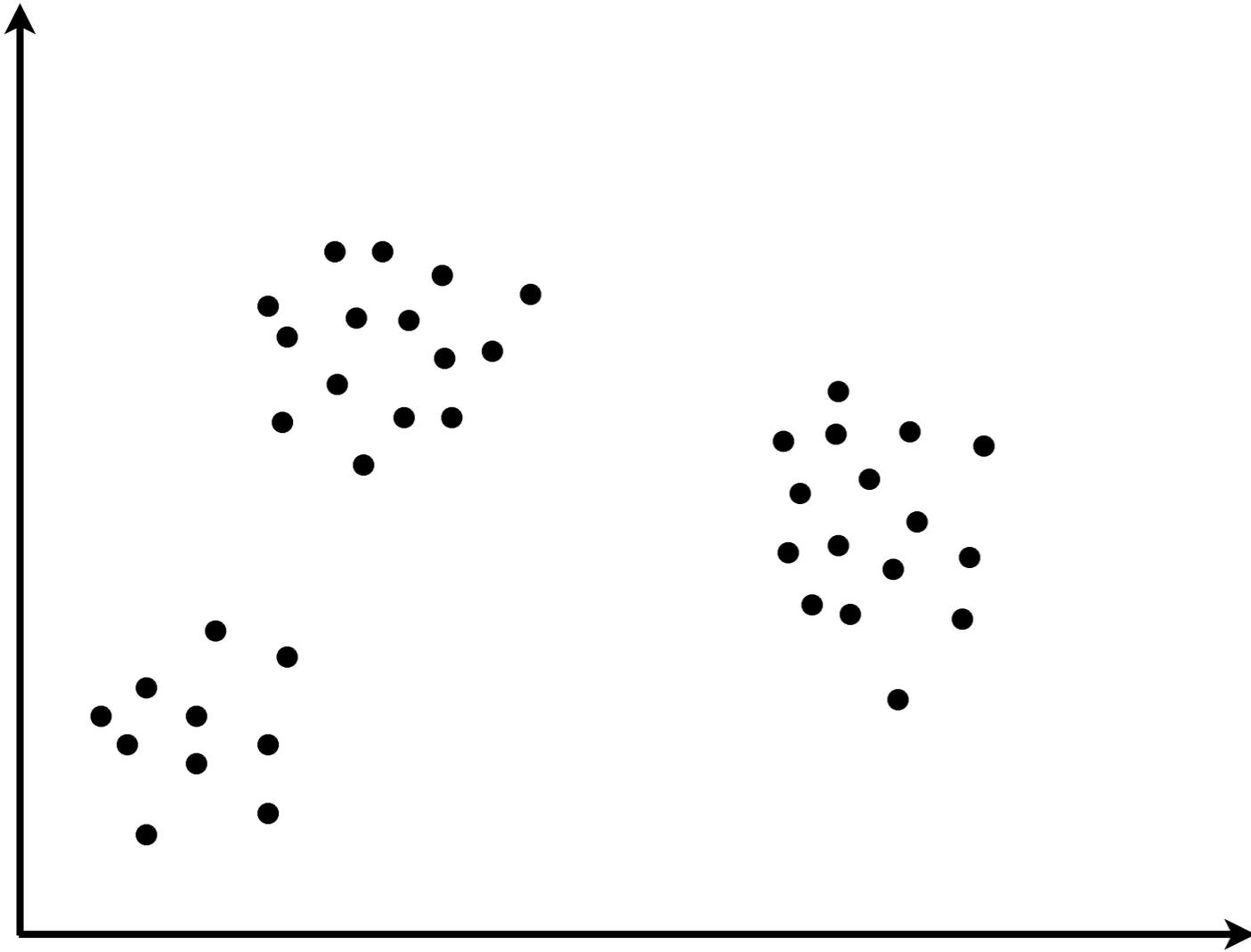




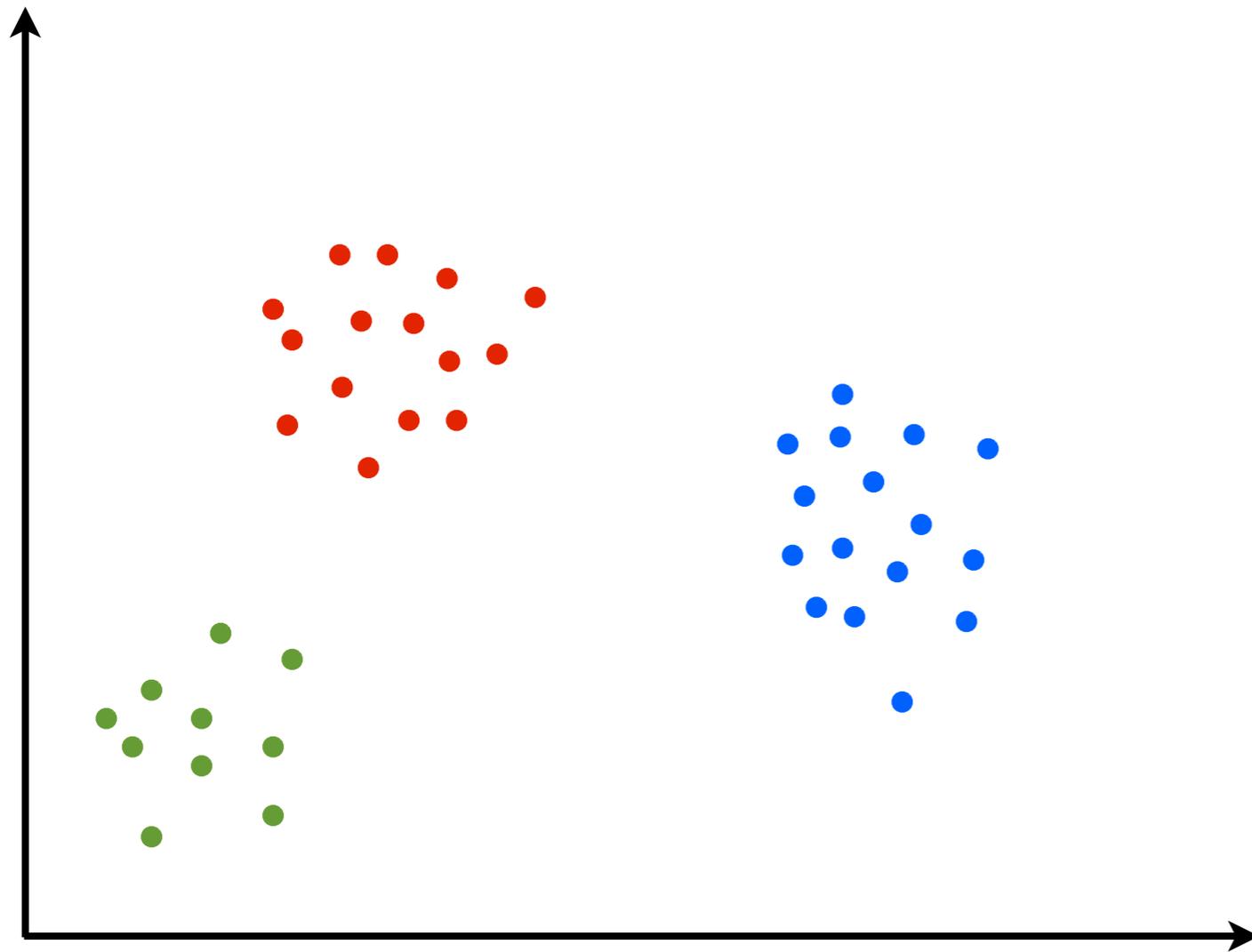
# Feature allocations, probability functions, and paintboxes

Tamara Broderick  
UC Berkeley  
(MIT starting Spring 2015)

# Clustering/Partition

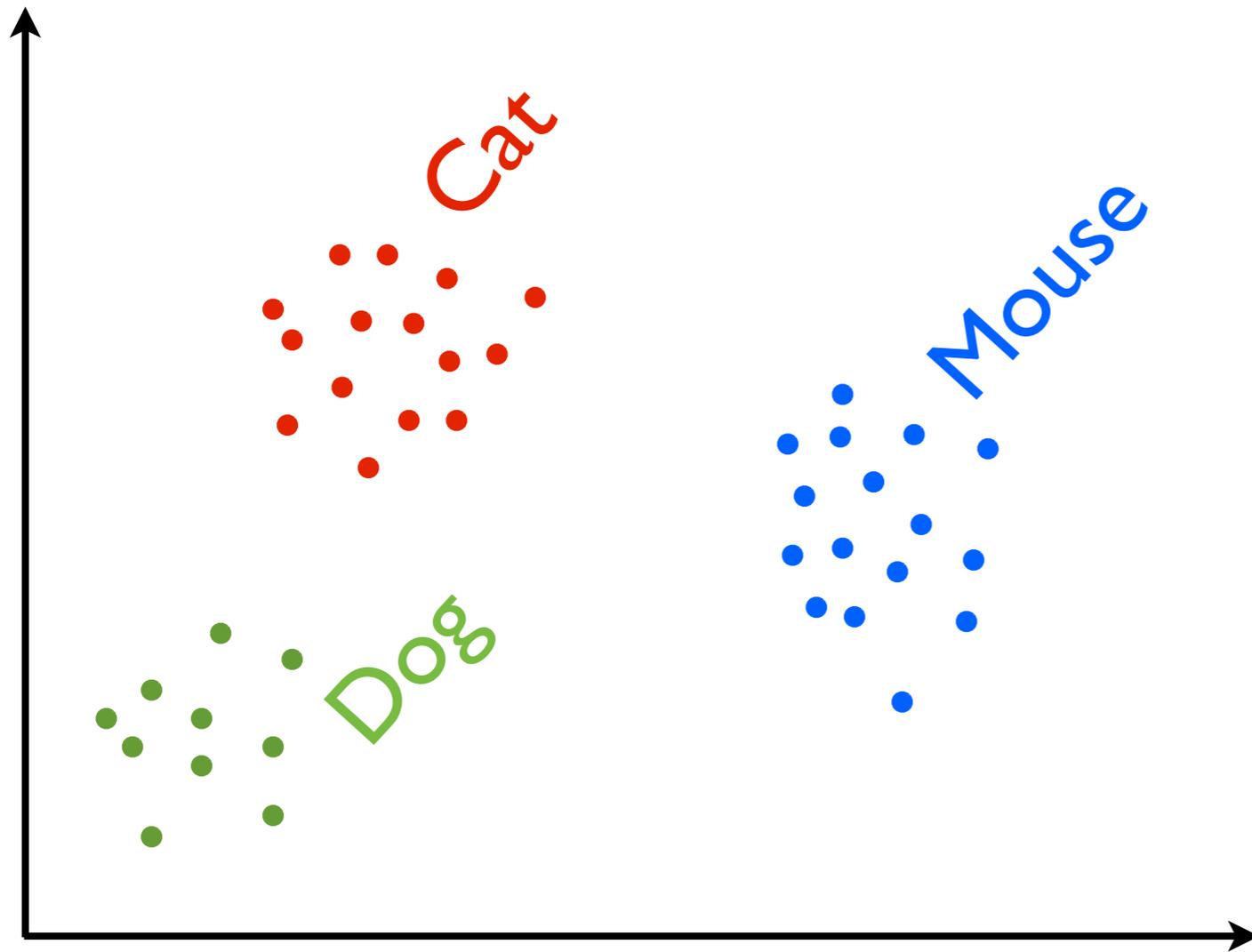


# Clustering/Partition



“clusters”,  
“classes”,  
“blocks (of a partition)”

# Clustering/Partition



“clusters”,  
“classes”,  
“blocks (of a partition)”

# Clustering/Partition

	Cat	Dog	Mouse	Lizard	Sheep
Picture 1	■				
Picture 2	■				
Picture 3		■			
Picture 4			■		
Picture 5		■			
Picture 6				■	
Picture 7	■				

# Latent feature allocation

	Cat	Dog	Mouse	Lizard	Sheep
Picture 1	■				■
Picture 2	■			■	■
Picture 3	■	■		■	■
Picture 4			■	■	■
Picture 5		■			■
Picture 6				■	■
Picture 7					

“features”,  
“topics”

# Latent feature allocation

	Cat	Dog	Mouse	Lizard	Sheep
Picture 1	■				■
Picture 2	■			■	■
Picture 3	■	■		■	■
Picture 4			■	■	■
Picture 5		■			■
Picture 6				■	■
Picture 7					

“features”,  
“topics”

- Exchangeable
- Finite # of features per data point

# Characterizations

- Exchangeable cluster distributions are characterized
- What about exchangeable feature distributions?

# Exchangeable probability functions

$$\mathbb{P} \left( \begin{array}{c} 1 \\ 2 \\ \vdots \\ N \end{array} \begin{array}{ccccc} 1 & 2 & \dots & K & \\ \blacksquare & \square & \square & \square & \square \\ \blacksquare & \square & \square & \square & \square \\ \square & \blacksquare & \square & \square & \square \\ \square & \square & \blacksquare & \square & \square \\ \square & \blacksquare & \square & \square & \square \\ \square & \square & \square & \blacksquare & \square \\ \blacksquare & \square & \square & \square & \square \end{array} \right)$$

# Exchangeable probability functions

$$\mathbb{P} \left( \begin{array}{c} 1 \\ 2 \\ \vdots \\ N \end{array} \begin{array}{c} 1 \ 2 \ \dots \ K \\ \begin{array}{|c|c|c|c|c|} \hline \blacksquare & \square & \square & \square & \square \\ \hline \blacksquare & \square & \square & \square & \square \\ \hline \square & \blacksquare & \square & \square & \square \\ \hline \square & \square & \blacksquare & \square & \square \\ \hline \square & \blacksquare & \square & \square & \square \\ \hline \square & \square & \square & \blacksquare & \square \\ \hline \blacksquare & \square & \square & \square & \square \\ \hline \end{array} \end{array} \right) = p(S_{N,1}, \dots, S_{N,K})$$

# Exchangeable probability functions

1 2 ... K

1  
2  
⋮  
N


) =  $p(S_{N,1}, \dots, S_{N,K})$

Size of  $K$ th cluster

↓

# Exchangeable probability functions

## Exchangeable partition probability function (EPPF)

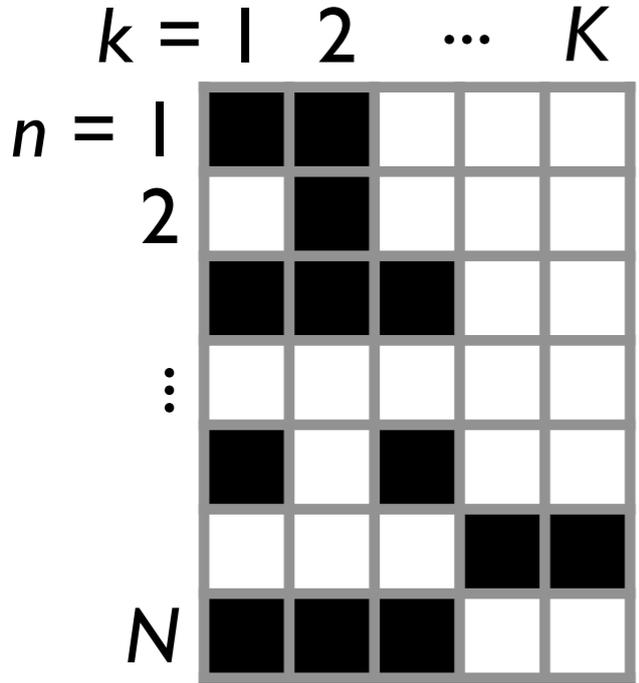
$$\mathbb{P} \left( \begin{array}{c} 1 \\ 2 \\ \vdots \\ N \end{array} \begin{array}{c} 1 \ 2 \ \dots \ K \\ \begin{array}{|c|c|c|c|c|} \hline \blacksquare & & & & \\ \hline \blacksquare & & & & \\ \hline & \blacksquare & & & \\ \hline & & \blacksquare & & \\ \hline & \blacksquare & & & \\ \hline & & & \blacksquare & \\ \hline \blacksquare & & & & \\ \hline \end{array} \end{array} \right) = p(S_{N,1}, \dots, S_{N,K})$$

# Exchangeable probability functions

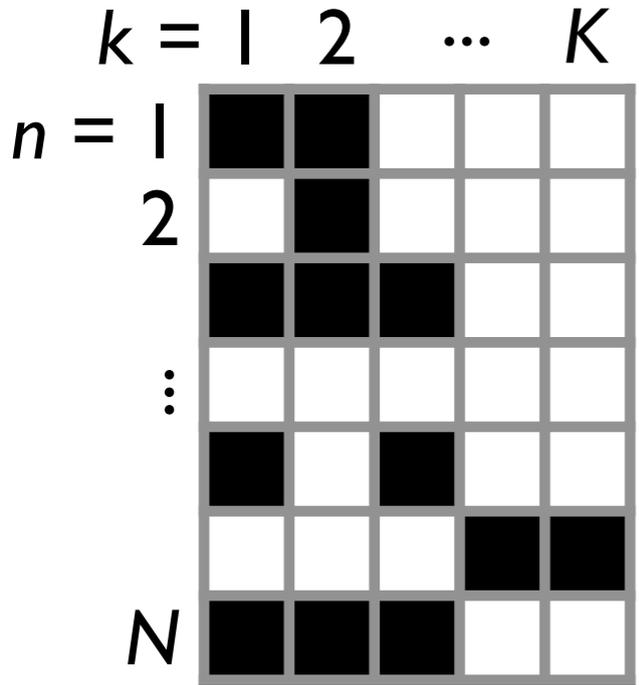
**“Exchangeable feature probability function” (EFPF)?**

# Example: Indian buffet process

# Example: Indian buffet process



# Example: Indian buffet process



For  $n = 1, 2, \dots, N$

# Example: Indian buffet process

	$k = 1$	$2$	$\dots$	$K$
$n = 1$	■	■		
$2$		■		
$\vdots$	■	■	■	
	■		■	
				■
$N$	■	■	■	

For  $n = 1, 2, \dots, N$

1. Data point  $n$  has an existing feature  $k$  that has already occurred  $S_{n-1,k}$  times with probability  $\frac{S_{n-1,k}}{\theta + n - 1}$

# Example: Indian buffet process

	$k = 1$	2	...	$K$
$n = 1$	■	■		
2		■		
⋮	■	■	■	
	■		■	
				■
$N$	■	■	■	

For  $n = 1, 2, \dots, N$

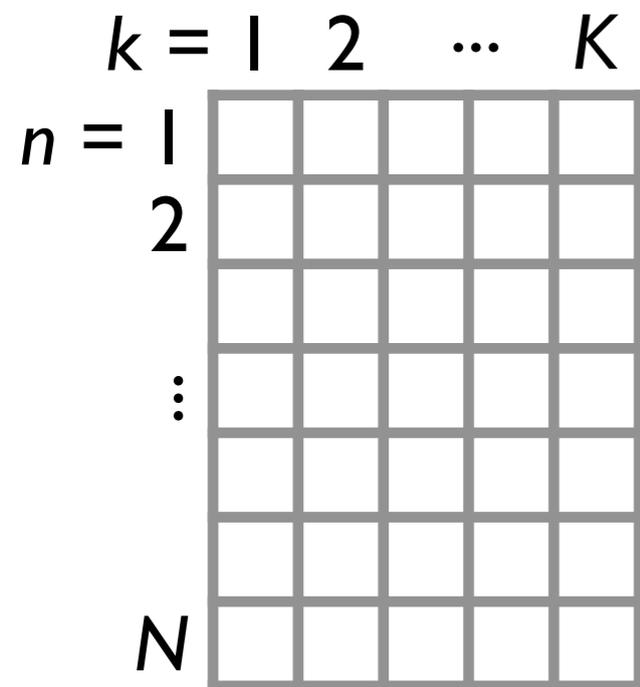
1. Data point  $n$  has an existing feature  $k$  that has already occurred  $S_{n-1,k}$  times with probability

$$\frac{S_{n-1,k}}{\theta + n - 1}$$

2. Number of new features for data

point  $n$ :  $K_n^+ = \text{Poisson} \left( \gamma \frac{\theta}{\theta + n - 1} \right)$

# Example: Indian buffet process



For  $n = 1, 2, \dots, N$

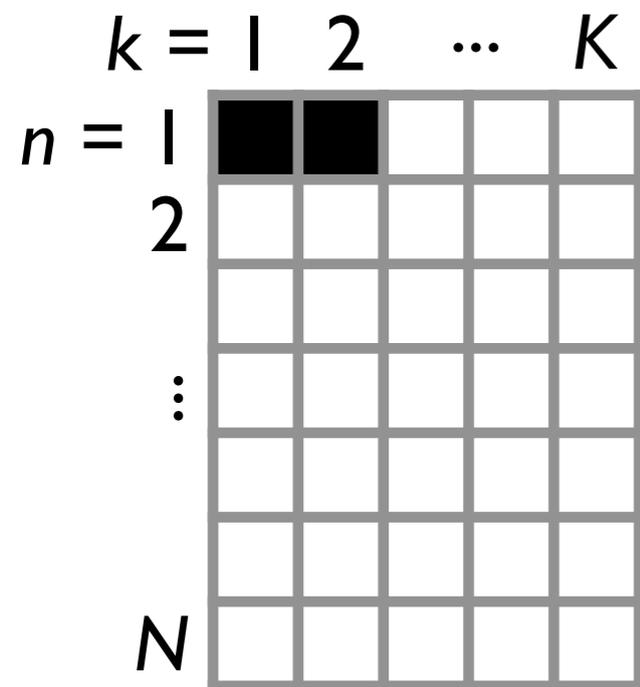
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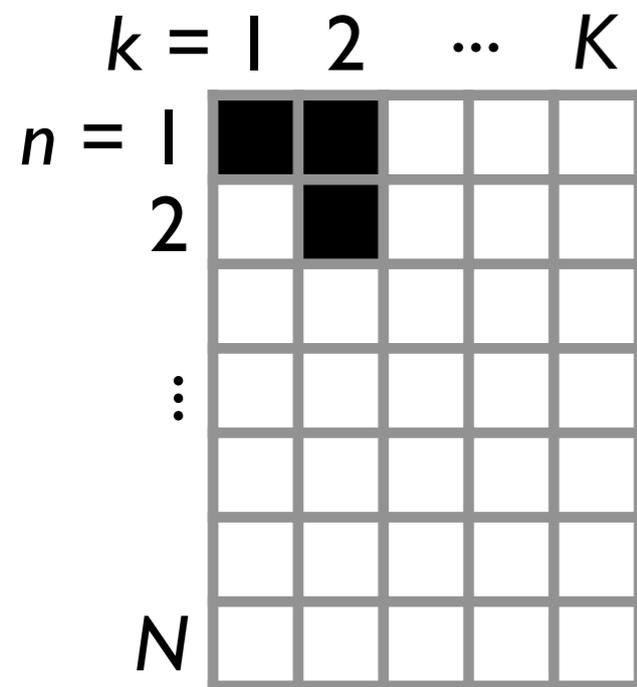
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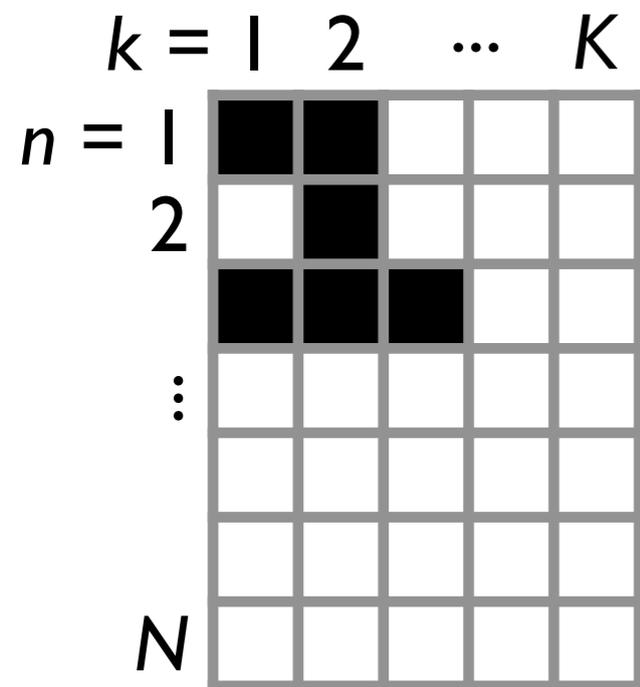
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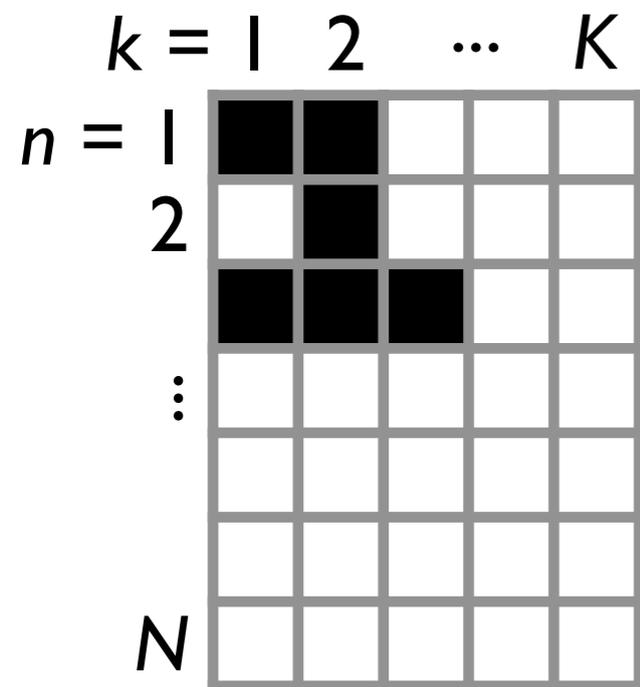
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# Example: Indian buffet process



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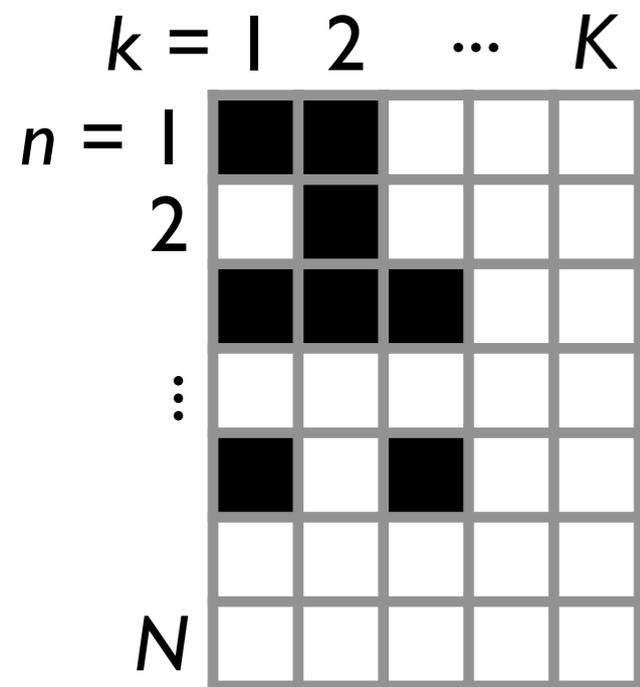
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# Example: Indian buffet process



For  $n = 1, 2, \dots, N$

1. Data point  $n$  has an existing feature

$k$  that has already occurred  $S_{n-1,k}$

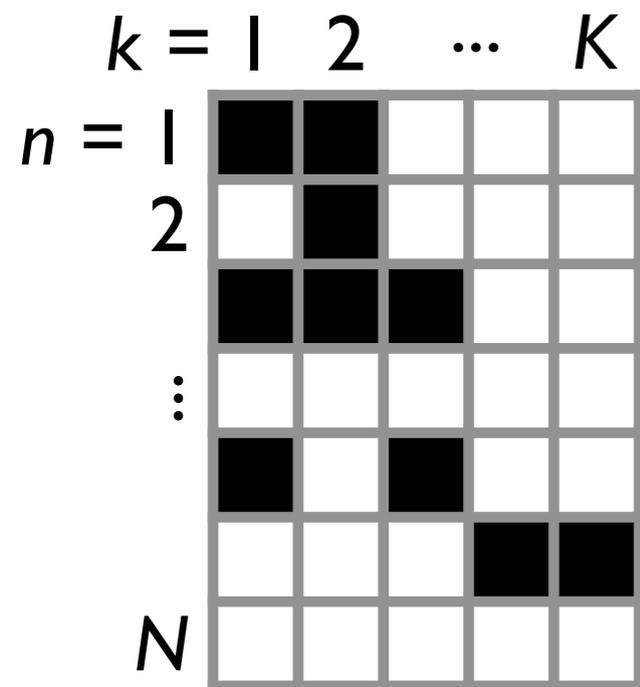
times with probability  $\frac{S_{n-1,k}}{\theta + n - 1}$

$$\frac{S_{n-1,k}}{\theta + n - 1}$$

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	$k = 1$	2	...	$K$
$n = 1$	■	■		
2		■		
⋮	■	■	■	
	■		■	
				■
$N$	■	■	■	

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# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

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“Exchangeable feature probability function” (EFPF)?

