

# Statistical modeling with stochastic processes

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Lecture 6, Wednesday March 16

# Program for today

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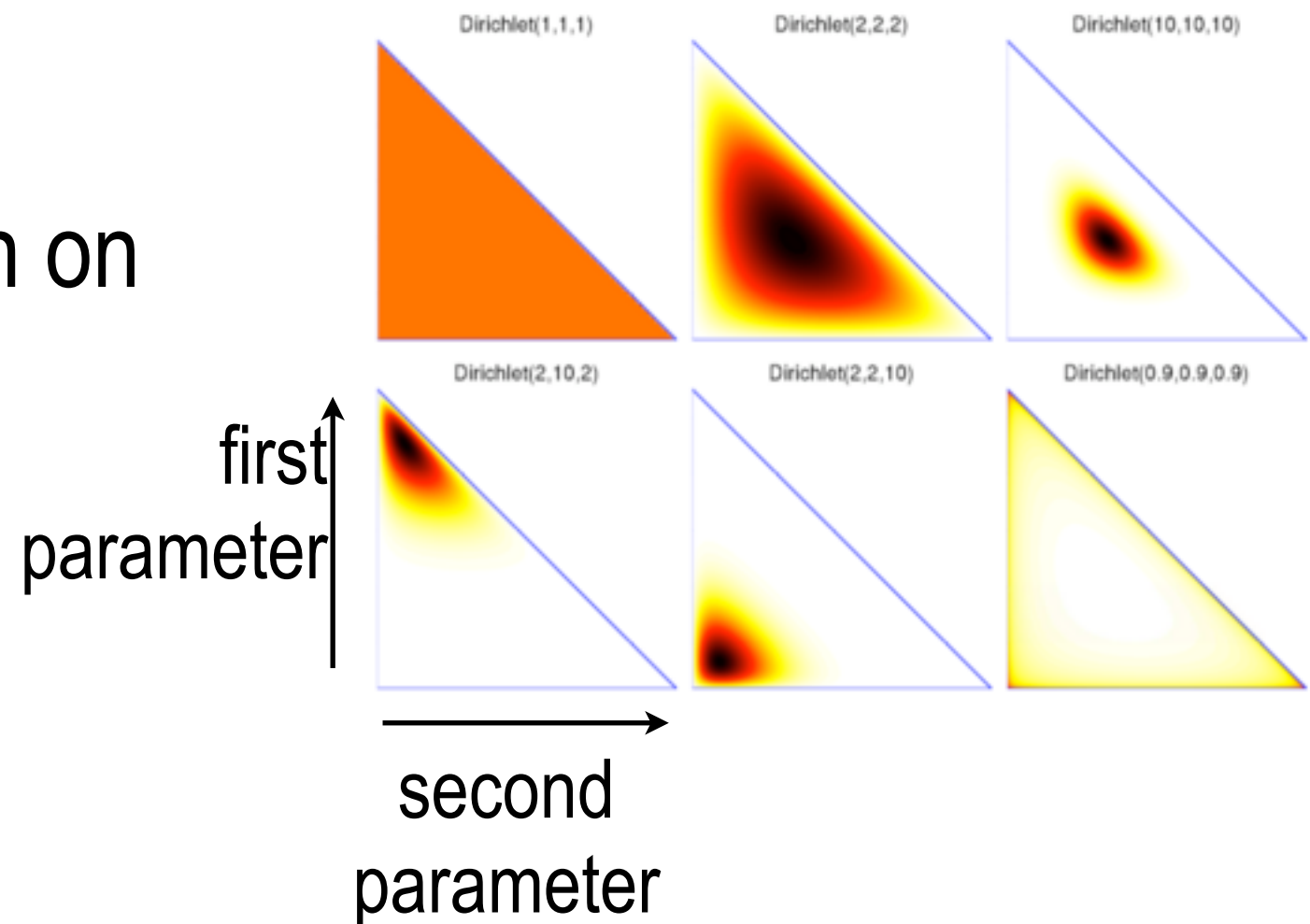
- Introduction to Bayesian non-parametrics
  - The Dirichlet Process: Theoretical foundations
  - Basic properties: posterior conjugacy, predictive distribution, etc
  - Chinese Restaurant, Polya Urn, etc.
- Basic probabilistic inference
  - Collapsed sampler
  - Slice sampler

