#### Persification

Richard P. Stanley U. Miami & M.I.T.

January 31, 2020

### **Dedication**

**D**elving

**/** nto

**A**lgebraic

**C**ombinatorics

Originates

**N**ew,

Intriguing

**S** tories

#### **Thanks**

Profoundly Enhanced Richard Stanley's Interests

#### **Definition of Persification**

per·si·fi·ca·tion noun

#### **Definition of Persification**

#### per·si·fi·ca·tion noun

1. Persianization, i.e., sociological process of cultural change in which something becomes "Persianate" (acclimated to Persian culture).

#### **Definition of Persification**

#### per·si·fi·ca·tion noun

- 1. Persianization, i.e., sociological process of cultural change in which something becomes "Persianate" (acclimated to Persian culture).
- 2. The process of turning a mathematical result into a "story" explaining how this result applies to a concrete or real world situation, usually related to probability theory, in the manner of Persi Diaconis.

per·si·fy verb

**PERSONIFICATION** 

of

#### **PERSONIFICATION**

of

**PERSONIFICATION** 

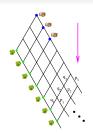
of

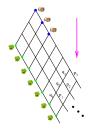
PERS IFICATION

**PERSONIFICATION** 

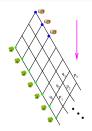
of

**PERSIFICATION** 

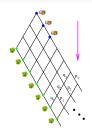




• Top hamster starts walking downhill at t=0, next at t=1, and next at t=2 (for persification only).

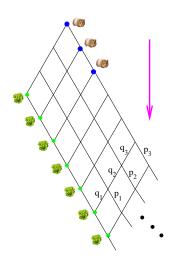


- Top hamster starts walking downhill at t = 0, next at t = 1, and next at t = 2 (for persification only).
- When distance *i* from food, they walk right with probability  $p_i$  and left with probability  $q_i = 1 p_i$ .



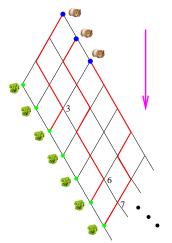
- Top hamster starts walking downhill at t = 0, next at t = 1, and next at t = 2 (for persification only).
- When distance *i* from food, they walk right with probability  $p_i$  and left with probability  $q_i = 1 p_i$ .
- They are aggressive Syrian hamsters and hence very territorial.
   If they meet they will fight to the death.

# Larger figure



#### **Last location**

Specify last location of each hamster before they reach food.



#### **Schur functions**

**Lindström-Wilf-Gessel-Viennot**: probability of reaching a, b, c one step from food is  $(q_2q_3)^3s_{c-3,b-2,a-1}(p_1,p_2,p_3)$  (Schur function).

#### **Schur functions**

**Lindström-Wilf-Gessel-Viennot**: probability of reaching a, b, c one step from food is  $(q_2q_3)^3s_{c-3,b-2,a-1}(p_1,p_2,p_3)$  (Schur function).

Probability of reaching food after one more step each:

$$q_1^3(q_2q_3)^3s_{c-3,b-2,a-1}(p_1,p_2,p_3)$$

#### A Schur function sum

Probability P(p) of all hamsters reaching food:

$$egin{aligned} Pig(p_1,p_2,p_3ig) &= (q_1q_2q_3)^3 \sum_{\substack{\lambda \in \operatorname{Par} \\ \ell(\lambda) \leq 3}} s_\lambda(p_1,p_2,p_3) \ &= (q_1q_2q_3)^3 \sum_{\lambda \in \operatorname{Par}} s_\lambda(p_1,p_2,p_3) \ &= rac{(q_1q_2q_3)^3}{\prod_{i=1}^3 (1-p_i) \cdot \prod_{1 \leq 1 \leq i \leq 3} (1-p_ip_i)} \end{aligned}$$

#### A Schur function sum

Probability P(p) of all hamsters reaching food:

$$egin{aligned} Pig(p_1,p_2,p_3ig) &= (q_1q_2q_3)^3 \sum_{\substack{\lambda \in \operatorname{Par} \\ \ell(\lambda) \leq 3}} s_\lambda(p_1,p_2,p_3) \ &= (q_1q_2q_3)^3 \sum_{\lambda \in \operatorname{Par}} s_\lambda(p_1,p_2,p_3) \ &= rac{(q_1q_2q_3)^3}{\prod_{i=1}^3 (1-p_i) \cdot \prod_{1 \leq 1 \leq i \leq 3} (1-p_ip_j)} \end{aligned}$$

