study of rates of convergence of Markov chains is treated in the textbook of Brémaud [11]. The identities and inequalities that appear above are derived in the very useful treatment by Saloff-Coste [49]. He shows how tools of analysis can be brought to bear. The recent monograph of Levin, Peres and Wilmer [37] is readable by non-specialists and covers both analytic and probabilistic techniques.

### 2.3 Auxiliary variables

This is a method of constructing a reversible Markov chain with \( \pi \) as stationary distribution. It was invented by Edwards and Sokal [20] as an abstraction of the remarkable Swendsen–Wang algorithm. The Swendsen–Wang algorithm was introduced as a superfast method for simulating from the Ising and Potts models of statistical mechanics. It is a block-spin procedure which changes large pieces of the current state. A good overview of such block spin algorithms is in [32]. The abstraction to auxiliary variables is itself equivalent to several other classes of widely used procedures, data augmentation and the hit-and-run algorithm. For these connections and much further literature, see [14].
To describe auxiliary variables, let $\pi(x) > 0$, $\sum_x \pi(x) = 1$ be a probability distribution on a finite set $\mathcal{X}$. Let $I$ be an auxiliary index set. For each $x \in \mathcal{X}$, let $w_x(i)$ be a probability distribution on $I$ (the chance of moving to $i$). These define a joint distribution $f(x, i) = \pi(x)w_x(i)$ and a marginal distribution $m(i) = \sum_x f(x, i)$. Let $f(x|\lambda) = f(x, i)/m(i)$ denote the conditional distribution. The final ingredient needed is a Markov matrix $M_i(x, y)$ with $f(x|i)$ as reversing measure $(f(x|i)) = f(y|i)M_i(y, x)$ for all $x, y$). This allows for defining

\begin{equation}
M(x, y) = \sum_i w_x(i)M_i(x, y).
\end{equation}

The Markov chain $M$ has the following interpretation: from $x$, choose $i \in I$ from $w_x(i)$ and then $y \in \mathcal{X}$ from $M_i(x, y)$. The resulting kernel is reversible with respect to $\pi$:

\begin{equation}
\pi(x)M(x, y) = \sum_i \pi(x)w_x(i)M_i(x, y) = \sum_i \pi(y)w_y(i)M_i(y, x)
= \pi(y)\sum_i w_y(i)M_i(y, x) = \pi(y)M(y, x).
\end{equation}

We now specialize things to $\mathcal{P}_k$, the space of partitions of $k$. Take $\mathcal{X} = \mathcal{P}_k$, $I = \cup_{i=1}^k \mathcal{P}_i$. The stationary distribution is as in (1.2):

\begin{equation}
\pi(\lambda) = \pi_{\lambda,t}(\lambda) = \frac{Z}{z\lambda(q, t)}.
\end{equation}

From $\lambda \in \mathcal{P}_k$, the algorithm chooses some parts to delete, call these $\lambda_{J'}$, leaving parts $\lambda_{J''} = \lambda \backslash \lambda_{J'}$. Thus if $\lambda = 322111$ and $\lambda_{J'} = 31$, $\lambda_{J''} = 2211$. We allow $\lambda_{J'} = \lambda$ but demand $\lambda_{J'} \neq \emptyset$. Clearly, $\lambda$ and $\lambda_{J'}$ determine $\lambda_{J''}$ and $(\lambda, \lambda_{J''})$ determine $\lambda_{J'}$. We let $\lambda_{J''}$ be the auxiliary variable. The choice of $\lambda_{J''}$ given $\lambda$ is made with probability

\begin{equation}
w_{\lambda}(\lambda_{J''}) = \frac{1}{q^k - 1} \prod_{i=1}^k \left( \frac{a_i(\lambda)}{a_i(\lambda_{J''})} \right) \left( q^i - 1 \right)^{a_i(\lambda_{J''})}
= \frac{1}{q^k - 1} \prod_{i=1}^k \left( \frac{a_i(\lambda)}{a_i(\lambda_{J''})} \right) \left( q^i - 1 \right)^{a_i(\lambda) - a_i(\lambda_{J''})}.
\end{equation}

Thus, for $\lambda = 13232$; $\lambda_{J'} = 13$, $\lambda_{J''} = 1223$; $w_{\lambda}(\lambda_{J''}) = \frac{1}{q^k - 1} \prod_{i=1}^k \left( \frac{3}{2} \frac{1}{1} \right) \left( q^i - 1 \right)^{a_i(\lambda_{J''})}$. It is shown in Section 2.4 below that $w_{\lambda}(\lambda_{J''})$ is a probability distribution with a simple interpretation. Having chosen $\lambda_{J'}$ with $0 < |\lambda_{J'}| \leq k$, the algorithm chooses $\mu \vdash |\lambda_{J'}|$ with probability $\pi_{\lambda_{J'}, \mu}(\lambda_{J''})$ given in (1.4). Adding these parts to $\lambda_{J''}$ gives $\nu$. More carefully,

\begin{equation}
M_{\lambda_{J''}, \lambda}(\lambda, \nu) = \pi_{\lambda_{J''}, \mu}(\lambda_{J''}) = \frac{t}{t - 1} \frac{1}{z\lambda(\mu)} \prod_i \left( 1 - \frac{1}{u_i} \right)^{a_i(\mu)}.
\end{equation}

Here it is assumed that $\lambda_{J''}$ is a part of both $\lambda$ and $\nu$; the kernel $M_{\lambda_{J''}, \lambda}(\lambda, \nu)$ is zero otherwise.

It is shown in Section 2.4 below that $M_{\lambda_{J''}, \lambda}$ has a simple interpretation which is easy to sample from. The joint density $f(\lambda, \lambda_{J''}) = \pi(\lambda)w_{\lambda}(\lambda_{J''})$ is proportional to $f(\lambda|\lambda_{J''})$ and to

\begin{equation}
\frac{\prod_i (1 - 1/\mu_i)^{a_i(\lambda)}}{\prod_i i^{a_i(\lambda)} (a_i(\lambda) - a_i(\lambda_{J''}))!}.
\end{equation}
The normalizing constant depends on $\lambda Jc$ but this is fixed in the following. We must now check reversibility of $f(\lambda|\lambda Jc)$, $M_{\lambda Jc}(\lambda,\nu)$. For this, compute $f(\lambda|\lambda Jc)M_{\lambda Jc}(\lambda,\nu)$ (up to a constant depending on $\lambda Jc$) as

$$
\prod_i (1 - 1/t^i)^{a_i(\lambda)+a_i(\nu)} \prod_i \frac{a_i(\lambda) - a_i(\lambda Jc))! (a_i(\nu) - a_i(\lambda Jc))!}{a_i(\lambda Jc)}.
$$

This is symmetric in $\lambda,\nu$ and so equals $f(\nu|\lambda Jc)M_{\lambda Jc}(\nu,\lambda)$. This proves the following:

**Proposition 2.1.** With definitions (2.11)–(2.14), the kernel on $P_k$, $M(\lambda,\nu) = \sum_{\lambda Jc} w(\lambda Jc) M_{\lambda Jc}(\lambda,\nu)$ generates a reversible Markov chain with $\pi_{q,t}(\lambda)$ as stationary distribution.

**Example 1.** With $k = 2$, let

$$
\pi_{q,t}(2) = \frac{Z (t^2 - 1)}{2 (q^2 - 1)}, \quad \pi_{q,t}(1^2) = \frac{Z}{2} \left( \frac{t - 1}{q - 1} \right)^2 \quad \text{for} \quad Z = \frac{(1 - q)(1 - q^2)}{(1 - t)(1 - tq)}.
$$

From the definitions, with rows and columns labeled (2), 12, the transition matrix is (2.15)

$$
M = \begin{pmatrix}
\frac{1}{2} \left( 1 + \frac{1}{t} \right) & \frac{1}{2} \left( 1 - \frac{1}{t} \right) \\
\frac{q - 1}{q + 1} \left( 1 + \frac{1}{t} \right) & \frac{4t + (q - 1)(t - 1)}{2(q + 1)t}
\end{pmatrix}
\begin{pmatrix}
t + 1 \\
\frac{(q - 1)(t + 1)}{q + 1} & \frac{t - 1}{q + 1} + \frac{4t + (q - 1)(t - 1)}{q + 1}
\end{pmatrix}.
$$

In this $k = 2$ example, it is straightforward to check that $\pi_{q,t}$ sums to 1, the rows of $M$ sum to 1, and that $\pi_{q,t}(\lambda)M(\lambda,\nu) = \pi_{q,t}(\nu)M(\nu,\lambda)$.

### 2.4 Measures on partitions and permutations

The measure $\pi_{q,t}$ of (1.2) has familiar specializations: to the distribution of conjugacy classes of a uniform permutation ($q = t$), and the Ewens sampling measure ($q^a = t \to 0$). After recalling these, the measures $w_{\lambda Jc}(\cdot)$ and $M_{\lambda Jc}(\lambda, \cdot)$ used in the auxiliary variables algorithm are treated. Finally, there is a brief review of the many other, nonuniform distributions used on partitions $P_k$ and permutations $S_k$. Along the way, many results on the “shape” of a typical partition drawn from $\pi_{q,t}$ appear.

#### 2.4.1 Uniform permutations ($q = t$)

If $\sigma$ is chosen uniformly on $S_k$, the chance that the cycle type of $\sigma$ is $\lambda$ is $1/z(\lambda) = \pi_{q,q}(\lambda)$. There is a healthy literature on the structure of random permutations (number of fixed points, cycles of length $i$, number of cycles, longest and shortest cycles, order, . . . ). This is reviewed in [22, 46], which also contain extensions to the distribution of conjugacy classes of finite groups of Lie type.

One natural appearance of the measure $1/z(\lambda)$ comes from the coagulation/fragmentation process. This is a Markov chain on partitions of $k$ introduced by chemists and physicists.
to study clump sizes. Two parts are chosen with probability proportional to their size. If different parts are chosen, they are combined. If the same part is chosen twice, it is split uniformly into two parts. This Markov chain has stationary distribution $1/z\lambda$. See [2] for a review of a surprisingly large literature and [17] for recent developments. These authors note that the coagulation/fragmentation process is the random transpositions walk, viewed on conjugacy classes. Using the Metropolis algorithm (as in Section 2.4.6 below) gives a similar process with stationary distribution $\pi_{\lambda,t}$.

Algorithmically, a fast way to pick $\lambda$ with probability $1/z\lambda$ is by uniform stick-breaking: Pick $U_1 \in \{1, \ldots, k\}$ uniformly. Pick $U_2 \in \{1, \ldots, k - U_1\}$ uniformly. Continue until the first time $T$ that the uniform choice equals its maximum value. The partition with parts $U_1, U_2, \ldots, U_T$ equals $\lambda$ with probability $1/z\lambda$.

2.4.2 Ewens and Jack measures

Set $q = t^{\alpha}$ and let $t \to 1$. Then $\pi_{q,t}(\lambda)$ converges to

\begin{equation}
(2.16) \quad \pi_{\alpha}(\lambda) = \frac{Z\alpha^{-\ell(\lambda)}}{z\lambda^\alpha}, \quad Z = \frac{\alpha^k k!}{\prod_{i=1}^{k-1} (i\alpha + 1)}, \quad \ell(\lambda) \text{ the number of parts of } \lambda.
\end{equation}

In population genetics, setting $\alpha = 1/\theta$, with $\theta > 0$ a “fitness parameter,” this measure is called the Ewens sampling formula. It has myriad practical appearances through its connection with Kingman’s coalescent process, and has generated a large enumerative literature in the combinatorics and probability community [4, 32, 47]. It also makes numerous appearances in the statistics literature through its occurrence in non-parametric Bayesian statistics via Dirichlet random measures and the Dubins–Pitman Chinese restaurant process [24], [47, sec. 3.1].

Algorithmically, a fast way to pick $\lambda$ with probability $\pi_{1/\theta}(\lambda)$ is by the Chinese restaurant construction. Picture a collection of circular tables. Person 1 sits at the first table. Successive people sit sequentially, by choosing to sit to the right of a (uniformly chosen) previously seated person (probability $\theta$) or at a new table (probability $1 - \theta$). When $k$ people have been seated, this generates the cycles of a random permutation with probability $\pi_{1/\theta}$. It would be nice to have a similar construction for the measures $\pi_{q,t}$.

The Macdonald polynomials associated to this weight function are called the Jack symmetric functions [39, VI Sect. 1]. Hanlon [15, 31] uses properties of Jack polynomials to diagonalize a related Markov chain; see Section 4. When $\alpha = 1/2$, the Jack polynomials become the zonal-spherical functions of $GL_n/O_n$. Here, an analysis closely related to the present paper is carried out for a natural Markov chain on perfect matchings and phylogenetic trees [12, Chap. X], [16].