# Review

# (Finite) Dirichlet distribution

Distribution on the parameters of categorical/multinomial distributions

**Equivalent:** distribution on the simplex

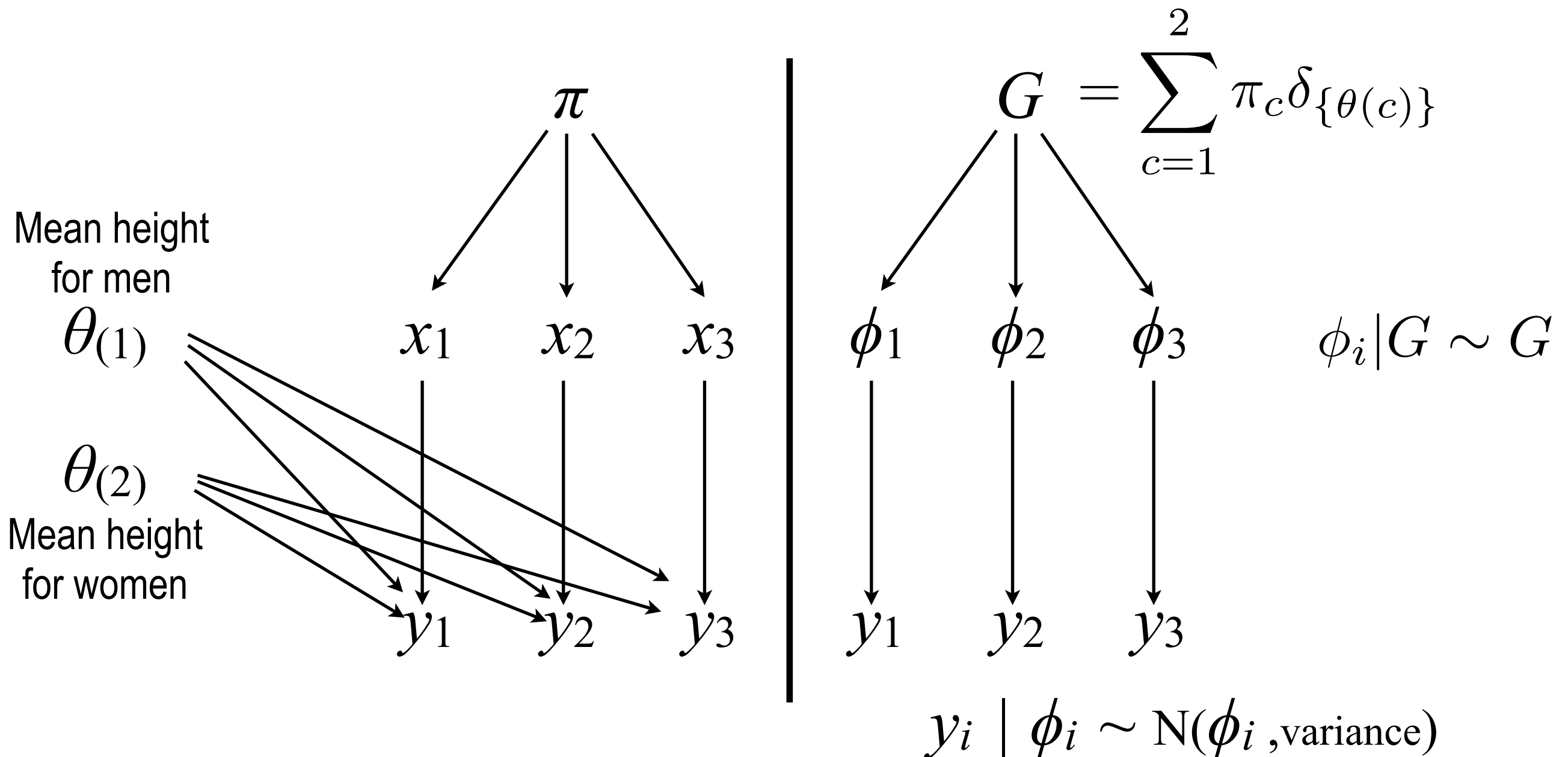


**Density:** for  $\alpha_i > 0$

$$\frac{1}{Z(\alpha)} \prod_{i=1}^K x_i^{\alpha_i - 1} \cdot \mathbf{1} \left[ \sum_i x_i = 1, x_i \geq 0 \right]$$