Clearly generalizes to any (finite) number of hamsters.

$$p_1 = p_2 = p_3$$

Let 
$$p_1 = p_2 = p_2 = p$$
. Then

$$P(p,p,p) = \frac{(1-p)^9}{(1-p)^3(1-p^2)^3} = \left(\frac{1-p}{1+p}\right)^3.$$

$$p_1 = p_2 = p_3$$

Let  $p_1 = p_2 = p_2 = p$ . Then

$$P(p, p, p) = \frac{(1-p)^9}{(1-p)^3(1-p^2)^3} = \left(\frac{1-p}{1+p}\right)^3.$$

For n hamsters at distance n from food,

$$P(p,\ldots,p)=\left(\frac{1-p}{1+p}\right)^{\binom{n}{2}}.$$

$$p_1 = p_2 = p_3$$

Let  $p_1 = p_2 = p_2 = p$ . Then

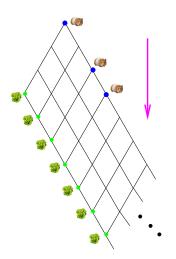
$$P(p, p, p) = \frac{(1-p)^9}{(1-p)^3(1-p^2)^3} = \left(\frac{1-p}{1+p}\right)^3.$$

For n hamsters at distance n from food,

$$P(p,\ldots,p)=\left(\frac{1-p}{1+p}\right)^{\binom{n}{2}}.$$

Simple reason?

# More general starting points



#### A difficult sum

$$P = (q_1q_2q_3)^3 \sum_{\substack{(1,1,0) \subseteq \lambda \ \ell(\lambda) \leq 3}} s_{\lambda/(1,1,0)}(p_1,p_2,p_3)$$

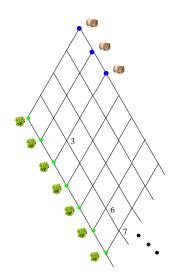
#### A difficult sum

$$P = (q_1q_2q_3)^3 \sum_{\substack{(1,1,0) \subseteq \lambda \ \ell(\lambda) \leq 3}} s_{\lambda/(1,1,0)}(p_1,p_2,p_3)$$

There is a nice formula for  $\sum_{(1,1,0)\subseteq\lambda} s_{\lambda/(1,1,0)}$ , but it is no longer true that

$$s_{\lambda/(1,1,0)}(x_1,x_2,x_3)\neq 0 \Rightarrow \ell(\lambda)\leq 3.$$

## Farther from food



#### Another difficult sum

$$(q_1q_2q_3q_4)^3\sum_{\substack{\lambda\in\mathrm{Par}\\\ell(\lambda)\leq 3}}s_\lambda(p_1,p_2,p_3,p_4)$$

#### Another difficult sum

$$(q_1q_2q_3q_4)^3\sum_{\substack{\lambda\in\mathrm{Par}\\\ell(\lambda)\leq 3}}s_\lambda(p_1,p_2,p_3,p_4)$$

Again no longer true that

$$s_{\lambda}(x_1, x_2, x_3, x_4) \neq 0 \Rightarrow \ell(\lambda) \leq 3.$$

#### A formula of Gessel

#### **Gessel** showed

$$\sum_{\ell(\lambda) \le 2m+1} s_{\lambda} = h \cdot \det(c_{i-j} - c_{i+j})_{i,j=1}^m,$$

where  $h=h_0+h_1+h_2+\cdots$  and

$$c_i = \sum_{n \geq 0} h_n h_{n+i}.$$

#### A formula of Gessel

#### **Gessel** showed

$$\sum_{\ell(\lambda) \le 2m+1} s_{\lambda} = h \cdot \det(c_{i-j} - c_{i+j})_{i,j=1}^m,$$

where  $h=h_0+h_1+h_2+\cdots$  and

$$c_i = \sum_{n \geq 0} h_n h_{n+i}.$$

Difficult to extract probability.