Example: Indian buffet process (IBP)

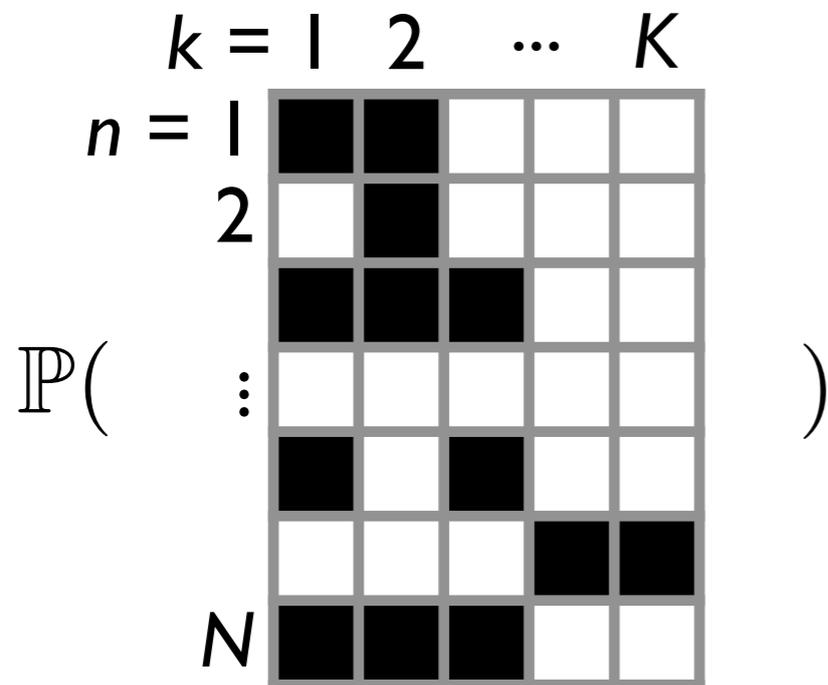
	$k = 1$	$2$	$\dots$	$K$
$n = 1$	■	■	□	□
$2$	□	■	□	□
$\vdots$	■	■	■	□
	□	□	□	□
	■	□	■	□
	□	□	□	■
$N$	■	■	■	□

$\mathbb{P}( \quad )$

# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

Example: Indian buffet process (IBP)

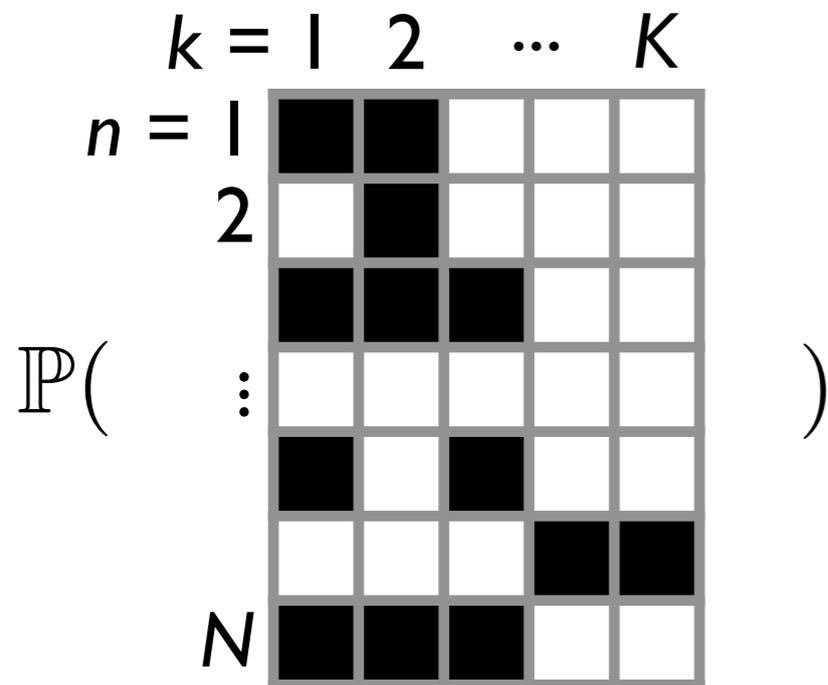


$$= \frac{1}{K_N!} (\theta \gamma)^{K_N} \exp \left( -\theta \gamma \sum_{n=1}^N (\theta + n - 1)^{-1} \right) \prod_{k=1}^{K_N} \frac{\Gamma(S_{N,k}) \Gamma(N - S_{N,k} + \theta)}{\Gamma(N + \theta)}$$

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Example: Indian buffet process (IBP)



Size of  $k$ th feature

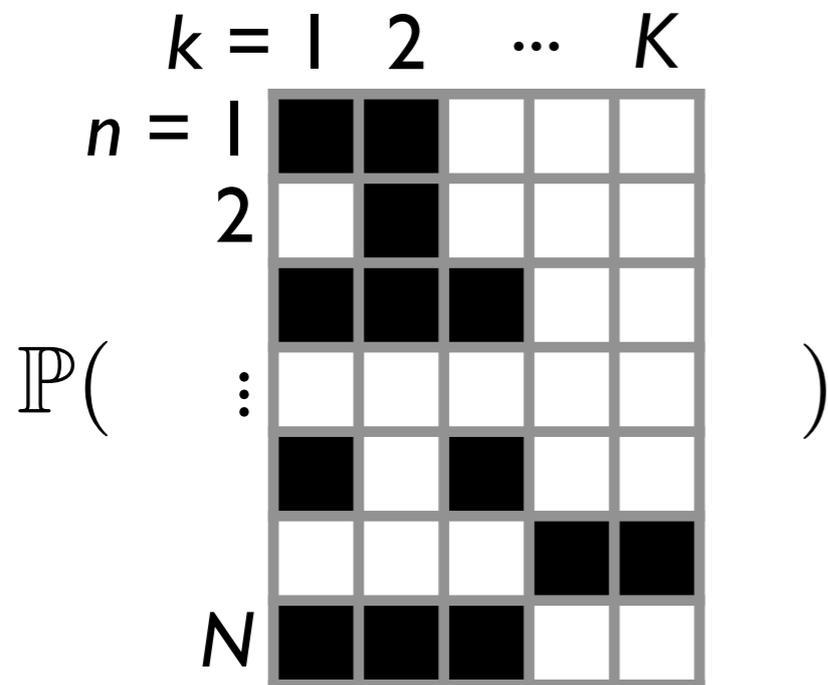
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↓

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“Exchangeable feature probability function” (EFPF)?

Example: Indian buffet process (IBP)



Number of features

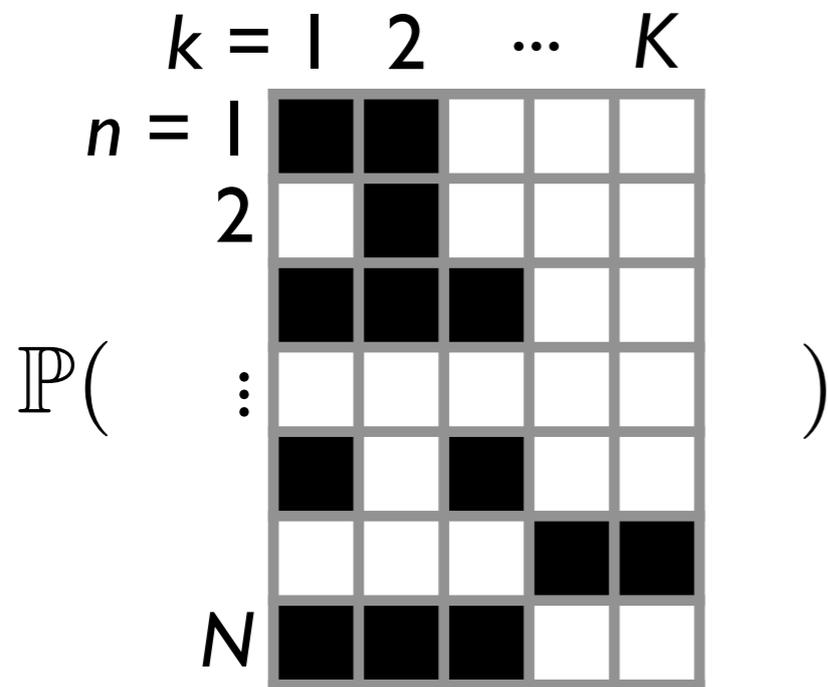
Size of  $k$ th feature

$$= \frac{1}{K_N!} (\theta\gamma)^{K_N} \exp\left(-\theta\gamma \sum_{n=1}^N (\theta + n - 1)^{-1}\right) \prod_{k=1}^{K_N} \frac{\Gamma(S_{N,k})\Gamma(N - S_{N,k} + \theta)}{\Gamma(N + \theta)}$$

# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

Example: Indian buffet process (IBP)



Number of data points

Size of  $k$ th feature

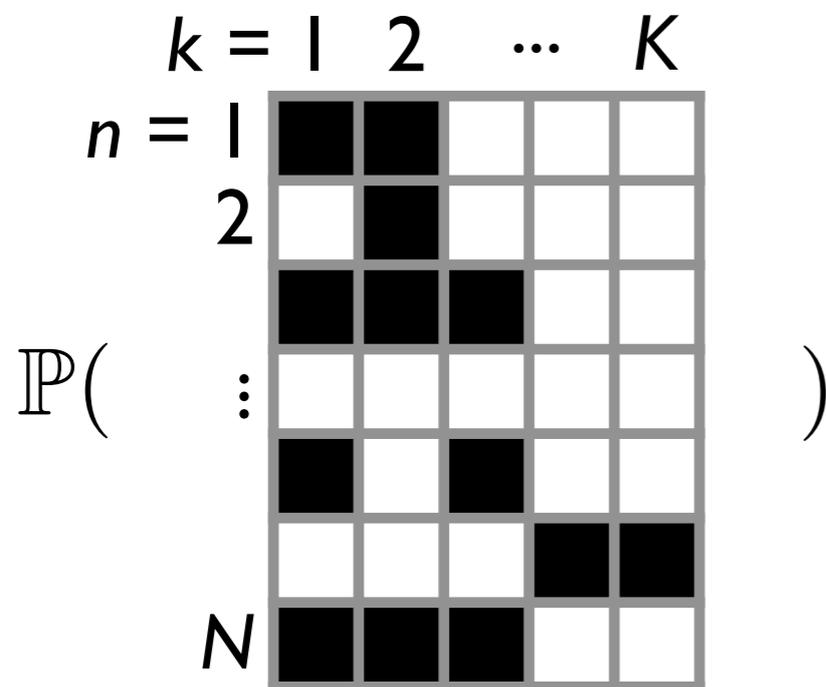
Number of features

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Example: Indian buffet process (IBP)



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Size of  $k$ th feature

Number of features

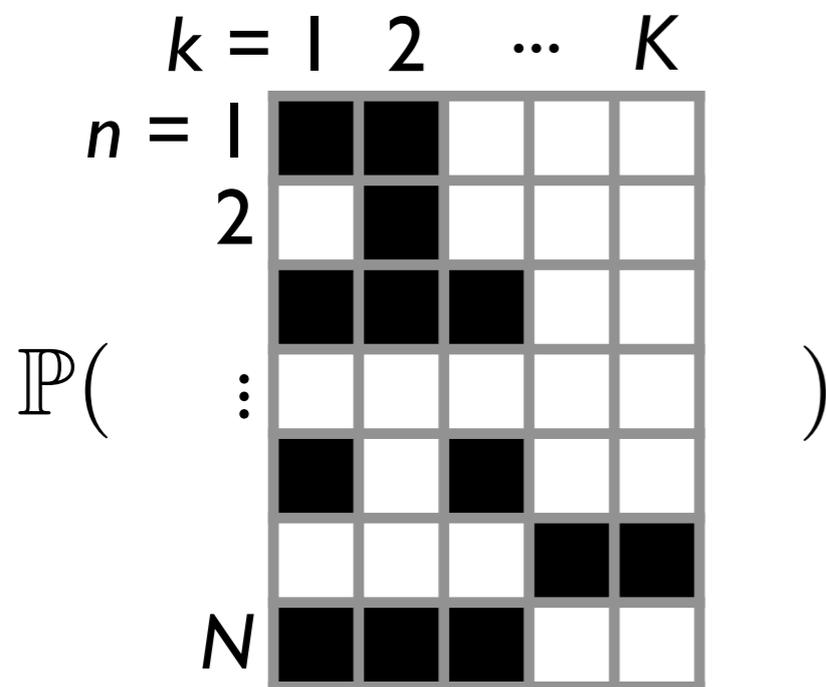
$$= \frac{1}{K_N!} (\theta \gamma)^{K_N} \exp \left( -\theta \gamma \sum_{n=1}^N (\theta + n - 1)^{-1} \right) \prod_{k=1}^{K_N} \frac{\Gamma(S_{N,k}) \Gamma(N - S_{N,k} + \theta)}{\Gamma(N + \theta)}$$

$$= p(N; S_{N,1}, S_{N,2}, \dots, S_{N,K})$$

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Example: Indian buffet process (IBP)



Number of data points

Size of  $k$ th feature

Number of features

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“EFPF”

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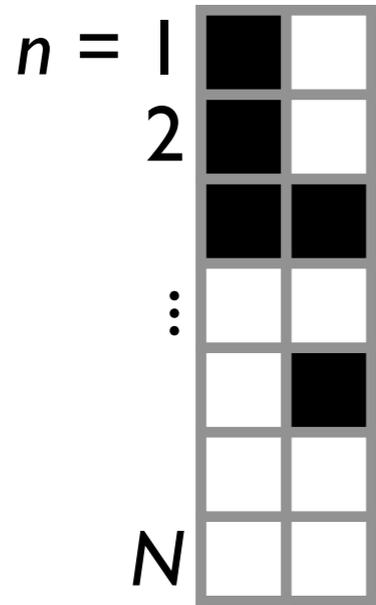
Counterexample

$n = 1$	■	□
2	■	□
	■	■
⋮	□	□
	□	■
	□	□
$N$	□	□

# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

Counterexample



$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \end{array}) = p_1$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \blacksquare \\ \hline \end{array}) = p_2$$

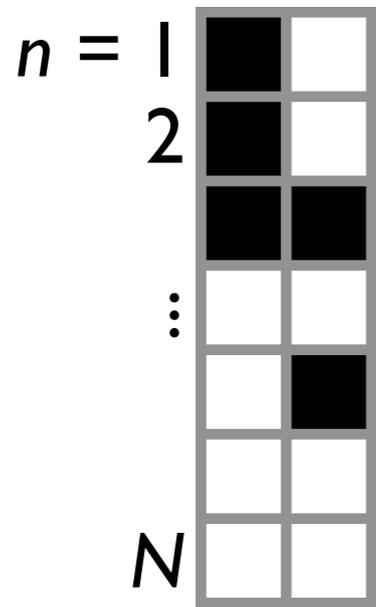
$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \blacksquare \\ \hline \end{array}) = p_3$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$

# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

Counterexample

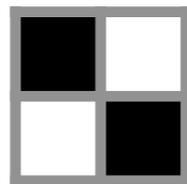


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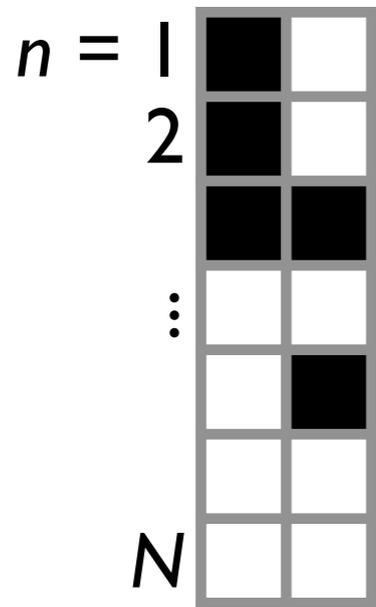
$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$



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Counterexample



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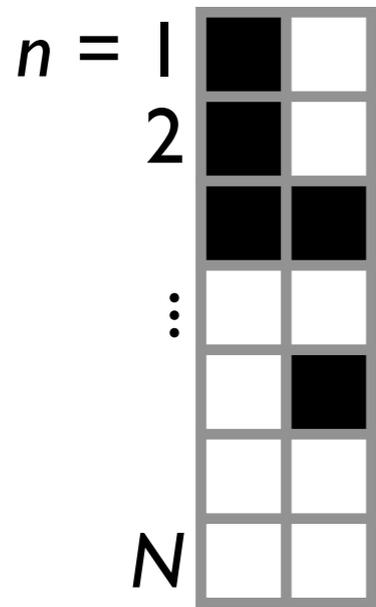
$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$

$$\mathbb{P}\left(\begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \square & \blacksquare \\ \hline \end{array}\right) \quad \mathbb{P}\left(\begin{array}{|c|c|} \hline \blacksquare & \blacksquare \\ \hline \square & \square \\ \hline \end{array}\right)$$

# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

Counterexample



$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \end{array}) = p_1$$

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$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$

$$\mathbb{P}(\begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \square & \blacksquare \\ \hline \end{array})$$

$$p_1 p_2$$

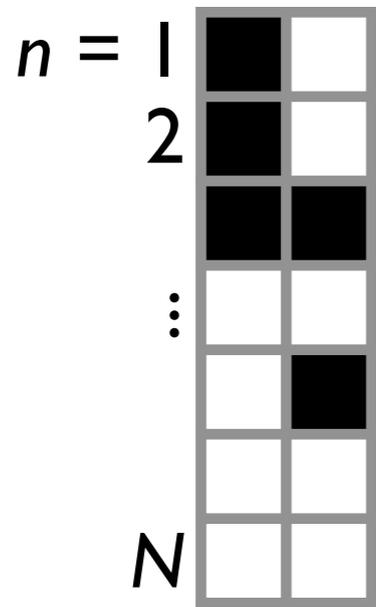
$$\mathbb{P}(\begin{array}{|c|c|} \hline \blacksquare & \blacksquare \\ \hline \square & \square \\ \hline \end{array})$$

$$p_3 p_4$$

# Exchangeable probability functions

“Exchangeable feature probability function” (EFPF)?

Counterexample



$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \end{array}) = p_1$$

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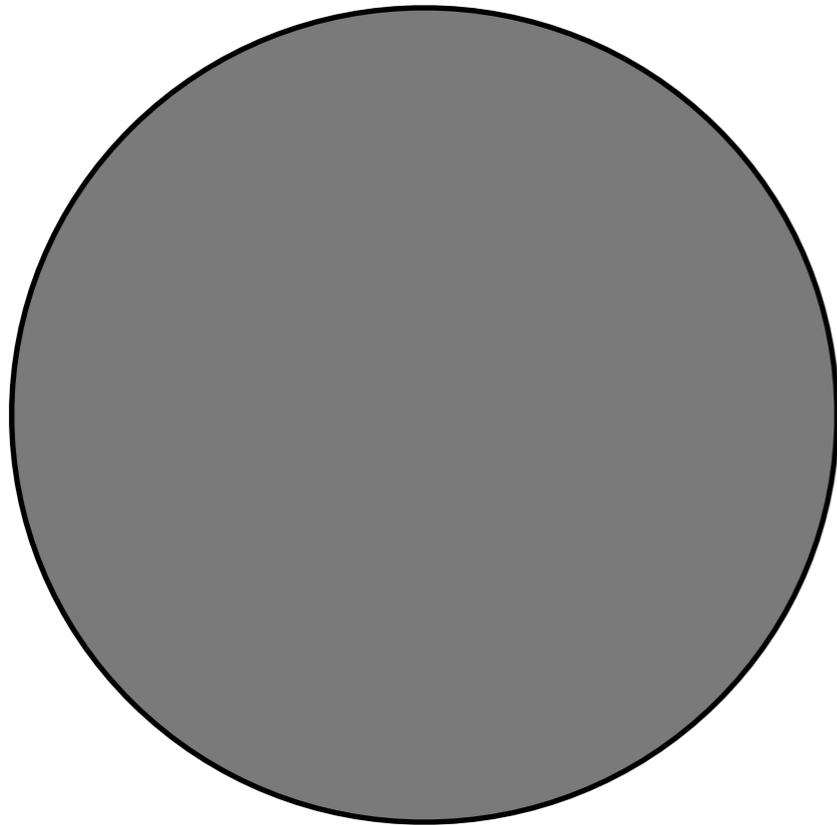
$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$

$$\mathbb{P}\left(\begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \square & \blacksquare \\ \hline \end{array}\right) \neq \mathbb{P}\left(\begin{array}{|c|c|} \hline \blacksquare & \blacksquare \\ \hline \square & \square \\ \hline \end{array}\right)$$

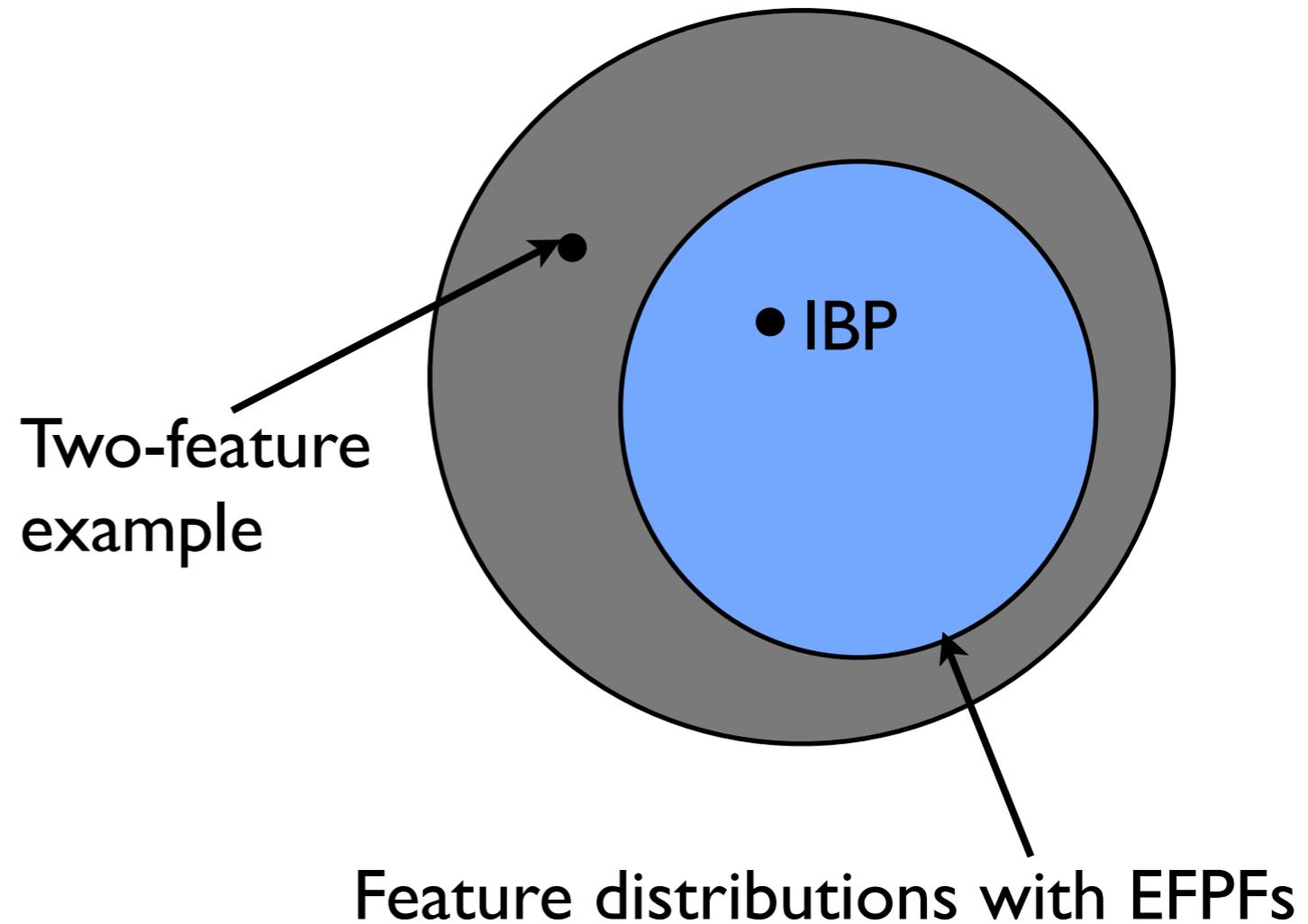
$$p_1 p_2 \neq p_3 p_4$$

# Exchangeable probability functions

Exchangeable cluster distributions  
= Cluster distributions with EPPFs



Exchangeable feature distributions



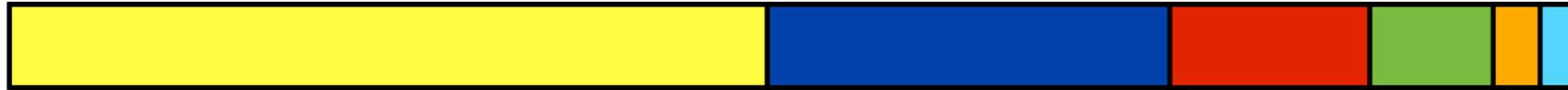
# Paintboxes

Exchangeable partition: Kingman paintbox



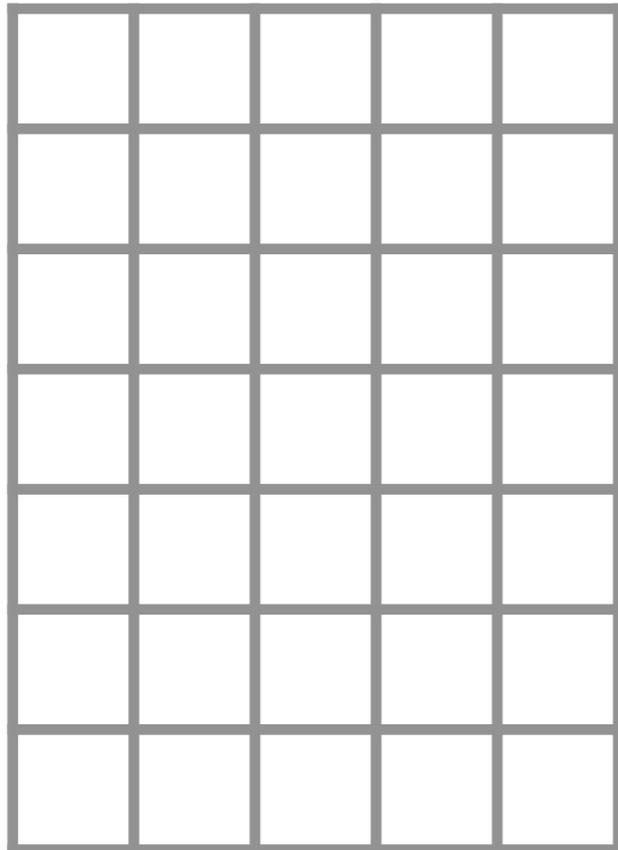
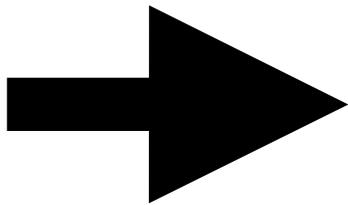
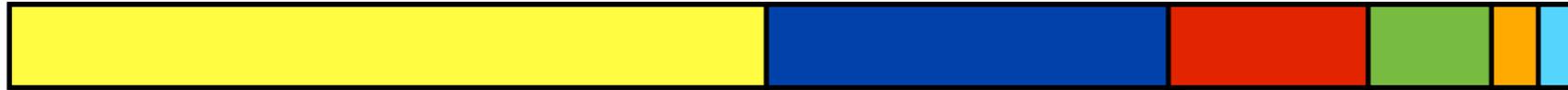
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Exchangeable partition: Kingman paintbox