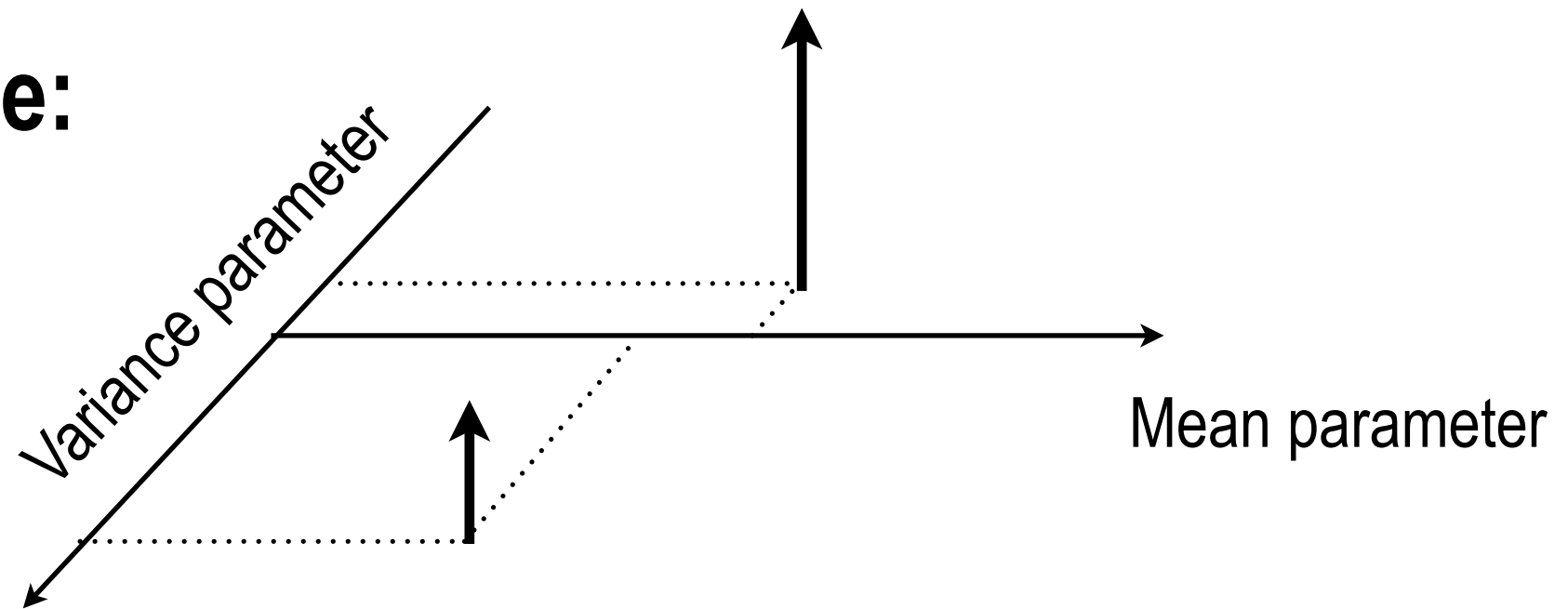
# Equivalent notation

**Mixture model:** (UBC student height with 2 components)  
say we have only 3 observations

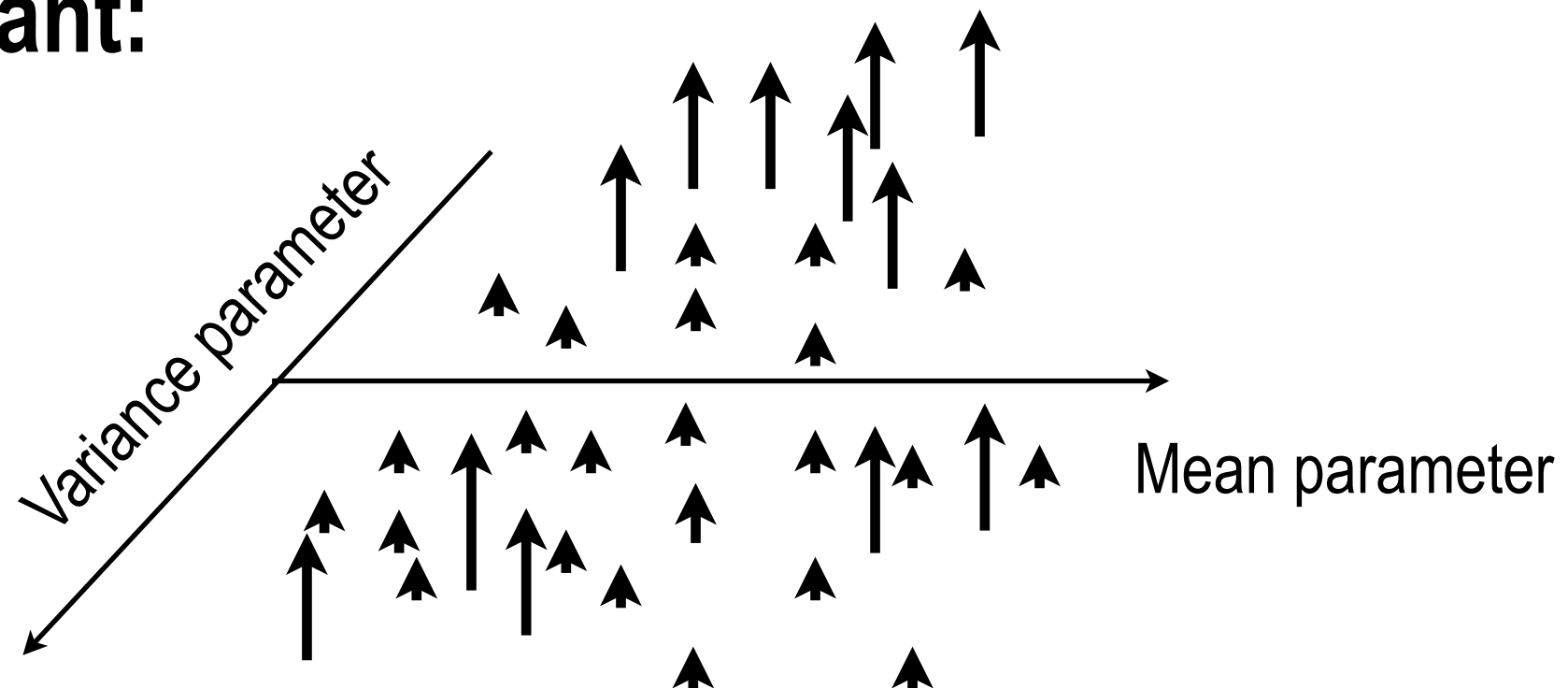


# Samples from $G$

**What we have:**



**What we want:**



# Definition: Dirichlet Process

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Let  $G_0$  be a distribution on a sample space  $\Omega$  (the base distribution)  $\alpha_0$  be a positive real number (the concentration), and  $(A_1, \dots, A_k)$  be a partition of  $\Omega$ . We say