2.4.3 The measure $w_\lambda$

Fix $\lambda \vdash k$ with $\ell$ parts and $q > 1$. Define, for $J \subseteq \{1, \ldots, \ell\}$, $J \neq \emptyset$,

\begin{equation}
(2.17) \quad w_\lambda(J) = \frac{1}{q^k - 1} \prod_{i \in J} (q^{\lambda_i} - 1).
\end{equation}

The auxiliary variables algorithm for sampling from $\pi_{q,t}$ involves sampling from $w_\lambda(J)$, and setting $\lambda_J = \{\lambda_i : i \in J\}$ (see [1.3] and (2.12)). The measure $w_\lambda(J)$ has the following
interpretation, which leads to a useful sampling algorithm: Consider \( k \) places divided into blocks of length \( \lambda_i \):

\[
\underbrace{\cdots}_{\lambda_1} \cdots \underbrace{\cdots}_{\lambda_2} \cdots \underbrace{\cdots}_{\lambda_l}, \quad \lambda_1 + \cdots + \lambda_l = k.
\]

Flip a \( 1/q \) coin for each place. Let, for \( 1 \leq i \leq \ell \),

\[
(2.18) \quad X_i = \begin{cases} 
1 & \text{if the } i\text{th block is not all ones,} \\
0 & \text{otherwise.}
\end{cases}
\]

Thus \( P(X_i = 1) = 1 - 1/q^{\lambda_i} \). Let \( J = \{ i : X_i = 1 \} \). So \( P\{ J = \emptyset \} = 1 - 1/q^{k} \) and

\[
(2.19) \quad P\{ J | J \neq \emptyset \} = \frac{1}{1 - \frac{1}{q^{k}}} \prod_{i \in J} \left( 1 - \frac{1}{q^{\lambda_i}} \right) \prod_{j \in J^c} \frac{1}{q^{\lambda_j}} = w_{\lambda}(J).
\]

This makes it clear that summing \( w_{\lambda}(J) \) over all non-empty subsets of \( \{1, \ldots, \ell \} \) gives 1.

The simple rejection algorithm for sampling from \( w_{\lambda} \) is: Flip coins as above. If \( J \neq \emptyset \), output \( \lambda_J = \{ \lambda_i : i \in J \} \). If \( J = \emptyset \), sample again. The chance of success is \( 1 - 1/q^{k} \). Thus, unless \( q \) is very close to 1, this is an efficient algorithm.

As \( q \) tends to infinity, \( w_{\lambda} \) converges to point mass at \( J = \{1, \ldots, k\} \). As \( q \) tends to one, \( w_{\lambda} \) converges to the measure putting mass \( \lambda_i/k \) on \( \{i\} \).

### 2.4.4 The measure \( \pi_{\infty,t} \)

Generating from the kernel \( M_{\lambda,\nu}(\lambda, \nu) \) of (2.13) with \( r = |\lambda \setminus \nu| \), requires generating a partition in \( P_r \) from

\[
\pi_{\infty,t}(\mu) = \left( \frac{t}{t-1} \right) \frac{1}{z_{\mu}} \prod_{i} \left( 1 - \frac{1}{t^{i}} \right)^{a_{i}(\mu)}.
\]

This measure has the following interpretation: Pick \( \mu^{(1)} \vdash r \) with probability \( 1/z_{\mu^{(1)}} \). This may be done by picking a random permutation in \( S_r \) uniformly and reporting the cycle decomposition, or by the uniform stick-breaking of Section 2.4.1 above. For each part \( \mu^{(1)}_j \) of \( \mu^{(1)} \), flip a \( 1/t \) coin \( \mu^{(1)}_j \) times. If this comes up tails at least once, and this happens simultaneously for each \( i \), set \( \mu = \mu^{(1)} \). If some part of \( \mu^{(1)} \) produces all heads, start again and choose \( \mu^{(2)} \vdash r \) with probability \( 1/z_{\mu^{(2)}} \). . . . The chance of failure is \( 1/t \), independent of \( r \). Thus, unless \( t \) is close to 1, this gives a simple, useful algorithm.

The shape of a typical pick from \( \pi_{\infty,t} \) is described in the following section. When \( t \) tends to infinity, the measure converges to \( 1/z_{\mu} \). When \( t \) tends to one, the measure converges to point mass at the one part partition \( (r) \).

### 2.4.5 Multiplicative measures

For \( \eta = (\eta_1, \eta_2, \ldots, \eta_k) \), \( \eta_i > 0 \), define a probability on \( P_k \) (equivalently, \( S_k \)) by

\[
(2.20) \quad \pi_{\eta}(\lambda) = \frac{Z}{z_{\lambda}} \prod_{i=1}^{k} \eta_i^{a_i(\lambda)} \quad \text{with} \quad Z^{-1} = \sum_{\mu \vdash k} \frac{1}{z_{\mu}} \prod_{i} \eta_i^{a_{i}(\mu)}.
\]
Such multiplicative measures are classical objects of study. They are considered in [4] and [52], where many useful cases are given. The measures $\pi_{q,t}$ fall into this class with $\eta_i = \frac{(q^i - 1)}{(q^i - 1)}$. If $x = (x_1, x_2, \ldots)$ and $y = (y_1, y_2, \ldots)$ are two sequences of numbers and $V_\lambda(x)$ is a multiplicative basis of $\Lambda_\lambda^k$ such as $\{e_\lambda\}$, $\{p_\lambda\}$, $\{h_\lambda\}$, setting $\eta_i = V_i(x)V_i(y)$ gives $\pi_\eta(\lambda) = \frac{Z}{\xi_\lambda}V_\lambda(x)V_\lambda(y)$. This is in rough analogy to the Schur measures defined in Section 2.4.7. For the choices $e_\lambda$, $p_\lambda$, $h_\lambda$, with $x_i$, $y_j$ positive numbers, the associated measures are positive. The power sums, with all $x_i = a$, $y_i = b$, gives the Ewens measure with $\alpha = ab$. Setting $x_1 = y_1 = c$, $x_i = y_j = 0$ otherwise, gives the measure $1/z_\lambda$ after normalization. To our knowledge, general multiplicative measures have not been previously studied. Multiplicative systems are studied in [39, VI Sect. 1 Ex.].

It is natural to try out the simple rejection algorithms of Section 2.4.3 and Section 2.4.4 for the measures $\pi_\eta$. To begin, suppose that $0 < \eta_i < 1$ for all $i$. The measure $\pi_\eta$ has the following interpretation: Pick $\lambda' \in \mathcal{P}_k$ with probability $1/z_{\lambda'}$. As above, for each part of $\lambda'$ of size $i$, generate a random variable taking values 1 or 0 with probability $\eta_i, 1 - \eta_i$. If the values for all parts equal 1, set $\lambda = \lambda'$. If not, try again. For more general $\eta_i$, divide all $\eta_i$ by $\eta_{\text{max}}$, and generate from $\eta_i/\eta_{\text{max}}$. This yields the measure $\pi_\eta$ on partitions.

Alas, this algorithm performs poorly for $\eta_i$ and $k$ in ranges of interest. For example, with $\eta_i = \frac{t^i - 1}{q^i - 1}$ for $t = 2, q = 4$, when $k = 10, 11, 12, 13$, the chance of success (empirically) is $1/2000, 1/4000, 1/7000, 1/12000$. We never succeeded in generating a partition for any $k \geq 15$.

The asymptotic distribution of the parts of a partition chosen from $\pi_\eta$ when $k$ is large can be studied by classical tools of combinatorial enumeration. For fixed values of $q, t$, these problems fall squarely into the domain of the logarithmic combinatorial structures studied in [4]. A series of further results for more general $\eta$ have been developed by Jiang and Zhao [34]. The following brief survey of their results gives a good picture of typical partitions.

Of course, the theorems vary with the choice of $\eta_i$. One convenient condition, which includes the measure $\pi_{q,t}$ for fixed $q, t > 1$, is

$$\sum_{i=1}^{\infty} \left| \frac{\eta_i - 1}{i} \right| < \infty. \tag{2.21}$$

**Theorem 2.2.** Suppose $\eta_i, 1 \leq i < \infty$, satisfy (2.21). If $\lambda \in \mathcal{P}_k$ is chosen from $\pi_\eta$ of (2.20), then, for $j$ large:

For any $j$, the distribution of $(a_1(\lambda), \ldots, a_j(\lambda))$ converges to the distribution

$$\text{of an independent Poisson vector with parameters } \eta_i/i, \ 1 \leq i \leq j. \tag{2.22}$$

The number of parts of $\lambda$ has mean and variance asymptotic to $\log k$

$$\text{and, normalized by its mean and standard deviation,} \tag{2.23}$$

$$\text{a limiting standard normal distribution.}$$

The length of the $k$ largest parts of $\lambda$ converge to

$$\text{the Poisson–Dirichlet distribution } \mathcal{S} \tag{2.24}.$$
These and other results from [4, 34] show that the parts of a random partition are quite
similar to the cycles of a uniformly chosen random permutation, with the small cycles having
slightly adjusted parameters. These results are used to give a lower bound on the mixing
time of the auxiliary variables Markov chain in Proposition 3.2 below.

2.4.6 Simulation results

Table 1

| Partition λ ⊲ 10 | Probability π_{q=2,t=4}(λ) | Partition λ ⊲ 10 | Probability π_{q=2,t=4}(λ) |
|------------------|-------------------------------|------------------|-------------------------------|
| 10               | 0.164003                      | 4,4,2            | 0.018177                      |
| 9,1              | 0.121365                      | 4,4,1,1          | 0.010098                      |
| 8,2              | 0.081762                      | 4,3,3            | 0.016955                      |
| 8,1,1            | 0.045423                      | 4,3,2,1          | 0.030520                      |
| 7,3              | 0.068948                      | 4,3,1,1,1        | 0.005652                      |
| 7,2,1            | 0.062054                      | 4,2,2,2          | 0.004120                      |
| 7,1,1,1          | 0.011491                      | 4,2,2,1,1        | 0.006867                      |
| 6,4              | 0.063387                      | 4,2,1,1,1,1     | 0.001272                      |
| 6,3,1            | 0.053214                      | 4,1,1,1,1,1,1,1 | 0.000047                      |
| 6,2,2            | 0.021552                      | 3,3,3,1          | 0.004745                      |
| 6,2,1,1          | 0.023946                      | 3,3,2,2          | 0.005765                      |
| 6,1,1,1,1        | 0.002217                      | 3,3,2,1,1        | 0.006405                      |
| 5,5              | 0.030873                      | 3,3,1,1,1,1     | 0.000593                      |
| 5,4,1            | 0.049942                      | 3,2,2,2,1        | 0.003459                      |
| 5,3,2            | 0.037734                      | 3,2,2,1,1,1     | 0.001922                      |
| 5,3,1,1          | 0.020963                      | 3,2,1,1,1,1,1,1 | 0.000214                      |
| 5,2,2,1          | 0.016980                      | 3,1,1,1,1,1,1,1,1 | 0.000006                     |
| 5,2,1,1,1        | 0.006289                      | 2,2,2,2,2        | 0.000140                      |
| 5,1,1,1,1,1,1,1  | 0.000349                      | 2,2,2,2,1,1      | 0.000389                      |
|                  |                               | 2,2,2,1,1,1,1,1 | 0.000144                      |
|                  |                               | 2,1,1,1,1,1,1,1,1,1 | 0.000016                   |
|                  |                               | 1,1,1,1,1,1,1,1,1,1,1 | 0.000000                  |

The distribution π_{q,t}(λ) can be far from uniform. An example, with k = 10, q = 4, t = 2,
is shown in Table 1. π_{4,2}(10) \approx 0.16, \; π_{4,2}(1^6) \approx 0. The auxiliary variables algorithm for
the measure π_{q,t} has been programmed by Jiang and Zhao [34]. It seems to work well over
a wide range of q and t. A tiny example, 100 steps when k = 10, q = 4, t = 2, is shown
in Table 2. A comparison of the simulations with the exact distribution (easily computed
from (1.2) when k = 10) shows perfect agreement. In our experiments, the choice of q and
t does not seriously affect the running time, and simulations seem possible for k up to 10^6.

The distribution of the largest part, for q = 4, t = 2 and k = 10, k = 100, and k = 1000,
based on 10^6 steps of the algorithm, is shown in Figure 1. Comparison with the limiting
results of Theorem 2.2 above seems good. The blip at the right side of the figures comes
from \(k\); the rest of the distribution follows the limit (2.24) approximately.