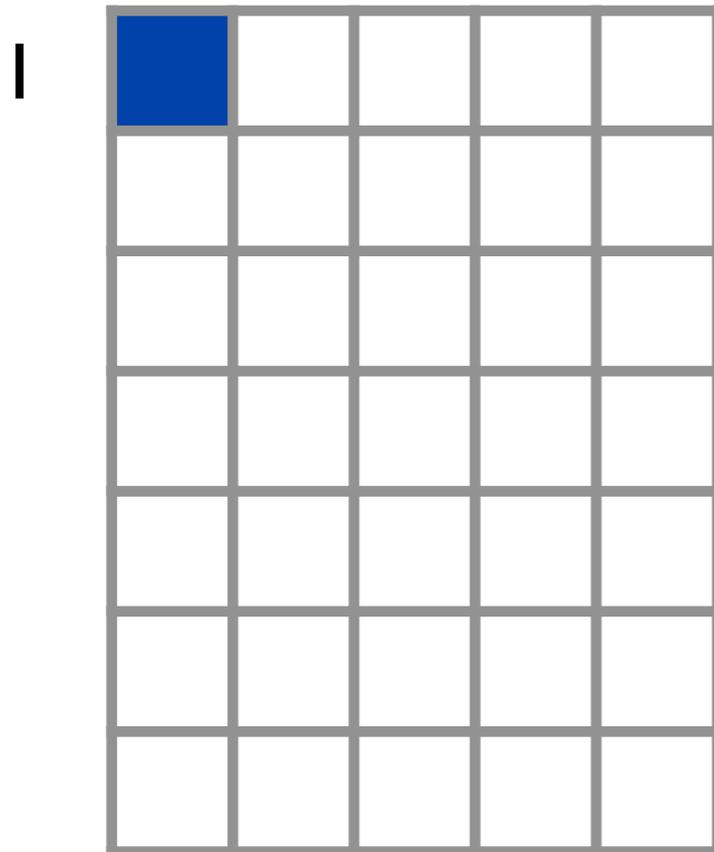
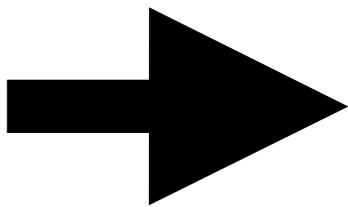
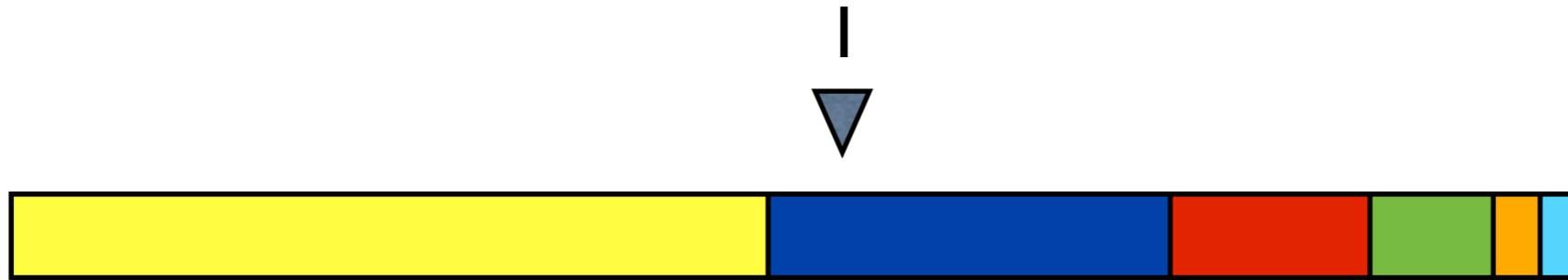
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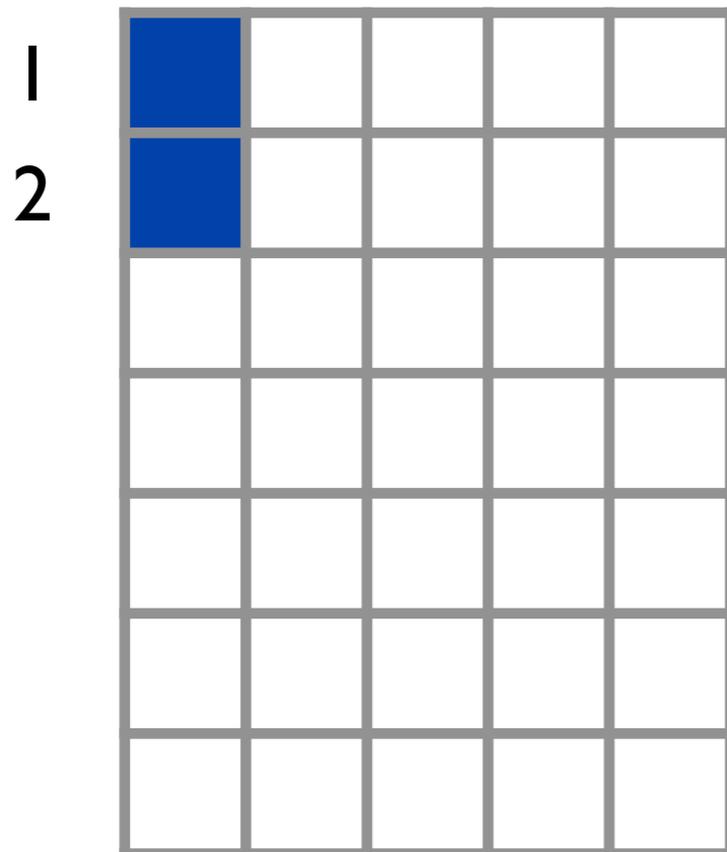
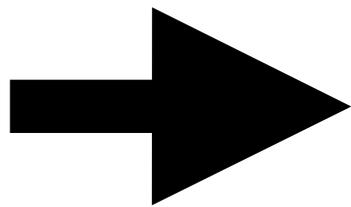
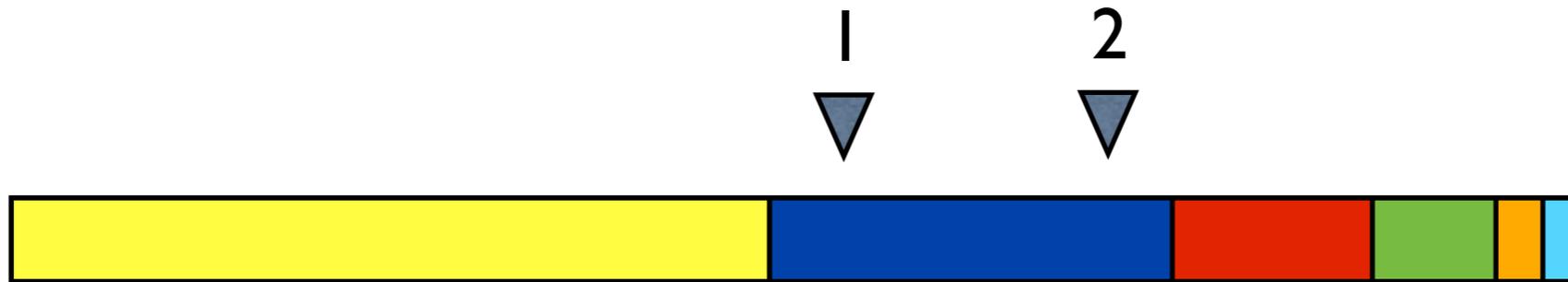
# Paintboxes

Exchangeable partition: Kingman paintbox



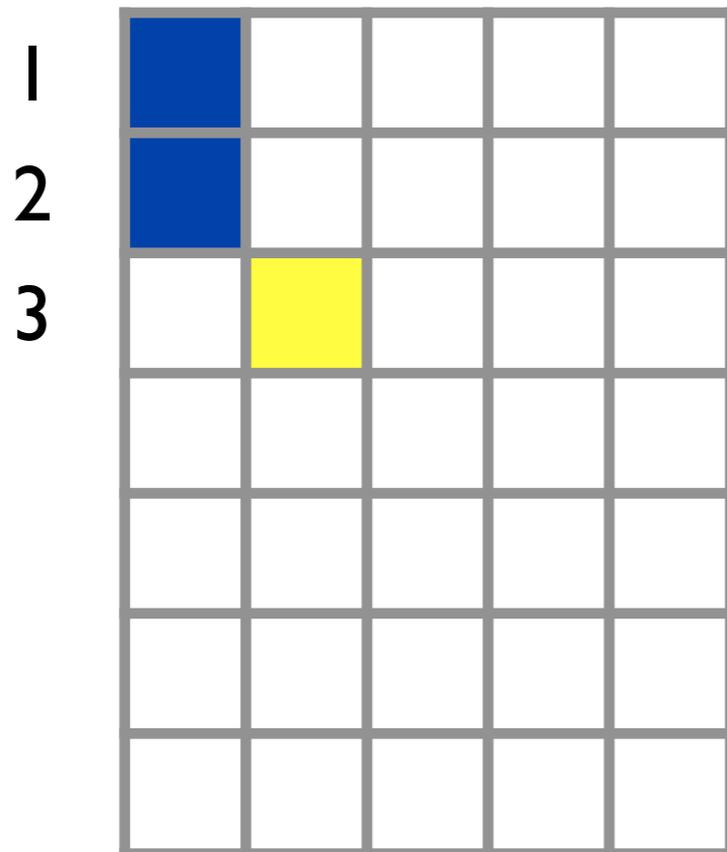
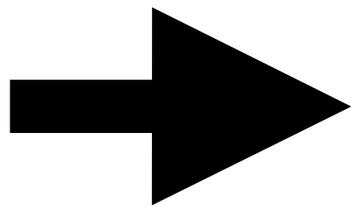
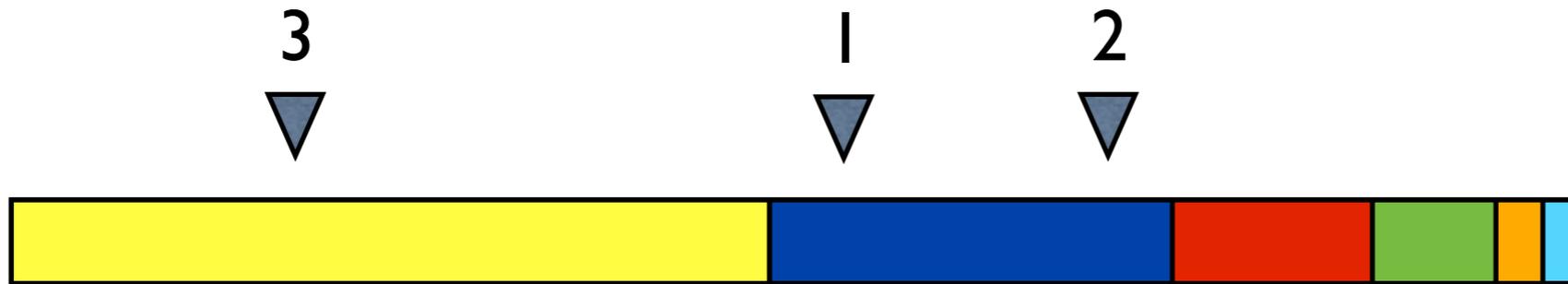
# Paintboxes

Exchangeable partition: Kingman paintbox



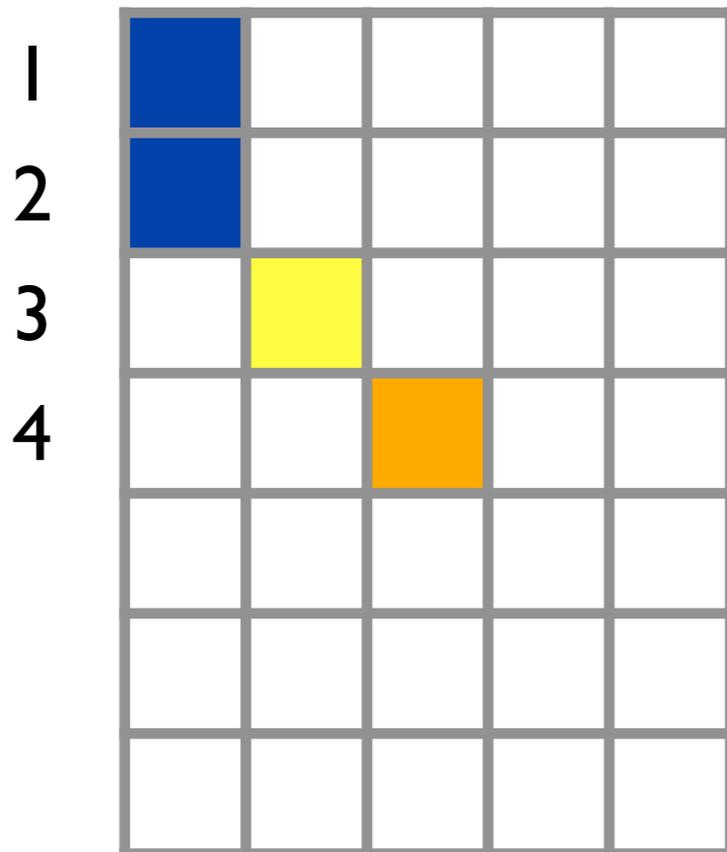
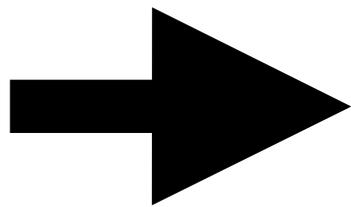
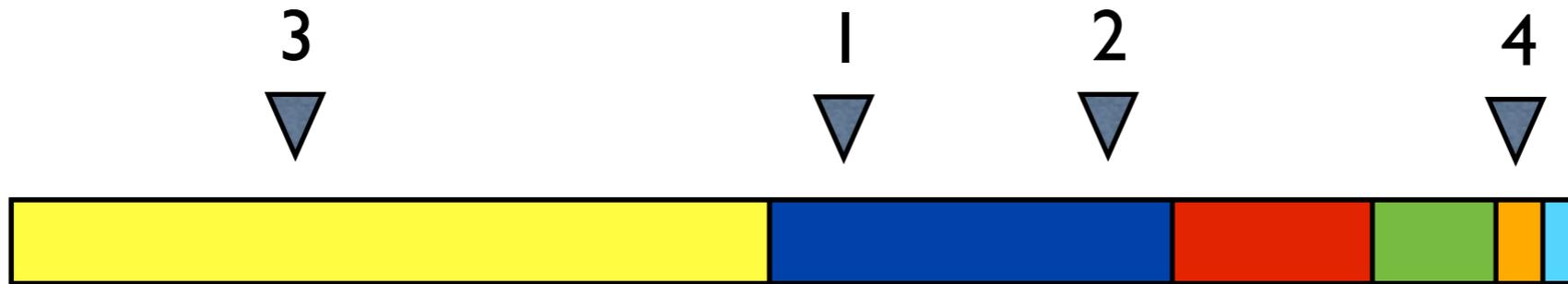
# Paintboxes

Exchangeable partition: Kingman paintbox



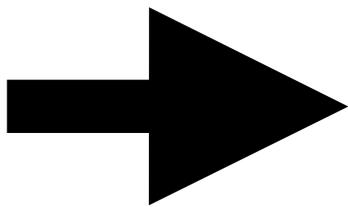
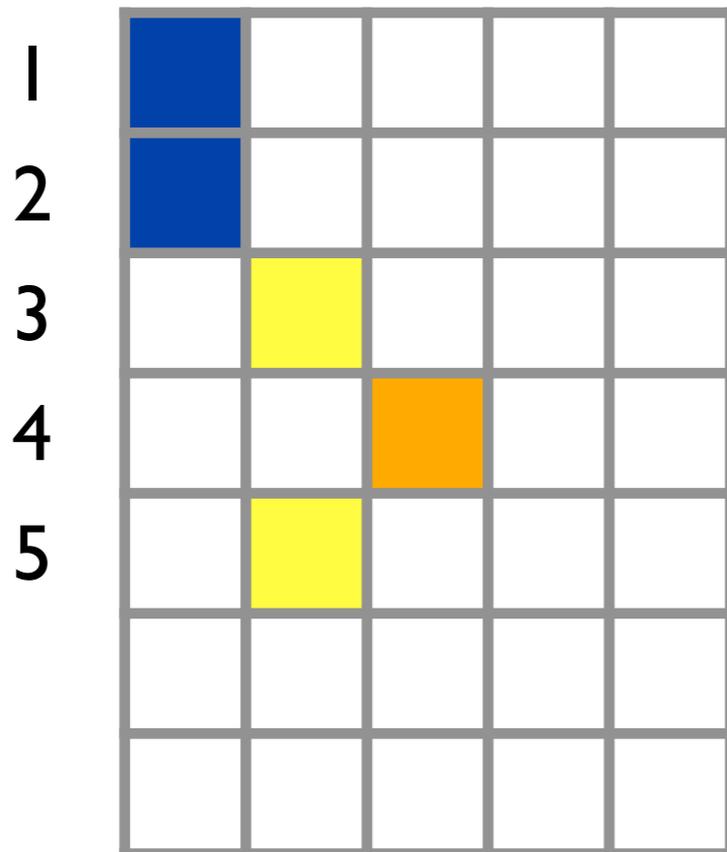
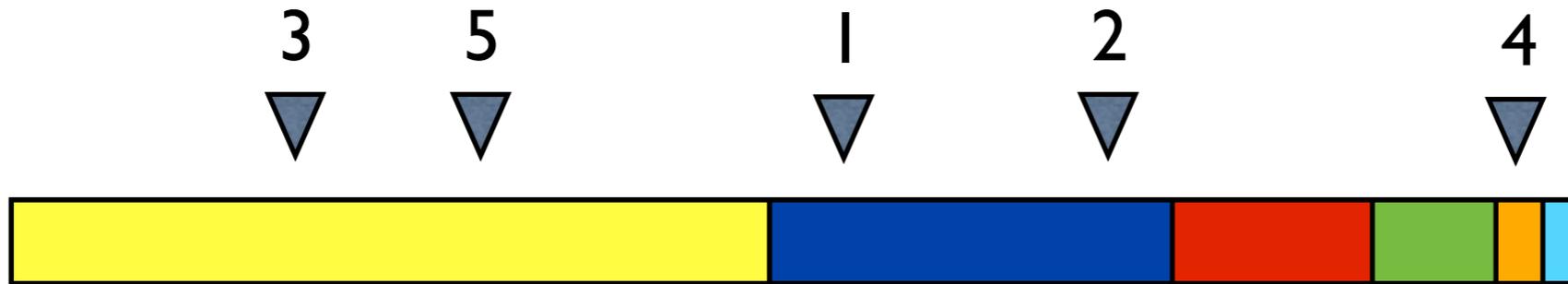
# Paintboxes

Exchangeable partition: Kingman paintbox



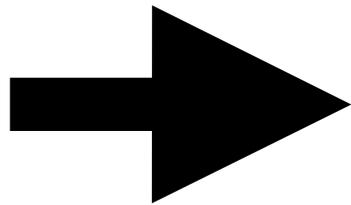
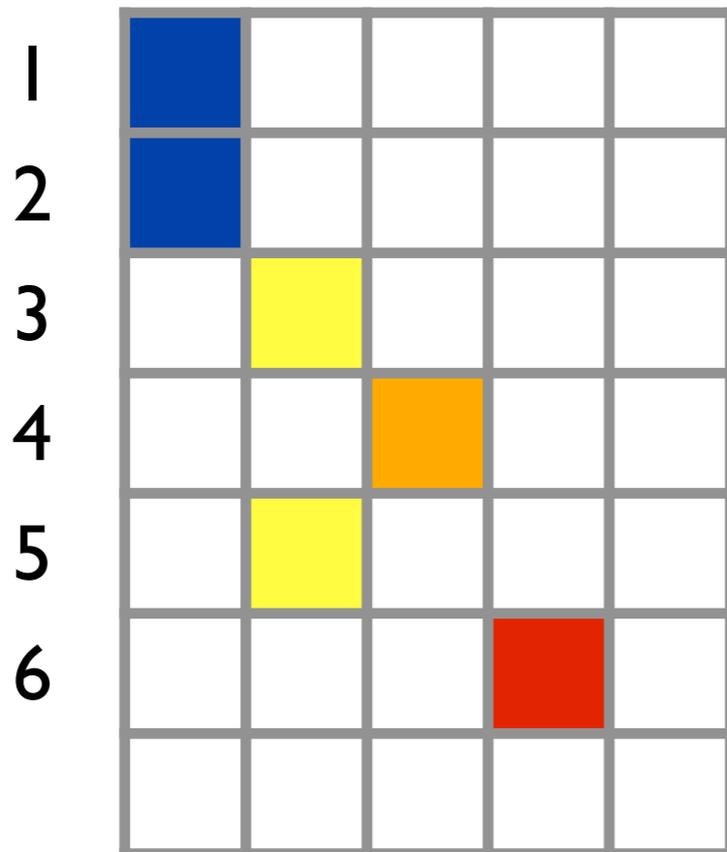
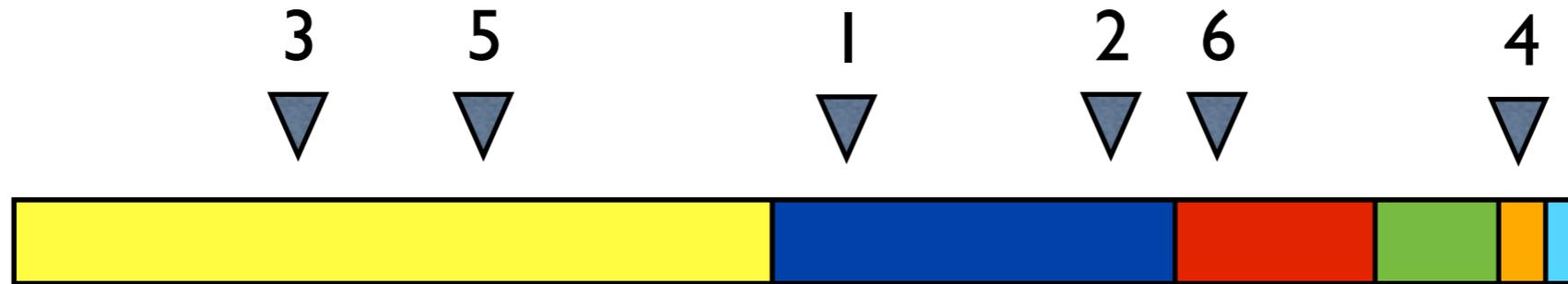
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Exchangeable partition: Kingman paintbox



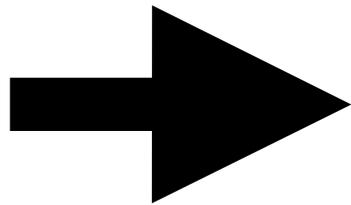
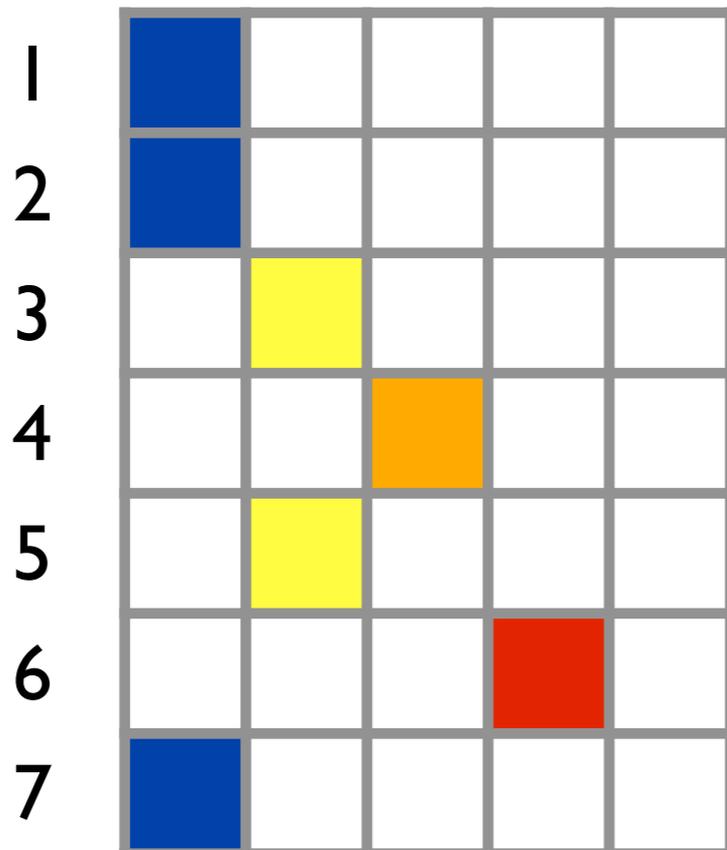
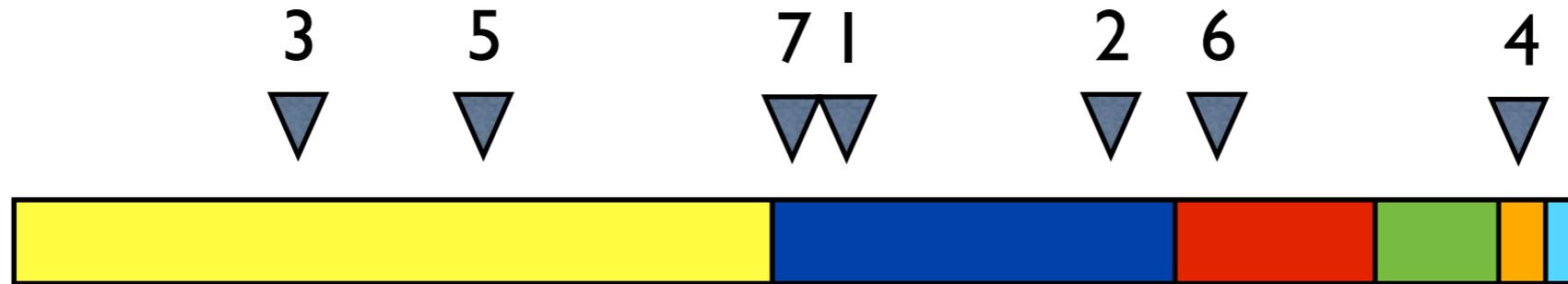
# Paintboxes