$$G \sim \text{DP}(\alpha_0, G_0)$$

i.e.,  $G$  is a Dirichlet Process, if

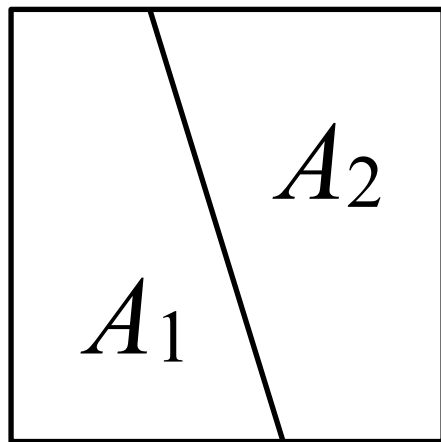
$$(G(A_1), \dots, G(A_k)) \sim \text{Dir}(\alpha_0 G_0(A_1), \dots, \alpha_0 G_0(A_k))$$

for all partitions and all  $k$ .

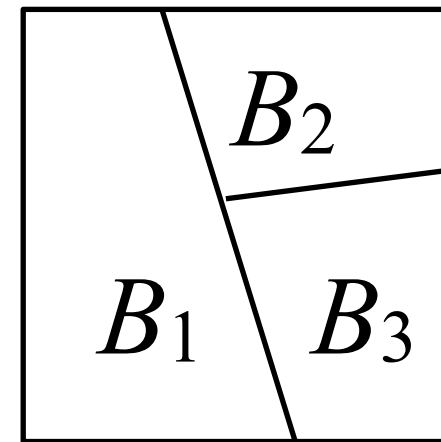
# Does this make sense/exists?

**Kolmogorov consistency:** check the marginals are consistent under marginalization

**In this case:** check that the marginals are consistent when refining partitions



$$(G(A_1), G(A_2))$$
$$(U_1, U_2)$$



$$(G(B_1), G(B_2), G(B_3))$$
$$(V_1, V_2, V_3)$$



# Constructive argument

**Claim:** the random probability distribution constructed below is the Dirichlet process with base distribution  $G_0$  and concentration  $\alpha_0$

$$\beta_j \stackrel{\text{iid}}{\sim} \text{Beta}(1, \alpha_0)$$

$$\theta_c \stackrel{\text{iid}}{\sim} G_0$$

We will denote  
this distribution  
over  $\pi$  by  
 $\text{GEM}(\alpha_0)$

Start with a stick of length 1, and break a segment of length  $\beta_1$  for  $\pi_1$ , keep the rest

$$\pi_1 = \beta_1 \quad \text{---|---}$$

At step  $c$ , if the length of the stick remaining is  $L$ , set:

$$\pi_c = \beta_c L = \beta_c \prod_{j:j < c} (1 - \beta_j) \quad \text{---+---}$$

$$c = 1, 2, 3, \dots$$

$$\theta_c$$

Likelihood  
mixture  
component  
parameters

$$j = 1, 2, 3, \dots$$

$$\beta_j$$

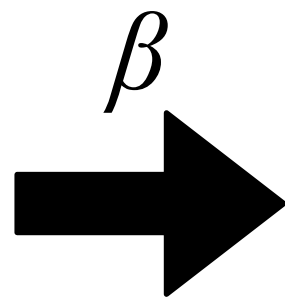
$$c = 1, 2, 3, \dots$$

$$\pi_c$$

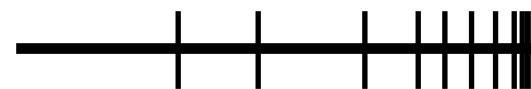
$$G' = \sum_{c=1}^{\infty} \pi_c \delta_{\{\theta(c)\}}$$