We have compared the auxiliary variables algorithm with the rejection algorithm of
Section 2.4.5 and the Metropolis algorithm. As reported in Section 2.4.5, rejection fails
Table 2

Sample 100-step walk for Auxiliary Variables

|   | 26 | 51 | 76 | 27 | 52 | 77 |
|---|----|----|----|----|----|----|
| 1 | 10 | 6,4| 7,2,1 | 6,2,1,1| 7,2,1 |
| 2 | 26 | 30,8,2 | 7,2,1 | 6,2,1,1| 7,2,1 |
| 3 | 6,4,3 | 29,8,1,1 | 53,7,3 | 54,8,2 | 79,9,1 |
| 4 | 5,5 | 30,8,2 | 55,6,2,2 | 80,5,4,1 | 10,10 |
| 5 | 9,1 | 31,7,3 | 56,6,4 | 81,10 |
| 6 | 6,2,2 | 32,9,1 | 57,4,2,2 | 82,6,3,1 |
| 7 | 9,1 | 33,8,2 | 58,5,3,2 | 83,6,3,1 |
| 8 | 4,4,2 | 34,8,2 | 59,6,4 | 84,5,4,1 |
| 9 | 4,4,1,1 | 35,8,2 | 60,10 | 85,8,1,1 |
| 10 | 4,3,1,1,1 | 36,10 | 61,9,1 | 86,5,3,2 |
| 11 | 7,2,1 | 37,7,1,1,1 | 62,6,3,1 | 87,5,3,1,1 |
| 12 | 5,3,1,1 | 38,10 | 63,4,3,3 | 88,5,2,2,1 |
| 13 | 6,4 | 39,5,3,2 | 64,10 | 89,10 |
| 14 | 10 | 40,4,3,3 | 65,5,5 | 90,5,3,2 |
| 15 | 5,3,2 | 41,8,2 | 66,8,2 | 91,8,2 |
| 16 | 4,3,3 | 42,7,3 | 67,5,4,1 | 92,5,3,2 |
| 17 | 9,1 | 43,6,3,1 | 68,3,3,2,1,1 | 93,6,3,1 |
| 18 | 7,3 | 44,10 | 69,6,4 | 94,5,4,1 |
| 19 | 7,3 | 45,5,5 | 70,6,1,1,1,1 | 95,4,3,2,1 |
| 20 | 5,3,2 | 46,6,3,1 | 71,4,3,2,1 | 96,7,3 |
| 21 | 5,3,1,1 | 47,8,1,1 | 72,5,4,1 | 97,7,2,1 |
| 22 | 5,3,1,1 | 48,6,1,1,1,1 | 73,10 | 98,7,2,1 |
| 23 | 6,3,1 | 49,10 | 74,5,2,1,1,1 | 99,5,2,2,1 |
| 24 | 5,3,2 | 50,9,1 | 75,5,2,2,1 | 100,4,2,2,1,1 |
| 25 | 5,3,2 | 50,9,1 | 75,5,2,2,1 | 100,4,2,2,1,1 |

completely for \( n \geq 15 \). The Metropolis algorithm we used works by simulating permutations from \( \pi_{q,t} \) lifted to \( S_k \). From the current permutation \( \sigma \), propose \( \sigma' \) by making a random transposition (all \( \binom{n}{2} \) choices equally likely). If \( \pi_{q,t}(\sigma') \geq \pi_{q,t}(\sigma) \), move to \( \sigma' \). If \( \pi_{q,t}(\sigma')/\pi_{q,t}(\sigma) < 1 \), flip a coin with probability \( \pi_{q,t}(\sigma')/\pi_{q,t}(\sigma) \) and move to \( \sigma' \) if the coin comes up heads; else stay at \( \sigma \). For small values of \( k \), Metropolis is competitive with auxiliary variables. [Jiang and Zhao] have computed the mixing time for \( k = 10, 20, 30, 40, 50 \) by a clever sampling algorithm. For \( q = 4, t = 2 \), the following table shows the number of steps required to have total variation distance less than \( 1/10 \) starting from the partition \( (k) \). Also shown is \( p(k) \), the number of partitions of \( k \), to give a feeling for the size of the state space.

|   | 10 | 20 | 30 | 40 | 50 |
|---|----|----|----|----|----|
| Aux | 1 | 1 | 1 | 1 | 1 |
| Met | 8 | 17 | 26 | 37 | 53 |
| \( p(k) \) | 42 | 627 | 5604 | 37338 | 204,226 |

The theorems of [Section 3] show that auxiliary variables requires a bounded number of
Figure 1: Left: Probability of largest part $i$ for partitions of $k = 10$ under $\pi_{q,t}$ with $q = 4$, $t = 2$. Right: Probability of largest part $i$ for partitions of $k = 100$ under $\pi_{q,t}$ with $q = 4$, $t = 2$.

steps for arbitrary $k$. In the computations above, the distance to stationarity after one step of the auxiliary variables is 0.093 (within a 1% error in the last decimal) for $k = 10, \ldots, 50$. For larger $k$ (e.g., $k = 100$), the Metropolis algorithm seemed to need a very large number of steps to move at all. This is consistent with other instances of auxiliary variables, such as the Swendsen–Wang algorithm for the Ising and Potts model (away from the critical temperature; see [9]).

2.4.7 Other measures on partitions

This portmanteau section gives pointers to some of the many other measures that have been studied on $\mathcal{P}_k, S_k$. Often these studies are fascinating, deep, and extensive. All measures studied here seem distinct from $\pi_{q,t}$.

A remarkable two-parameter family of measures on partitions has been introduced by Jim Pitman. For $\theta \geq 0$, $0 \leq \alpha \leq 1$, and $\lambda \vdash k$ with $\ell$ parts, set

$$P_{\theta,\alpha}(\lambda) = \frac{k!}{z_\lambda} \frac{\theta^{(\alpha,\ell-1)}}{(\theta + 1 - \alpha)^{(1,\ell-1)}} \prod_{j=1}^{k} \left(1 - \alpha\right)^{(1,j-1)} a_j(\lambda),$$

where

$$\theta^{(a,m)} = \begin{cases} 1 & \text{if } m = 0, \\ \theta(\theta + a) \cdots (\theta + (m - 1)a) & \text{for } m = 1, 2, 3, \ldots. \end{cases}$$

These measures specialize to $1/z_\lambda$ ($\theta = 1, \alpha = 0$), and the Ewens measure ($\theta$ fixed, $\alpha = 0$), see [47, sec. 3.2]. They arise in a host of probability problems connected to stable stochastic problems of index $\alpha$. They are also being used in applied probability connected to genetics and Bayesian statistics. They satisfy elegant consistency properties as $k$ varies. For example, deleting a random part gives the corresponding measure on $\mathcal{P}_{k-1}$. For these and many other developments, see the book-length treatments of [7, 47, sec. 3.2].

One widely studied measure on partitions is the Plancherel measure,

$$p(\lambda) = f(\lambda)^2/k!,$$

with $f(\lambda)$ the dimension of the irreducible representation of $S_k$ associated to shape $\lambda$. This measure was perhaps first studied in connection with Ulam’s problem on the distribution of the length of the longest increasing sequence in a random permutation; see [38, 51]. For extensive developments and references, see [11, 35].
The Schur measures of \([10, 43, 44, 45]\) are generalizations of the Plancherel measure. Here the chance of \(\lambda\) is taken as proportional to \(s_\lambda(x)s_\lambda(y)\), with \(s_\lambda\) the Schur function and \(x, y\) collections of real-valued entries. Specializing \(x\) and \(y\) in various ways yields a variety of previously studied measures. One key property, if the partition is “tilted 135°” to make a v-shape and the local maxima projected onto the x-axis, the resulting points form a determinantal point process with a tractable kernel. This gives a fascinating collection of shape theorems for the original partition.

One final distribution, the uniform distribution on \(P_k\), has also been extensively studied. For example, a uniformly chosen partition has order \(\frac{\pi}{\sqrt{6k}}\) parts of size 1, the largest part is of size \(\sqrt{6k}\log(\sqrt{6k}/\pi)\), the number of parts is of size \(\sqrt{6k}\log(k/(2\pi))\). A survey with much more refined results is in [21].

The above only scratches the surface. The reader is encouraged to look at [43, 44, 45] to see the breadth and depth of the subject as applied to Gromov–Witten theory, algebraic geometry, and physics. The measures there seem closely connected to the “Plancherel dual” of our \(\pi_{q,t}\). This dual puts mass proportional to \(c(\lambda)c'(\lambda)\) on \(\lambda\), with \(c, c'\) the arm-leg length products defined in Section 3.1 below.

### 3 Main results

This section shows that the auxiliary variables Markov chain \(M\) with stationary distribution \(\pi_{q,t}(\lambda)\), \(\lambda \in P_k\), is explicitly diagonalizable with eigenfunctions \(f_\lambda(\mu)\) essentially the coefficients of the Macdonald polynomials expanded in the power sum basis. The result is stated in Section 3.1. The proof, given in Section 3.3, is somewhat computational. An explanatory overview is in Section 3.2. In Section 5, these eigenvalue/eigenvector results are used to bound rates of convergence of \(M\).

#### 3.1 Statement of main results

Fix \(q, t > 1\) and \(k \geq 2\). Let \(M(\lambda, \mu) = \sum_{\lambda_j} w_\lambda(\lambda_j)M_{\lambda_j}(\lambda, \mu)\) be the auxiliary variables Markov chain on \(P_k\). Here, \(w_\lambda(\cdot)\) and \(M_{\lambda_j}(\lambda, \mu)\) are defined in (2.12), (2.13), and studied in Section 2.4.3 and Section 2.4.4. For a partition \(\lambda\), let

\[
c_\lambda(q, t) = \prod_{s \in \lambda} \left(1 - q^{a(s)}t^{l(s)+1}\right) \quad \text{and} \quad c'_\lambda(q, t) = \prod_{s \in \lambda} \left(1 - q^{a(s)+1}t^{l(s)}\right),
\]

where the product is over the boxes in the shape \(\lambda\), and \(a(s)\) is the arm length and \(l(s)\) the leg length of box \(s\) [39, VI (8.1)].

**Theorem 3.1.**

1. The Markov chain \(M(\lambda, \nu)\) is reversible and ergodic with stationary distribution \(\pi_{q,t}(\lambda)\) defined in (1.2). This distribution is properly normalized.

2. The eigenvalues of \(M\) are \(\{\beta_\lambda\}_{\lambda \in P_k}\) given by

\[
\beta_\lambda = \frac{t}{q^k - 1} \sum_{i=1}^{\ell(\lambda)} (q^{\lambda_i} - 1) t^{-i}.
\]

Thus, \(\beta_k = 1, \beta_{k-1,1} = t \frac{q^{k-1} - 1}{q^k - 1} + \frac{q^{-1}}{q^k - 1}, \ldots\).
(3) The corresponding right eigenfunctions are

\[ f_\lambda(\rho) = X_\rho^\lambda(q,t) \prod_{i=1}^{\ell(\rho)} (1 - q^{\rho_i}) \]

with \( X_\rho^\lambda(q,t) \) the coefficients occurring in the following expansion of the Macdonald polynomials in terms of the power sums \([39, VI (8.19)]\):

\[ P_\lambda(x; q, t) = \frac{1}{c_\lambda(q,t)} \sum_{\rho} z_{\rho}^{-1} \prod_{i=1}^{\ell(\rho)} (1 - t^{\rho_i}) X_\rho^\lambda(q,t) p_\rho(x), \]

(3.2)

(4) The \( f_\lambda(\rho) \) are orthogonal in \( L^2(\pi_{q,t}) \) with

\[ \langle f_\lambda, f_\mu \rangle = \delta_{\lambda\mu} c_\lambda(q,t) c'_\lambda(q,t) (q,q)_k (t,q)_k. \]

Example 2. When \( k = 2 \), from \([2.15]\), the matrix \( M \) with rows and columns indexed by \( 2, 1^2 \), is

\[ M = \frac{1}{2t} \begin{pmatrix} t + 1 & t - 1 \\ (q-1)(t+1) & 4t + (q-1)(t-1) q + 1 & q + 1 \end{pmatrix}. \]

Macdonald \([39, p. 359]\) gives tables of \( K(\lambda, \mu) \) for \( 2 \leq k \leq 6 \). For \( k = 2 \), \( K(\lambda, \mu) \) is \( \left( \begin{array}{cc} 1 & 1 \\ 1/q & 1 \end{array} \right) \). The character matrix is \( \begin{pmatrix} 1 & 1 \\ -1 & 1 \end{pmatrix} \), and the product is \( \begin{pmatrix} 1 - q & 1 + q \\ t - 1 & t + 1 \end{pmatrix} \). From Theorem 3.1(3), the rows of this matrix, multiplied coordinate-wise by \( (1 - q^2), (1 - q^2) \), give the right eigenvectors:

\[ f_2(2) = f_2(1^2) = (1 - q)^2(1 + q), \]
\[ f_{12}(2) = (t - 1)(1 - q^2), \]
\[ f_{12}(1^2) = (t + 1)(1 - q^2). \]

Then \( f_2(\rho) \) is a constant function, and \( f_{12}(\rho) \) satisfies \( \sum_\rho M(\lambda, \rho) f_{12}(\rho) = \beta_{12} f_{12}(\lambda) \), with \( \beta_{12} = \frac{1+t-1}{1+q} \).