Exchangeable partition: Kingman paintbox



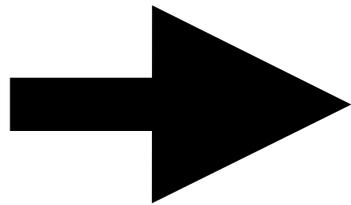
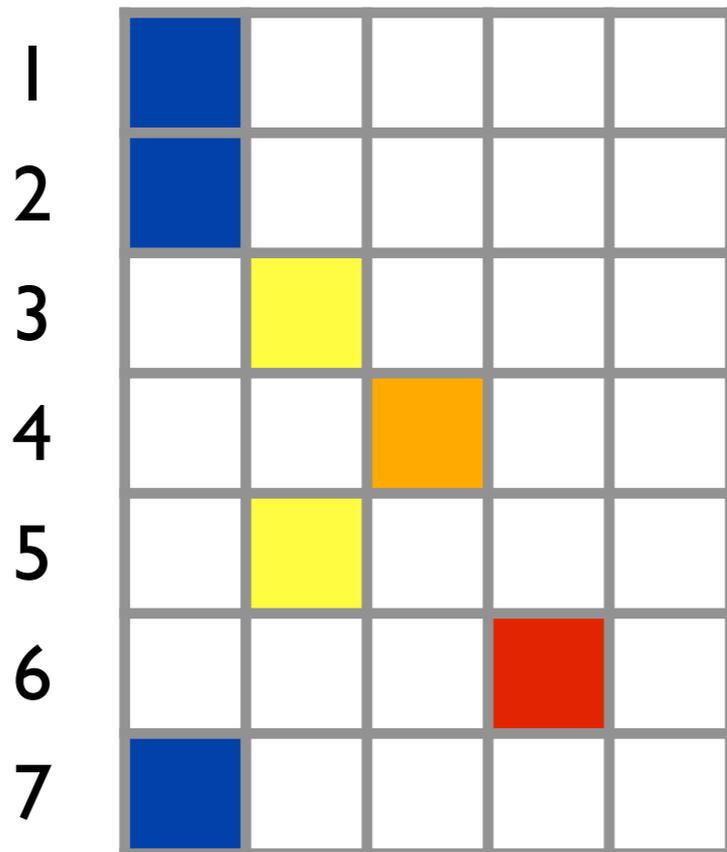
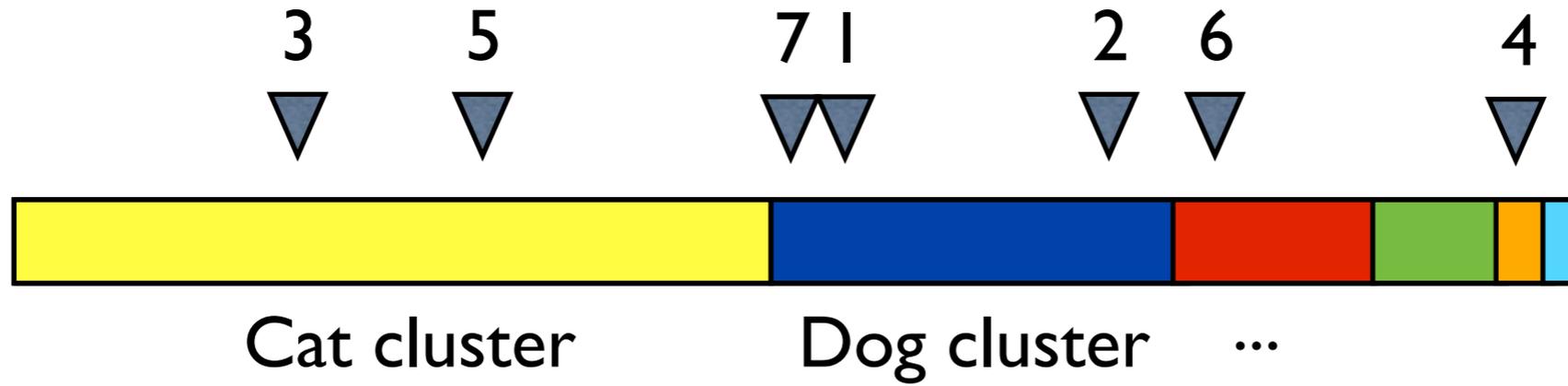
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Exchangeable partition: Kingman paintbox



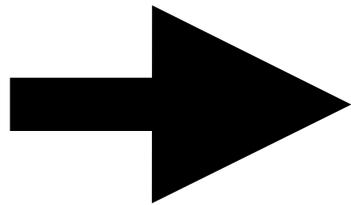
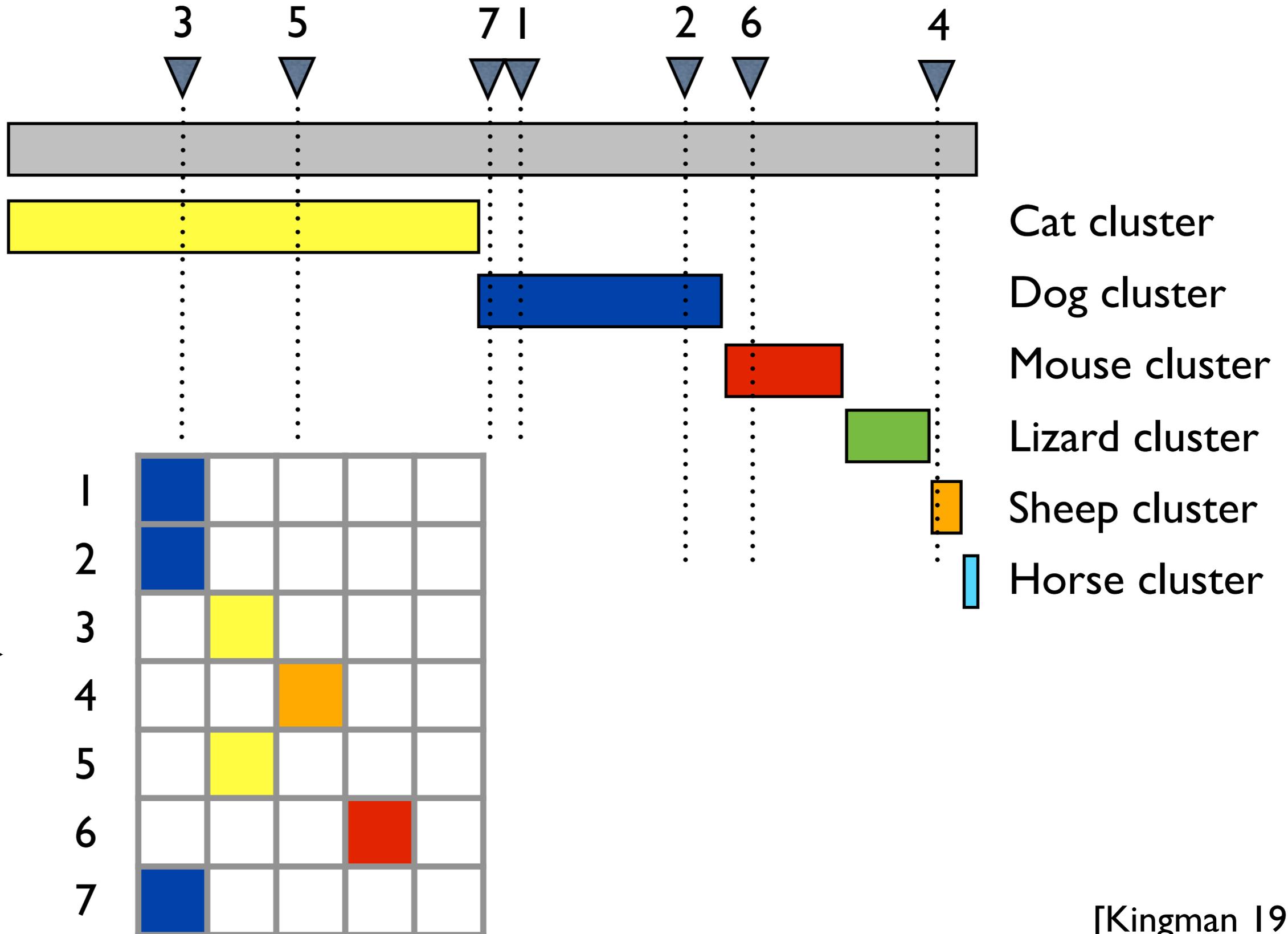
# Paintboxes