# II. Graded posets

**P**: finite graded poset of rank n with  $\hat{0}$  and  $\hat{1}$ , so every maximal chain has the form

$$\hat{0} = t_0 < t_1 < \cdots < t_n = \hat{1}$$

# II. Graded posets

**P**: finite graded poset of rank n with  $\hat{0}$  and  $\hat{1}$ , so every maximal chain has the form

$$\hat{0} = t_0 < t_1 < \cdots < t_n = \hat{1}$$

 $\rho$ : rank function of P, so  $\rho(t_i) = i$  above. In particular,

$$\rho(\hat{0})=0, \quad \rho(\hat{1})=n.$$

# Flag *f*-vectors

$$\textbf{S} = \{a_1 < a_2 < \dots < a_k\} \subseteq [n-1] = \{1, \dots, n-1\}$$

# Flag *f*-vectors

$$S = \{a_1 < a_2 < \cdots < a_k\} \subseteq [n-1] = \{1, \ldots, n-1\}$$

flag f-vector  $\alpha_P$ :

$$\alpha_P(S) = \#\{\hat{0} < t_1 < \dots < t_k < \hat{1} : \rho(t_i) = a_i\}, \ S \subseteq [n-1]$$

# Flag *f*-vectors

$$S = \{a_1 < a_2 < \dots < a_k\} \subseteq [n-1] = \{1, \dots, n-1\}$$

flag f-vector  $\alpha_P$ :

$$\alpha_P(S) = \#\{\hat{0} < t_1 < \dots < t_k < \hat{1} : \rho(t_i) = a_i\}, \ S \subseteq [n-1]$$

$$\alpha_P(\emptyset) = 1$$
 $\alpha_P(\{i\}) = \#\{t \in P : \rho(t) = i\}$ 
 $\alpha_P([n-1]) = \#(\text{maximal chains})$ 

### Flag *h*-vectors

flag *h*-vector  $\beta_P$ :

$$\beta_P(S) = \sum_{T \subseteq S} (-1)^{\#(S-T)} \alpha_P(T)$$

## Flag *h*-vectors

flag *h*-vector  $\beta_P$ :

$$\beta_P(S) = \sum_{T \subseteq S} (-1)^{\#(S-T)} \alpha_P(T)$$

Equivalently,

$$\alpha_P(S) = \sum_{T \subseteq S} \beta_P(T).$$

### Flag *h*-vectors

#### flag *h*-vector $\beta_P$ :

$$\beta_P(S) = \sum_{T \subseteq S} (-1)^{\#(S-T)} \alpha_P(T)$$

Equivalently,

$$\alpha_P(S) = \sum_{T \subset S} \beta_P(T).$$

Many nice properties and applications.

## The boolean algebra $B_n$

 $B_n$ : all subsets of  $\{1,\ldots,n\}$ , ordered by  $\subseteq$ 

$$\beta_n(S) := \beta_{B_n}(S)$$

## The boolean algebra $B_n$

 $B_n$ : all subsets of  $\{1,\ldots,n\}$ , ordered by  $\subseteq$ 

$$\beta_n(S) := \beta_{B_n}(S)$$

**Theorem.** Let  $S \subseteq [n-1]$ . Then

$$\beta_n(S) = \#\{w = w_1 \cdots w_n \in \mathfrak{S}_n : D(w) = S\},\$$

where  $D(w) = \{i : w_i > w_{i+1}\}$  (descent set).

### **Quasisymmetric functions**

Let  $\mathbb{P} = \{1, 2, 3, \dots\}$ . A power series  $F(x_1, x_2, \dots)$  (over  $\mathbb{Q}$ , say) of bounded degree is **quasisymmetric** if for all  $(a_1, \dots, a_k) \in \mathbb{P}^k$  and all  $1 \leq j_1 < \dots < j_k$ ,

$$[x_{j_1}^{a_1}\cdots x_{j_k}^{a_k}]F = [x_1^{a_1}\cdots x_k^{a_k}]F,$$

where  $[\cdots]$  denotes "coefficient of."

### **Quasisymmetric functions**

Let  $\mathbb{P} = \{1, 2, 3, \dots\}$ . A power series  $F(x_1, x_2, \dots)$  (over  $\mathbb{Q}$ , say) of bounded degree is **quasisymmetric** if for all  $(a_1, \dots, a_k) \in \mathbb{P}^k$  and all  $1 \leq j_1 < \dots < j_k$ ,

$$[x_{j_1}^{a_1}\cdots x_{j_k}^{a_k}]F=[x_1^{a_1}\cdots x_k^{a_k}]F,$$

where  $[\cdots]$  denotes "coefficient of."