Further useful formulae, used in Section 5, are \([39, VI Sect. 8 Ex. 8]\):

\[ X_\rho^{(k)}(q,t) = (q,q)_k \prod_{i=1}^{\ell(\rho)} (1 - t^{\rho_i}) \]
\[ X_\rho^{(1^k)}(q,t) = (-1)^{|\rho| - \ell(\rho)} (t,t)_k \prod_{i=1}^{\ell(\rho)} (1 - t^{\rho_i})^{-1} \]
\[ X_{(k)}^\lambda(q,t) = \prod_{\substack{(i,j) \in \lambda \\ (i,j) \neq (1,1)}} (t^{i-1} - q^{j-1}) \]
\[ X_{(1^k)}^\lambda(q,t) = \frac{\varphi_\lambda(q,t)}{(1-t)_k} \sum_T \varphi_T(q,t) \]

with the sum over standard tableaux \( T \) of shape \( \lambda \), and \( \varphi_T(q,t) \) from \([39, VI p. 341 (1)]\) and \([39, VI (7.11)]\).
3.2 Overview of the argument

Macdonald [39, VI] defines the Macdonald polynomials as the eigenfunctions of the operator $D_{q,t}^1 : \Lambda_n \rightarrow \Lambda_n$ from (2.2). As described in Section 2.1 above, $D_{q,t}^1$ is self-adjoint for the Macdonald inner product and sends $\Lambda_k^n$ into itself [39, VI (4.15)]. For $\lambda \vdash k$, $k \leq n$,

$$D_{q,t}^1 P_{\lambda}(x; q, t) = \bar{\beta}_{\lambda} P_{\lambda}(x; q, t), \quad \text{with} \quad \bar{\beta}_{\lambda} = \sum_{i=1}^{\ell(\lambda)} q^{\lambda_i} t^{k-i}. \quad (3.4)$$

The Markov chain $M$ is related to an affine rescaling of the operator $D_{q,t}^1$, which [39, VI (4.1)] calls $E_n$. We work directly with $D_{q,t}^1$ to give direct access to Macdonald’s formulae. The affine rescaling is carried out at the end of Section 3.3 below.

The integral form of Macdonald polynomials [39, VI Sect. 8] is

$$J_{\lambda}(x; q, t) = c_{\lambda}(q, t) P_{\lambda}(x; q, t) \quad \text{for} \quad c_{\lambda} \text{defined in (3.1)}.$$  

This is our equation (3.2) above. In Proposition 3.2 below, we compute the action of $D_{q,t}^1$ on the power sum basis: for $\lambda$ with $\ell$ parts,

$$D_{q,t}^1 P_{\lambda} \overset{\text{def}}{=} \sum_{\mu} \bar{M}(\lambda, \mu) p_{\mu}$$

$$= [n] p_{\lambda} + \frac{t^n}{t - 1} \sum_{J \subseteq \{1, \ldots, \ell\}} \prod_{k \in J} \left( q^{\lambda_k} - 1 \right) \prod_{\mu \vdash |J|} \prod_{m} \left( 1 - t^{-\mu_m} \right) \frac{p_{\mu}}{z_{\mu}}. \quad (3.6)$$

On the right, the coefficient of $p_{\lambda,J} p_{\mu}$ is essentially the Markov chain $M$; we use $\bar{M}$ for this unnormalized version. Indeed, we first computed (3.6) and then recognized the operator as a special case of the auxiliary variables operator.

Equations (3.4)–(3.6) show that simply scaled versions of $X_{\rho}^\lambda$ are eigenvectors of the matrix $\bar{M}$ as follows. From (3.4), (3.5),

$$\bar{\beta}_{\lambda} P_{\lambda}(x; q, t) = D_{q,t}^1 P_{\lambda}(x; q, t) = \frac{1}{c_{\lambda}} D_{q,t}^1 (J_{\lambda})$$

$$= \frac{1}{c_{\lambda}} D_{q,t}^1 \left( \sum_{\rho} X_{\rho}^\lambda \frac{1}{z_{\rho}} p_{\rho}(x; t) \right) = \frac{1}{c_{\lambda}} \sum_{\rho} X_{\rho}^\lambda \prod_{\mu} \left( 1 - t^{\mu_m} \right) \frac{p_{\mu}}{z_{\rho}}$$

$$= \frac{1}{c_{\lambda}} \sum_{\rho} p_{\rho} \prod_{\mu} \left( 1 - t^{\mu_m} \right) X_{\rho}^\lambda \bar{M}(\rho, \mu) p_{\mu}(x)$$

$$= \frac{1}{c_{\lambda}} \sum_{\mu} p_{\mu} \prod_{\rho} \left( 1 - t^{\mu_m} \right) X_{\rho}^\lambda \bar{M}(\rho, \mu). \quad (3.7)$$
Also, from (3.4) and (3.5),

\( (3.8) \quad \bar{\beta}_\lambda P_\lambda(x; q, t) = \frac{\bar{\beta}_\lambda}{c_\lambda} J_\lambda(x; q, t) = \bar{\beta}_\lambda \sum_\mu X_\mu^\lambda \frac{1}{z_\mu} \prod_i (1 - t^{\mu_i}) p_\mu(x). \)

Equating coefficients of \( p_\mu(x) \) on both sides of (3.7), (3.8), gives

\( (3.9) \quad \frac{\bar{\beta}_\lambda}{c_\lambda} X_\mu^\lambda \frac{1}{z_\mu} \prod_i (1 - t^{\mu_i}) = \frac{1}{c_\lambda} \sum_\rho X_\rho^\lambda \prod_i (1 - t^{\rho_i}) M(\rho, \mu). \)

This shows that \( h_\lambda(\mu) = \frac{X_\mu^\lambda \prod_i (1 - t^{\mu_i})}{z_\mu} \) is a left eigenfunction for \( \bar{M} \) with eigenvalue \( \bar{\beta}_\lambda \). It follows from reversibility \( (\pi_{q,t}(\rho) \bar{M}(\rho, \mu) = \pi_{q,t}(\mu) \bar{M}(\mu, \rho)) \) that \( \frac{h_\lambda(\mu)}{\pi_{q,t}(\mu)} \) is a right eigenfunction for \( \bar{M} \).

3.3 Proof of Theorem 3.1

As explained in Section 2.1 above, the Macdonald polynomials diagonalize a family of operators \( D_{q,t}^r \), \( 0 \leq r \leq n \). The argument above applies to all of these. In essence, the method consists of interpreting equations such as (3.5) as linear combinations of partitions, equating \( p_\lambda \) with \( \lambda \).

Proposition 3.2.

(a) If \( f \) is homogeneous, then

\( D_{q,t}^0 f = f, \quad D_{q,t}^n f = q^{\deg(f)} f, \quad \text{and} \quad D_{q,t}^{n-1} f = t^{\deg(f)+n(n-1)/2} q^{\deg(f)} D_{q,t}^{1,1} f. \)

(b) If \( \lambda = (\lambda_1, \ldots, \lambda_\ell) \) is a partition then

\( (3.10) \quad D_{q,t}^1 p_\lambda = [n] p_\lambda + \sum_{J \subseteq \{1, \ldots, \ell\}} p_{\lambda,J} \left( \prod_{k \in J} (q^{\lambda_k} - 1) \right) \frac{1}{t^{|J| - 1}} \sum_{\mu = \lambda, |J|} \left( \prod_{m=1}^{\ell(\mu)} (1 - t^{-\mu_m}) \right) \frac{1}{z_\mu} p_\mu. \)

Proof of Proposition 3.2.

(a) If \( f \) is homogeneous then

\( (3.11) \quad D_{q,t}^n f = \sum_{I \subseteq \{1, \ldots, n\}} A_I(x; t) \prod_{i \in I} T_{q,x_i} f = T_{q,x_1} T_{q,x_2} \cdots T_{q,x_n} f = q^{\deg(f)} f. \)
By definition,

\[(3.12) \quad A_f(x; t) = \frac{1}{a_\delta} \left( \prod_{i \in I} T_{t, x_i} \right) a_\delta = t^{(r-1)/2} \prod_{i \in I} \left( t x_i - x_j \right). \]

Letting \( x^\gamma = x_1^{\gamma_1} \cdots x_n^{\gamma_n} \) for \( \gamma = (\gamma_1, \ldots, \gamma_n), \)

\[ T_{q, x_1} T_{q, x_2} \cdots T_{q, x_n} x^\gamma = q^{\gamma_1+\cdots+\gamma_n-\gamma_j} x_1^{\gamma_1} \cdots x_n^{\gamma_n} = q^{\deg(x^\gamma)} q^{-\gamma_j x_j} = q^{\deg(x^\gamma)} T_{q^{-1}, x_j} x^\gamma, \]

and it follows that

\[(3.13) \quad T_{q, x_1} T_{q, x_2} \cdots T_{q, x_n} f = q^{\deg(f)} T_{q^{-1}, x_j} f, \]

if \( f \) is homogeneous. Thus,

\[ D_{q, t}^{n-1} f = \sum_{I \subseteq \{1, \ldots, n\} \atop |I| = n-1} A_f(x; t) \left( \prod_{i \in I} T_{q, x_i} \right) f \]

\[ = \sum_{j=1}^{n} A(j) \gamma(x; t) T_{q, x_1} \cdots \hat{T}_{q, x_j} \cdots T_{q, x_n} f \]

\[ = \sum_{j=1}^{n} \frac{1}{a_\delta} T_{t, x_1} \cdots \hat{T}_{t, x_j} \cdots T_{t, x_n} a_\delta T_{q, x_1} \cdots \hat{T}_{q, x_j} \cdots T_{q, x_n} f \]

\[ = \sum_{j=1}^{n} \frac{1}{a_\delta} t^{\deg(f)+\deg(a_\delta)} T_{t^{-1}, x_j} a_\delta q^{\deg(f)} T_{q^{-1}, x_j} f \]

\[ = t^{\deg(f)+n(n-1)/2} q^{\deg(f)} \sum_{j=1}^{n} A_j \left( x; t^{-1} \right) T_{q^{-1}, x_j} f \]

\[ = t^{\deg(f)+n(n-1)/2} q^{\deg(f)} D_{q^{-1}, t^{-1}}^{1} f. \]

Hence,

\[(3.14) \quad D_{q, t}^{n-1} f = t^{\deg(f)+n(n-1)/2} q^{\deg(f)} D_{q^{-1}, t^{-1}}^{1} f. \]

(b) By [39 VI (3.7),(3.8)]

\[ D_{1, t}(z) m_\lambda = \sum_{\beta \in S_n \lambda} \left( \prod_{i=1}^{n} (1 + z t^{n-i}) \right) s_\beta = \left( \prod_{i=1}^{n} (1 + z t^{n-i}) \right) \sum_{\beta \in S_n \lambda} s_\beta \]

\[ = \left( \prod_{i=1}^{n} (1 + z t^{n-i}) \right) m_\lambda = \sum_{r=0}^{n} t^{r(r-1)/2} \left[ \begin{array}{c} n \\ r \end{array} \right] z^r m_\lambda, \]

where \( m_\lambda \) denotes the monomial symmetric function. Thus, since \( D_{q, t}(z) = \sum_{r=0}^{n} D_{q, t}^{r} z^r \)

and

\[ D_{1, t}^{r} = \sum_{I \subseteq \{1, \ldots, n\} \atop |I| = r} A_f(x; t) \prod_{i \in I} T_{1, x_i} = \sum_{I \subseteq \{1, \ldots, n\} \atop |I| = r} A_f(x; t), \]
it follows that

\begin{equation}
\sum_{j=1}^{n} A_j(x; t) f = D_{1,t}^1 f = [n] f
\end{equation}

for a symmetric function \( f \). By [39] VI Sect. 3 Ex. 2],

\begin{equation}
(t - 1) \sum_{i=1}^{n} A_i(x; t) x_i^r = t^n g_r(x; 0, t^{-1}) - \delta_0 r,
\end{equation}

where, from [39] VI (2.9),

\[
g_r(x; q, t) = \sum_{\lambda \vdash n} z_\lambda(q, t)^{-1} p_\lambda(x),
\]

with \( z_\lambda(q, t) \) as in (1.1).

Let \( \lambda = (\lambda_1, \ldots, \lambda_\ell) \) be a partition, and

for \( J \subseteq \{1, \ldots, \ell\} \), let \( \lambda_J = (\lambda_{j_1}, \ldots, \lambda_{j_k}) \) if \( J = \{j_1, \ldots, j_k\} \).

Then, using

\begin{equation}
T_{q,x_i p_r} = q^r x_i^r - x_i^r + p_r = (q^r - 1) x_i^r + p_r,
\end{equation}

(3.16), and (3.15),

\[
D_{q,t}^1 p_\lambda = \sum_{j=1}^{n} A_j(x; t) T_{q,x_j p_{\lambda_1} \cdots p_{\lambda_\ell}}
\]

\[
= \sum_{j=1}^{n} A_j(x; t) \left( (q^{\lambda_1} - 1) x_j^{\lambda_1} + p_{\lambda_1} \right) \cdots \left( (q^{\lambda_\ell} - 1) x_j^{\lambda_\ell} + p_{\lambda_\ell} \right)
\]

\[
= \sum_{j=1}^{n} A_j(x; t) \sum_{J \subseteq \{1, \ldots, \ell\}} \left( \prod_{k \in J} (q^{\lambda_k} - 1) \right) x_j^{\left| \lambda_J \right|} \prod_{s \notin J} p_{\lambda_s}
\]

\[
= \sum_{J \subseteq \{1, \ldots, \ell\}} \prod_{s \notin J} p_{\lambda_s} \left( \prod_{k \in J} (q^{\lambda_k} - 1) \right) \sum_{j=1}^{n} A_j(x; t) x_j^{\left| \lambda_J \right|}
\]

\[
= \sum_{j=1}^{n} A_j(x; t) p_\lambda + \sum_{J \subseteq \{1, \ldots, \ell\} \setminus \emptyset} p_{\lambda_J} \left( \prod_{k \in J} (q^{\lambda_k} - 1) \right) \frac{t^n}{t - 1} g_{|\lambda_J|}(x; 0, t^{-1})
\]

\[
= [n] p_\lambda + \sum_{J \subseteq \{1, \ldots, \ell\} \setminus \emptyset} p_{\lambda_J} \left( \prod_{k \in J} (q^{\lambda_k} - 1) \right) \frac{t^n}{t - 1} \sum_{\mu \vdash |\lambda_J|} \frac{1}{z_\mu (0; t^{-1})} p_\mu
\]

\[
= [n] p_\lambda + \sum_{J \subseteq \{1, \ldots, \ell\} \setminus \emptyset} p_{\lambda_J} \left( \prod_{k \in J} (q^{\lambda_k} - 1) \right) \frac{t^n}{t - 1} \sum_{\mu \vdash |\lambda_J|} \binom{\ell(\mu)}{m=1} (1 - t^{-m}) \frac{1}{z_\mu}. \quad \square
\]
Let us show that the measure $\pi_{q,t}(\lambda)$ is properly normalized and compute the normalization of the eigenvectors.