Exchangeable partition: Kingman paintbox

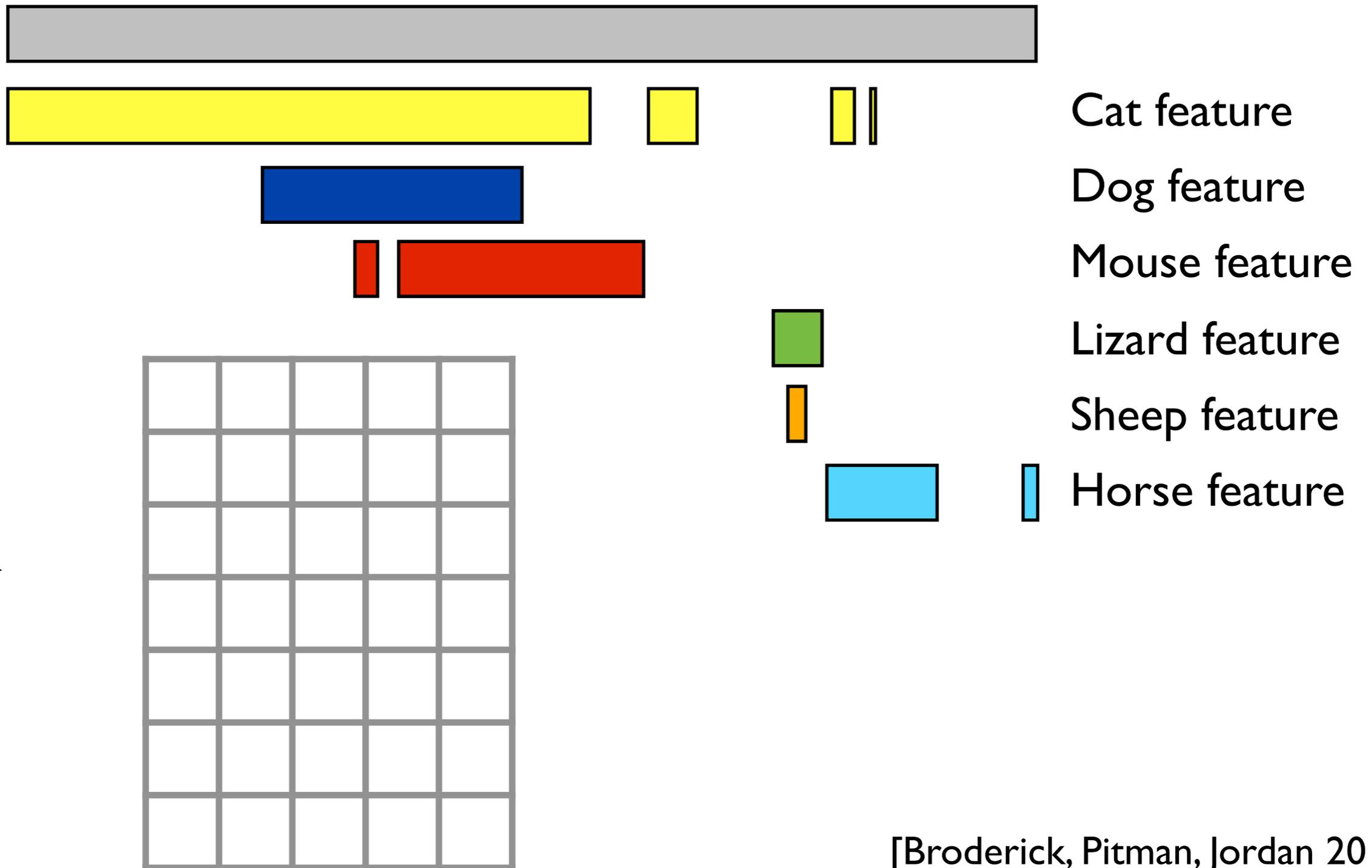


# Paintboxes

Exchangeable partition: Kingman paintbox

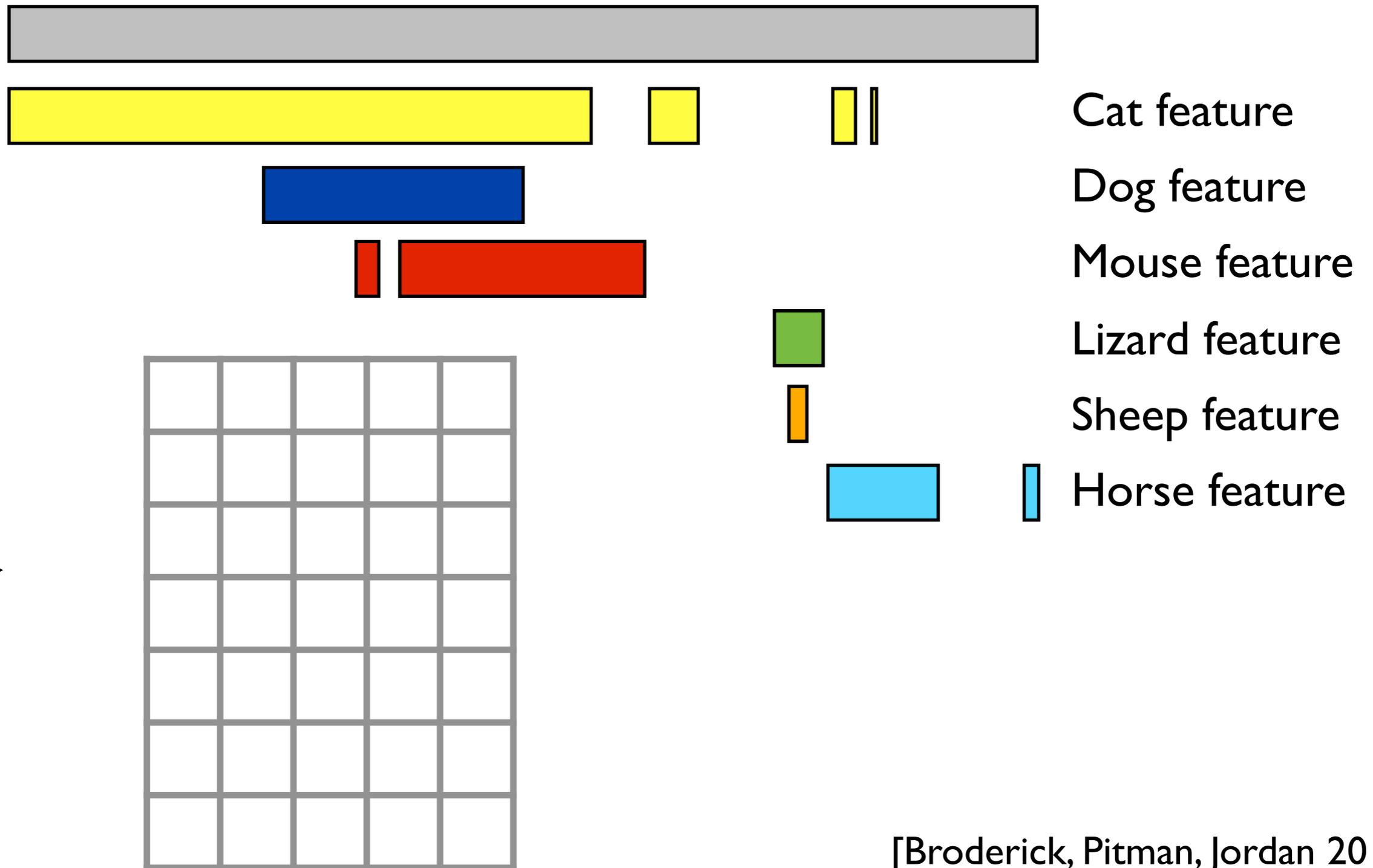


# Paintboxes



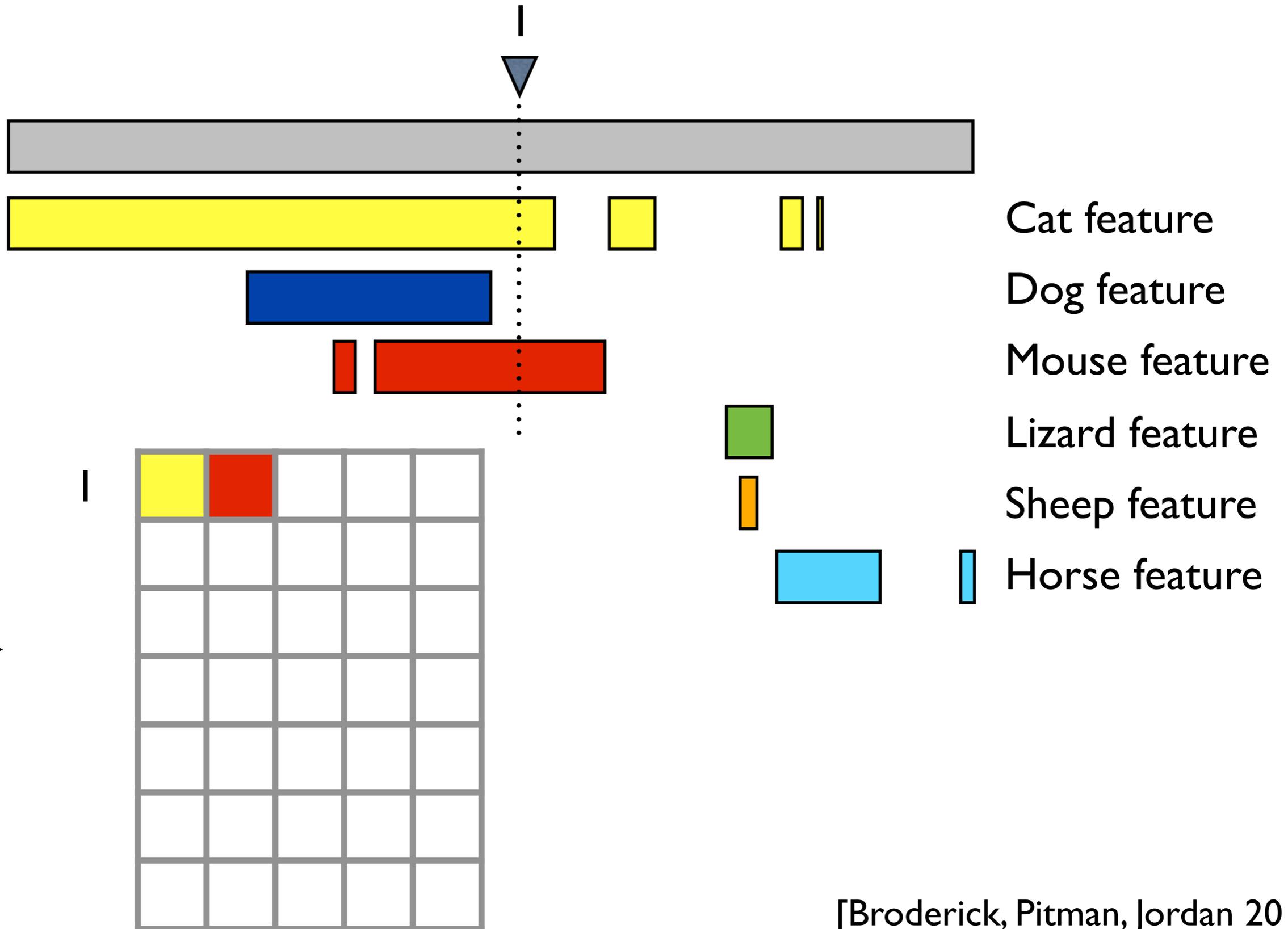
# Paintboxes

Exchangeable feature allocation: feature paintbox



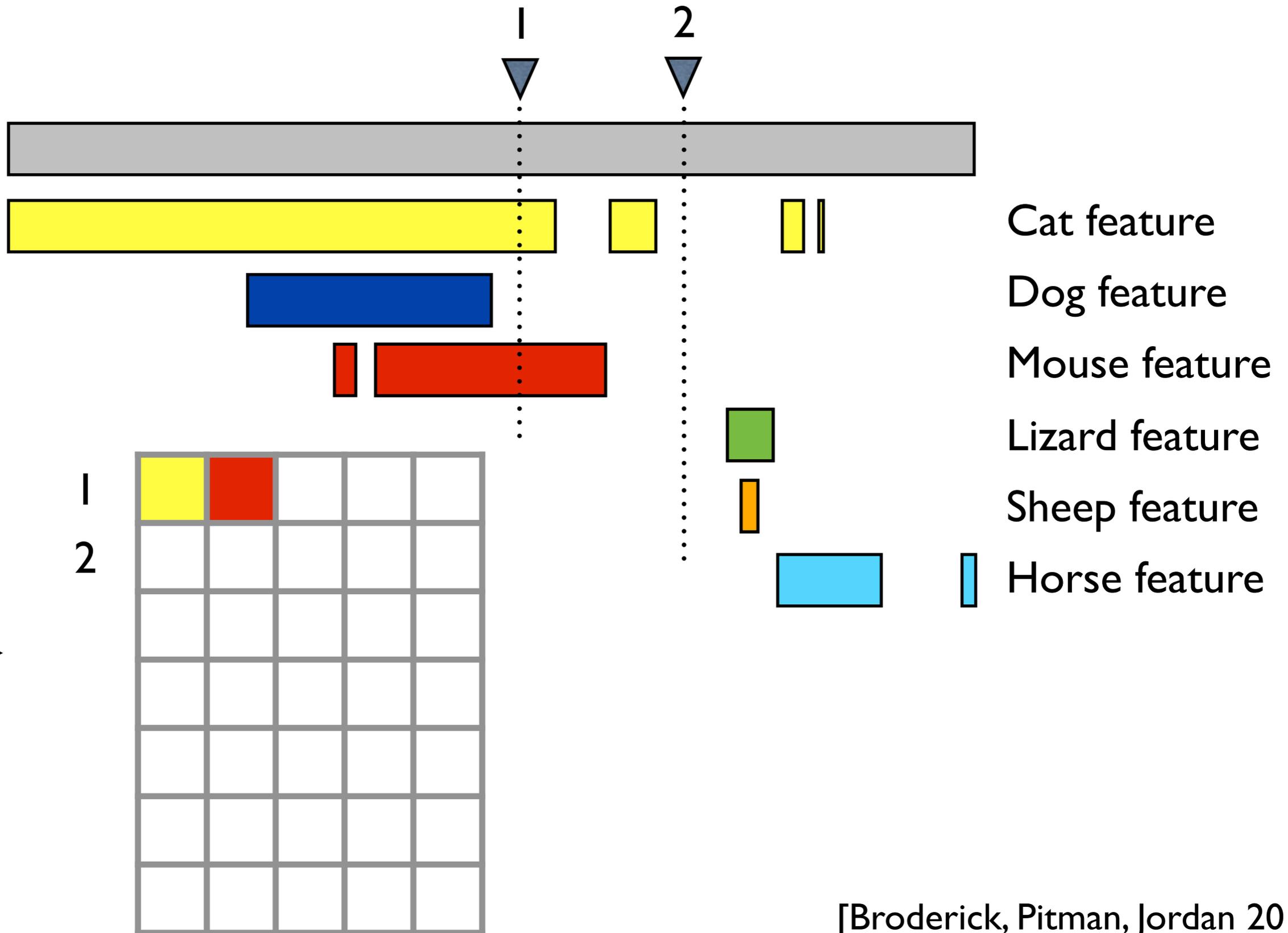
# Paintboxes

Exchangeable feature allocation: feature paintbox



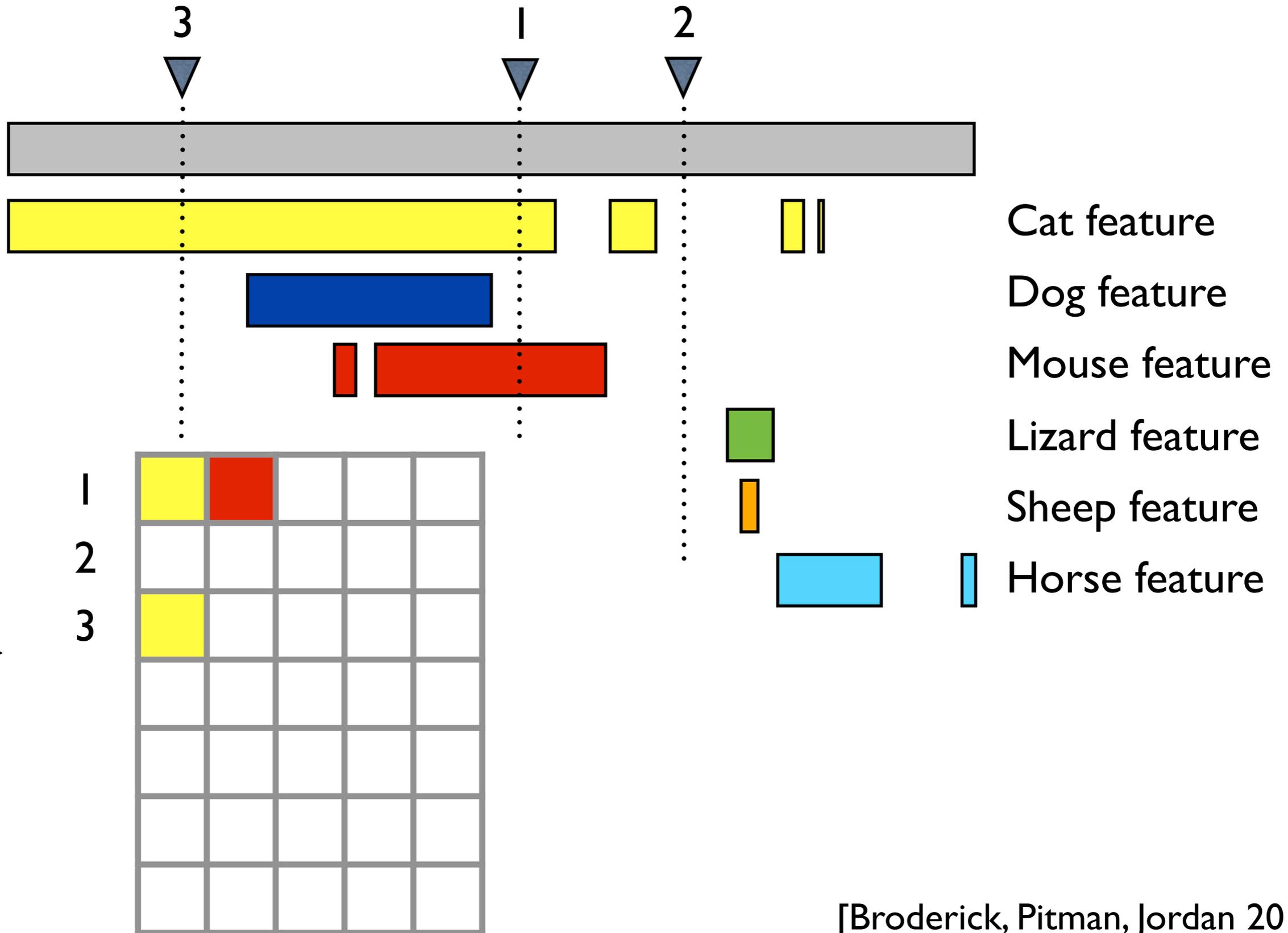
# Paintboxes

Exchangeable feature allocation: feature paintbox



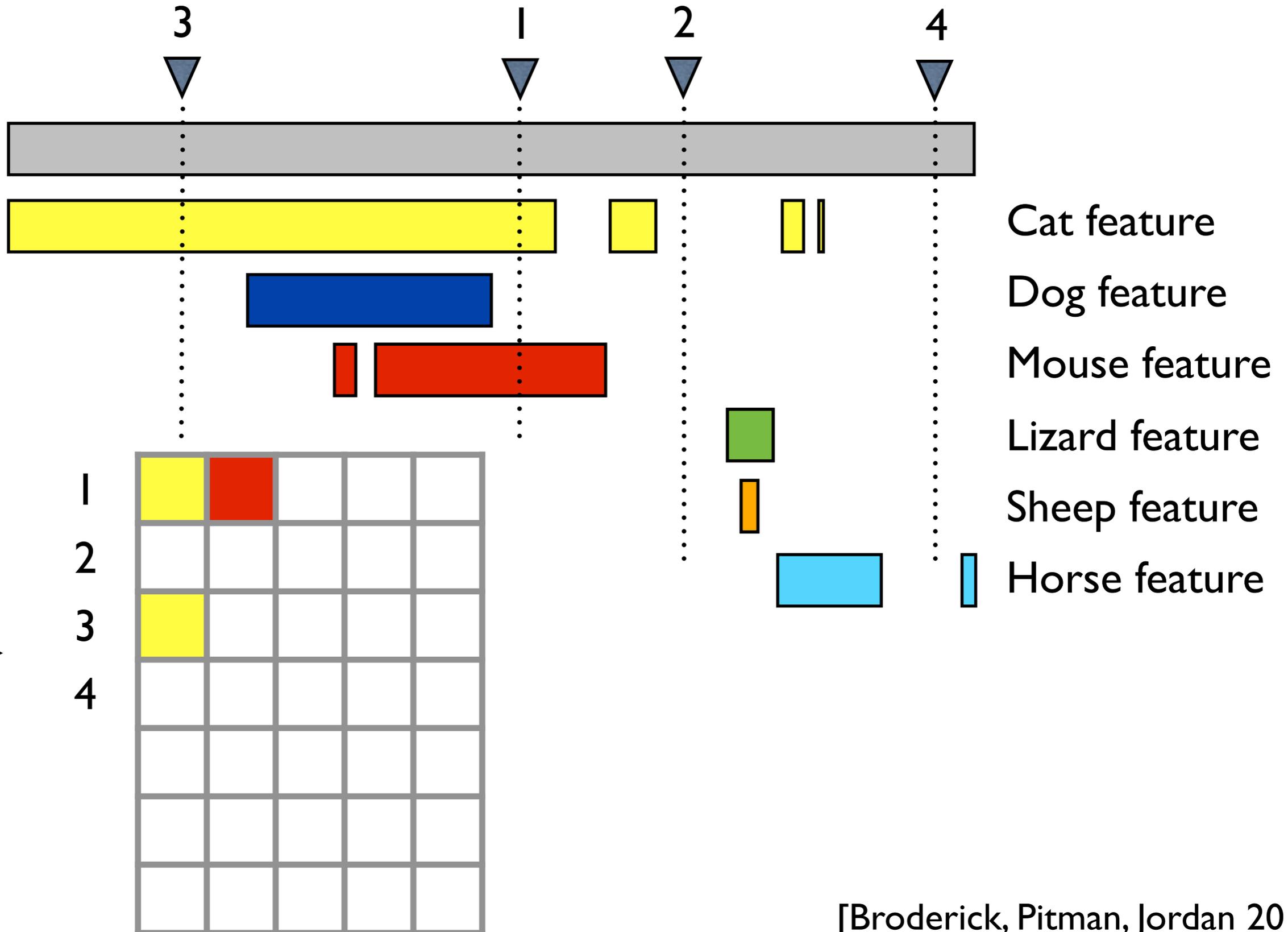
# Paintboxes

Exchangeable feature allocation: feature paintbox



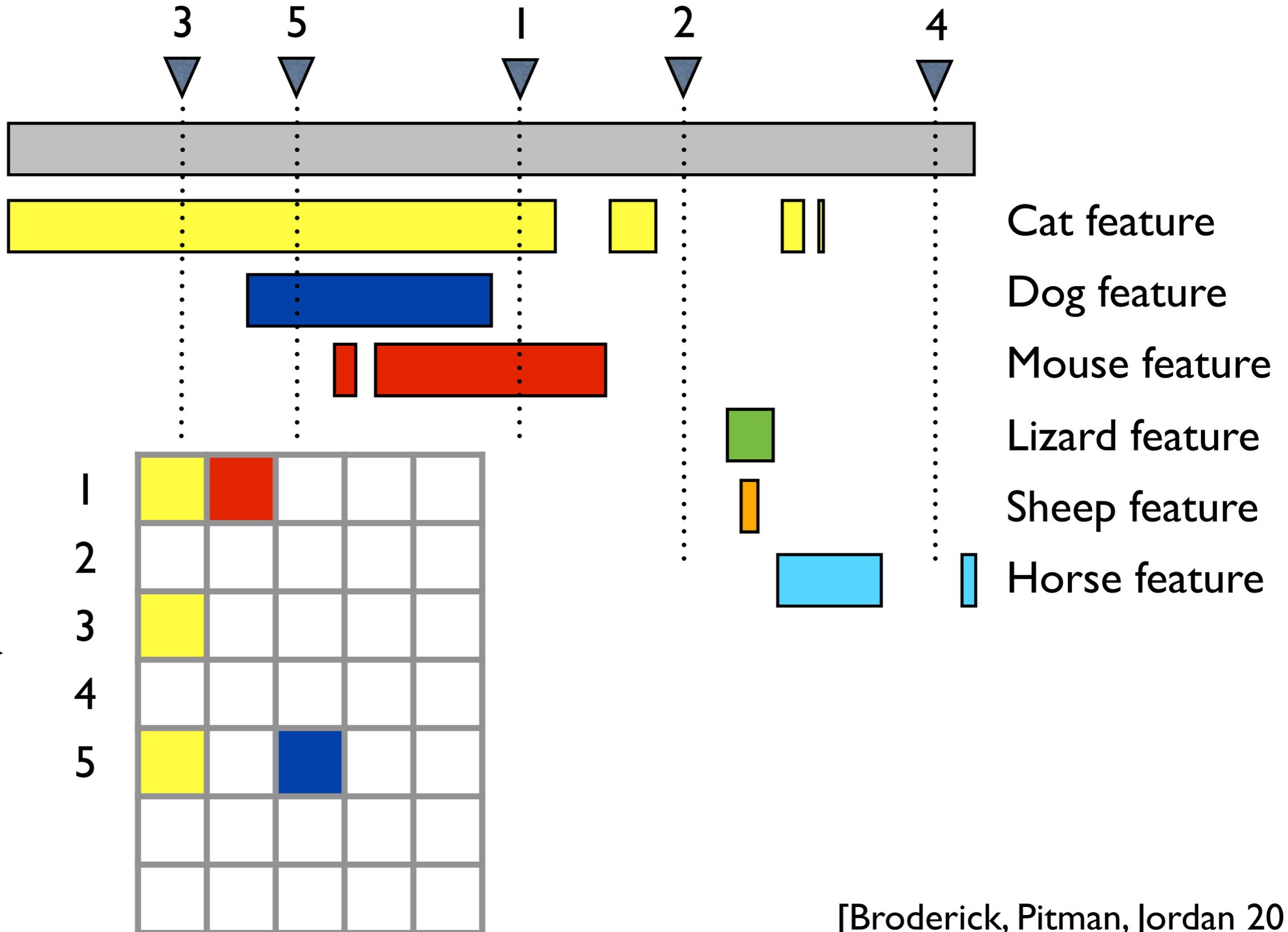
# Paintboxes

Exchangeable feature allocation: feature paintbox



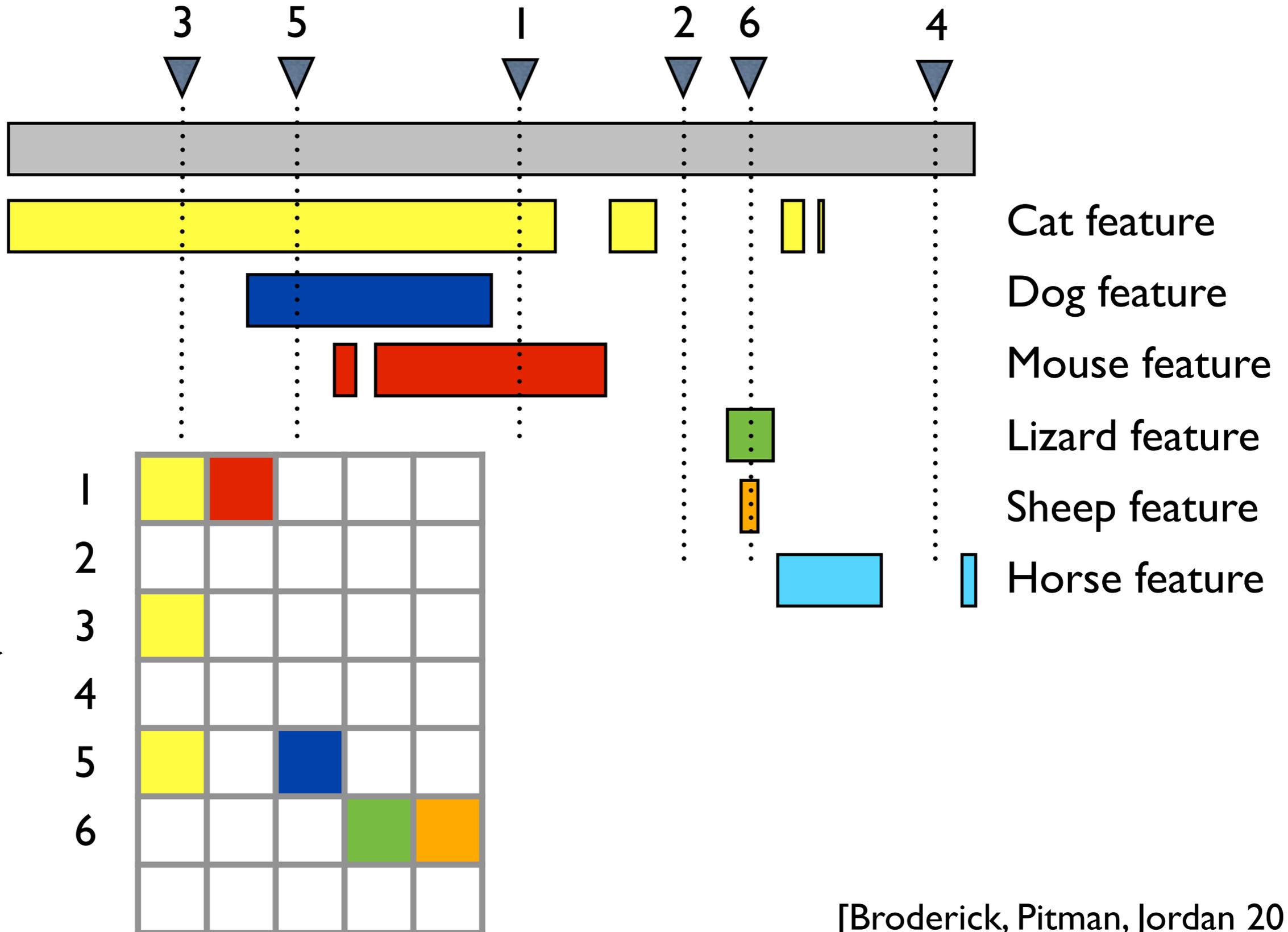
# Paintboxes

Exchangeable feature allocation: feature paintbox



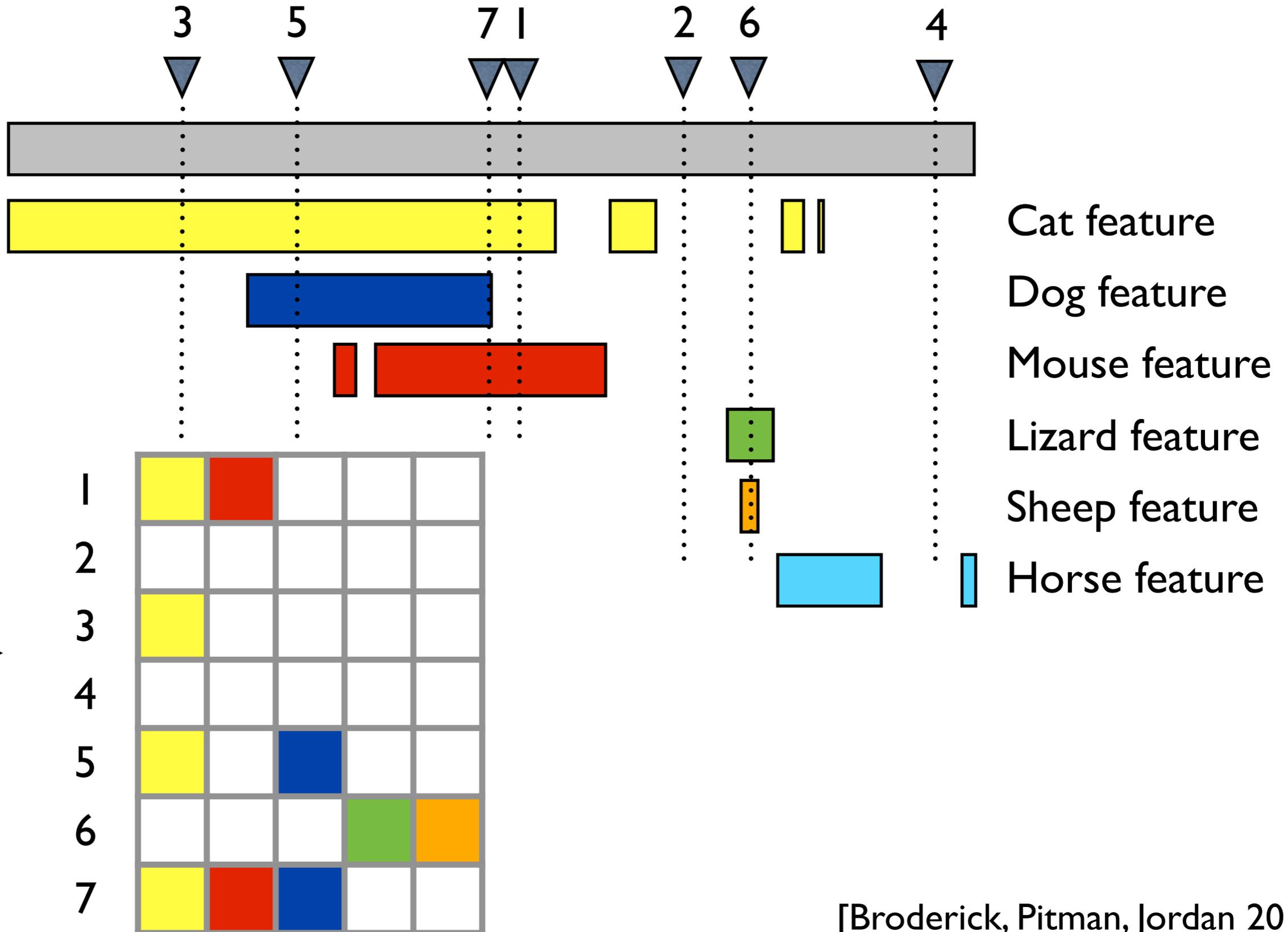
# Paintboxes

Exchangeable feature allocation: feature paintbox



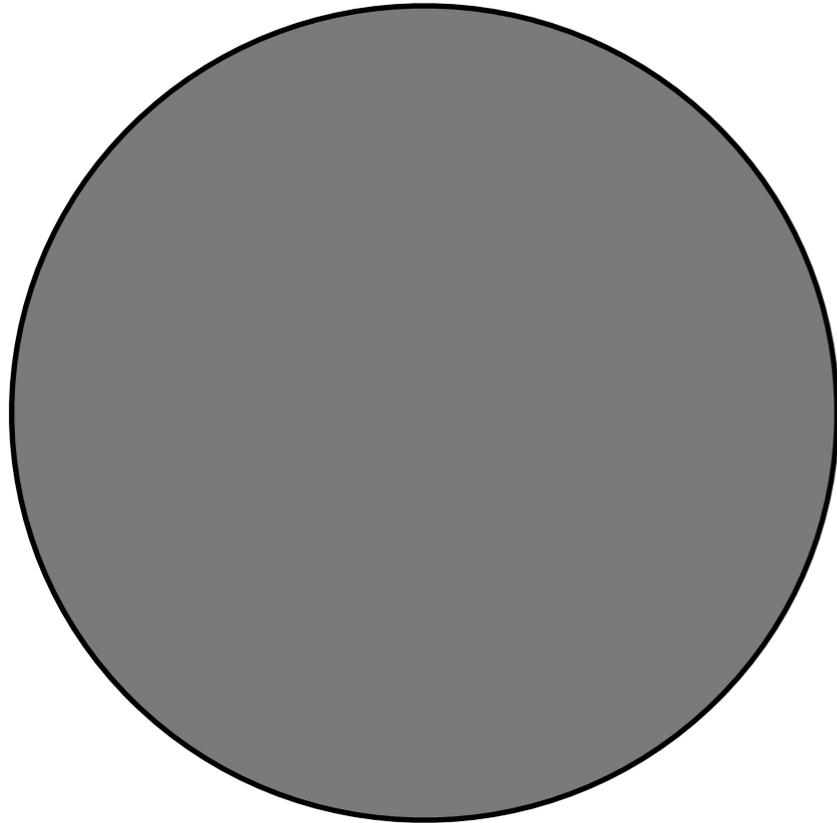
# Paintboxes

Exchangeable feature allocation: feature paintbox

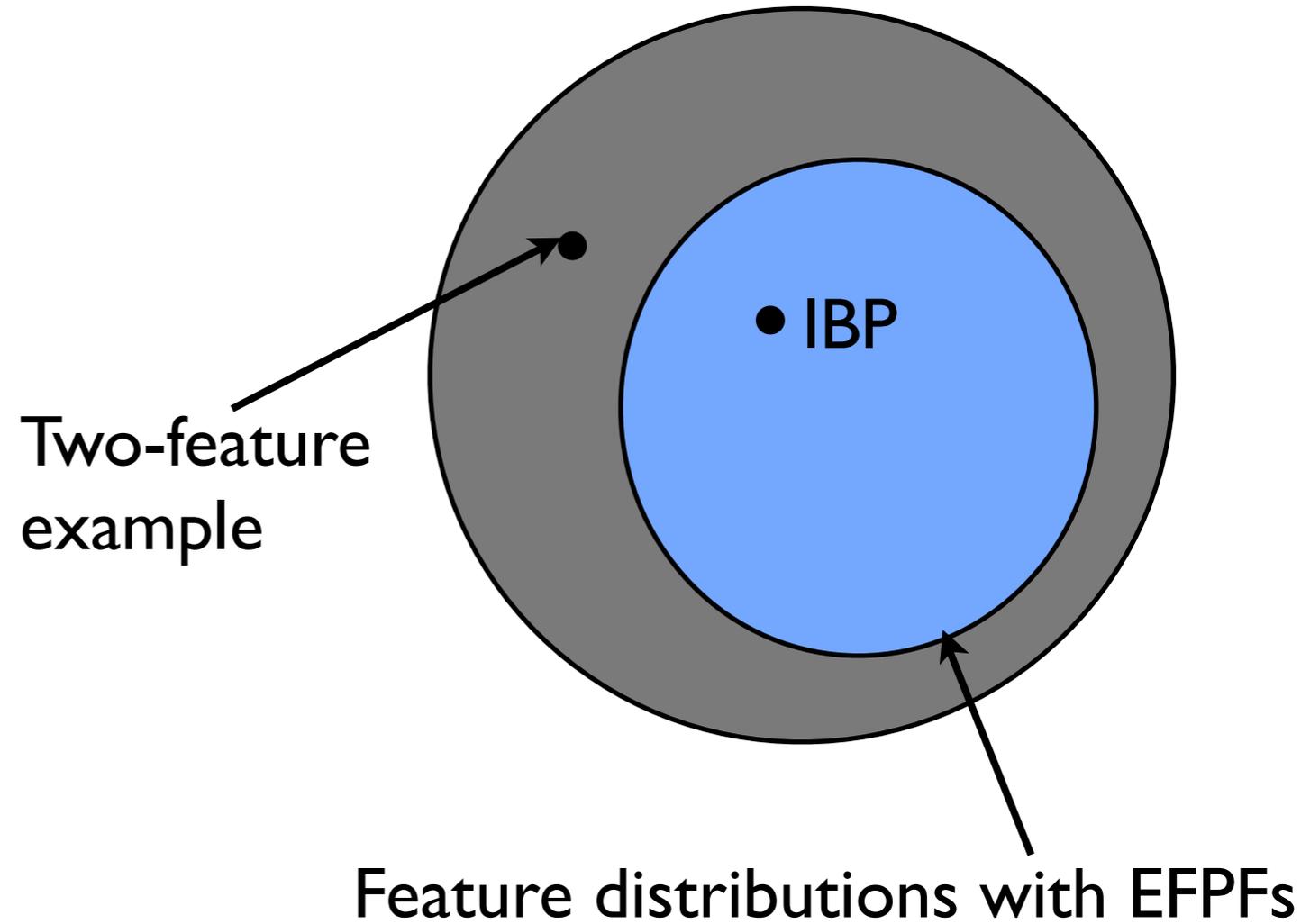


# Paintboxes

Exchangeable cluster distributions  
= Cluster distributions with EPPFs

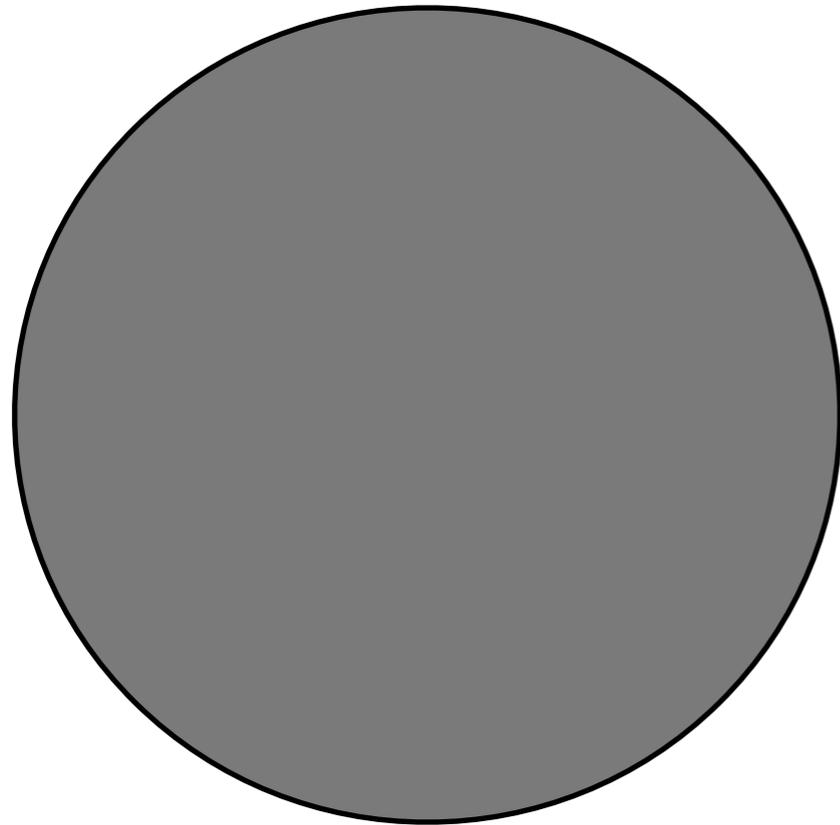


Exchangeable feature distributions

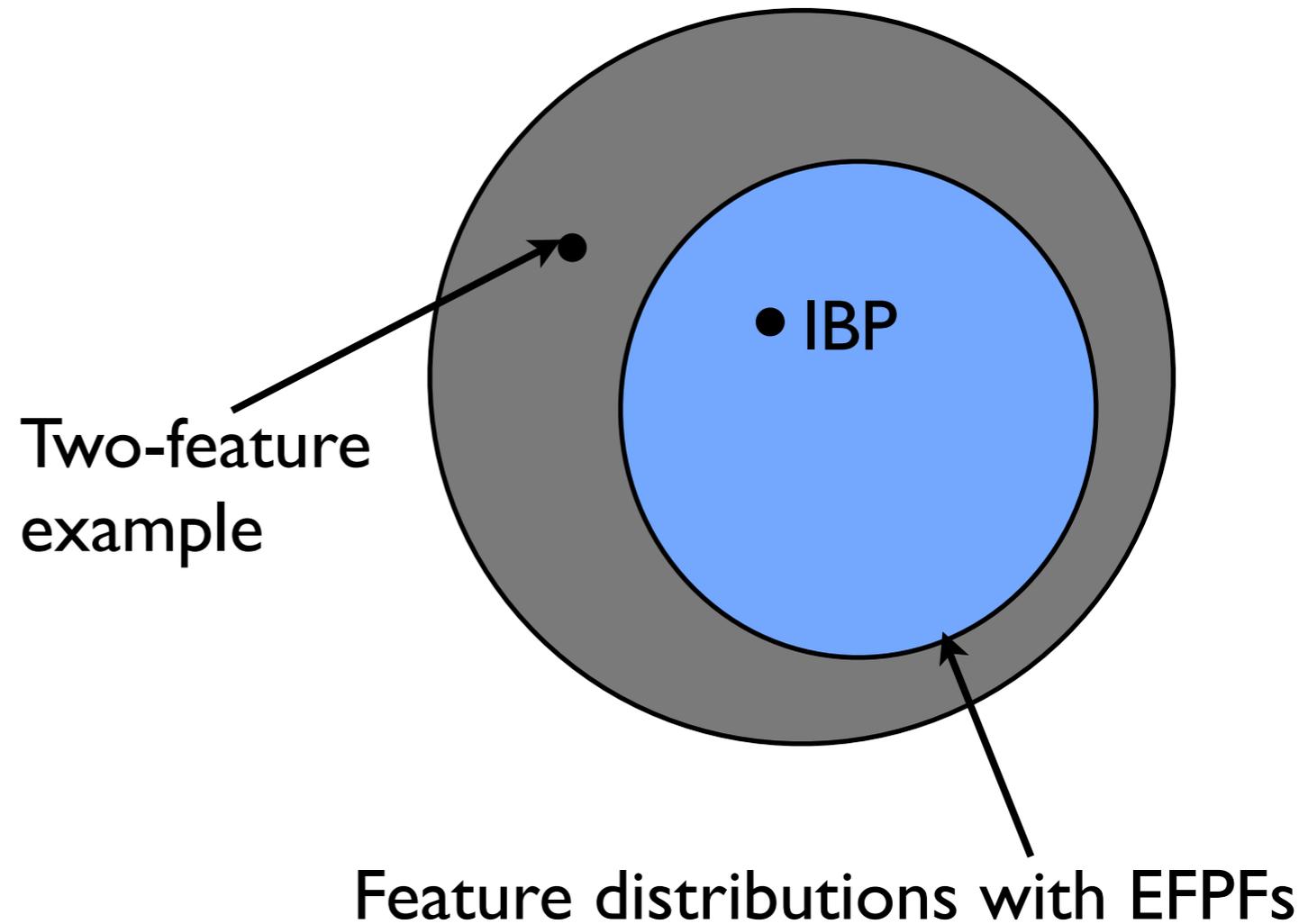


# Paintboxes

Exchangeable cluster distributions  
= Cluster distributions with EPPFs  
= Kingman paintbox partitions

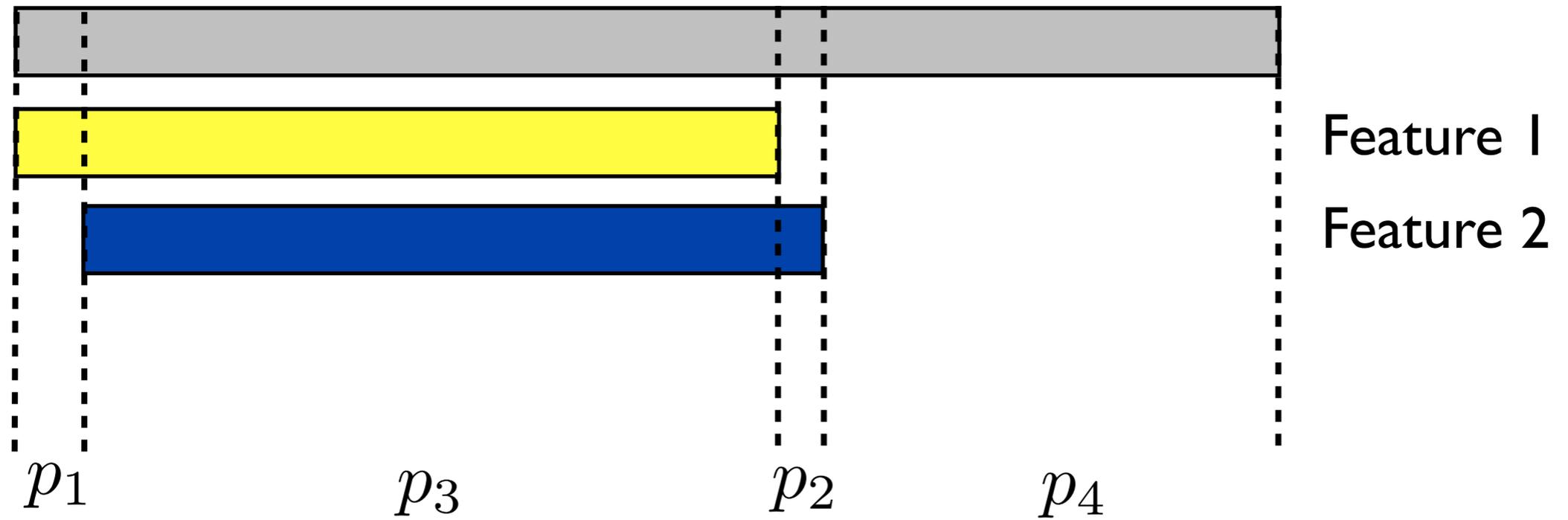


Exchangeable feature distributions  
= Feature paintbox allocations



# Paintboxes

## Two feature example



$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \end{array}) = p_1$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \blacksquare \\ \hline \end{array}) = p_2$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \blacksquare \\ \hline \end{array}) = p_3$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$