**Example.**  $x_1^2x_2 + x_1^2x_3 + 2x_1x_2^2 + 2x_1x_3^2 + \cdots$  is quasisymmetric (so far), but

$$x_1^2x_2 + 2x_3^2x_5 + \cdots$$

is not.

### Gessel's fundamental quasisymmetric function

**Gessel**: Fix n, and let  $S \subseteq [n-1]$ . Define the **fundamental quasisymmetric function**  $L_S$  in the variables  $x_1, x_2, ...$  by

$$L_{S} = \sum_{\substack{1 \leq i_{1} \leq i_{2} \leq \cdots \leq i_{n} \\ i_{j} < i_{j+1} \text{ if } j \in S}} x_{i_{1}} \cdots x_{i_{n}}.$$

### Gessel's fundamental quasisymmetric function

**Gessel**: Fix n, and let  $S \subseteq [n-1]$ . Define the **fundamental quasisymmetric function**  $L_S$  in the variables  $x_1, x_2, ...$  by

$$L_{S} = \sum_{\substack{1 \leq i_{1} \leq i_{2} \leq \cdots \leq i_{n} \\ i_{j} < i_{j+1} \text{ if } j \in S}} x_{i_{1}} \cdots x_{i_{n}}.$$

Let n = 3. Then

$$\begin{array}{rclcrcl} L_{\emptyset} & = & \sum_{1 \leq a \leq b \leq c} x_{a} x_{b} x_{c}, & L_{1} & = & \sum_{1 \leq a < b \leq c} x_{a} x_{b} x_{c} \\ L_{2} & = & \sum_{1 \leq a \leq b < c} x_{a} x_{b} x_{c}, & L_{1,2} & = & \sum_{1 \leq a < b < c} x_{a} x_{b} x_{c}. \end{array}$$

### Gessel's fundamental quasisymmetric function

**Gessel**: Fix n, and let  $S \subseteq [n-1]$ . Define the **fundamental quasisymmetric function**  $L_S$  in the variables  $x_1, x_2, ...$  by

$$L_{S} = \sum_{\substack{1 \leq i_{1} \leq i_{2} \leq \cdots \leq i_{n} \\ i_{j} < i_{j+1} \text{ if } j \in S}} x_{i_{1}} \cdots x_{i_{n}}.$$

Let n = 3. Then

$$\begin{array}{rclcrcl} L_{\emptyset} & = & \sum_{1 \leq a \leq b \leq c} x_{a} x_{b} x_{c}, & L_{1} & = & \sum_{1 \leq a < b \leq c} x_{a} x_{b} x_{c} \\ L_{2} & = & \sum_{1 \leq a \leq b < c} x_{a} x_{b} x_{c}, & L_{1,2} & = & \sum_{1 \leq a < b < c} x_{a} x_{b} x_{c}. \end{array}$$

**Note.**  $\{L_S : S \subseteq [n-1]\}$  is a  $\mathbb{Q}$ -basis for all homogeneous quasisymmetric functions of degree n.

## Ehrenborg's generating function for $\beta_P(S)$

**Ehrenborg**: Let P be a finite poset, graded of rank n, with  $\hat{0}$  and  $\hat{1}$ . Define

$$\begin{array}{ll} \textbf{\textit{E}}_{P} & = & \displaystyle\sum_{\hat{0}=t_{0}\leq t_{1}\leq \cdots \leq t_{k-1} < t_{k}=\hat{1}} x_{1}^{\rho(t_{1})-\rho(t_{0})} x_{2}^{\rho(t_{2})-\rho(t_{1})} \cdots x_{k}^{\rho(t_{k})-\rho(t_{k-1})} \\ & = & \displaystyle\sum_{S\subseteq[n-1]} \beta_{P}(S) L_{S} \text{ (homogeneous of degree } n). \end{array}$$

## Ehrenborg's generating function for $\beta_P(S)$

**Ehrenborg**: Let P be a finite poset, graded of rank n, with  $\hat{0}$  and  $\hat{1}$ . Define

$$\mathbf{E}_{P} = \sum_{\hat{0}=t_{0} \leq t_{1} \leq \cdots \leq t_{k-1} < t_{k} = \hat{1}} x_{1}^{\rho(t_{1})-\rho(t_{0})} x_{2}^{\rho(t_{2})-\rho(t_{1})} \cdots x_{k}^{\rho(t_{k})-\rho(t_{k-1})}$$

$$= \sum_{S \subseteq [n-1]} \beta_{P}(S) L_{S} \text{ (homogeneous of degree } n).$$

In general, difficult to extract information form  $E_P$ . Nicest situation:  $E_P$  is a symmetric function.

