

# A probabilistic interpretation of Macdonald polynomials <sup>(1)</sup>

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## Markov chains

State space  $\{w \mid w \in S_n\}$

$w = \begin{array}{ccc} \times & \times & \times \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{array} \in S_n$  the symmetric group

## Operator

$$M = \frac{1}{\binom{n}{2}} \sum_{1 \leq i < j \leq n} s_{ij}$$

where  $s_{ij} = \text{||||} \begin{array}{c} \text{||||} \\ \text{||||} \end{array} \text{||||}$ , the transposition switching  $i$  and  $j$ .

Starting state: 1

The story: A deck of cards. Choose 2 cards  $i$  and  $j$  and switch them.

How long does it take to get random?

## Stationary distribution

$$\pi = \frac{1}{n!} \sum_{w \in S_n} w, \text{ the uniform distribution}$$

## Distances to stationarity

$$4 \|M^k \cdot 1 - \pi\|_{TV}^2 = \left( \sum_{y \in S_n} |(M^k \cdot 1)(y) - \pi(y)| \right)^2 \quad L^1\text{-norm}$$

$$\leq \|M^k \cdot 1 - \pi\|_2^2 = \sum_{y \in S_n} \frac{((M^k \cdot 1)(y) - \pi(y))^2}{\pi(y)} \quad L^2\text{-norm}$$



The Metropolis algorithm (following Hanlon...) (3)

$l(\lambda) = \#$  of parts of  $\lambda$

For  $\alpha$ ,  $0 < \alpha < 1$ . A step of  $M_\alpha$  is

- if  $l(\tau(s_{ij}w)) = l(\tau(w)) + 1$  move to  $s_{ij}w$ ,
- if  $l(\tau(s_{ij}w)) = l(\tau(w)) - 1$  move to  $s_{ij}w$  with probability  $1/\alpha$ .

The new chain  $M_\alpha$  has

stationary distribution  $\pi_\alpha = \sum_{\mu} \alpha^{-l(\mu)} z_\mu p_\mu$

eigenvectors  $J_\lambda^\alpha = \sum_{\mu} \alpha^{l(\mu)} p_\mu$  Jack polynomials

eigenvalues  $M_\alpha J_\lambda^\alpha = \beta_\lambda(\alpha) J_\lambda^\alpha$

where  $\beta_\lambda(\alpha) = \sum_{i=1}^n \alpha \lambda_i + n - i$

## Unlumping to polynomials

(4)

In the world of symmetric functions

$$P_\mu = P_{\mu_1} P_{\mu_2} \cdots P_{\mu_n} \text{ for } \mu = (\mu_1, \mu_2, \dots, \mu_n)$$

where

$$P_k = x_1^k + x_2^k + \cdots + x_n^k \text{ for } k \in \mathbb{Z} > 0.$$

The operator

$$D_\alpha = \frac{\alpha}{2} \sum_{i=1}^n x_i^2 \frac{\partial}{\partial x_i^2} + \sum_{i \neq j} \frac{x_i^2}{x_i - x_j} \frac{\partial}{\partial x_i}$$

acts on  $\mathcal{A}[x_1, x_2, \dots, x_n]$  with

eigenvectors  $J_\lambda^\alpha$  and eigenvalues  $\beta_\lambda(\alpha)$ .

Now we are in the world of

Harmonic analysis: Spectra of Laplacians

Mathematical Physics: Spectra of Hamiltonians.

For  $\alpha = \frac{1}{2}, 1, 2$  the  $J_\lambda^\alpha$  are

the classical spherical functions (zonal polynomials)

$$\text{for } \frac{GL_n(\mathbb{H})}{U_n(\mathbb{H})}, \quad \frac{GL_n(\mathbb{C})}{U_n(\mathbb{C})}, \quad \frac{GL_n(\mathbb{R})}{O_n(\mathbb{R})}$$

(5)  
Auxiliary variables = data augmentation = hit and run

Defined by Edwards and Sokal (for fast Ising) and Potts

Generalizes Swendsen-Wang

The data

State space  $X$  Auxiliary set  $I$ .

Probability distribution on  $X$ :  $\pi(x)$

Probability distribution on  $I$ :  $w_x(i)$   
for each  $x \in X$

~~Probability~~

Markov chain on  $X$ :  $M_i(x, y)$   
for each  $i \in I$

such that

$$\pi(x) w_x(i) M_i(x, y) = \pi(y) w_y(i) M_i(y, x).$$

This gives a Markov chain on  $X$ :

$$M(x, y) = \sum_i w_y(i) M_i(x, y)$$

## Our Auxiliary variables chain

(6)

$$X = P_n \text{ and } \mathcal{I} = \bigcup_{i=1}^n P_i$$

$$\pi(\lambda) = \frac{\text{const}}{z_\lambda \prod_i \binom{1-q^{\lambda_i}}{1-t\lambda_i}}$$

$$w_\lambda(\mu) = \frac{1}{(q^n-1)} \frac{\prod_{i=1}^n \binom{a_i(\lambda)}{a_i(\mu)}}{\binom{q^i-1}{a_i(\mu)}}, \text{ and}$$

$$M_p(\lambda, \mu) = \begin{cases} \frac{1}{z_\mu (1-t^{-1})} \prod_i \binom{1-t^{-i}}{a_i(\mu)}, & \text{if } \mu = p \cup v \\ 0, & \text{otherwise} \end{cases}$$

The story: Start with  $\lambda$

- Delete some parts to get  $\lambda - \delta$   
with probability  $w_\lambda(\lambda - \delta)$
- Add some parts to get  $\mu$   
with probability  $M_{\lambda - \delta}(\lambda, \mu)$

This gives a Markov chain

$$M_{\lambda \in \mathcal{I}}(\lambda, \mu) \text{ on } P_n = \{P_\lambda \mid \lambda \text{ is a partition of } n\}$$

## Macdonald polynomials

(7)

Theorem The eigenvectors of  $M_{q,t}$  are

$$P_\lambda(q,t) = \sum_{\mu} X_{\mu}^{\lambda}(q,t) q_{\mu}$$

the Macdonald polynomials, and

$$M_{q,t} P_\lambda(q,t) = p_\lambda(q,t) P_\lambda(q,t)$$

where

$$p_\lambda(q,t) = \sum_{i=1}^{\ell(\lambda)} q^{\lambda_i} t^{n-i}$$

## Remarks

- $P_\lambda(0,0) = s_\lambda =$  Schur functions  
= characters of compact Lie groups
- $P_\lambda(0,t) =$  Hall-Littlewood polynomials  
= spherical functions for  $G(\mathbb{Q}_p)/G(\mathbb{Z}_p)$
- $\lim_{t \rightarrow 1} P_\lambda(t^x, t) = J_\lambda^x$ , the Jack polynomials
- For type  $(C_n^v, C_n)$ ,  $P_\lambda(q,t)$  are the Koornwinder polynomials
- For type  $(G^v, G)$ ,  $P_\lambda(q,t)$  are the Askey-Wilson polynomials