# Paintboxes

Indian buffet process: beta feature frequencies

# Paintboxes

Indian buffet process: beta feature frequencies

For  $m = 1, 2, \dots$   
1. Draw  $K_m^+ = \text{Poisson} \left( \gamma \frac{\theta}{\theta + m - 1} \right)$

# Paintboxes

Indian buffet process: beta feature frequencies

For  $m = 1, 2, \dots$

1. Draw  $K_m^+ = \text{Poisson} \left( \gamma \frac{\theta}{\theta + m - 1} \right)$

Set  $K_m = \sum_{j=1}^m K_j^+$

2. For  $k = K_{m-1} + 1, \dots, K_m$

Draw a frequency of size

$$q_k \sim \text{Beta}(1, \theta + m - 1)$$

# Paintboxes

Indian buffet process: beta feature frequencies

For  $m = 1, 2, \dots$

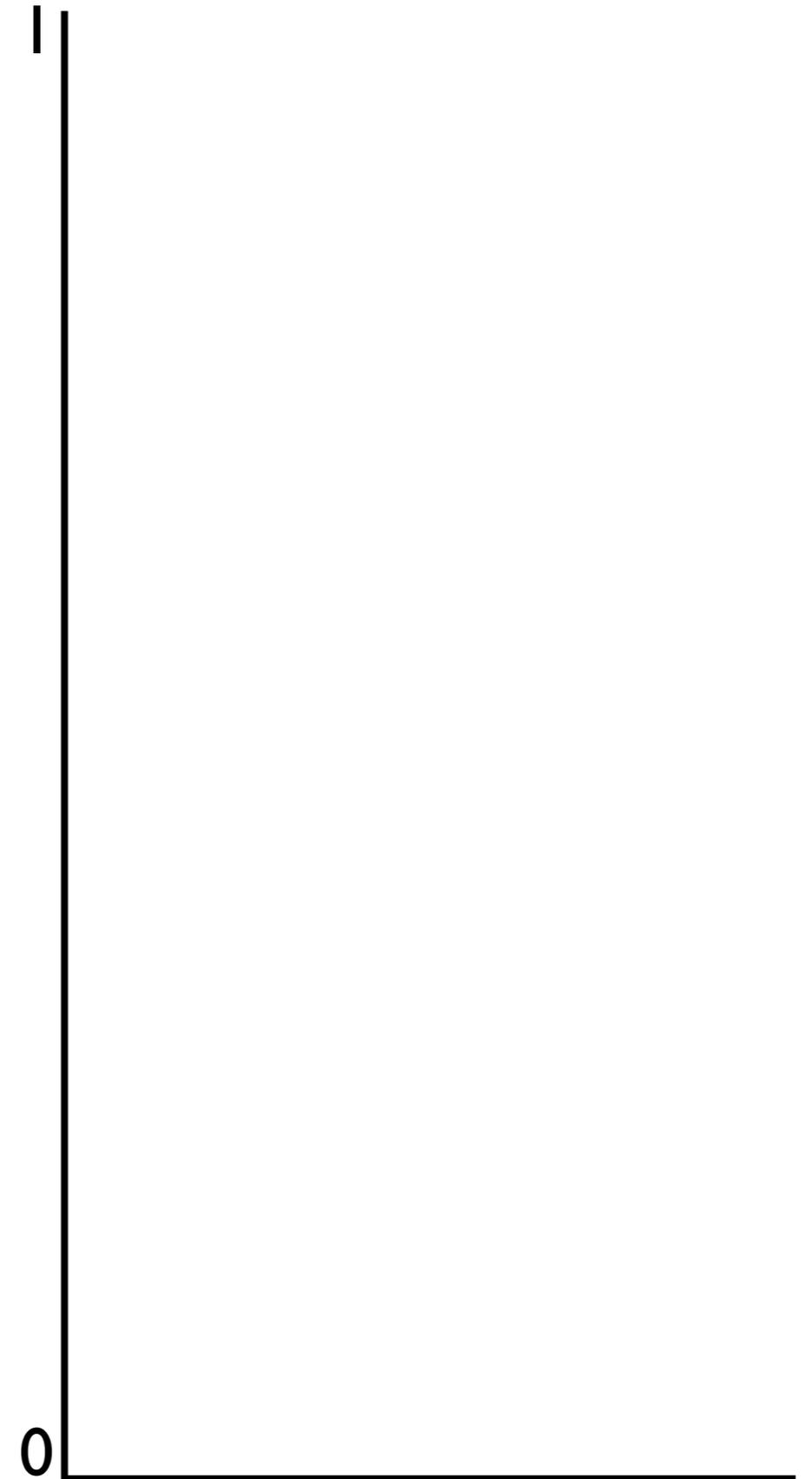
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Indian buffet process: beta feature frequencies

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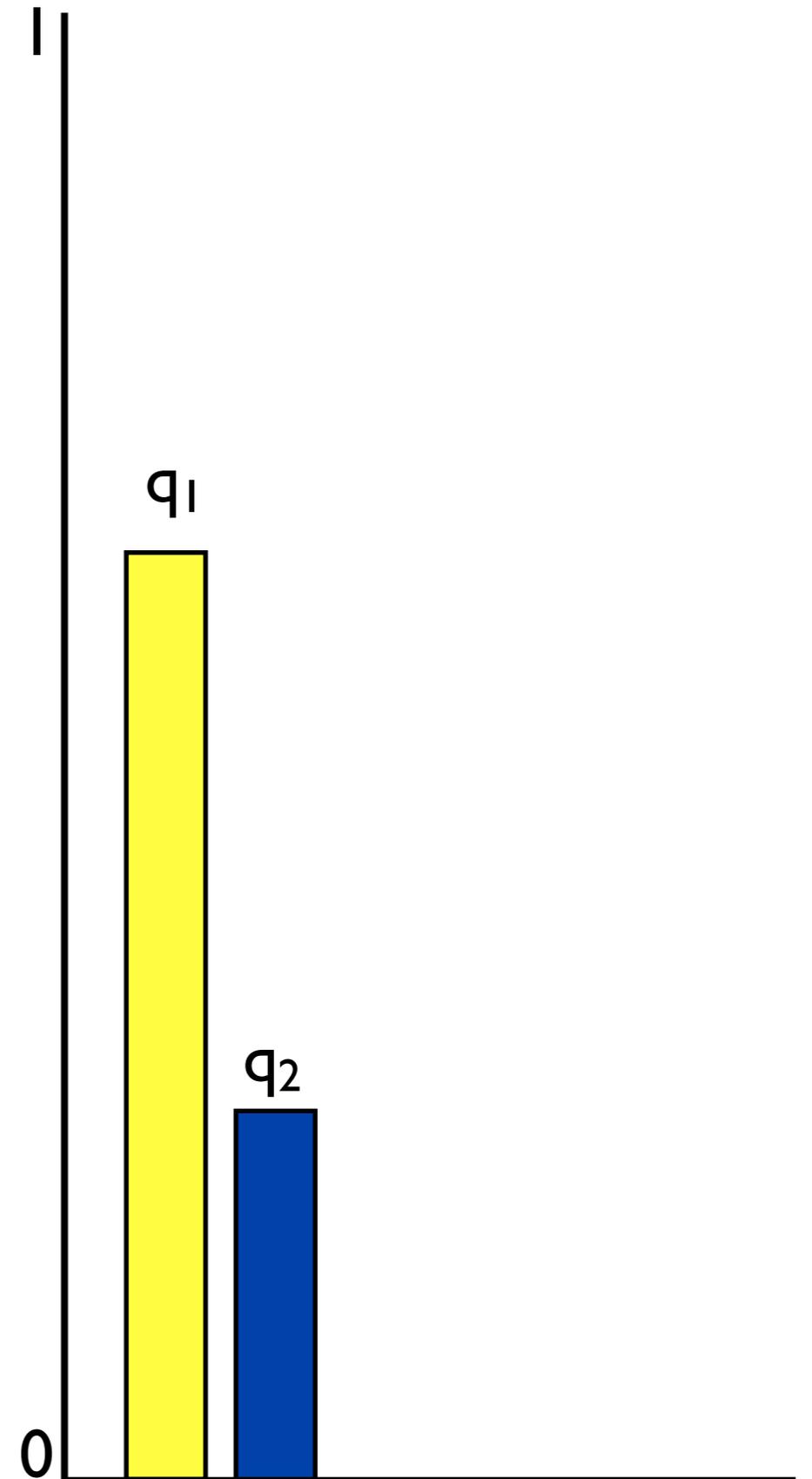
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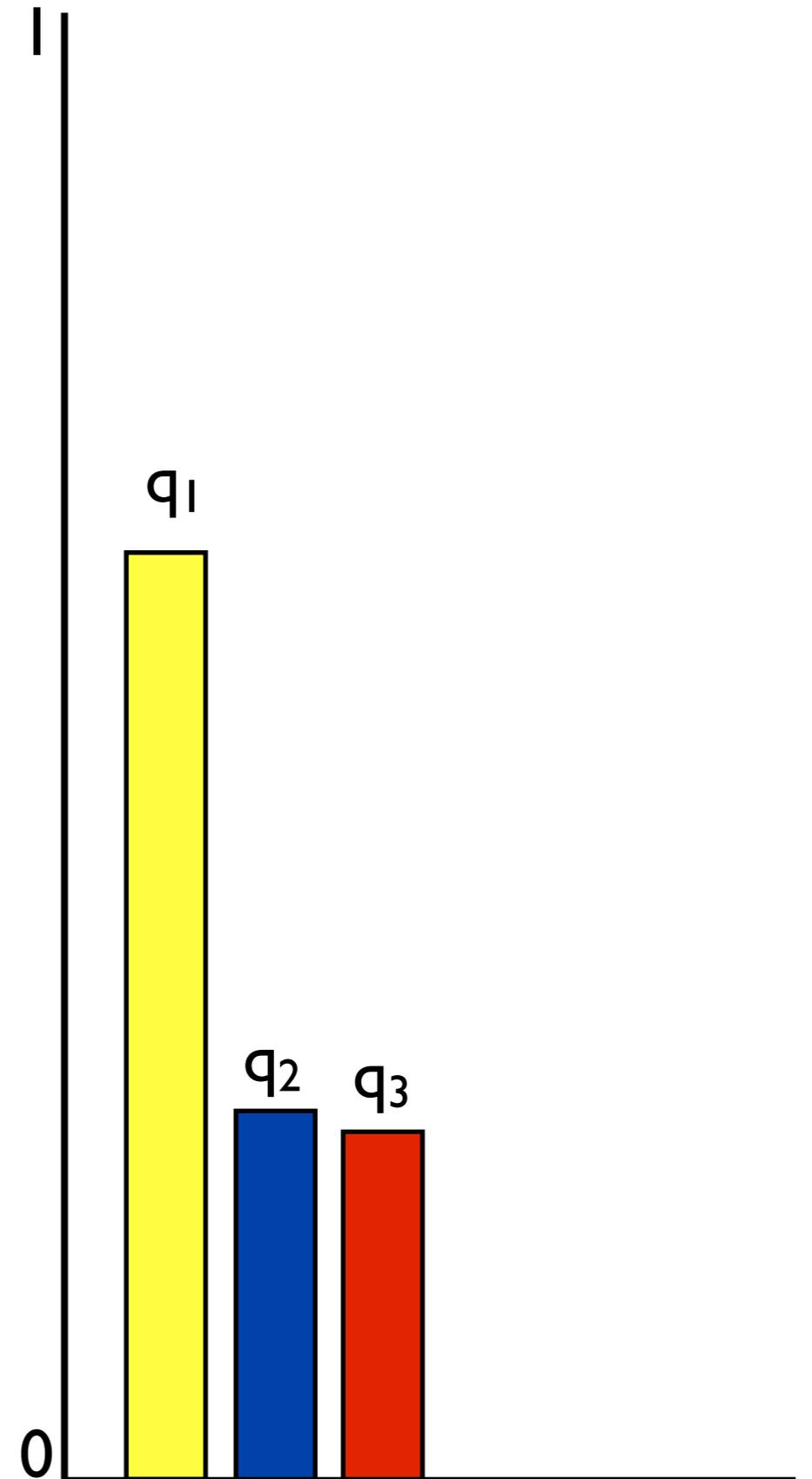
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Indian buffet process: beta feature frequencies

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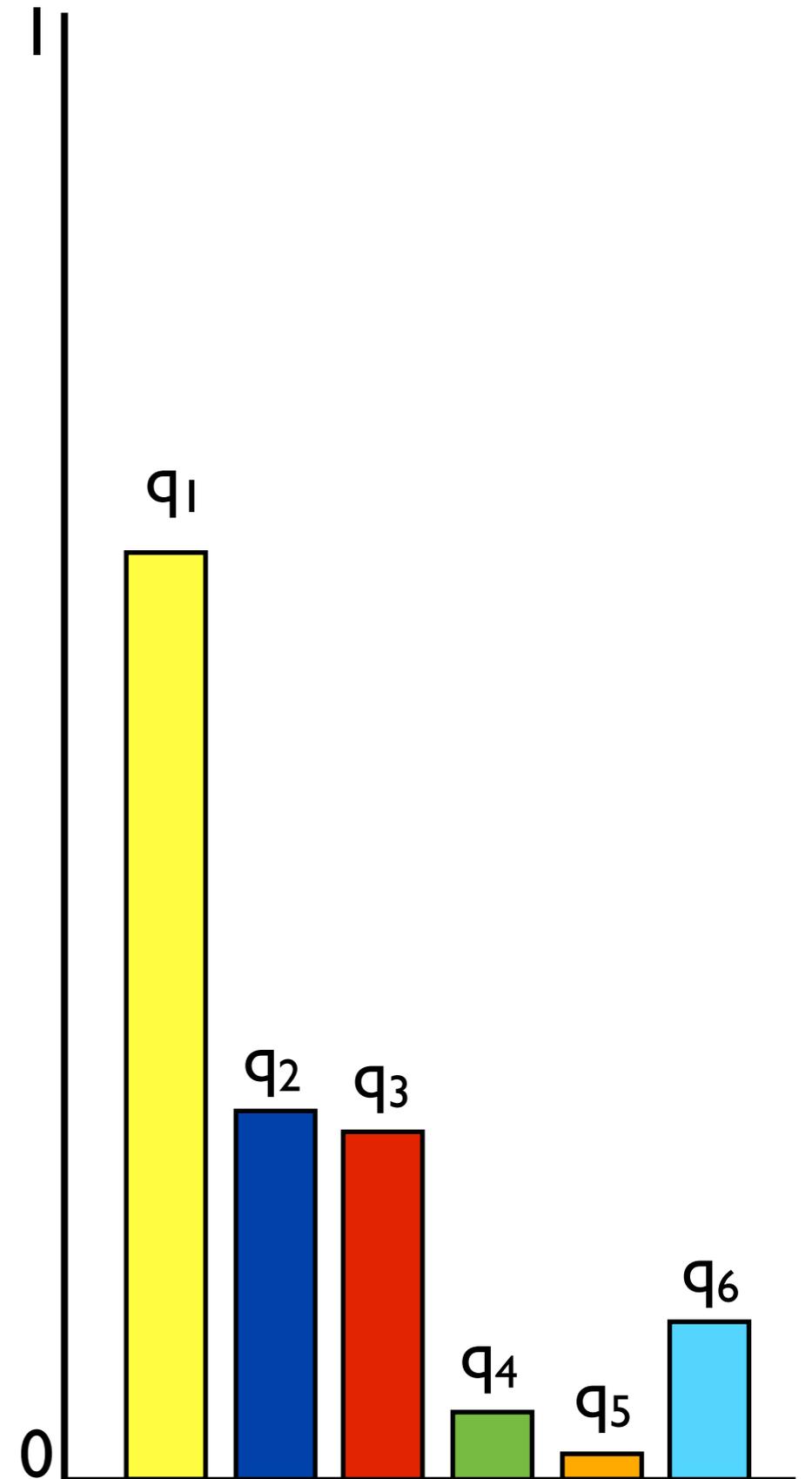
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Indian buffet process: beta feature frequencies

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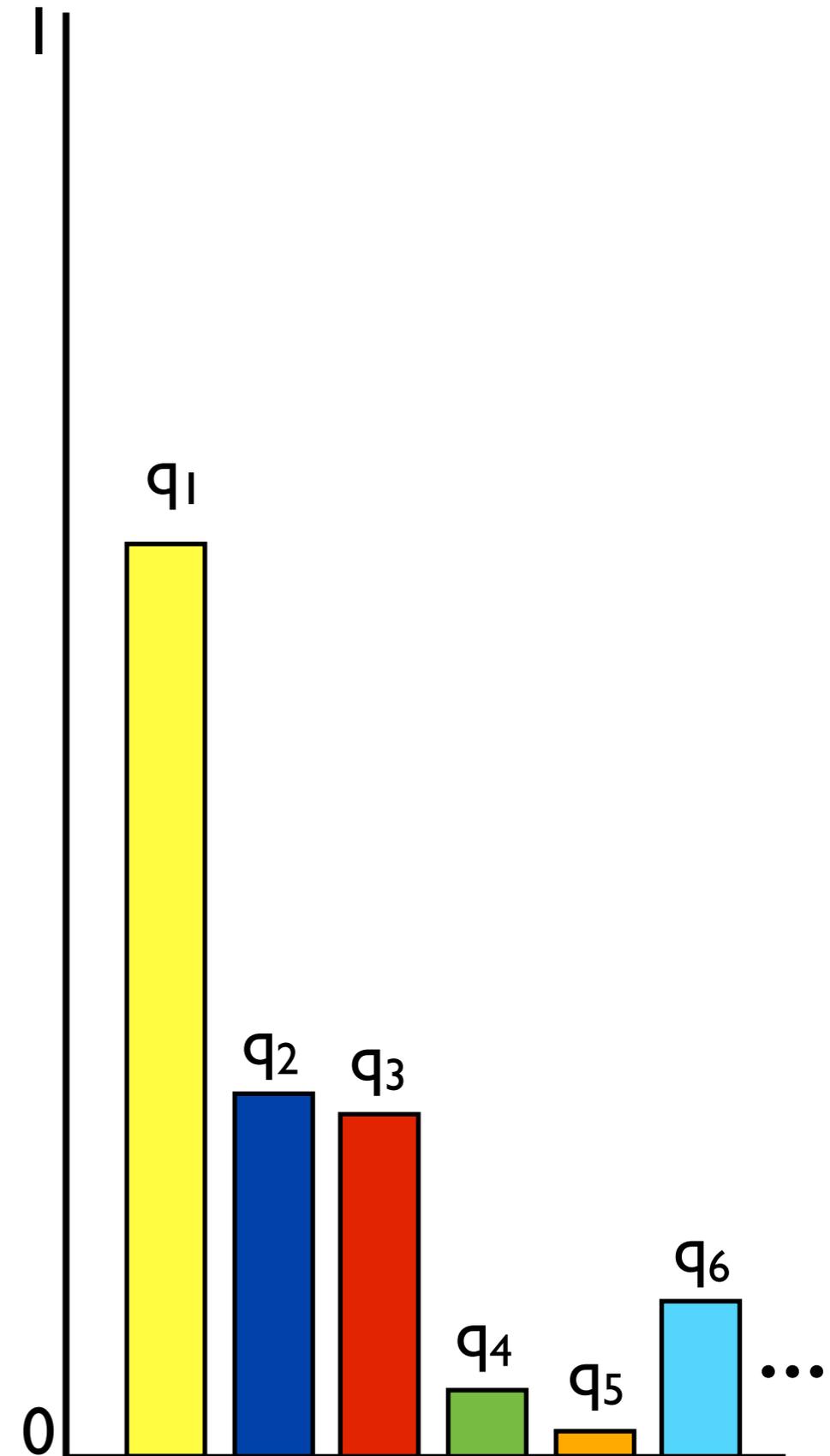
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# Paintboxes

Indian buffet process: beta feature frequencies

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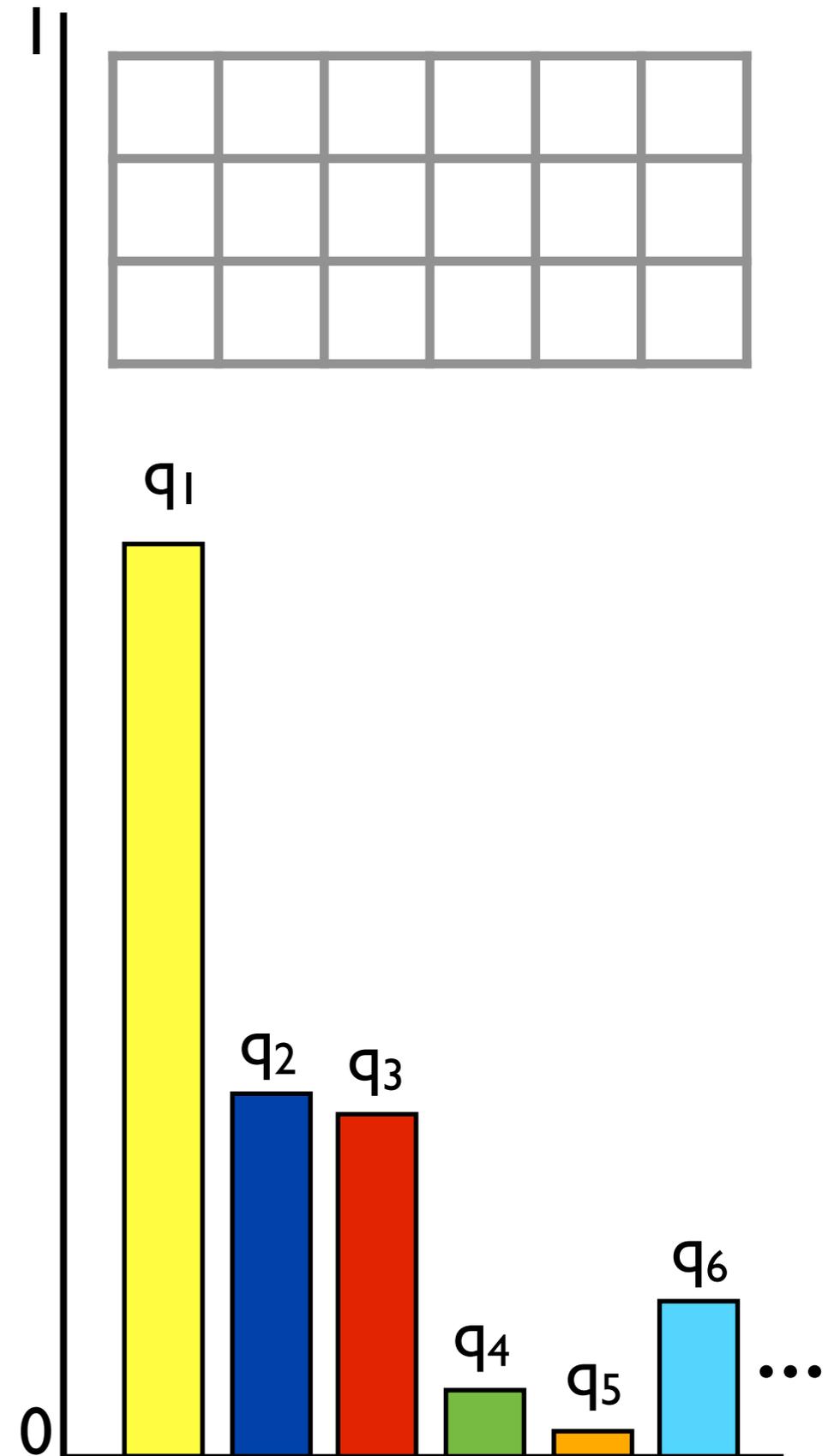
1. Draw  $K_m^+ = \text{Poisson} \left( \gamma \frac{\theta}{\theta + m - 1} \right)$

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# Paintboxes

Indian buffet process: beta feature frequencies

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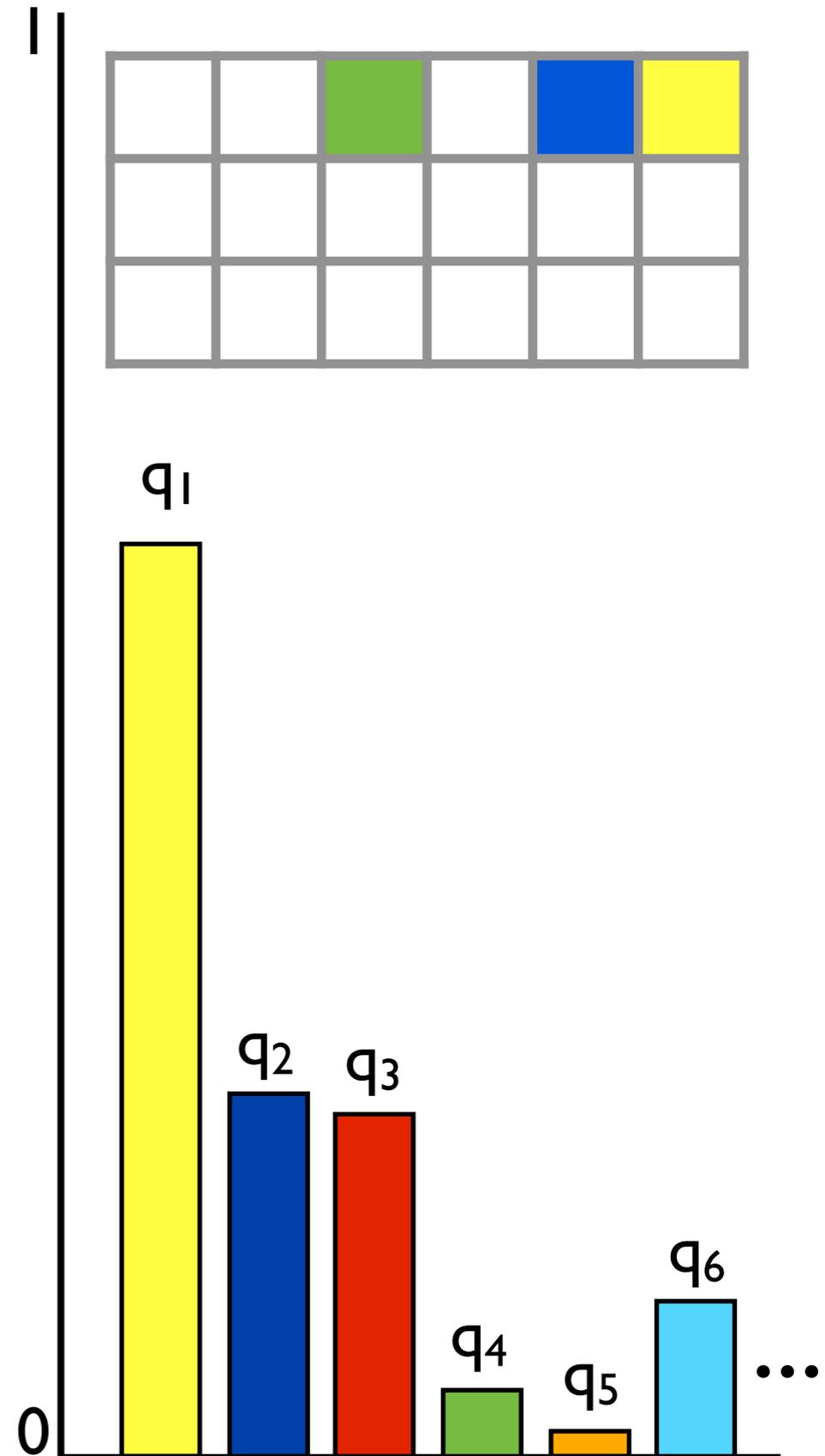
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# Paintboxes