**Lemma 3.3.** Let $\pi_{q,t}(\lambda)$ be as in (1.2) and let $f_\lambda(\rho) = X_\rho^{\ell(\rho)} \prod_{i=1}^{\ell(\rho)} (1 - q^{\rho_i})$ be as in Theorem 3.1(3) Then

$$\sum_{\lambda \vdash k} \pi_{q,t}(\lambda) = 1 \quad \text{and} \quad \sum_{\rho \vdash k} f_\lambda^2(\rho) \pi_{q,t}(\lambda) = (q, q)_k (t, q)_k c_\lambda c'_\lambda.$$

**Proof of Lemma 3.3.** From [39] VI (2.9),(4.9), the Macdonald polynomial $P_k(x; q, t)$ can be written

$$P_k = \frac{(q, q)_k}{(t, q)_k} g_k = \frac{(q, q)_k}{(t, q)_k} \sum_{\lambda \vdash k} z_\lambda(q, t)^{-1} p_\lambda.$$

From [39] VI (4.11),(6.19)],

$$\langle P_\lambda, P_\lambda \rangle = c_\lambda / c_\lambda,$$

and it follows that

$$\sum_{\lambda \vdash k} \pi_{q,t}(\lambda) = \sum_{\lambda \vdash k} \frac{(q, q)_k}{(t, q)_k} z_\lambda(q, t)^{-1} = \frac{(t, q)_k}{(q, q)_k} \langle P_k, P_k \rangle = \frac{(t, q)_k c'_\lambda}{(q, q)_k c(\lambda)} = 1.$$

To get the normalization of $f_\lambda(\rho) = X_\rho^{\ell(\rho)} \prod_{i=1}^{\ell(\rho)} (1 - q^{\rho_i})$ in Theorem 3.1(4), use (3.5) and $c_\lambda c'_\lambda = (c_\lambda)^2 \langle P_\lambda, P_\lambda \rangle = \langle J_\lambda, J_\lambda \rangle$

$$= \sum_{\rho \vdash k} z_\rho^{-1} \left( X_\rho^{\lambda}(q, t) \prod_{i=1}^{\ell(\rho)} (1 - t^{\rho_i}) \right)^2 \langle p_\rho, p_\rho \rangle = \sum_{\rho \vdash k} z_\rho^{-1} \left( X_\rho^{\lambda}(q, t) \prod_{i=1}^{\ell(\rho)} (1 - t^{\rho_i}) \right)^2 \prod_{i=1}^{\ell(\rho)} \frac{1 - q^{\rho_i}}{1 - t^{\rho_i}}$$

$$= \sum_{\rho \vdash k} f_\lambda^2(\rho) z_\rho^{-1}(q, t) = \frac{(t, q)_k}{(q, q)_k} \sum_{\rho \vdash k} f_\lambda^2(\rho) \pi_{q,t}(\lambda). \quad \square$$

We next show that an affine renormalization of the discrete version $\tilde{M}$ (3.5) of the Macdonald operator equals the auxiliary variables Markov chain of Section 2.3. Along with Macdonald [39] VI (4.1)], define

$$E_k = t^{-k} D_{q,t} - \sum_{i=1}^{k} t^{-i}, \quad \text{and let} \quad \tilde{E}_k = \frac{t}{q^k - 1} E_k,$$

operating on $\Lambda^k_n$. From (3.3), the eigenvalues of $E_k$ are $\beta_\lambda = \sum_{i=1}^{\ell(\lambda)} (q^{\lambda_i} - 1) t^{-i}$. Noting that $\beta_{(k)} = \frac{q^k - 1}{t}$, the operator $\tilde{E}_k$ is a normalization of $E_k$ with top eigenvalue 1. From Proposition 3.2(b), for $\lambda$ a partition with $\ell$ parts,

$$\tilde{E}_k p_\lambda = \frac{1}{(1 - t^{-1})(q^k - 1)} \sum_{J \subseteq \{1, \ldots, \ell\}, k \in J} \prod_{J \neq \emptyset} \left( q^{\lambda_k} - 1 \right) p_{\lambda_J} \sum_{\mu \vdash |\lambda_j|} \prod_{i=1}^{\ell(\mu)} \left( 1 - t^{-k} \right) \frac{p_\mu}{z_\mu}.$$
Using $p_\lambda$ as a surrogate for $\lambda$ as in Section 3.2, the coefficient of $\nu = \lambda, \mu$ is exactly $M(\lambda, \nu)$ of Section 2.3.

This completes the proof of Theorem 3.1.

\textbf{Example 3.} When $k = 2$, from the definitions
\begin{align*}
\tilde{E}_2 p_2 &= \left( \frac{1 - t^{-1}}{2} \right) p_{12} + \left( \frac{1 + t^{-1}}{2} \right) p_2, \\
\tilde{E}_2 p_{12} &= \frac{1}{2(q + 1)} ((q + 3 - qt^{-1} + t^{-1}) p_{12} + (q - 1)(1 + t^{-1}) p_2).
\end{align*}

Thus, on partitions of 2, the matrix of $\tilde{E}_2$ is
\begin{equation*}
\begin{pmatrix}
\frac{1 + t^{-1}}{2} & \frac{1 - t^{-1}}{2} \\
\frac{(1 + t^{-1})(q - 1)}{2(q + 1)} & \frac{3 + q + t^{-1} - t^{-1}q}{2(q + 1)}
\end{pmatrix}.
\end{equation*}

This is the matrix of (2.15) derived there from the probabilistic description.

\section{Jack polynomials and Hanlon’s walk}

The Jack polynomials are a one-parameter family of bases for the symmetric polynomials, orthogonal for the weight $\langle p_\lambda, p_\mu \rangle_\alpha = \alpha^\ell(\lambda) z_\lambda \delta_{\lambda\mu}$. They are an important precursor to the full two-parameter Macdonald polynomial theory, containing several classical bases: the limits $\alpha = 0$, $\alpha = \infty$, suitably interpreted, give the $\{e_\lambda\}, \{m_\lambda\}$ bases; $\alpha = 1$ gives Schur functions; $\alpha = 2$ gives zonal polynomials for $GL_n/O_n$; $\alpha = \frac{1}{2}$ gives zonal polynomials for $GL_n(\mathbb{H})/U_n(\mathbb{H})$ where $\mathbb{H}$ is the quaternions (see [39, VII]). A good deal of the combinatorial theory for Macdonald polynomials was first developed in the Jack case. Further, the Jack theory has been developed in more detail [31, 36, 50] and [39, VI Sect. 10].

Hanlon [31] managed to interpret the differential operators defining the Jack polynomials as the transition matrix of a Markov chain on partitions with stationary distribution $\pi_\alpha(\lambda) = Z \alpha^{-\ell(\lambda)}/z_\lambda$, described in Section 2.4.2 above. In later work [15], this Markov chain was recognized as the Metropolis algorithm for generating $\pi_\alpha$ from the proposal of random transpositions. This gives one of the few cases where this important algorithm can be fully diagonalized. See [33] for a different perspective.

Our original aim was to extend Hanlon’s findings, adding a second “sufficient statistic” to $\ell(\lambda)$, and discovering a Metropolis-type Markov chain with the Macdonald coefficients as eigenfunctions. It did not work out this way. The auxiliary variables Markov chain makes more vigorous moves than transpositions, and there is no Metropolis step. Nevertheless, as shown below, Hanlon’s chain follows from interpreting a limiting case of $D_1^1$, one of Macdonald’s $D_\alpha$ operators. We believe that all of the operators $D_\alpha$ should have interesting interpretations. In this section, we derive Hanlon’s chain from the Macdonald operator perspective.
Overview

There are several closely related operators used to develop the Jack theory. Macdonald \cite{39} VI Sect. 3 Ex. 3] uses $D_\alpha(u)$ and $D^\alpha_n$, defined by

$$D_\alpha(u) = \sum_{r=0}^{n} D^r_n u^{n-r} = \frac{1}{a_\delta} \sum_{u \in S_n} \det(w) x^u \prod_{i=1}^{n} \left( u + (w \delta)_i + \alpha x_i \frac{\partial}{\partial x_i} \right)$$

where $\delta = (n-1, n-2, \ldots, 1, 0)$, $a_\delta$ is the Vandermonde determinant, and $x^\gamma = x_1^{\gamma_1} \cdots x_n^{\gamma_n}$ for $\gamma = (\gamma_1, \ldots, \gamma_n)$. He shows \cite{39} VI Sect. 3 Ex. 3c] that

$$D_\alpha(u) = \lim_{\ell \to 1} \frac{z^n}{(\ell - 1)^n} D^\alpha_n(z^{-1})$$

so that the Jack operators are a limiting case of Macdonald polynomials.

Macdonald \cite{39} VI Sect. 4 Ex. 2b] shows that the Jack polynomials $J^\alpha_n$ are eigenfunctions of $D_\alpha(u)$ with eigenvalues $\beta_\lambda(n) = \prod_{i=0}^{n-1} (u + n - i + \alpha \lambda_i)$. Stanley \cite{50} Pf. of Th. 3.1] and Hanlon \cite{31} (3.5)] use $D(\alpha)$ defined as follows. Let

$$\partial_i = \frac{\partial}{\partial x_i}, \quad U_n = \frac{1}{2} \sum_{i=1}^{n} x_i^2 \partial_i^2, \quad V_n = \sum_{i \neq j} \frac{x_i^2}{x_i - x_j} \partial_i,$$

and

$$D(\alpha) = \alpha U_n + V_n.$$

Hanlon computes the action of $D(\alpha)$ on the power sums in the form (see (4.7))

$$D(\alpha)p_\lambda = (n-1)r_p \lambda + \alpha \binom{r}{2} \sum_{\mu} \ell_{\mu \lambda}(\alpha)p_\mu,$$

where $n$ is the number of variables and $\lambda$ is a partition of $r$.

The matrix $\ell_{\mu \lambda}(\alpha)$ can be interpreted as the transition matrix of the following Markov chain on the symmetric group $S_n$. For $w \in S_n$, set $c(w) = \#$ cycles. If the chain is currently at $w_1$, pick a transposition $(i, j)$ uniformly; set $w_2 = w_1(i, j)$. If $c(w_2) = c(w_1) + 1$, move to $w_2$. If $c(w_2) = c(w_1) - 1$, move to $w_2$ with probability $1/\alpha$; else stay at $w_1$. This Markov chain has transition matrix

$$H_\alpha(w_1, w_2) = \begin{cases} \frac{r}{\alpha \binom{r}{2}} & \text{if } w_2 = w_1(i, j) \text{ and } c(w_2) = c(w_1) + 1 \\ \frac{1}{\alpha \binom{r}{2}} & \text{if } w_2 = w_1(i, j) \text{ and } c(w_2) = c(w_1) - 1 \\ \frac{n(w_1)(1 - \alpha^{-1})}{\binom{r}{2}} & \text{if } w_1 = w_2 \end{cases}$$

where $n(w_1) = \sum_i (i-1) \lambda_i$ for $w_1$ of cycle type $\lambda$. Hanlon notes that this chain only depends on the conjugacy class of $w_1$, and the induced process on conjugacy classes is still a Markov chain for which the transition matrix is the matrix of $\ell_{\mu \lambda}(\alpha)$ of (4.5).
The Jack polynomial theory now gives the eigenvalues of the Markov chain $H_\alpha(w_1, w_2)$, and shows that the corresponding eigenvectors are the coefficients when the Jack polynomials are expanded in the power sum basis. The formulae available for Jack polynomials then allow for a careful analysis of rates of convergence to stationarity; see [15].

We may see this from the present perspective as follows.