# Samples from $G$

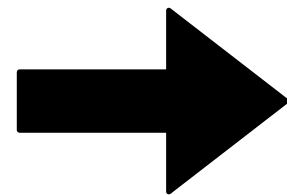
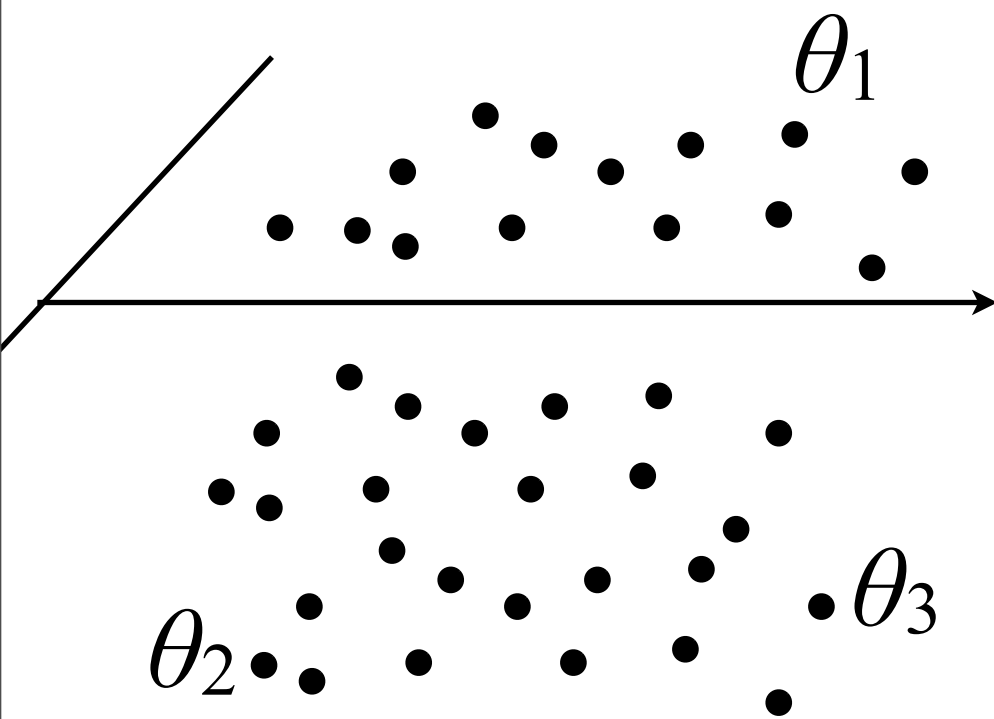
Unit length stick