### The QS-distribution

Let  $p_1,p_2,\dots\geq 0$ ,  $\sum p_i=1$  (probability distribution on  $\mathbb P$ )

### The QS-distribution

Let  $p_1, p_2, \dots \geq 0$ ,  $\sum p_i = 1$  (probability distribution on  $\mathbb{P}$ )

Given n, choose a random sequence  $\mathbf{x} = (x_1, ..., x_n)$ , each  $x_j$  independently from this distribution.

Standardize x, e.g.,

Defines a probability distribution on  $\mathfrak{S}_n$ , the **QS-distribution** (with respect to p).

### Probabilistic interpretation of $E_P$

**Easy theorem 1.** The probability of obtaining w under the QS-distribution is  $L_{D(w^{-1})}(p_1, p_2, \dots)$  (degree n).

### Probabilistic interpretation of $E_P$

**Easy theorem 1.** The probability of obtaining w under the QS-distribution is  $L_{D(w^{-1})}(p_1, p_2, \dots)$  (degree n).

**Persification** (easy). Let  $\mathbb{E}_{\mathbf{w}}$  denote expectation with respect to the QS-distribution on  $\mathbf{w} \in \mathfrak{S}_n$ . Then

$$E_P(p_1, p_2, \dots) = \mathbb{E}_w\left(\frac{\beta_P(D(w))}{\beta_n(D(w))}\right).$$

### A trivial example

**Example.** 
$$P = B_n$$
. Then  $E_{B_n} = h_1^n = (x_1 + x_2 + \cdots)^n$ , so  $E_{B_n}(p_1, p_2, \dots) = 1$ .

### A trivial example

**Example.** 
$$P = B_n$$
. Then  $E_{B_n} = h_1^n = (x_1 + x_2 + \cdots)^n$ , so  $E_{B_n}(p_1, p_2, \dots) = 1$ .

Clear since we are computing

$$\mathbb{E}_w\left(\frac{\beta_n(D(w))}{\beta_n(D(w))}\right).$$

#### **Products of chains**

 $C_i$ : chain of length j (or with j+1 elements)

For 
$$\lambda = (\lambda_1, \dots, \lambda_k)$$
, define

$$C_{\lambda} = C_{\lambda_1} \times \cdots \times C_{\lambda_k}.$$

E.g., 
$$C_{1,...,1} \cong B_n \ (n \ 1's)$$
.

#### **Products of chains**

 $C_j$ : chain of length j (or with j+1 elements)

For  $\lambda = (\lambda_1, \dots, \lambda_k)$ , define

$$C_{\lambda} = C_{\lambda_1} \times \cdots \times C_{\lambda_k}.$$

E.g.,  $C_{1,...,1} \cong B_n \ (n \ 1's)$ .

**Theorem.** Let  $\sum \lambda_i = n$ ,  $M = \{1^{\lambda_1}, \dots, k^{\lambda_k}\}$  (multiset), and  $S \subseteq [n-1]$ . Then

$$\beta_{C_{\lambda}}(S) = \#\{w \in \mathfrak{S}_{M} : D(w) = S\}.$$

# $E_{C_{\lambda}}$

#### **Easy fact:**

$$E_{C_{\lambda}}=h_{\lambda}=h_{\lambda_1}\cdots h_{\lambda_k},$$

the **complete symmetric function** indexed by  $\lambda$ .

# $E_{C_{\lambda}}$

#### **Easy fact:**

$$E_{C_{\lambda}}=h_{\lambda}=h_{\lambda_1}\cdots h_{\lambda_k},$$

the **complete symmetric function** indexed by  $\lambda$ .

**Corollary.** Let  $\sum \lambda_i = n$ . Then

$$\mathbb{E}_{w}\left(\frac{\beta_{C_{\lambda}}(D(w))}{\beta_{n}(D(w))}\right)\left(\frac{1}{k},\ldots,\frac{1}{k}\right)=\frac{1}{n^{k}}\prod_{i=1}^{k}\binom{\lambda_{i}+k-1}{\lambda_{i}}.$$

### Majorization

Given  $c_1, \ldots, c_n$ , let  $c_1^{\uparrow} \leq \cdots \leq c_n^{\uparrow}$  be its increasing rearrangement.