**Proposition 4.1.** Let $D_\alpha(u)$ and $D(\alpha)$ be defined by (4.1), (4.4).

(a) Let $D_0^\alpha$ be the coefficient of $u^{n-t}$ in $D_\alpha(u)$ (see [39] VI Sect. 3 Ex. 3d). If $f$ is a homogeneous polynomial in $x_1, \ldots, x_n$ of degree $r$, then

$$
D_0^\alpha f = f, \quad D_1^\alpha(f) = \left(\alpha r + \frac{1}{2} n(n-1)\right) f, \quad \text{and} \quad D_2^\alpha f = (-\alpha^2 U_n - \alpha V_n + c_n) f,
$$

where

$$
c_n = \frac{1}{2} \alpha^2 r(r-1) + \frac{1}{2} \alpha n(n-1) + \frac{1}{24} n(n-1)(n-2)(3n-1).
$$

(b) From [50] Pf. of Th. 3.1,

$$
D(\alpha)p_\lambda = \frac{1}{2}\left(\sum_{k=1}^s \alpha \lambda_k (\lambda_k - 1) + \alpha \sum_{j,k=1}^s \frac{\lambda_j \lambda_k - 1}{p_{\lambda_j} p_{\lambda_k}} + \alpha \sum_{j,k=1}^s \frac{\lambda_j \lambda_k - 1}{p_{\lambda_j} p_{\lambda_k}}\right).
$$

**Remark.** From part (a), up to affine rescaling, $D_2^\alpha$ is the Stanley–Hanlon operator. From part (b), this operates on the power sums in precisely the way that the Metropolis algorithm operates. Indeed, multiplying a permutation $w$ by a transposition $(i, j)$ changes the number of cycles by one; the change takes place by fusing two cycles (the first term in (4.7)) or by breaking one of the cycles in $w$ into parts (the second term in (4.7)). The final term constitutes the “holding” probability from the Metropolis algorithm.

**Proof of Proposition 4.1.**

(a) $D_0^\alpha$ is the coefficient of $u^n$ in $D_\alpha(u)$, so

$$
D_0^\alpha f = \frac{1}{a_\delta} \sum_{w \in S_n} \det(w) x^w f = \frac{1}{a_\delta} a_\delta f = f.
$$

$D_1^\alpha$ is the coefficient of $u^{n-1}$ in $D_\alpha(u)$, so

$$
D_1^\alpha f = \frac{1}{a_\delta} \sum_{w \in S_n} \det(w) x^w f = \frac{1}{a_\delta} \sum_{i=1}^n \left(\alpha x_i \partial_i\right) f.
$$

$$
D_1^\alpha f = \frac{1}{a_\delta} \sum_{w \in S_n} \det(w) x^w f = \frac{1}{a_\delta} \sum_{i=1}^n \left(\alpha x_i \partial_i\right) f = \frac{1}{a_\delta} \sum_{i=1}^n \left(\alpha x_i \partial_i\right) f.
$$
$D^2_\alpha$ is the coefficient of $u^{n-2}$ in $D_\alpha(u)$, so

\[(4.8) \quad D^2_\alpha f = \frac{1}{a_\delta} \sum_{w \in S_n} \left( \det(w)x^{w \delta} \prod_{1 \leq i < j \leq n} ((w\delta)_i + \alpha x_i \partial_i)((w\delta)_j + \alpha x_j \partial_j) \right) f.\]

Since $x_i \partial_i x_j \partial_j = x_j \partial_j x_i \partial_i$ for all $1 \leq i, j \leq n$, and $x_i \partial_i x_j \partial_j = x_i x_j \partial_i \partial_j$ for $i \neq j$,

\[r^2 = \left( \sum_{i=1}^n x_i \partial_i \right)^2 = \sum_{i=1}^n x_i \partial_i x_i \partial_i + 2 \sum_{1 \leq i < j \leq n} x_i x_j \partial_i \partial_j\]

so that the coefficient of $\alpha^2$ in (4.8) is

\[\frac{1}{a_\delta} \sum_{w \in S_n} \det(w)x^{w \delta} \left( \sum_{1 \leq i < j \leq n} x_i \partial_i x_j \partial_j \right) f = \sum_{1 \leq i < j \leq n} x_i x_j \partial_i \partial_j f\]

\[= \frac{1}{2} \left( r^2 - \sum_{i=1}^n x_i \partial_i x_i \partial_i \right) f\]

\[= \frac{1}{2} \left( r^2 - \sum_{i=1}^n x_i \partial_i + x_i^2 \partial_i^2 \right) f\]

\[= \left( \frac{1}{2} r^2 - \frac{1}{2} r - \frac{1}{2} \sum_{i=1}^n x_i^2 \partial_i^2 \right) f\]

\[= \left( \frac{1}{2} (r^2 - r) - U_n \right) f.\]

The coefficient of $\alpha^0$ in equation (4.8) is

\[\frac{1}{a_\delta} \sum_{w \in S_n} \left( \det(w)x^{w \delta} \sum_{1 \leq i < j \leq n} (w\delta)_i (w\delta)_j \right) f\]

\[= \frac{1}{a_\delta} \sum_{w \in S_n} \left( \det(w)x^{w \delta} \frac{1}{2} \left( \left( \sum_{i=1}^n (w\delta)_i \right)^2 - \sum_{i=1}^n (w\delta_i)^2 \right) \right) f\]

\[= \frac{1}{2} \left( \frac{1}{4} n^2 (n-1)^2 - \frac{1}{6} n(n-1)(2n-1) \right) f\]

\[= \frac{1}{24} n(n-1)(n-2)(3n-1) f\]

since, for each $w \in S_n$,

\[\sum_{i=1}^n (w\delta)_i = \sum_{i=1}^n i - 1 = \frac{1}{2} n(n-1) \quad \text{and} \quad \sum_{i=1}^n (w\delta)^2_i = \sum_{i=1}^n (i-1)^2 = \frac{1}{6} n(n-1)(2n-1).\]
Since $a_\delta = \sum_{w \in S_n} \det(w)x^{w\delta} = \prod_{1 \leq i < j \leq n} (x_i - x_j)$, then, for fixed $i$,

$$\frac{1}{a_\delta} \sum_{w \in S_n} \det(w)(w\delta)_i x^{w\delta} = \frac{1}{a_\delta} \sum_{w \in S_n} \det(w)x_i \partial_i x^{w\delta}$$

$$= \frac{1}{a_\delta} x_i \partial_i \sum_{w \in S_n} \det(w)x^{w\delta} = \frac{1}{a_\delta} x_i \partial_i a_\delta$$

$$= \frac{1}{a_\delta} x_i \left( \sum_{j=1}^{i-1} \frac{a_\delta}{x_j - x_i} \partial_i (x_j - x_i) + \sum_{j=i+1}^{n} \frac{a_\delta}{x_i - x_j} \partial_i (x_i - x_j) \right)$$

$$= \frac{1}{a_\delta} x_i \left( a_\delta \sum_{j \neq i} \frac{1}{x_i - x_j} \right)$$

$$= \sum_{j \neq i} \frac{x_i}{x_i - x_j}$$

so that the coefficient of $\alpha$ in (4.8) is

$$\frac{1}{a_\delta} \sum_{w \in S_n} \det(w)x^{w\delta} \sum_{1 \leq i < j \leq n} ((w\delta)_i x_j \partial_j + (w\delta)_j x_i \partial_i) f$$

$$= \frac{1}{a_\delta} \sum_{w \in S_n} \det(w)x^{w\delta} \left( \sum_{i=1}^{n} x_i \partial_i \sum_{j=1}^{n} (w\delta)_j - \sum_{i=1}^{n} (w\delta)_i x_i \partial_i \right) f$$

$$= \frac{1}{2} n(n-1) rf - \sum_{i=1}^{n} \left( \frac{1}{a_\delta} \sum_{w \in S_n} \det(w)x^{w\delta} (w\delta)_i \right) x_i \partial_i f$$

$$= \frac{1}{2} n(n-1) rf - \sum_{i=1}^{n} \sum_{j \neq i} \frac{x_i}{x_i - x_j} x_i \partial_i f$$

$$= \left( \frac{1}{2} n(n-1) - V_n \right) f.$$
(b) Since $\partial_i p_\ell = \ell x_i^{\ell-1}$,

$$
\alpha U_n p_\lambda = \frac{\alpha}{2} \sum_{i=1}^{n} x_i^2 \partial_i \partial_\ell p_\lambda = \frac{\alpha}{2} \sum_{i=1}^{n} x_i^2 \partial_i \partial_\ell p_{\lambda_1} p_{\lambda_2} \cdots p_{\lambda_s}
$$

$$
= \frac{\alpha}{2} \sum_{i=1}^{n} x_i^2 \partial_\ell \left( \sum_{j=1}^{s} \frac{\lambda_j x_i^{\lambda_j-1}}{p_{\lambda_j}} p_\lambda \right)
$$

$$
= \frac{\alpha}{2} \sum_{i=1}^{n} x_i^2 \left( \sum_{j,k=1}^{s} \frac{\lambda_j \lambda_k x_i^{\lambda_j-1} x_i^{\lambda_k-1}}{p_{\lambda_j} p_{\lambda_k}} p_\lambda + \sum_{j=1}^{s} \frac{\lambda_j (\lambda_j - 1) x_i^{\lambda_j-2}}{p_{\lambda_j}} p_\lambda \right)
$$

$$
= \frac{\alpha}{2} \left( \sum_{j,k=1}^{s} \frac{\lambda_j \lambda_k x_i^{\lambda_j} x_i^{\lambda_k}}{p_{\lambda_j} p_{\lambda_k}} p_\lambda + \sum_{j=1}^{s} \frac{\lambda_j (\lambda_j - 1) x_i^{\lambda_j} p_\lambda}{p_{\lambda_j}} \right)
$$

$$
= \frac{\alpha}{2} \left( \sum_{j=1}^{s} \lambda_j (\lambda_j - 1) p_\lambda + \sum_{j,k=1}^{s} \frac{\lambda_j \lambda_k p_{\lambda_j} + \lambda_k}{p_{\lambda_j} p_{\lambda_k}} p_\lambda \right).
$$

Since

$$
p_{\lambda_k-m} p_m = \left( \sum_{i=1}^{n} x_i^{\lambda_k-m} \right) \left( \sum_{j=1}^{n} x_j^{m} \right) = \sum_{i=1}^{n} x_i^{\lambda_k} + \sum_{i,j=1}^{n} x_i^{\lambda_k-m} x_j^m,
$$

then

$$
p_{\lambda_k-m} p_m - p_{\lambda_k} = \sum_{i,j=1}^{n} x_i^{\lambda_k-m} x_j^m.
$$
The formula for $D(\alpha)p_\lambda = (\alpha U_n + V_n)p_\lambda$ now follows.

5 Rates of convergence

This section uses the eigenvectors and eigenvalues derived above to give rates of convergence for the auxiliary variables Markov chain. Section 5.1 states the main results: starting from the partition $(k)$ a bounded number of steps suffice for convergence, independent of $k$. Section 5.2 contains an overview of the argument and needed lemmas. Section 5.3 gives the proof of Theorem 5.1 and Section 5.4 develops the analysis starting from $(1^k)$, showing that $\log_q(k)$ steps are needed.

5.1 Statement of main results

Fix $q, t > 1$ and $k \geq 2$. Let $P_k$ be the partitions of $k$, $\pi_{q,t}(\lambda) = Z/z_{\alpha}(q, t)$ the stationary distribution defined in (1.2), and $M(\lambda, \nu)$ the auxiliary variables Markov chain defined in Proposition 2.1. The total variation distance $\|M_{(k)}^{\ell} - \pi_{q,t}\|_{TV}$ used below is defined in (2.7).

**Theorem 5.1.** Consider the auxiliary variables Markov chain on partitions of $k \geq 4$. Then, for all $\ell \geq 2$

$$4 \|M_{(k)}^{\ell} - \pi_{q,t}\|_{TV}^2 \leq \frac{1}{(1 - q^{-1})^{3/2}(1 - q^{-2})^2} \left(1 + \frac{1}{tq^{k/2}}\right)^{2\ell} + k \left(\frac{t}{t - 1}\right) \left(\frac{2}{q^{k/4}}\right)^{2\ell}.$$
For example, if \( q = 4, t = 2, \) and \( k = 10 \) the bound becomes \( 1.76(.26)^{2\ell} + 20(1/512)^{2\ell} \). Thus, when \( \ell = 2 \) the total variation distance is at most .05 in this example.

5.2 Outline of proof and basic lemmas

Let \( \{ f_\lambda, \beta_\lambda \}_{\lambda=k} \) be the eigenfunctions and eigenvalues of \( M \) given in Theorem 3.1. From Section 2.2 for any starting state \( \rho \),

\[
4\| M_\rho^\ell - \pi_{q,t} \|_{TV}^2 \leq \sum_\lambda \left( \frac{M_\rho^\ell(\rho, \lambda) - \pi_{q,t}(\lambda)}{\pi_{q,t}(\lambda)} \right)^2 \sum_{\lambda \neq (k)} \bar{f}_\lambda^2(\rho)\beta_\lambda^{2\ell}
\]

with \( \bar{f}_\lambda \) right eigenfunctions normalized to have norm one. At the end of this subsection we prove the following:

\[
\sum_\lambda \bar{f}_\lambda^2(\rho) = \frac{1}{\pi_{q,t}(\rho)}, \quad \text{for any } \rho \in \mathcal{P}_k.
\]

\[
\left( \frac{1-t^{-k}}{1-t^{-1}} \right) \frac{1}{k\pi_{q,t}(k)} \quad \text{is an increasing sequence bounded by } (1-q^{-1})^{-1/2}.
\]

\( \beta_\lambda \) is monotone increasing in the usual partial order (moving up boxes); in particular, \( \beta_{k-1,1} \) is the second largest eigenvalue and all \( \beta_\lambda > 0 \).

\[
\beta_{k-r,r} \sim \frac{2}{q^r}.
\]

Using these results, consider the sum on the right side of \((5.2)\), for \( \lambda \) with largest part \( \lambda_1 \) less than \( k - r \). Using monotonicity, \((5.5)\), and the bound \((5.3)\),

\[
\sum_{\lambda: \lambda_1 \leq k-r} \bar{f}_\lambda^2(k)\beta_\lambda^{2\ell} \leq \left( \frac{2}{q^r} \right)^{\ell} \pi_{q,t}^{-1}(k) \leq \frac{t}{t-1} \left( \frac{2}{q^r} \right)^{\ell} k,
\]

By taking \( r = k/4 \) gives the second term on the right hand side of \((5.1)\).