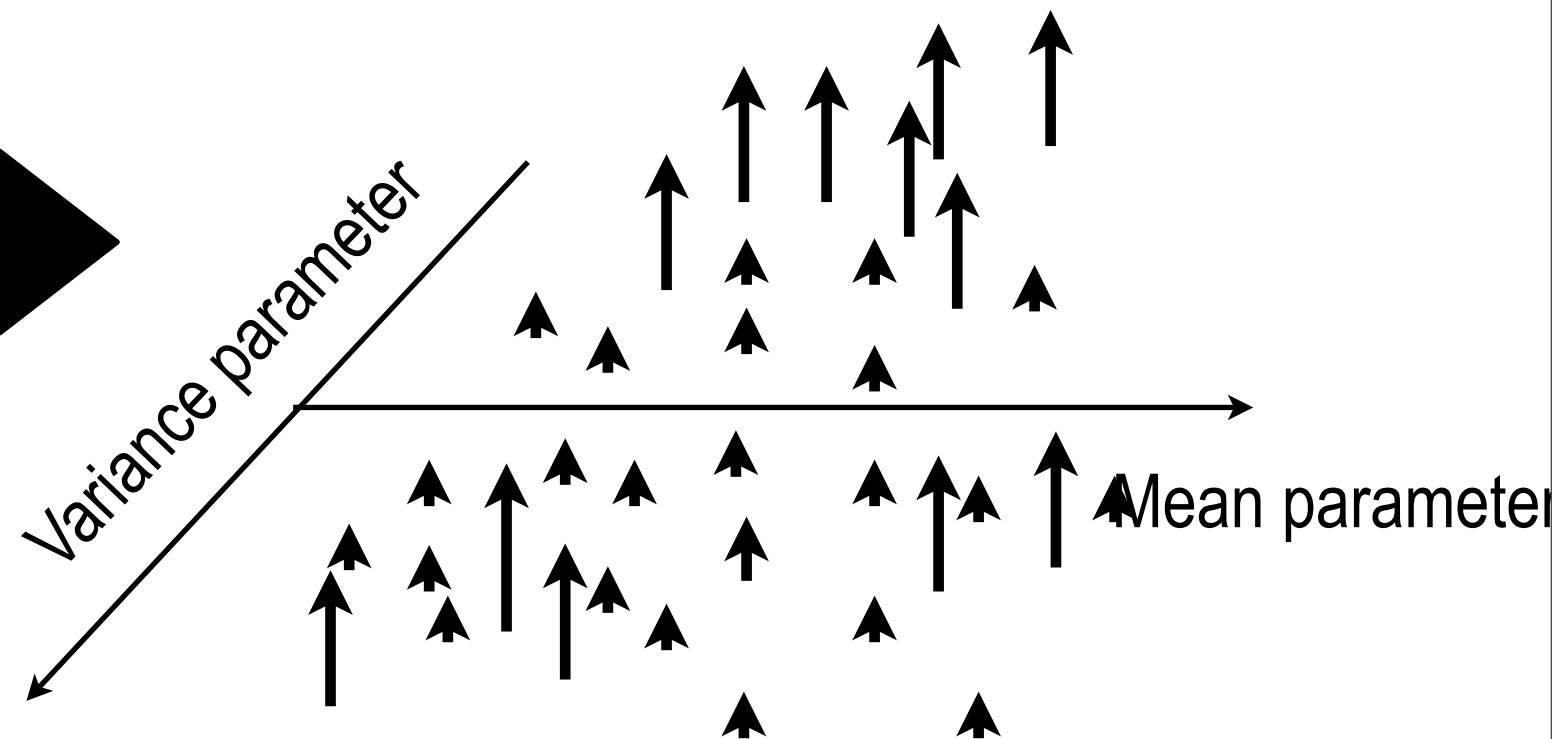
Mixture proportions



Ordered iid  $G_0$  locations



Variance parameter



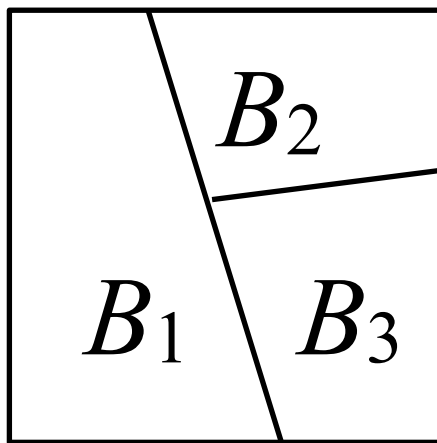
A sample from  $G'$ : a distribution with countably infinite support

Back to the proof that  
 $G = G'$  in distribution

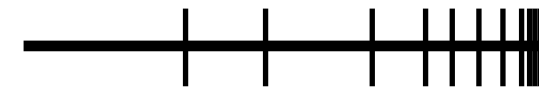
**Reference:** 'A constructive definition of Dirichlet Priors' (1994) Jayaram Sethuraman.

# Goal: showing two definitions are equivalent

**Kolmogorov consistency**



**Stick-breaking construction**



**Strategy:** showing that for all partitions  $(A_1, \dots, A_k)$ , the constructed process  $G'$  has finite Dirichlet marginals

$$(G'(A_1), \dots, G'(A_k)) \sim \text{Dir}(\alpha_0 G_0(A_1), \dots, \alpha_0 G_0(A_k))$$

# Key observation: 'self-similarity'

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**Definitions:**

$$G' = f(\beta, \theta) = \sum_{c=1}^{\infty} \pi_c \delta_{\{\theta(c)\}}$$
$$\beta^* = (\beta_1, \beta_2, \dots)^* = (\beta_2, \beta_3, \dots)$$

**Observation:**

$$G' = \pi_1 \delta_{\{\theta(1)\}} + (1 - \pi_1) f(\beta^*, \theta^*)$$
$$= \pi_1 \delta_{\{\theta(1)\}} + (1 - \pi_1) G'' \quad \text{for } G' \stackrel{d}{=} G''$$

**Notation:**

$$G' \stackrel{st}{=} \pi_1 \delta_{\{\theta(1)\}} + (1 - \pi_1) G' \quad *$$

**How we'll use it:** we will show that if there is a distribution that satisfies this equation, it is unique; and that the finite Dirichlet distribution satisfies it

# Detailed plan

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Finite Dirichlet  
distributions satisfy  
equation (\*)

**Equation (\*) has a  
unique solution**

$G'$  satisfies  
equation (\*)  $\implies$  The marginals of  $G'$  satisfy  
equation (\*)  $\implies G'$  has Dirichlet  
marginals

$$G \stackrel{d}{=} G'$$

# Lemma: uniqueness of the solution of \*

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**Notation:**

$$\begin{array}{c} G' \\ \blacktriangledown \\ V \end{array} = \pi_1 \delta_{\{\theta(1)\}} + (1 - \pi_1) \begin{array}{c} G'' \\ \blacktriangledown \\ V \end{array}$$
$$\begin{array}{c} \blacktriangledown \\ U \end{array} + \begin{array}{c} \blacktriangledown \\ W \end{array}$$

\*

**Properties we use:**

- $G''$  is independent of  $(U, W)$
- $P(0 < W < 1/2) > 0$

(Proof of uniqueness on the board)

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# Lemmas

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**Lemma 1.** Let:  $U \sim \text{Dir}(\alpha_1, \dots, \alpha_k),$   $\alpha_0 = \sum_{i=1}^k \alpha_i$   
 $V \sim \text{Dir}(\gamma_1, \dots, \gamma_k)$   
 $W \sim \text{Beta}(\alpha_0, \gamma_0)$  all indep.

Then:  $WU + (1 - W)V \sim \text{Dir}(\alpha + \gamma)$

**Proof:** Gamma/neutral representation

# Lemmas

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**Lemma 2.** Let:  $e_j$  = a unit basis vector

$$\bar{\gamma}_j = \frac{\gamma_j}{\gamma_0}$$

Then:  $\sum_{j=1}^k \bar{\gamma}_j \text{Dir}(\gamma + e_j) \sim \text{Dir}(\gamma)$

**Proof:** Exercise (next assignment)

# Main proof: finite Dirichlet satisfies \*

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**Goal:** showing that:

$$V \sim \text{Dir}(\gamma_1, \dots, \gamma_k)$$

satisfies equation (\*) projected to the marginal of a finite partition

**Steps:**

- 1- Condition on the partition indicator  $X$  in which the first atom falls in
- 2- Sum over the possible values of  $X$