### Majorization

Given  $c_1, \ldots, c_n$ , let  $c_1^{\uparrow} \leq \cdots \leq c_n^{\uparrow}$  be its increasing rearrangement.

Define 
$$(P_1, \dots, P_n) \preceq (R_1, \dots, R_n)$$
 if

$$P_1^{\uparrow} + \cdots + P_i^{\uparrow} \leq R_1^{\uparrow} + \cdots + R_i^{\uparrow}, \ 1 \leq i \leq n,$$

the majorization order.

## Schur convexity and concavity

 $f(P_1,\ldots,P_n)$  is **Schur convex** if

$$P \leq R \Rightarrow f(P) \leq f(R)$$

and Schur-concave if

$$P \leq R \Rightarrow f(P) \geq f(R)$$

### Schur convexity and concavity

 $f(P_1,\ldots,P_n)$  is **Schur convex** if

$$P \leq R \Rightarrow f(P) \leq f(R)$$

and Schur-concave if

$$P \leq R \Rightarrow f(P) \geq f(R)$$

**Example.** The elementary symmetric function  $e_k(P_1, \ldots, P_n)$  is Schur **concave** on  $P_i \ge 0$ , and thus so is any *e*-positive symmetric function.

## Schur convexity and concavity

 $f(P_1,\ldots,P_n)$  is **Schur convex** if

$$P \leq R \Rightarrow f(P) \leq f(R)$$

and Schur-concave if

$$P \leq R \Rightarrow f(P) \geq f(R)$$

**Example.** The elementary symmetric function  $e_k(P_1, \ldots, P_n)$  is Schur **concave** on  $P_i \ge 0$ , and thus so is any *e*-positive symmetric function.

Similarly, the complete symmetric function  $h_k(P_1, ..., P_n)$  is Schur convex on  $P_i \ge 0$ .

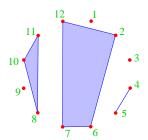
# Schur convexity of $E_{C_{\lambda}}$

**Corollary.**  $E_{C_{\lambda}}$  is h-positive, hence Schur convex on probability distributions  $p_1, p_2, \ldots$  Therefore  $\mathbb{E}_w \left( \frac{\beta c_{\lambda}(D(w))}{\beta_n(D(w))} \right) (p_1, \ldots, p_k)$  is minimized for  $p_i = 1/k$ .

### **Noncrossing partitions**

A noncrossing partition of  $\{1, 2, ..., n\}$  is a partition  $\{B_1, ..., B_k\}$  of  $\{1, ..., n\}$  such that

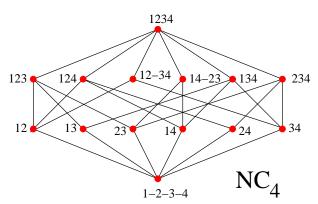
$$a < b < c < d, \ a, c \in B_i, \ b, d \in B_j \Rightarrow i = j.$$



**Theorem (H. W. Becker**, 1948–49) The number of noncrossing partitions of  $\{1, \ldots, n\}$  is the Catalan number  $C_n = \frac{1}{n+1} \binom{2n}{n}$ .

### The noncrossing partition lattice

**NC**<sub>n</sub>: noncrossing partitions of  $\{1, ..., n\}$ , ordered by refinement. NC<sub>n</sub> is graded of rank n-1.



# $E_{NC_{n+1}}$

$$E_{NC_{n+1}} = \frac{1}{n+1} [t^n] (1 + e_1 t + e_2 t^2 + \cdots)^{n+1}$$

## $E_{\mathrm{NC}_{n+1}}$

$$E_{\text{NC}_{n+1}} = \frac{1}{n+1} [t^n] (1 + e_1 t + e_2 t^2 + \cdots)^{n+1}$$
Corollary.  $\mathbb{E}_w \left( \frac{\beta_{\text{NC}_{n+1}}(D(w))}{\beta_n(D(w))} \right) \left( \frac{1}{k}, \dots, \frac{1}{k} \right) = \frac{1}{(n+1)k^n} \binom{k(n+1)}{n}$ 