Indian buffet process: beta feature frequencies

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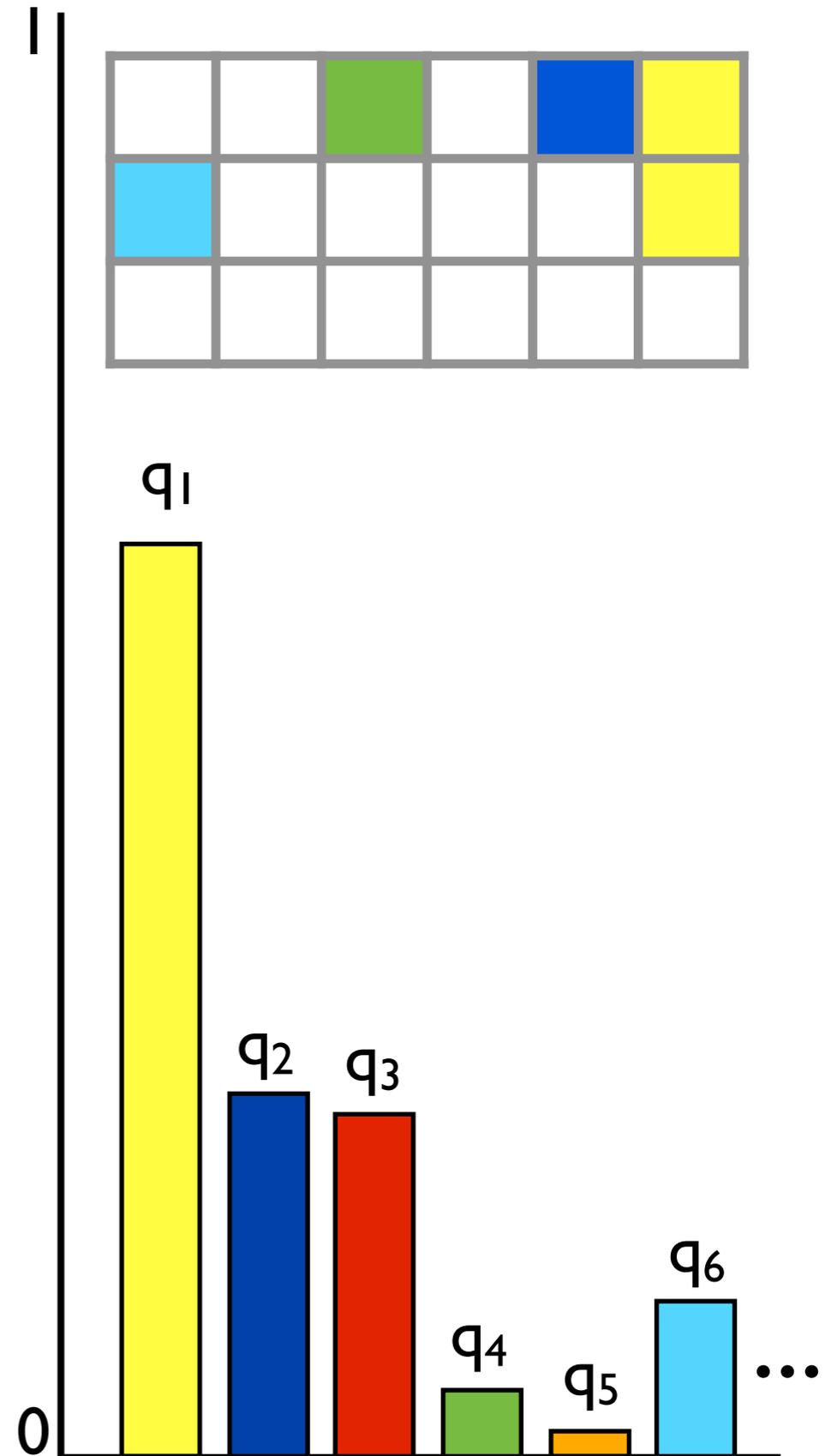
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# Paintboxes

Indian buffet process: beta feature frequencies

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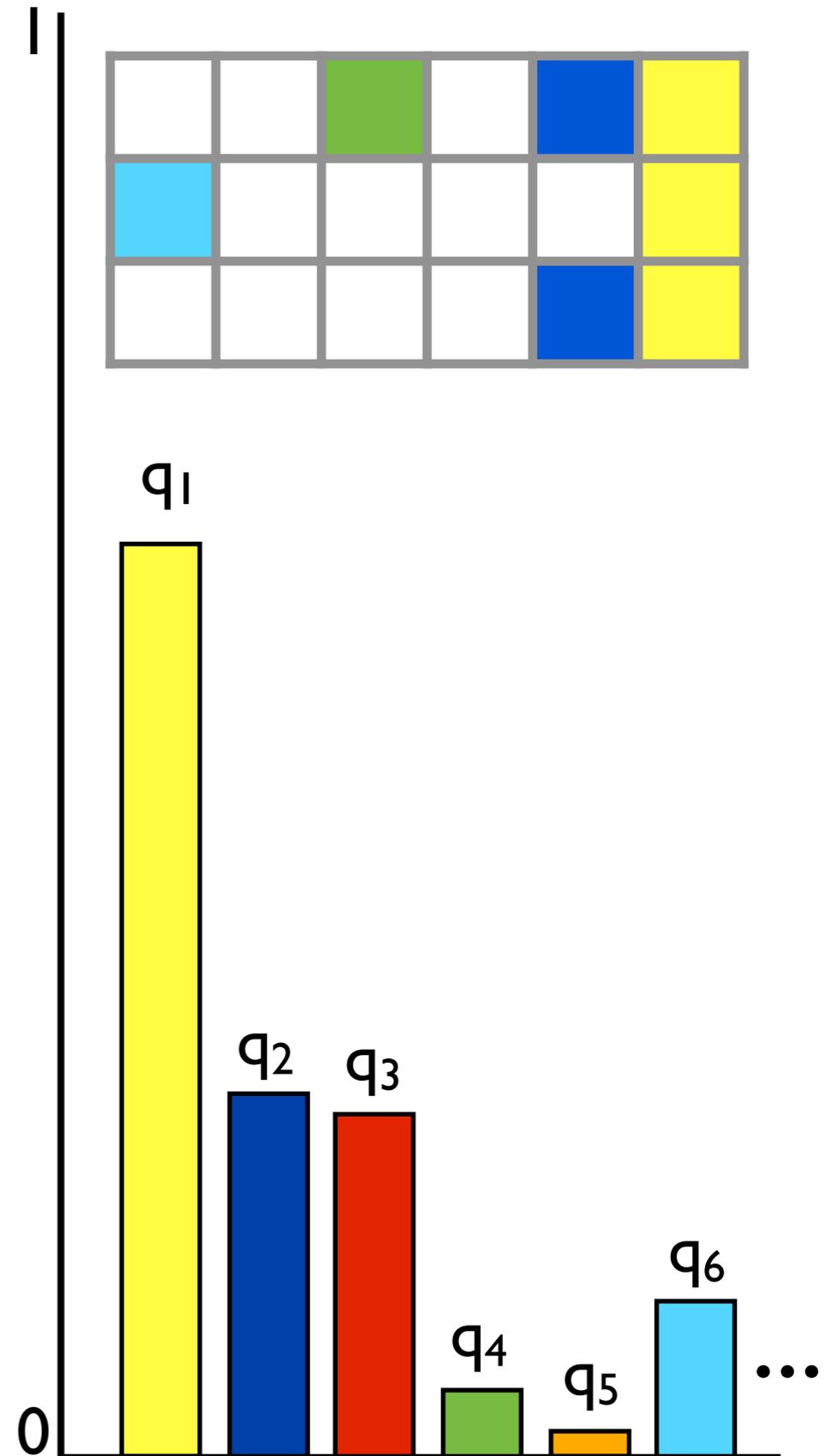
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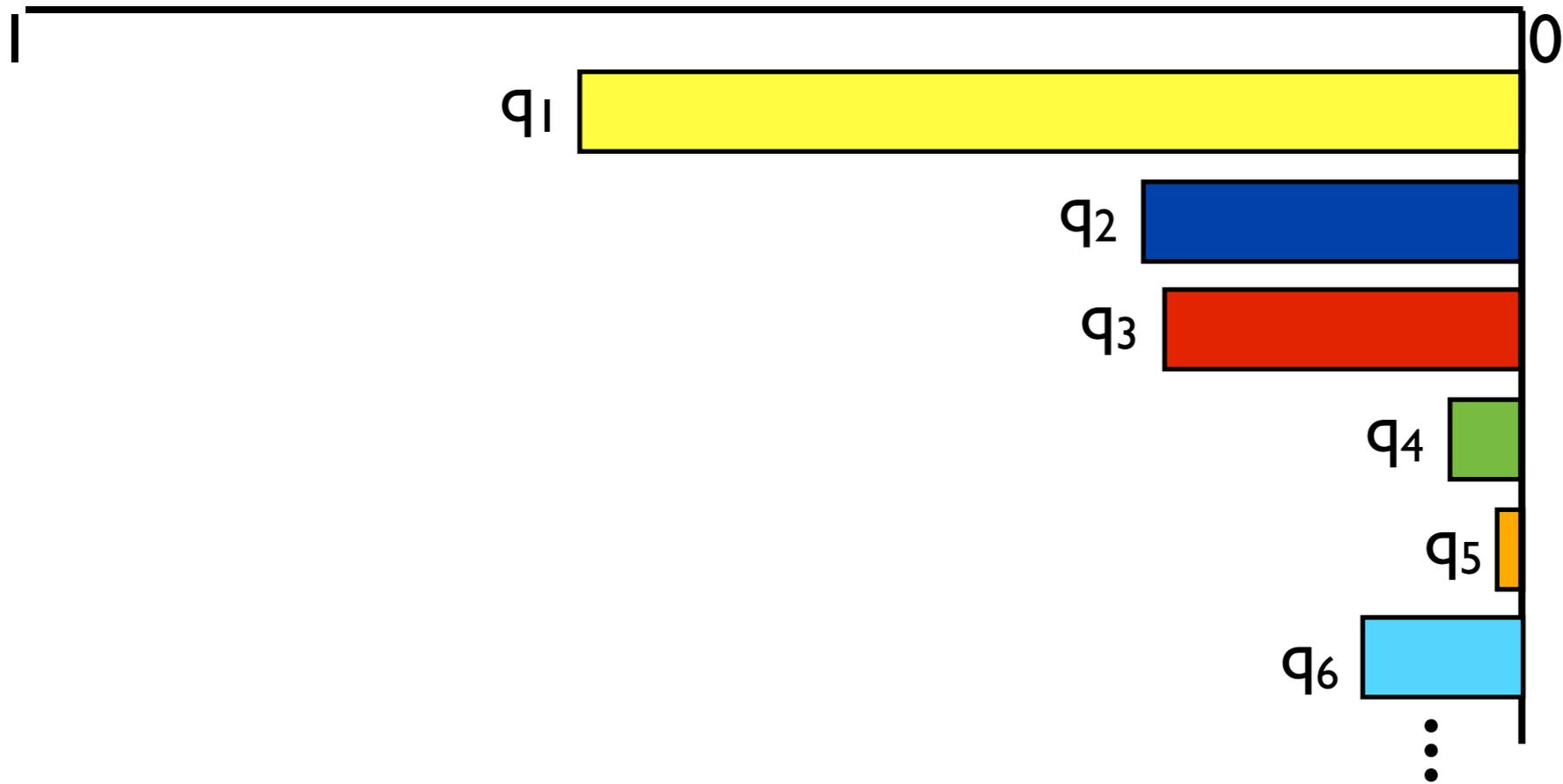
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# Paintboxes

Indian buffet process: beta feature frequencies



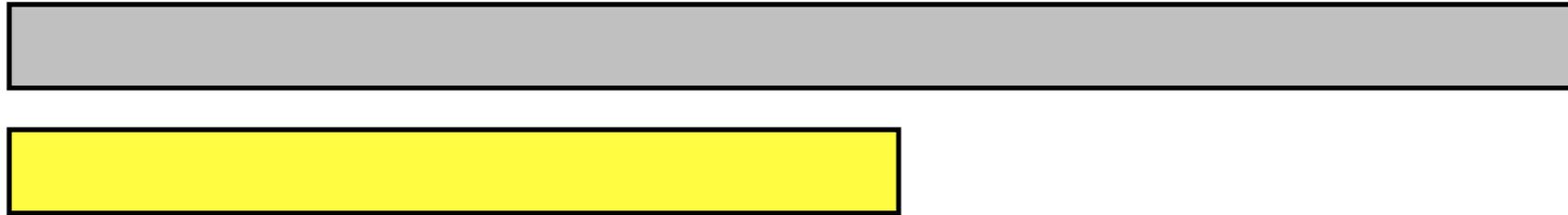
# Paintboxes

Indian buffet process: beta feature frequencies



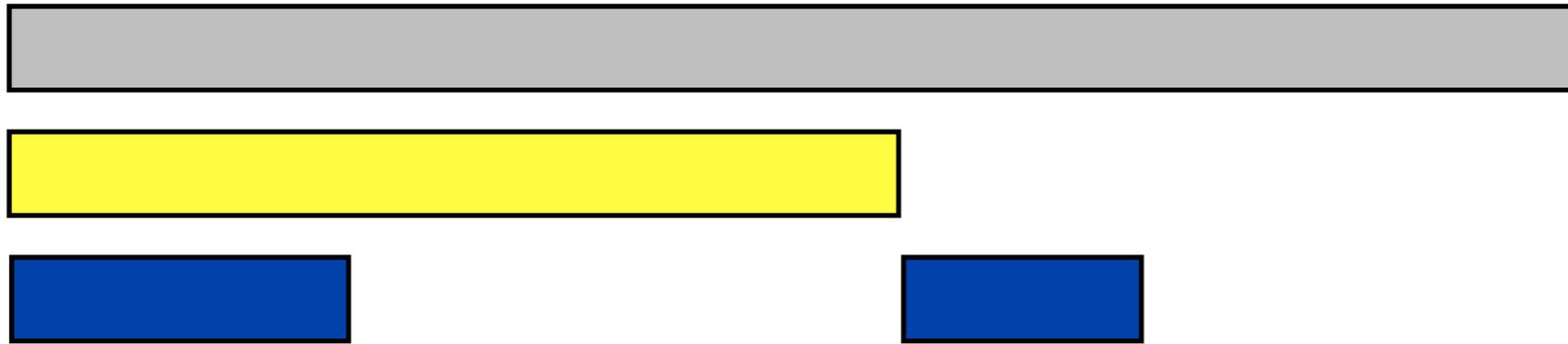
# Paintboxes

Indian buffet process: beta feature frequencies



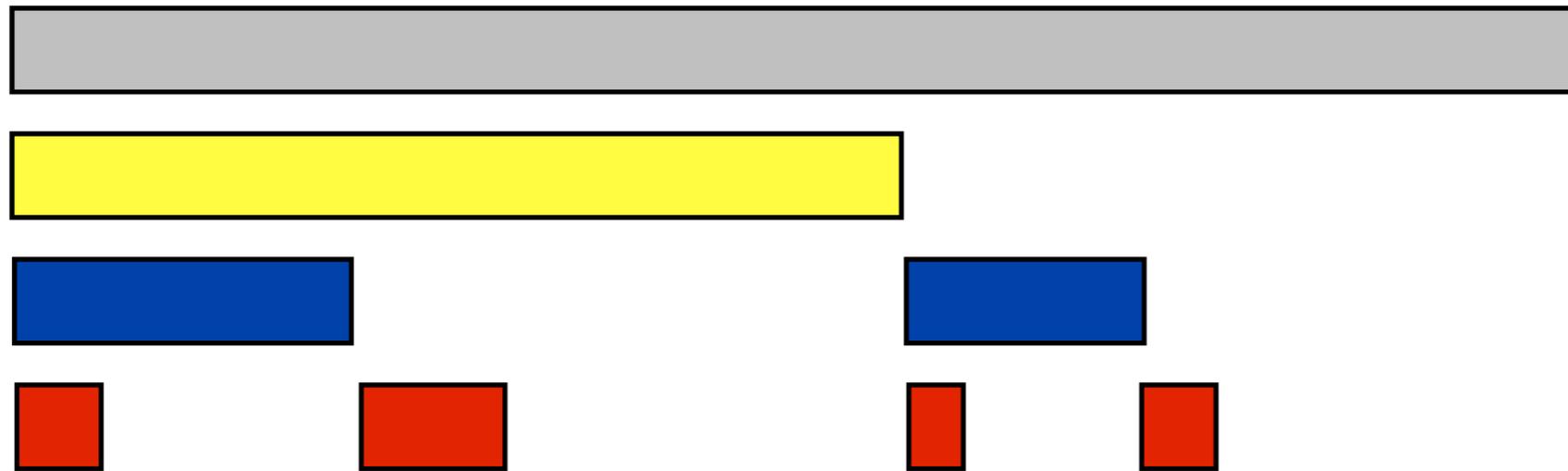
# Paintboxes

Indian buffet process: beta feature frequencies



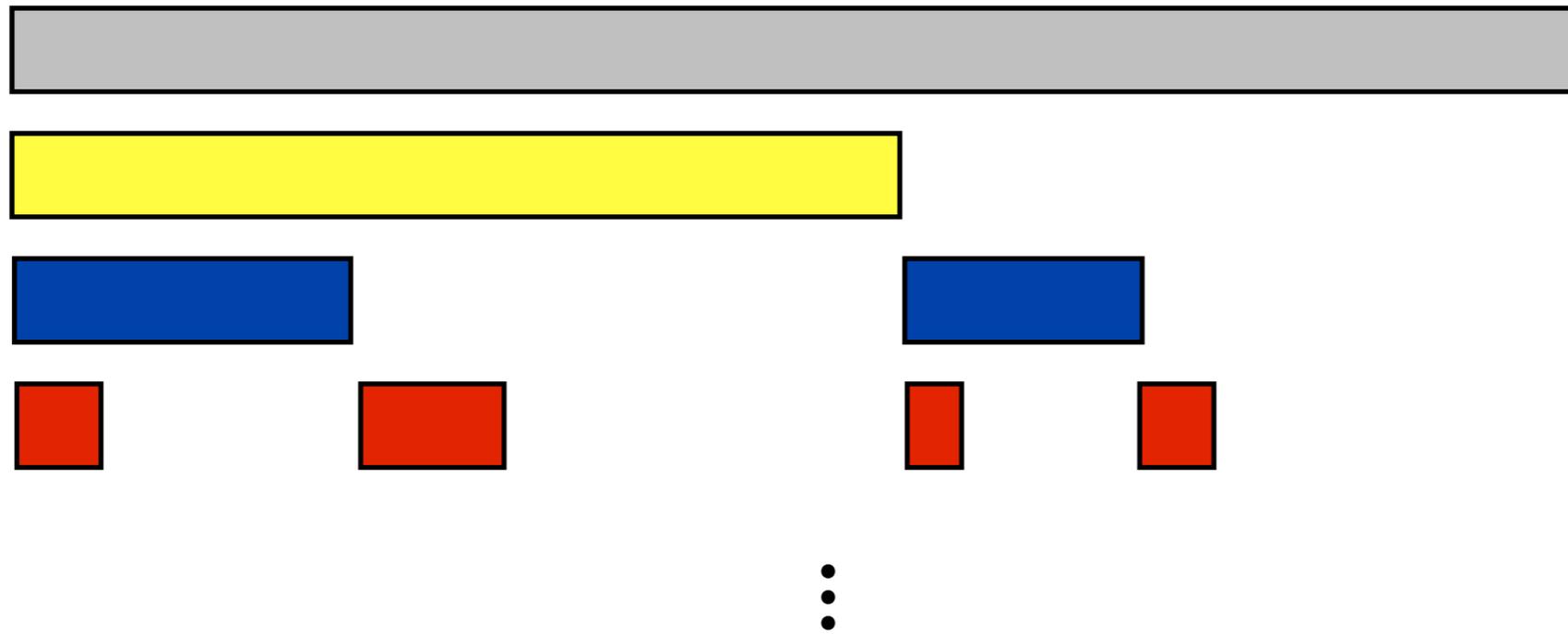
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Indian buffet process: beta feature frequencies

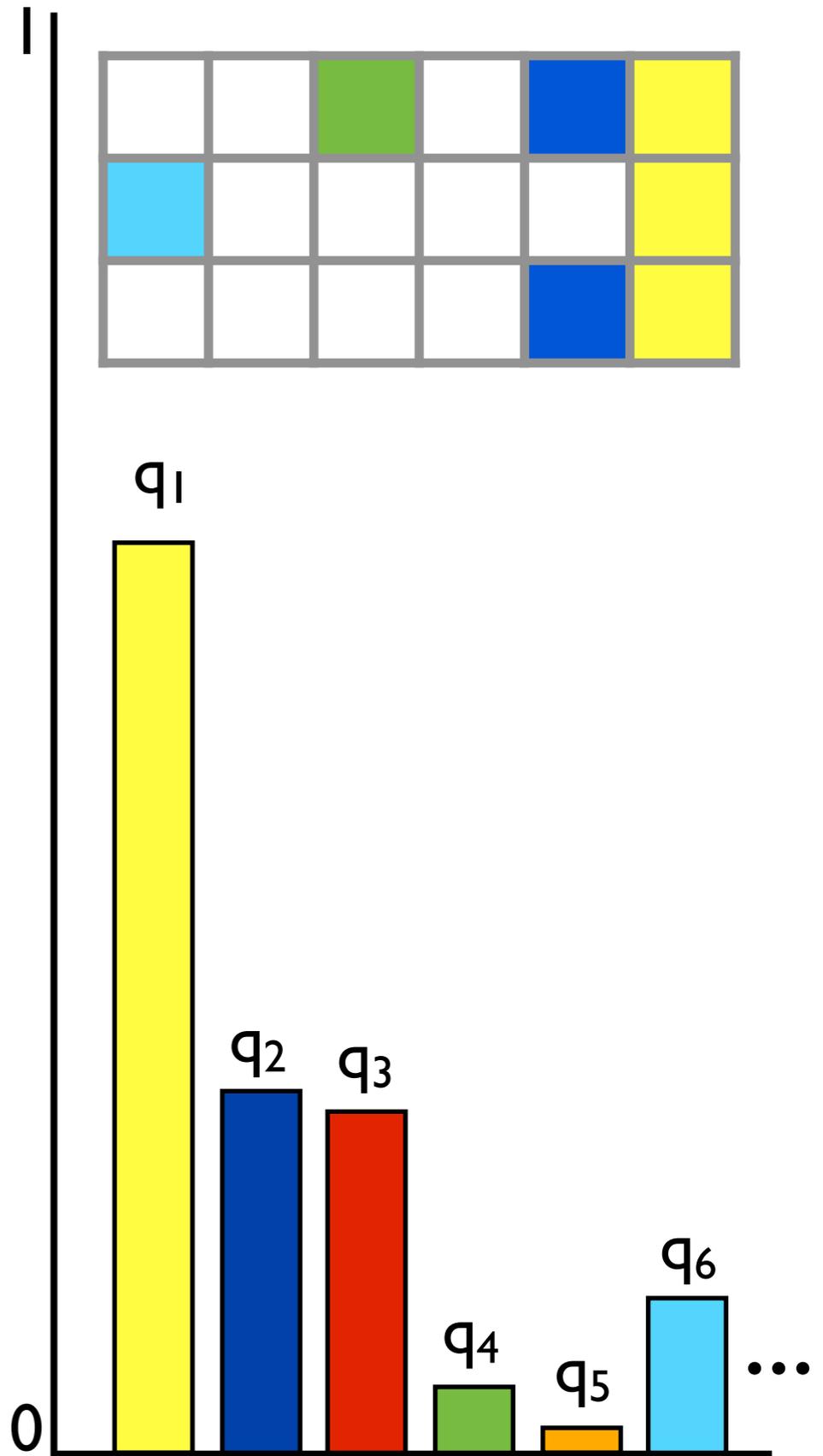


# Paintboxes

Indian buffet process: beta feature frequencies

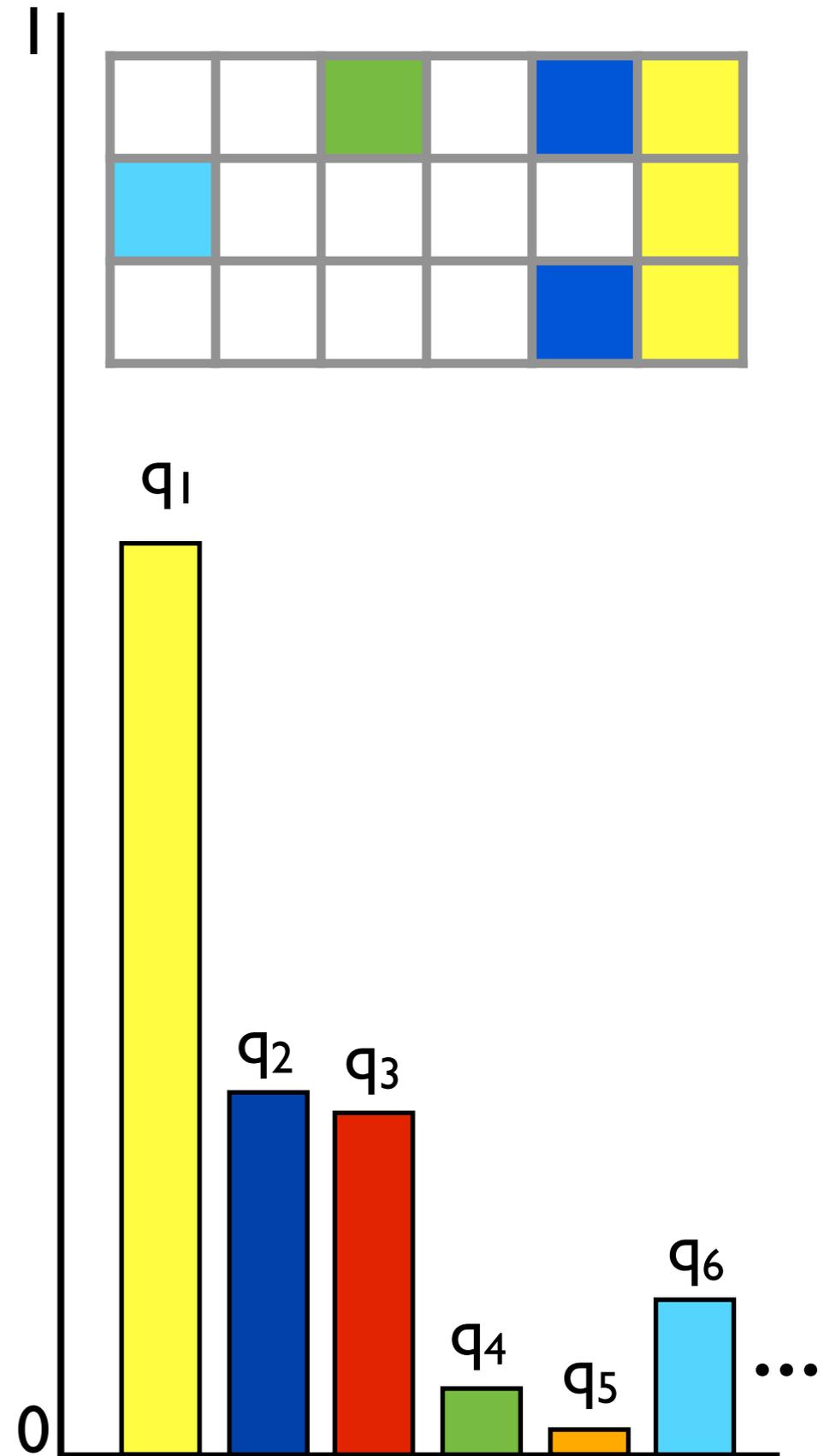


# Paintboxes



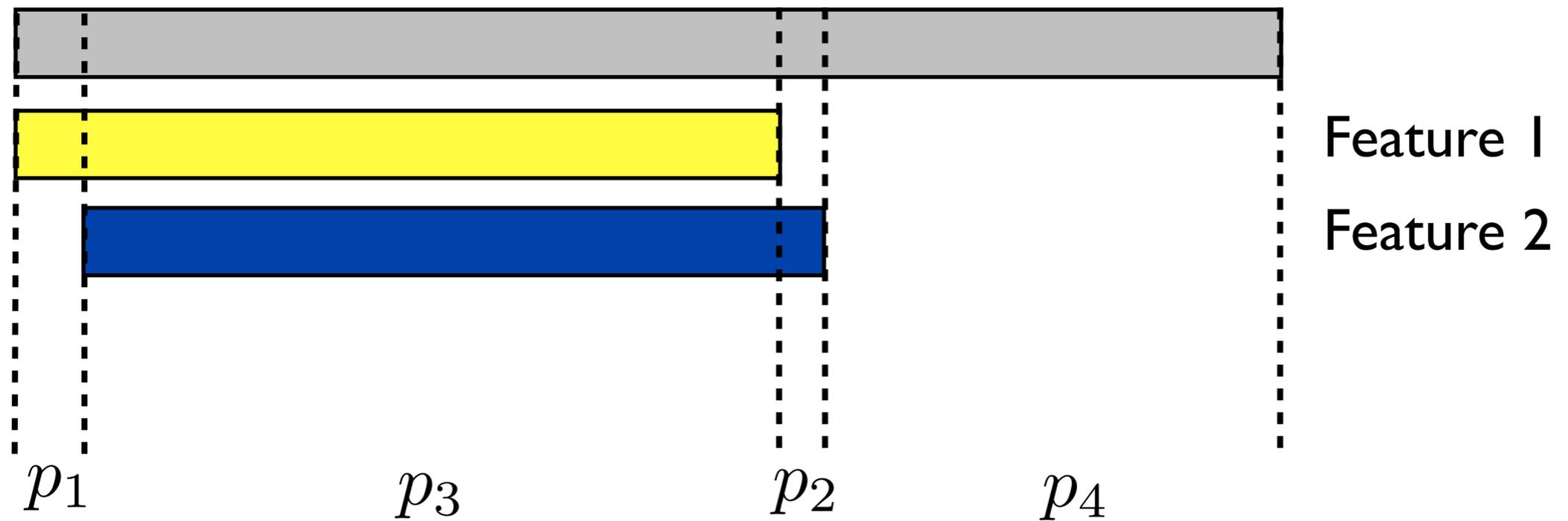
# Paintboxes

“Feature frequency models”