# Detailed plan

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Finite Dirichlet  
distributions satisfy  
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$$G \stackrel{d}{=} G'$$

# Main properties of Dirichlet Processes

# Moments

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Let  $G \sim \text{DP}(\alpha_0, G_0)$  and  $A$  be a measurable set

**Exercise:** find the first and second moments of  $G(A)$

(Derivation of the moments on the board)

# Towards conjugacy

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Let  $G \sim \text{DP}(\alpha_0, G_0)$  and  $(A_1, \dots, A_k)$  be a measurable partition. Let  $\theta$  be a draw from  $G$ , i.e.:  $\theta \mid G \sim G$

By multinomial-Dirichlet conjugacy, we have:

$$(G(A_1), \dots, G(A_k)) \mid \theta \sim \text{Dir}(\alpha_0 G_0(A_1) + \delta_{\{\theta\}}(A_1), \dots, \alpha_0 G_0(A_k) + \delta_{\{\theta\}}(A_k))$$

Since this is true for all partitions, this means the posterior is a Dirichlet process as well!

**Reference:** 'The theory of statistics' (1995) Mark J. Schervish

# Conjugacy

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**Found:**

$$\begin{aligned} & (G(A_1), \dots, G(A_k)) | \theta \sim \\ & \text{Dir}(\alpha_0 G_0(A_1) + \delta_{\{\theta\}}(A_1), \dots, \alpha_0 G_0(A_k) + \delta_{\{\theta\}}(A_k)) \end{aligned}$$

**Next:** Identifying the new parameters  $\alpha'_0$  and  $G'_0$  of the posterior distribution...

$$\begin{aligned} \alpha'_0 &= \sum_k \left( \alpha_0 G_0(A_k) + \delta_{\{\theta\}}(A_k) \right) = \alpha_0 + 1 \\ G'_0 &= \frac{\alpha_0}{\alpha_0 + 1} G_0 + \frac{1}{\alpha_0 + 1} \delta_{\{\theta\}} \end{aligned}$$



# General formula

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Suppose now we have several draws from  $G$ :

$$(G(A_1), \dots, G(A_k)) | \theta_1, \dots, \theta_n \sim \\ \text{Dir}(\alpha_0 G_0(A_1) + n_1, \dots, \alpha_0 G_0(A_k) + n_k)$$

where: 
$$n_j = \sum_{i=1}^n \delta_{\{\theta_i\}}(A_j)$$

Therefore the posterior parameters are:

$$\alpha'_0 = \alpha_0 + n$$

$$G'_0 = \frac{\alpha_0}{\alpha_0 + n} G_0 + \frac{1}{\alpha_0 + n} \sum_{i=1}^n \delta_{\{\theta_i\}}$$

# Predictive distribution

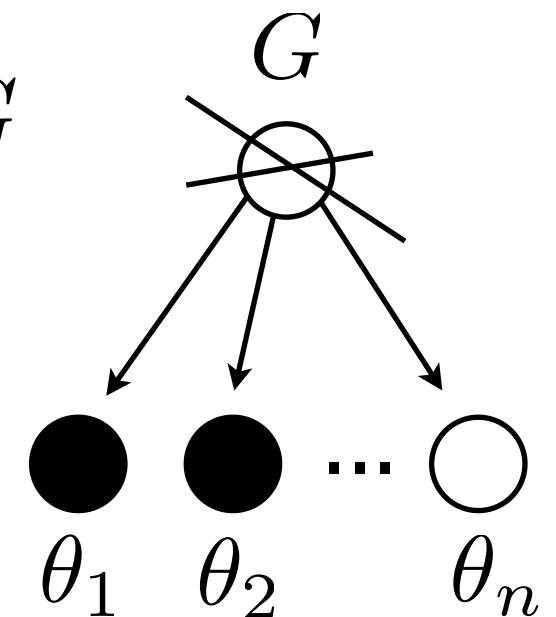
**Predictive distribution:**  $\theta_{n+1} | \theta_1, \dots, \theta_n$