Using monotonicity again,

\[
\sum_{\lambda \neq (k)} \bar{f}_\lambda^2(\rho)\beta_\lambda^{2\ell} \leq \sum_{r=1}^{j^*} \beta_{(k-r,r)}^{2\ell} \sum_{\gamma \neq r} \bar{f}_{(k-r,\gamma)}^2(k).
\]

The argument proceeds by looking carefully at \( \bar{f}_\lambda^2 \) and showing

\[
\bar{f}_{(k-r,\gamma)}^2(k) \leq c \bar{f}_\gamma^2(r)
\]

for a constant \( c \). In \((5.9)\) and throughout this section, \( c = c(q, t) \) denotes a positive constant which depends only on \( q \) and \( t \), but not on \( k \). Its value may change from line to line. Using \((5.3)\) on \( \mathcal{P}_r \) shows \( \sum_{\lambda_1 = r} \bar{f}_\lambda^2(r) = \pi_{q,t}^{-1}(r) \sim cr \). Using this and \((5.6)\) in \((5.8)\) gives an upper bound

\[
\sum_{\lambda \neq (k)} \bar{f}_\lambda^2(\rho)\beta_\lambda^{2\ell} \leq c \sum_{r=1}^{j^*} \left( \frac{2}{q^r} \right)^{\ell} r.
\]
This completes the outline for starting state \( (k) \).

This section concludes by proving the preliminary results announced above.

**Lemma 5.2.** For any \( \rho \in P_k \), the normalized eigenfunctions \( \bar{f}_\lambda(\rho) \) satisfy

\[
\sum_{\lambda \vdash k} \bar{f}_\lambda(\rho)^2 = \frac{1}{\pi_{q,t}(\rho)}.
\]

**Proof.** The \( \{\bar{f}_\lambda\} \) are orthonormal in \( L^2(\pi_{q,t}) \). Fix \( \rho \in P_k \) and let \( \delta_\rho(\nu) = \delta_{\rho \nu} \) be the measure concentrated at \( \rho \). Expand the function \( g(\nu) = \delta_\rho(\nu)/\pi_{q,t}(\rho) \) in this basis: \( g(\nu) = \sum_\lambda \langle g | \bar{f}_\lambda \rangle \bar{f}_\lambda(\nu) \). Using the Plancherel identity, \( \sum g(\nu)^2 \pi_{q,t}(\nu) = \sum_\lambda \langle g | \bar{f}_\lambda \rangle^2 \). Here, the left side equals \( \pi_{q,t}^{-1}(\rho) \) and \( \langle g | \bar{f}_\lambda \rangle = \sum_\nu g(\nu) \bar{f}_\lambda(\nu) \pi_{q,t}(\nu) = \bar{f}_\lambda(\rho) \). So the right side is the needed sum of squares. \( \square \)

The asymptotics in (5.4) follow from the following lemma.

**Lemma 5.3.** For \( q, t > 1 \), the sequence

\[
P_k = \left( \frac{1 - t^{-k}}{1 - t^{-1}} \right) \frac{1}{k \pi_{q,t}(k)} = \frac{(1 - q^{-k}) q^k (t, q)_k}{(1 - t^{-1}) q^k (q, q)_k} = \prod_{j=1}^{k-1} \frac{1 - t^{-1} q^{-j}}{1 - q^{-j}}
\]

is increasing and bounded by \( \frac{1}{\sqrt{1 - q^{-1}}} \).

**Proof.** The equalities follow from the definitions of \( \pi_{q,t}(\lambda), (t, q)_k \) and \( (q, q)_k \). Since \( \frac{1 - t^{-1} q^{-k}}{1 - q^{-k}} > 1 \), the sequence is increasing. The bound follows from

\[
\prod_{j=1}^{\infty} \frac{1 - t^{-1} q^{-j}}{1 - q^{-j}} = \exp \left( \sum_{j=1}^{\infty} \log(1 - t^{-1} q^{-j}) - \log(1 - q^{-j}) \right)
\]

\[
= \exp \left( \sum_{j=1}^{\infty} \sum_{n=1}^{\infty} \left( \frac{q^{-jn}}{n} - \frac{t^{-n} q^{-jn}}{n} \right) \right)
\]

\[
= \exp \left( \sum_{n=1}^{\infty} \sum_{j=1}^{\infty} q^{-jn} (1 - t^{-n}) \right)
\]

\[
= \exp \left( \sum_{n=1}^{\infty} \frac{(1 - t^{-n}) q^{-n}}{n - 1 - q^{-n}} \right)
\]

\[
= \exp \left( \sum_{n=1}^{\infty} \frac{(1 - t^{-n}) 1}{q^n - 1} \right)
\]

\[
\leq \exp \left( \sum_{n=1}^{\infty} \frac{1}{2 q^n n} \right)
\]

\[
= \exp \left( - \frac{1}{2} \log(1 - q^{-1}) \right) = \frac{1}{\sqrt{1 - q^{-1}}}.
\] \( \square \)
Remark. The function \( P_\infty = \lim_{k \to \infty} P_k \) is an analytic function of \( q, t \) for \(|q|, |t| > 1\), thoroughly studied in the classical theory of partitions [3, Sect. 2.2].

For the next lemma, recall the usual dominance partial order on \( \mathcal{P}_k : \lambda \geq \mu \) if \( \lambda_1 + \cdots + \lambda_i \geq \mu_1 + \cdots + \mu_i \) for all \( i \). This amounts to “moving up boxes” in the diagram for \( \mu \). Thus \((k)\) is largest, \((1^k)\) smallest. When \( k = 6 \), \((5,1) > (4,2) > (3,3)\), but \((3,3)\) and \((4,1,1)\) are not comparable. The following result shows that the eigenvalues \( \beta_\lambda \) are monotone in this order. A similar monotonicity holds for the random transpositions chain [19], the Ewens sampling chain [15], and the Hecke algebra deformation chain [18].

**Lemma 5.4.** For \( q, t > 1 \), the eigenvalues

\[
\beta_\lambda = \frac{t}{q^k - 1} \sum_{j=1}^{\ell(\lambda)} (q^{\lambda_j} - 1) t^{-j}
\]

are monotone in \( \lambda \).

**Proof.** Consider first a partition \( \lambda, i < j \), with \( a = \lambda_i \geq \lambda_j = b \), where moving one box from row \( i \) to row \( j \) is allowed. It must be shown that

\[
q^{a+1} + q^{b-1}t^{(j-i)} > q^{a} + q^{b}t^{(j-i)}
\]

or

\[
q^{a+1}t^{j-i} + q^{b-1} > q^{a}t^{j-i} + q^{b}
\]

or

\[
q^{a}t^{j-i}(q-1) > q^{b-1}(q-1).
\]

Since \( t^{j-i} > 1 \) and \( q^{a-b+1} > 1 \), this always holds.

By elementary manipulations, \( \frac{q^a - 1}{q^b - 1} < \frac{q^a}{q^b} = \frac{1}{q^{b-a}} \) for \( 1 < a < b \), so that

\[
(5.11) \quad \beta_{(k-r,r)} = \frac{t}{q^k - 1} \left( \frac{q^{k-r} - 1}{t} + \frac{q^r - 1}{t^2} \right) \leq \frac{1}{q^r} + \frac{1}{tq^{k-r}} = \frac{1}{q^r} \left( 1 + \frac{1}{tq^{k-2r}} \right),
\]

which establishes (5.6).

**5.3 Proof of Theorem 5.1**

From Theorem [3.1], the normalized eigenvectors are given by

\[
(5.12) \quad \bar{f}_\lambda(k)^2 = \frac{\left( X_\lambda^k (q^k - 1) \right)^2}{c_\lambda c'_\lambda (t,q)_k}, \quad (t,q)_k, \quad \text{where} \quad X_\lambda^k = \prod_{(i,j) \in \lambda \backslash (1,1)} (t^{i-1} - q^{j-1})
\]

and \( c_\lambda \) and \( c'_\lambda \) are given by (3.1).

**Lemma 5.5.** For \( \lambda = (k-r,\gamma) \), with \( \gamma \vdash r \) and \( r \leq k/2 \),

\[
\bar{f}_\lambda(k)^2 \leq \bar{f}_\gamma(r)^2 \frac{(1-q^{-k})^2 q^k (t,q)_k t^r (g,q)_r}{(1-q^{-r})^2 t^k (g,q)_k q^r (t,q)_r}.
\]
Thus, \[ \left( \frac{X^\lambda_{(k)}}{X^\gamma_{(r)}} \right)^2 = \prod_{(i,j) \in \lambda \setminus (i,j) \neq (1,1)} (t^{i-1} - q^{j-1})^2 \prod_{(i,j) \in \gamma \setminus (i,j) \neq (1,1)} (t^{i-1} - q^{j-1})^2 \]

\[ = \prod_{s \in L} (t^{i(s) - 1} - q^{j(s) - 1})^2 \prod_{s \in U} (t^{i(s) - 1} - q^{j(s) - 1})^2 \]

\[ = \prod_{m=1}^{\gamma_1} \left( t^{\gamma_m} - q^{m-1} \right)^2 \prod_{m=\gamma_1+1}^{k-r} \left( 1 - q^{m-1} \right)^2 \]

where \( \gamma_1' \) is the length of the \( m \)th column of \( \gamma \). Next,

\[ \frac{c_{\lambda}c_{\lambda}'}{c_{\gamma}c_{\gamma}'} = \prod_{s \in \lambda} \frac{\left( 1 - q^{a(s)}t^{l(s) + 1} \right) (1 - q^{a(s)} + 1)t^{l(s)}}{\prod_{s \in \gamma} \left( 1 - q^{a(s)}t^{l(s) + 1} \right) (1 - q^{a(s)} + 1)t^{l(s)}} \]

\[ = \prod_{s \in U} \left( 1 - q^{a(s)}t^{l(s) + 1} \right) \left( 1 - q^{a(s)} + 1 \right)t^{l(s)} \]

\[ = \prod_{m=1}^{\gamma_1} \left( 1 - q^{k-r-m}t^{\gamma_m + 1} \right) \left( 1 - q^{k-r-m} + 1 \right)t^{\gamma_m} \prod_{m=\gamma_1+1}^{k-r} \left( 1 - q^{k-r-m}t \right) \left( 1 - q^{k-r-m+1} \right) \]

\[ = q^{-2(k-r)(k-r-1)} \prod_{m=1}^{\gamma_1} \left( t^{\gamma_m + 1}q^{k-r-1} - q^{m-1} \right) \left( t^{\gamma_m}q^{k-r} - q^{m-1} \right) \]

\[ \cdot \prod_{m=\gamma_1+1}^{k-r} \left( tq^{k-r-1} - q^{m-1} \right) \left( q^{k-r} - q^{m-1} \right). \]