## $E_{\mathrm{NC}_{n+1}}$

$$E_{NC_{n+1}} = \frac{1}{n+1} [t^n] (1 + e_1 t + e_2 t^2 + \cdots)^{n+1}$$

Corollary. 
$$\mathbb{E}_{w}\left(\frac{\beta_{\mathrm{NC}_{n+1}}(D(w))}{\beta_{n}(D(w))}\right)\left(\frac{1}{k},\ldots,\frac{1}{k}\right) = \frac{1}{(n+1)k^{n}}\binom{k(n+1)}{n}$$

**Note.**  $\beta_{NC_{n+1}}(S)$  is equal to the number of parking functions of length n and descent set [n-1]-S.

## $E_{NC_{n+1}}$

$$E_{NC_{n+1}} = \frac{1}{n+1} [t^n] (1 + e_1 t + e_2 t^2 + \cdots)^{n+1}$$

Corollary. 
$$\mathbb{E}_{w}\left(\frac{\beta_{\mathrm{NC}_{n+1}}(D(w))}{\beta_{n}(D(w))}\right)\left(\frac{1}{k},\ldots,\frac{1}{k}\right) = \frac{1}{(n+1)k^{n}}\binom{k(n+1)}{n}$$

**Note.**  $\beta_{NC_{n+1}}(S)$  is equal to the number of parking functions of length n and descent set [n-1]-S.

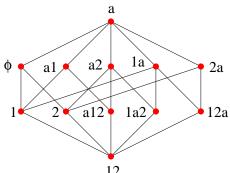
A parking function of length n is a sequence  $(a_1, \ldots, a_n) \in \mathbb{P}^n$  whose increasing rearrangement  $b_1 \leq \cdots \leq b_n$  satisfies  $b_i \leq i$ .

## Schur concavity of $E_{NC_{n+1}}$

Corollary.  $E_{\mathrm{NC}_{n+1}}$  is e-positive, hence Schur concave on probability distributions  $p_1, p_2, \ldots$  Therefore  $\mathbb{E}_w\left(\frac{\beta_{\mathrm{NC}_{n+1}}(D(w)}{\beta_n(D(w)}\right)(p_1,\ldots,p_k)$  is maximized for  $p_i=1/k$ .

### Shuffle posets

**C. Greene** (1988): let  $\alpha = a_1 \cdots a_j$  and  $\beta = b_1 \cdots b_k$  be disjoint words. Define the **shuffle poset**  $W_{mn}$  to consist of all shuffles of subwords of  $\alpha$  and  $\beta$ , with u < v if we can get from u to v by deleting elements of  $\alpha$  and adding elements of  $\beta$ .  $W_{mn}$  is graded of rank m + n with  $\hat{0} = \alpha$  and  $\hat{1} = \beta$ .



# $E_{W_{mn}}$

Simion-S., 1999:

$$E_{W_{mn}} = \sum_{j\geq 0} \binom{m}{j} \binom{n}{j} e_1^{m+n-2j} e_2^j$$

# $E_{W_{mn}}$

Simion-S., 1999:

$$E_{W_{mn}} = \sum_{j\geq 0} \binom{m}{j} \binom{n}{j} e_1^{m+n-2j} e_2^j$$

Corollary. 
$$\mathbb{E}_{w}\left(\frac{\beta_{W_{mn}}(D(w))}{\beta_{n}(D(w))}\right)\left(1/k,\ldots,1/k\right) = \sum_{j\geq 0}\binom{m}{j}\binom{n}{j}\binom{n}{j}\binom{k}{2}^{j}$$

## $E_{W_{mn}}$

Simion-S., 1999:

$$E_{W_{mn}} = \sum_{j\geq 0} \binom{m}{j} \binom{n}{j} e_1^{m+n-2j} e_2^j$$

Corollary. 
$$\mathbb{E}_{w}\left(\frac{\beta_{W_{mn}}(D(w))}{\beta_{n}(D(w))}\right)\left(1/k,\ldots,1/k\right) = \sum_{j\geq 0} \binom{m}{j}\binom{n}{j}\binom{n}{j}\binom{k}{2}^{j}$$

**Corollary.**  $E_{W_{mn}}$  is e-positive, hence Schur concave on probability distributions  $p_1, p_2, \ldots$  Therefore  $\mathbb{E}_w\left(\frac{W_{mn}(D(w))}{\beta_n(D(w))}\right)(p_1, \ldots, p_k)$  is **maximized** for  $p_i = 1/k$ .

### The final slide

### The final slide