**Motivation for marginalizing  $G$ :** posterior inference using MCMC on a *finite* state space

Let  $A$  be a measurable set,  $G \sim \text{DP}(G_0, \alpha_0)$

$$\theta_1, \dots, \theta_{n+1} | G \sim G$$

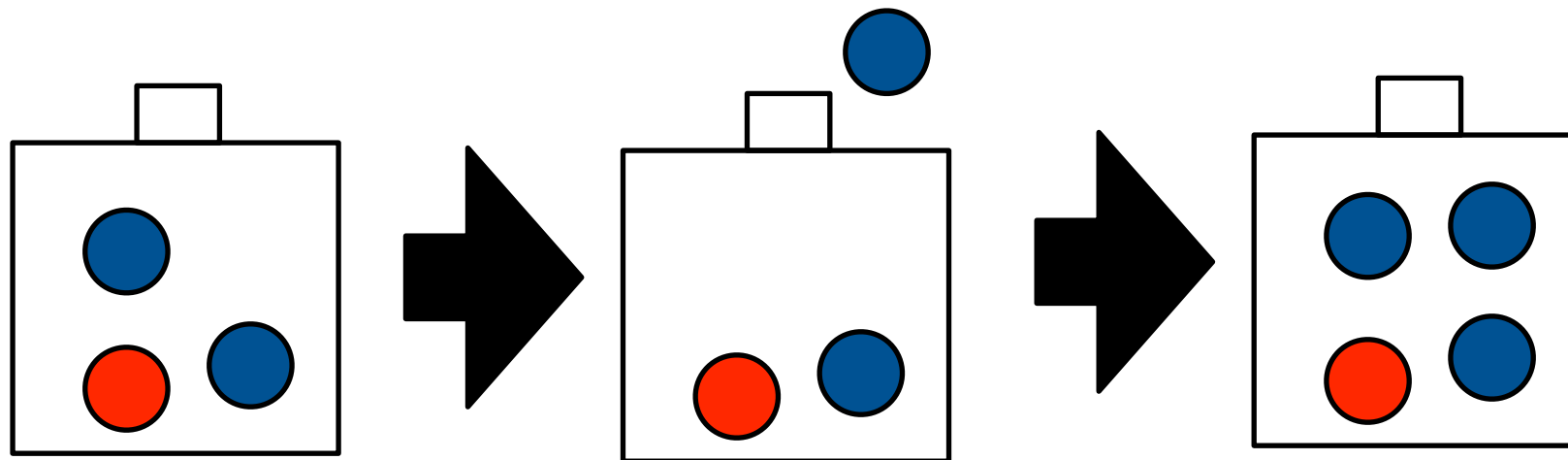
(Derivation of the predictive dist. on the board)



# Application: Pólya Urn

**Thought experiment:** Consider an urn, with initially  $R$  red marbles and  $B$  blue marbles.

At each step, draw one marble at random, and put it back in the urn after adding another one of the same color



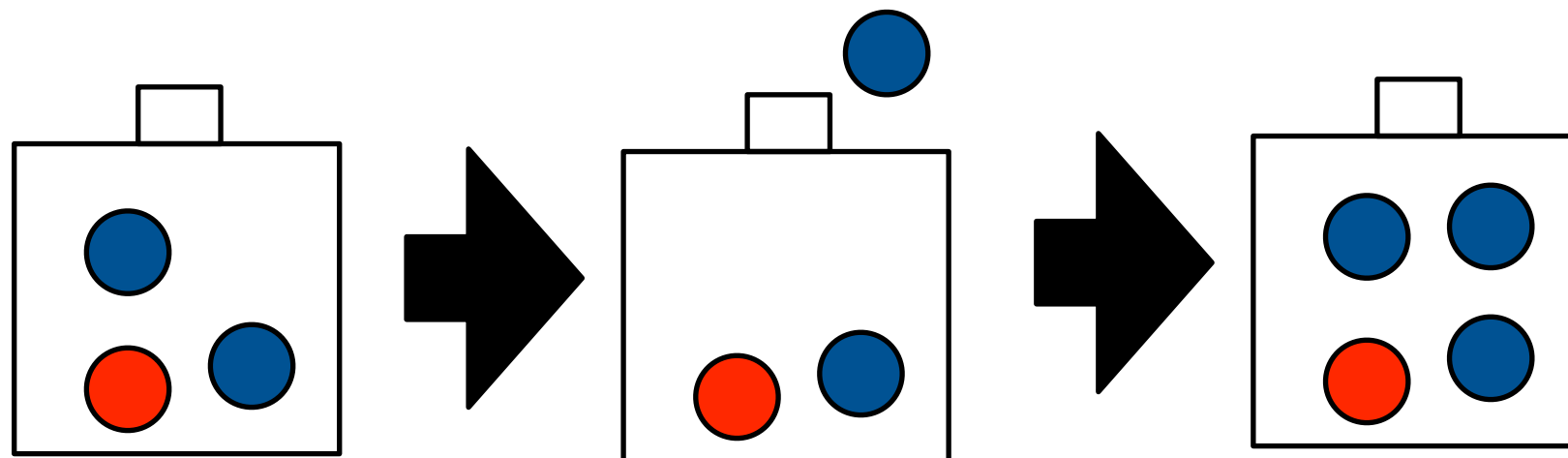
**Question:** does this process converge to a certain red:blue ratio? What is this ratio?

# Application: Pólya Urn

**Thought experiment:** Consider an urn, with initially  $R$  red marbles and  $B$  blue marbles.

**Question:** does this process converge to a certain red:blue ratio? What is this ratio?

**Hint:** Let  $\alpha_0 = R + B$        $G_0 = \text{Bern} \left( \frac{R}{B + R} \right)$



(Solution described on the board)

# Chinese Restaurant Process (CRP)

**Idea:** Instead of colors sharing colors, think about customers sharing tables in an infinite restaurant

**Initialization:** The first customer sits in the first empty table.

**Iterate:** If  $n$  customers are already sitting in the restaurant, the next customer starts a new table with probability  $\alpha_0 / (\alpha_0 + n)$ ; otherwise the customer joins an existing table with probability proportional to the number of people already at the table

**E.g.:**