Thus,

\[ \left( \frac{X^\lambda_{(k)}}{X^\gamma_{(r)}} \right)^2 \frac{c_{\gamma}c_{\gamma}'}{c_{\lambda}c_{\lambda}'} = q^{2(k-r)(k-r-1)} \prod_{m=1}^{\gamma_1} \frac{(t^{\gamma_m} - q^{m-1})}{(t^{\gamma_m + 1}q^{k-r-1} - q^{m-1})} \frac{(t^{\gamma_m} - q^{m-1})}{(t^{\gamma_m}q^{k-r} - q^{m-1})} \]

\[ \cdot \prod_{m=\gamma_1+1}^{k-r} \frac{(1 - q^{m-1})}{(tq^{k-r-1} - q^{m-1})} \frac{(1 - q^{m-1})}{(q^{k-r} - q^{m-1})}. \]
Since \( k - r - 1 \geq m - 1 \) and \( t > 1 \), then \( t^{r+1}q^{k-r-1} - q^{m-1} \geq 0 \), so that \( q^{-(k-r-1)t-1} < 1 \) implies
\[
\frac{t^{r+1}q^{m-1}}{t^{r+1}q^{k-r-1} - q^{m-1}} < q^{-(k-r-1)t-1}.
\]
Similarly, since \( k - r > m - 1 \) and \( t > 1 \), then \( t^{r}q^{k-r} - q^{m-1} \geq 0 \), so that \( q^{-(k-r)} \leq 1 \) implies
\[
\frac{t^{r}q^{m-1}}{t^{r}q^{k-r} - q^{m-1}} < q^{-(k-r)}.
\]
Similarly, \( t^{-1}q^{-(k-r-1)} \) and \( q^{-(k-r)} \leq 1 \) imply
\[
\frac{1 - q^{m-1}}{tq^{k-r-1} - q^{m-1}} < t^{-1}q^{-(k-r-1)} \quad \text{and} \quad \frac{1 - q^{m-1}}{q^{k-r} - q^{m-1}} < q^{-(k-r)}.
\]
So
\[
\left(\frac{X^\lambda_k}{X^\gamma_r}\right)^2 \frac{c_{\gamma'}c_{\lambda'}}{c_{\lambda}c_{\gamma'}} \leq q^{2(k-r)(k-r-1)} \prod_{m=1}^{\gamma} \left(q^{-(k-r-1)t-1}\right) \left(q^{-(k-r)}\right) \prod_{m=\gamma+1}^{k-r} \left(t^{-1}q^{-(k-r-1)}\right) \left(q^{-(k-r)}\right)
= q^{2(k-r)(k-r-1)} \gamma^{-1} \gamma^{-2} q^{-(k-r)(k-r-1)} = q^{-(k-r)t^{-1}(k-r)}.
\]
Thus,
\[
\bar{f}_\lambda(k)^2 \leq \frac{X^\lambda_k}{X^\gamma_r} \frac{c_{\gamma'}c_{\lambda'}}{c_{\lambda}c_{\gamma'}} \frac{q^{k-1}}{q^2} \frac{q(t,q)_k}{q(t,q)_r} \leq \frac{1}{q^{k-r}t^{-1}(k-r)} (q^{k-1})^2 \frac{q(t,q)_k}{q(t,q)_r}.
\]
We may now bound the upper bound sum on the right hand side of (5.2). Fix \( j^* \leq k/2 \). Using monotonicity (Lemma 5.4), Lemma 5.2, Lemma 5.3, and the definition of \( \pi_{q,t}(r) \) from (1.2),
\[
\sum_{\lambda \in \ell(k), \lambda_2 \geq k-j^*} \bar{f}_\lambda(k)^2 \beta_{\lambda} \leq \sum_{r=1}^{j^*} \sum_{\lambda=(k-r,\gamma)} \beta_{(k-r,\gamma)} \bar{f}_\lambda(k)^2 \leq \sum_{r=1}^{j^*} \sum_{\gamma \in \ell(r+1)} \beta_{(k-r,\gamma)} \frac{1}{\pi_{q,t}(r)} \frac{(1 - q^{-k})^2}{q^{k-1}} \frac{q(t,q)_k}{q(t,q)_r} \leq \sum_{r=1}^{j^*} \beta_{(k-r,\gamma)} \frac{1}{\pi_{q,t}(r)} (1 - q^{-r}) \frac{t}{q^{k-1}} \frac{q(t,q)_k}{q(t,q)_r} \leq \sum_{r=1}^{j^*} \beta_{(k-r,\gamma)} \frac{1}{\pi_{q,t}(r)} (1 - q^{-r}) \frac{(1 - q^{-r})^2}{q^{k-1}} \frac{q(t,q)_k}{q(t,q)_r} \leq (1 - q^{-k})^2 \frac{q(t,q)_k}{q^{k-1}} \sum_{r=1}^{j^*} \beta_{(k-r,\gamma)} \leq \frac{(1 - q^{-k})^2}{(1 - q^{-1})(1 - t^{-1})} \frac{q(t,q)_k}{q^{k-1}} \sum_{r=1}^{j^*} \beta_{(k-r,\gamma)}.
\]

Using (5.11) and Lemma 5.3 gives
\[
\sum_{\lambda_1 \geq k-j^*} \tilde{f}_\lambda(k)^2 \beta_\lambda^{2\ell} \leq \frac{(1 - q^{-k})}{(1 - q^{-1})} \left( \prod_{j=1}^{k-1} \frac{1 - t^{-1}q^{-j}}{1 - q^{-j}} \right) \sum_{j^*} r \frac{1}{q^{2\ell}} \left( 1 + \frac{1}{tq^{k-2\ell}} \right)^{2\ell}
\]
\[
\leq \frac{(1 - q^{-k})}{(1 - q^{-1})} \left( \prod_{j=1}^{\infty} \frac{1 - t^{-1}q^{-j}}{1 - q^{-j}} \right) \left( 1 + \frac{1}{tq^{k-2\ell}} \right)^{2\ell} \sum_{r=1}^{j^*} r \frac{1}{q^{2\ell}}
\]
\[
\leq \frac{(1 - q^{-k})}{(1 - q^{-1})} \left( \frac{1}{1 - q^{-2\ell}} \right) \left( 1 + \frac{1}{tq^{k-2\ell}} \right)^{2\ell} \left( \frac{1}{q} + \frac{1}{tq^{k-2\ell}} \right)^2
\]
by Lemma 5.2. Choose \( j^* \) (of order \( k/4 \)) so that \( k - 2j^* + 1 = k/2 \). Then
\[
\sum_{\lambda_1 \geq k-j^*} \tilde{f}_\lambda(k)^2 \beta_\lambda^{2\ell} \leq \frac{1}{(1 - q^{-1})^{3/2}(1 - q^{-2})^2} \left( \frac{1}{q} + \frac{1}{tq^{k/2}} \right)^{2\ell}.
\]
with \( a \) as in the statement of Theorem 5.1.

Now use
\[
\sum_{\lambda_1 < 3k/4} \tilde{f}_\lambda(k)^2 \beta_\lambda^{2\ell} \leq \sum_{\lambda_1 < 3k/4} \tilde{f}_\lambda(k)^2 \beta_\lambda^{2\ell} \left( \frac{2}{q^{2\ell}} \right)
\]
\[
\leq \sum_{\lambda} \tilde{f}_\lambda(k)^2 \beta_\lambda^{2\ell} \left( \frac{2}{q^{2\ell}} \right) \leq \frac{1}{\pi_{q,\ell}(k)} \beta_\lambda^{2\ell} \left( \frac{2}{q^{2\ell}} \right)
\]
\[
= \frac{t^k}{q^k} \left( \frac{k}{q} \right)^k \left( \frac{1 - t^{-k}}{1 - q^{-k}} \right) \left( \frac{1}{q^{k/4}} \right)^{2\ell}
\]
\[
\leq k \left( 1 - t^{-k} \right) \left( 1 - t^{-1} \right) \left( \prod_{j=1}^{k-1} \frac{1 - q^{-j}}{1 - t^{-1}q^{-j}} \right) \left( \frac{1}{q^{k/4}} \right)^{2\ell}
\]
so that
\[
(5.13) \quad \sum_{\lambda_1 < 3k/4} \tilde{f}_\lambda(k)^2 \beta_\lambda^{2\ell} \leq k \frac{t}{t - 1} \left( \frac{2}{q^{k/4}} \right)^{2\ell}.
\]
This completes the proof of Theorem 5.1.

5.4 Bounds starting at \( (1^k) \)

We have not worked as seriously at bounding the chain starting from the partition \( (1^k) \). The following results show that \( \log_q(k) \) steps are required, and offer evidence for the conjecture that \( \log_q(k) + \theta \) steps suffice (where the distance to stationarity tends to zero with \( \theta \), so there is a sharp cutoff at \( \log_q(k) \)).

The \( L^2 \) or chi-square distance on the right hand side of (5.2) has first term \( \beta_{k-1,1}^{2\ell} \tilde{f}_{k-1,1}^{2\ell}(1^k) \).
Lemma 5.6. For fixed $q, t > 1$, as $k$ tends to infinity,

$$
\bar{f}_{(k-1,1)}(1^k)^2 = \frac{\left(X_{(1^k)}^{(k-1,1)}(q - 1)^k\right)^2}{c_{(k-1,1)}c'_{(k-1,1)}(q, q)k/(t, q)k} \sim \left(\frac{1 - q^{-1}}{1 - t^{-1}}\right)^2 k^2.
$$

Proof. From (3.3) and the definition of $\varphi_T(q, t)$ from [39 VI p. 341 (1)] and [39 VI (7.11)],

$$
X_{(1^k)}^{(k-1,1)} = \frac{c'_{(k-1,1)}(q, t)}{(1 - t)^k} \sum_T \varphi_T(q, t) = \frac{c'_{(k-1,1)}}{(1 - q)^k} \left(\frac{1 - t}{1 - q}\right)^k = \frac{c'_{(k-1,1)}}{(1 - q)^k} \left(\frac{1 - t}{1 - q}\right)^k.
$$

With

$$
p = \left(\frac{1 - t^2}{1 - q^2} + \frac{1 - q^2}{1 - q^2} + \frac{1 - q^2}{1 - q^2} + \cdots + \frac{1 - q^2}{1 - q^2}\right).
$$

Using the definition of $c_{(k-1,1)}$ and $c'_{(k-1,1)}$ from (3.1), and the definition of $(t, q)k$ and $(q, q)k$ from [1.2],

$$
\bar{f}_{(k-1,1)}(1^k)^2 = \frac{\left(X_{(1^k)}^{(k-1,1)}(1 - q)^k\right)^2}{c_{(k-1,1)}c'_{(k-1,1)}(q, q)k} \frac{(t, q)k}{(q, q)k} \frac{c'_{(k-1,1)}(t, q)k}{c_{(k-1,1)}(q, q)k} = \left(\frac{1 - t^2}{1 - q^2}\right)^k \left(\frac{1 - q^2}{1 - q^2}\right)^k \left(\frac{1 - t}{1 - q}\right)^k = \left(\frac{1 - t}{1 - q}\right)^k
$$

and the result follows, since $p \sim k$ for $k$ large.

Corollary 5.7. There is a constant $c$ such that, for all $k, \ell \geq 2$,

$$
\chi^2_{(1^k)}(\ell) = \sum_{\lambda} \frac{(M_{(1^k)}(\ell, \lambda) - \pi_{q, k}(\lambda))^2}{\pi_{q, k}(\lambda)} \geq \left(\frac{1 - q^{-1}}{1 - t^{-1}}\right) \frac{k^2}{q^{2\ell}}.
$$

Proof. Using only the lead term in the expression for $\chi^2_{(1^k)}(\ell)$ in [5.4] gives the lower bound $\beta_{(k-1,1)}^2 \bar{f}_{(k-1,1)}(1^k)^2$. The formula for $\beta_{(k-1,1)}$ in Theorem 3.1(2) gives $\beta_{(k-1,1)} \geq \frac{1}{q}$, and the result then follows from Lemma 5.6.

The corollary shows that if $\ell = \log_q(k) + \theta$, $\chi^2_{(1^k)}(\ell) \geq \frac{\theta}{q^{2\ell}}$. Thus, more than $\log_q(k)$ steps are required to drive the chi-square distance to zero. In many examples, the asymptotics of the lead term in the bound [5.2] sharply controls the behavior of total variation and chi-square convergence. We conjecture this is the case here, and that there is a sharp cut-off at $\log_q(k)$.

It is easy to give a total variation lower bound:
**Proposition 5.8.** For the auxiliary variables chain $M(\lambda, \lambda')$, after $\ell$ steps with $\ell = \log_q(k) + \theta$, for $k$ large and $\theta < -\frac{t-1}{q-1}$,

$$\left\| M_{(1^k)}^{\ell} - \pi_{q,t} \right\|_{TV} \geq e^{-\frac{t-1}{q-1}} - e^{-\frac{1}{\theta}} + o(1).$$

**Proof.** Consider the Markov chain starting from $\lambda = (1^k)$. At each stage, the algorithm chooses some parts of the current partition to discard, with probability given by (1.3). From the detailed description given in Section 2.4.3, the chance of a specific singleton being eliminated is $1/q$. Of course, in the replacement stage (1.4) this (and more singletons) may reappear. Let $T$ be the first time that all of the original singletons have been removed at least once; this $T$ depends on the history of the entire Markov chain. Then $T$ is distributed as the maximum of $k$ independent geometric random variables $\{X_i\}_{i=1}^k$ with $P(X_i > \ell) = 1/q^\ell$ (here $X_i$ is the first time that the $i$th singleton is removed).

Let $A = \{\lambda \in \mathcal{P}_k : a_1(\lambda) > 0\}$. From the definition

$$\left\| M_{(1^k)}^{\ell} - \pi_{q,t} \right\|_{TV} = \max_{B \subseteq \mathcal{P}_k} M^\ell\left((1^k), B\right) - \pi_{q,t}(B) \geq M^\ell\left((1^k), A\right) - \pi_{q,t}(A)$$

and

$$M^\ell\left((1^k), A\right) \geq P\{T > \ell\} = 1 - P\{T \leq \ell\} = 1 - P(\max X_i \leq \ell) = 1 - P(X_1 \leq \ell)^k = 1 - e^{k \log(1 - P(X_1 > \ell))} = 1 - e^{k \log(1 - 1/q^\ell)} \sim 1 - e^{-k/q^{\ell}} = 1 - e^{-1/q^\theta}.$$ 

From the limiting results in Section 2.4.5 under $\pi_{q,t}$, $a_1(\lambda)$ has an approximate Poisson \(
\left(\frac{t-1}{q-1}\right)\) distribution. Thus, $\pi_{q,t}(A) \sim 1 - e^{-\frac{t-1}{q-1}}$. The result follows.

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