# Paintboxes

## Two feature example



$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \end{array}) = p_1$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \blacksquare \\ \hline \end{array}) = p_2$$

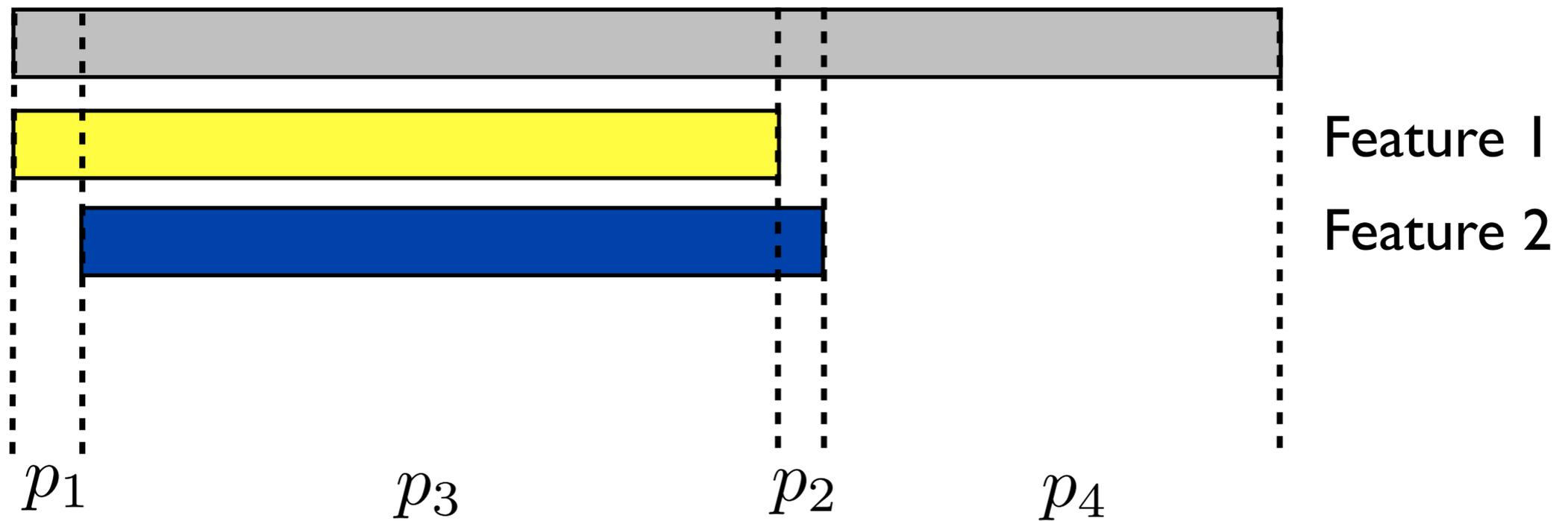
$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \blacksquare \\ \hline \end{array}) = p_3$$

$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \square \\ \hline \end{array}) = p_4$$

# Paintboxes

Two feature example

Not a feature frequency model



$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \blacksquare & \square \\ \hline \end{array}) = p_1$$

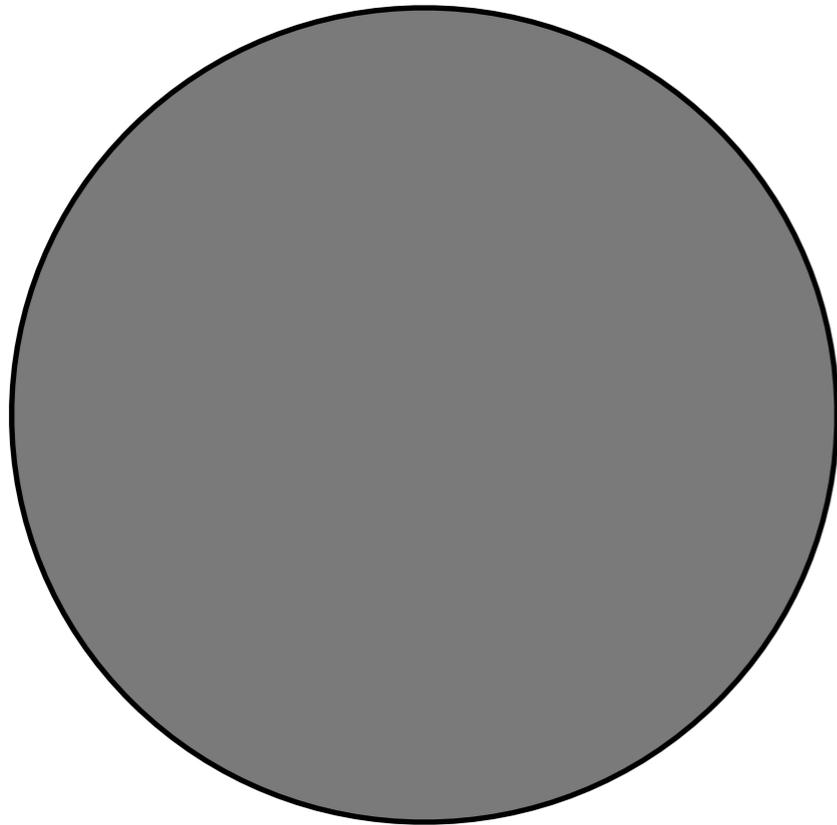
$$\mathbb{P}(\text{row} = \begin{array}{|c|c|} \hline \square & \blacksquare \\ \hline \end{array}) = p_2$$

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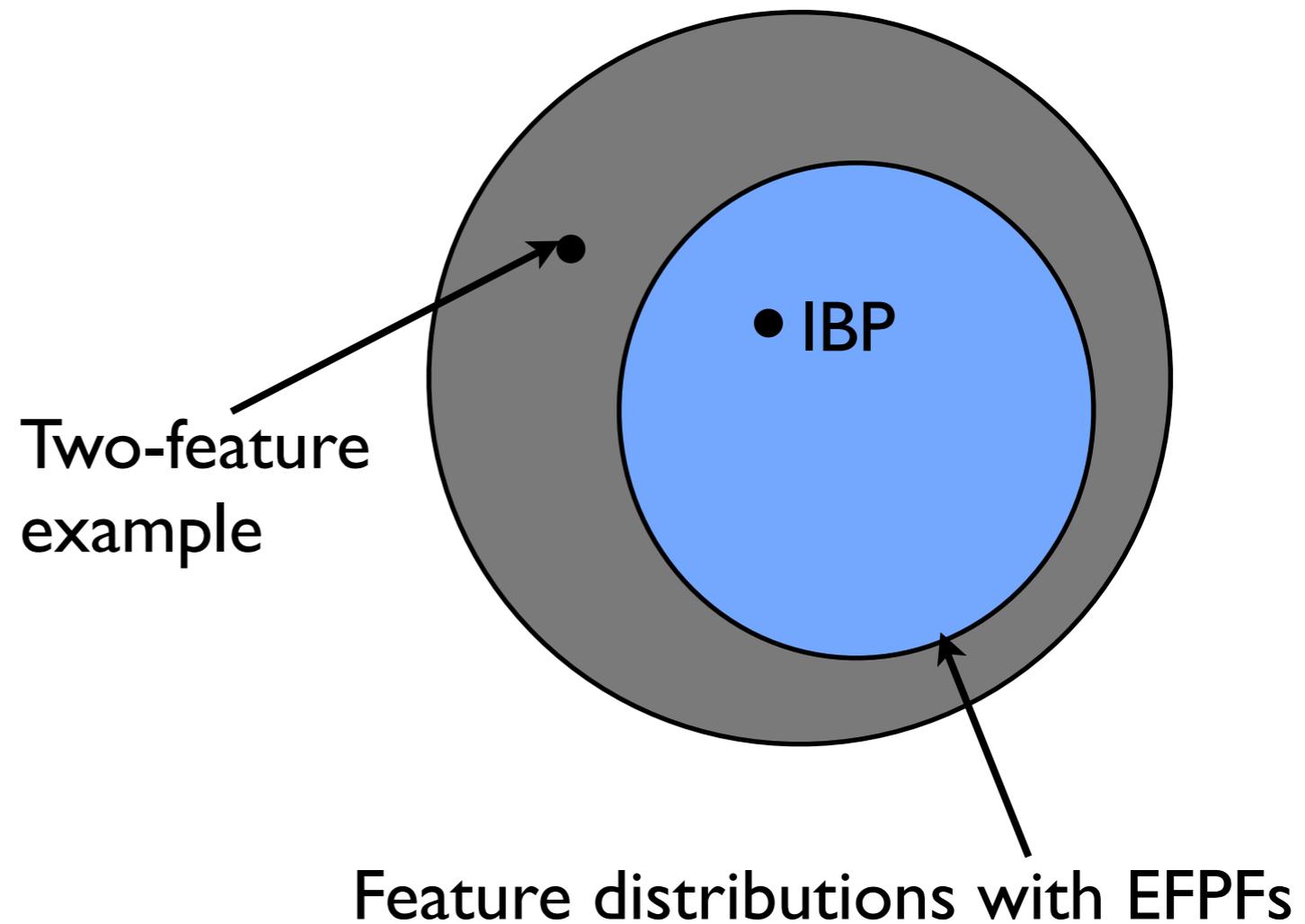
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# Paintboxes

Exchangeable cluster distributions  
= Cluster distributions with EPPFs  
= Kingman paintbox partitions

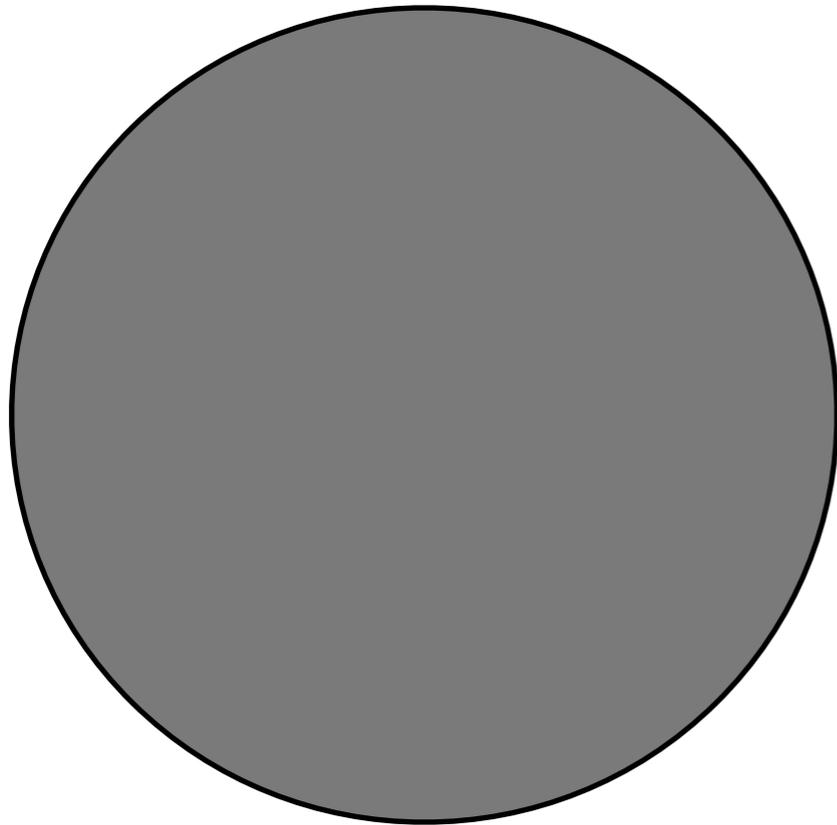


Exchangeable feature distributions  
= Feature paintbox allocations

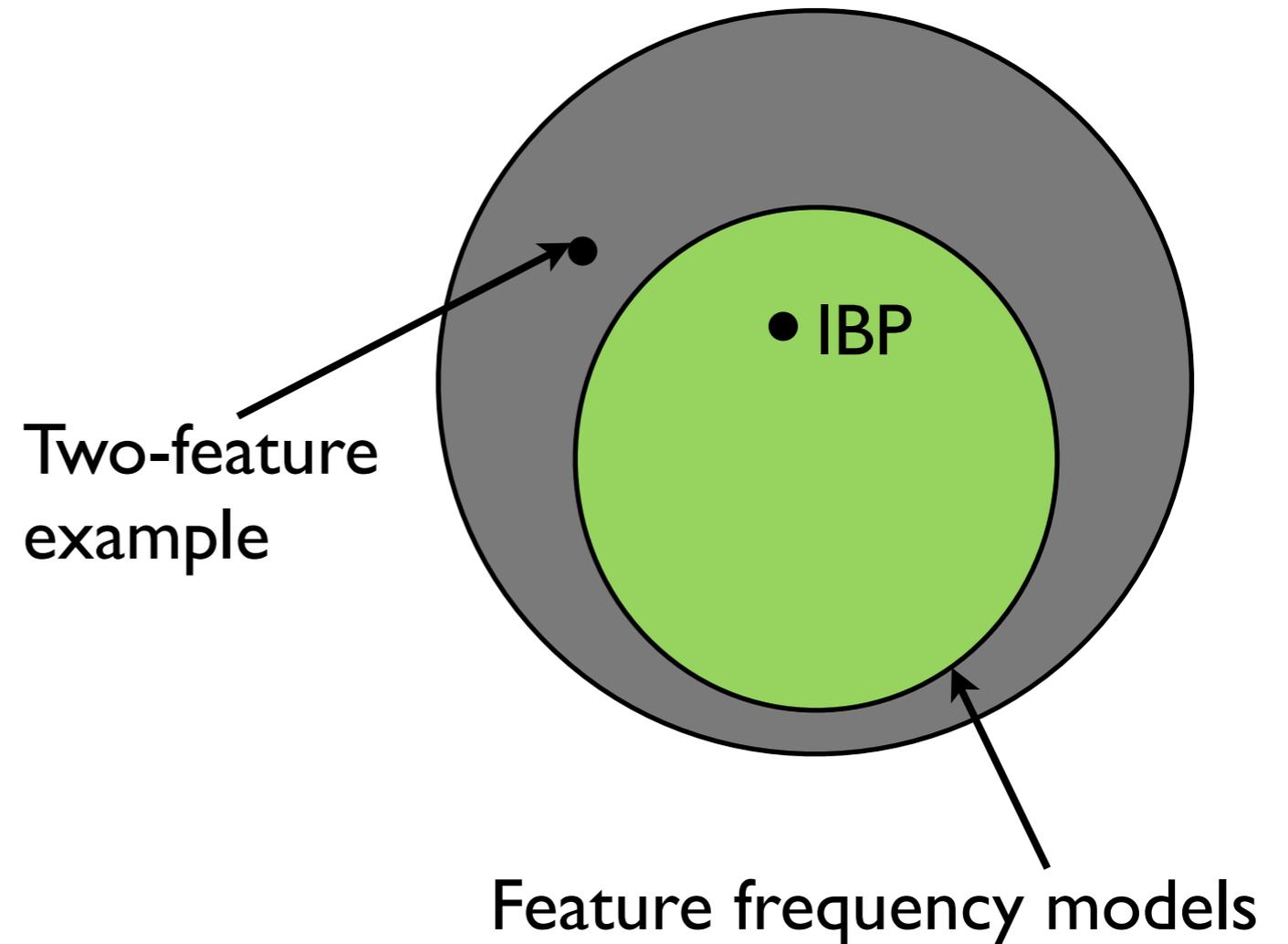


# Paintboxes

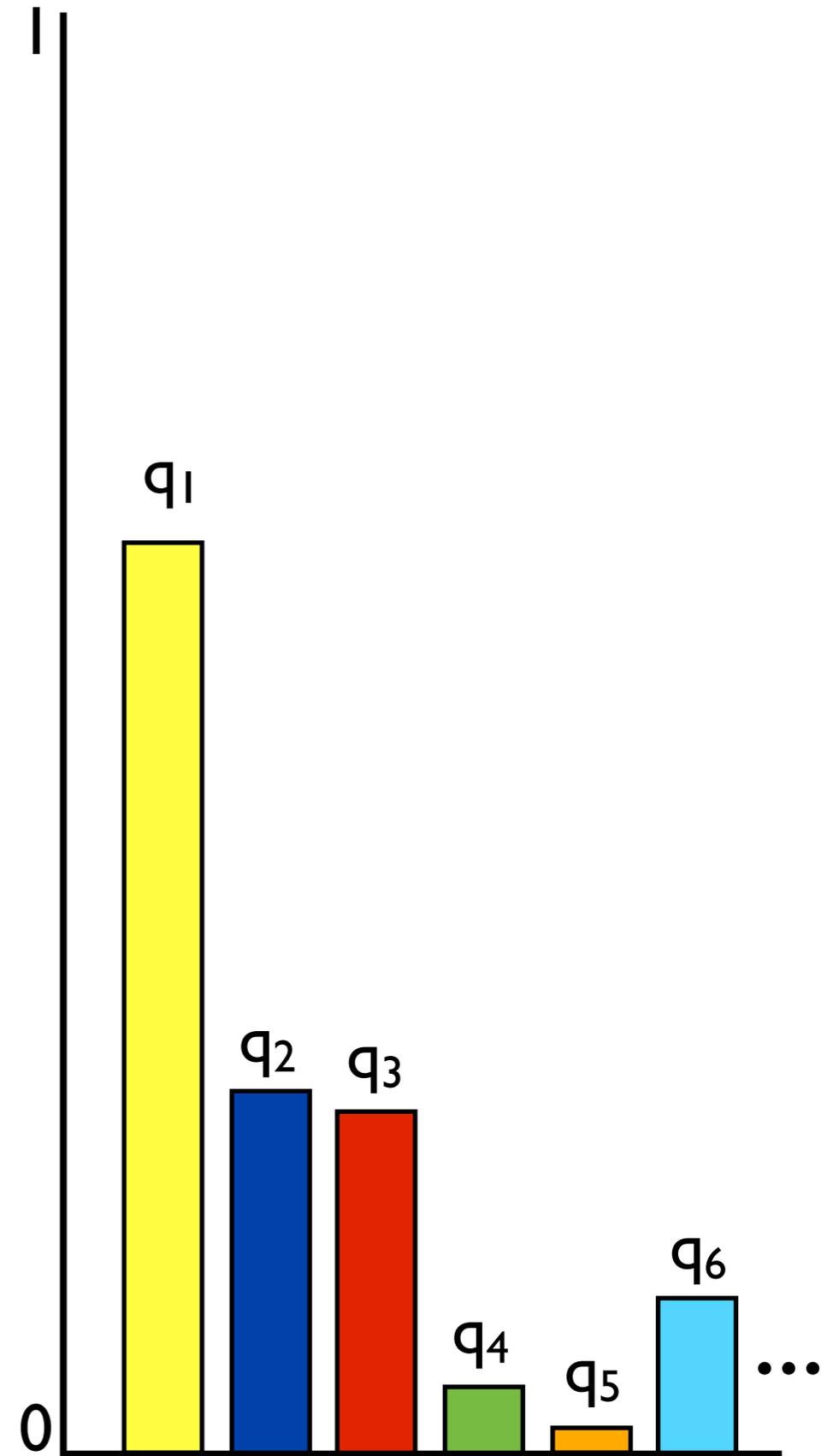
Exchangeable cluster distributions  
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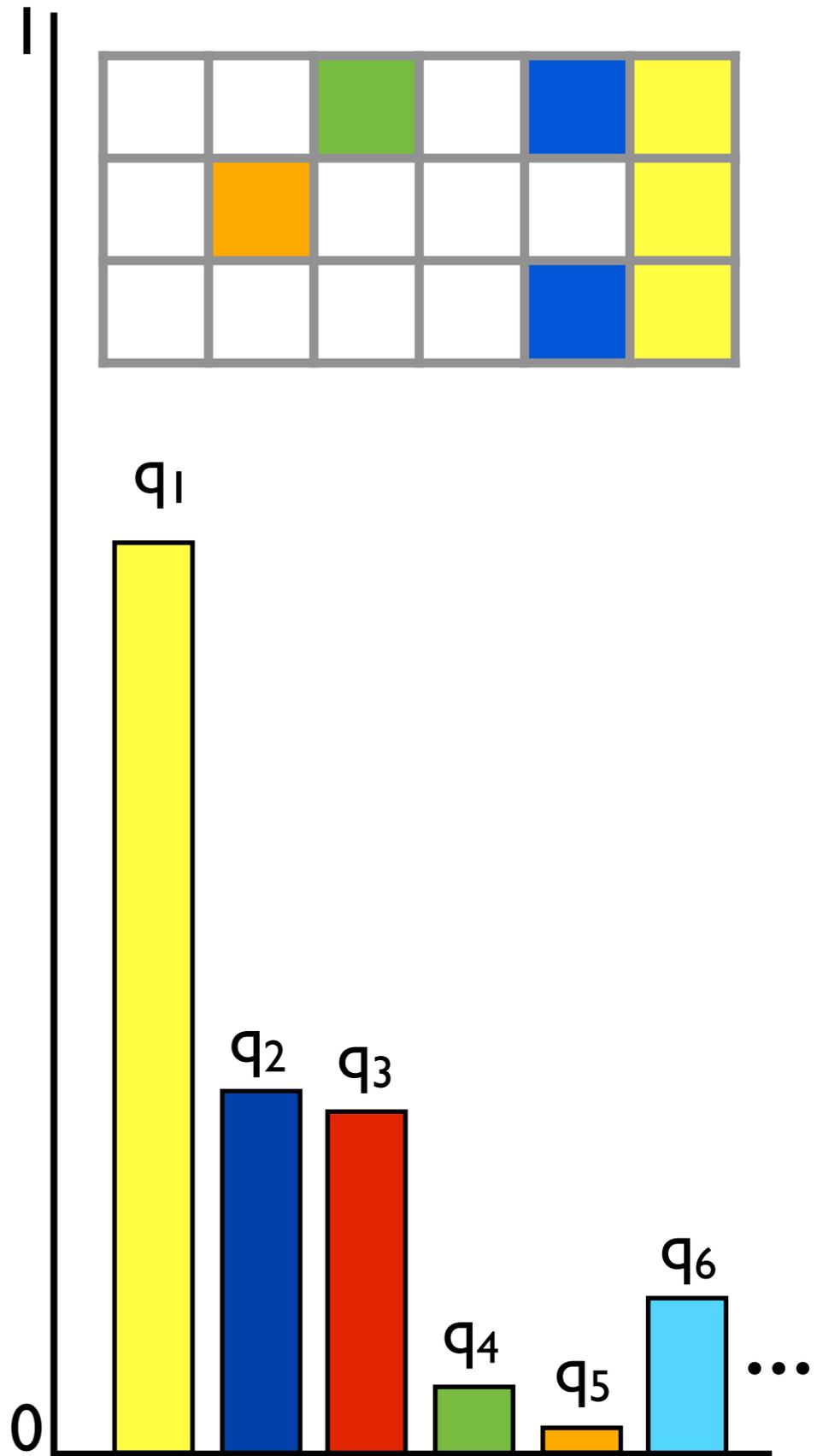
Exchangeable feature distributions  
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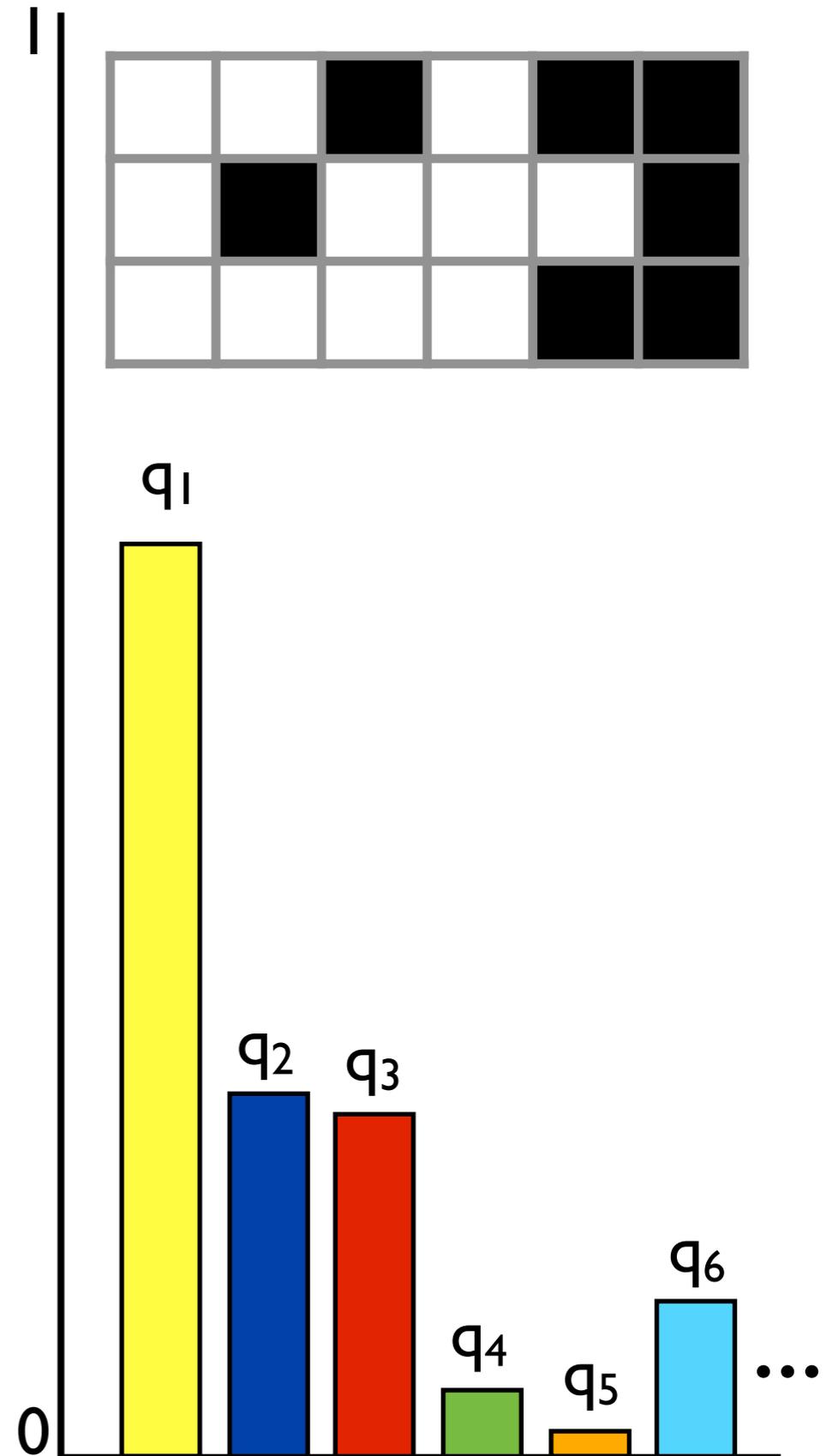
# Feature frequency models: EFPFs?



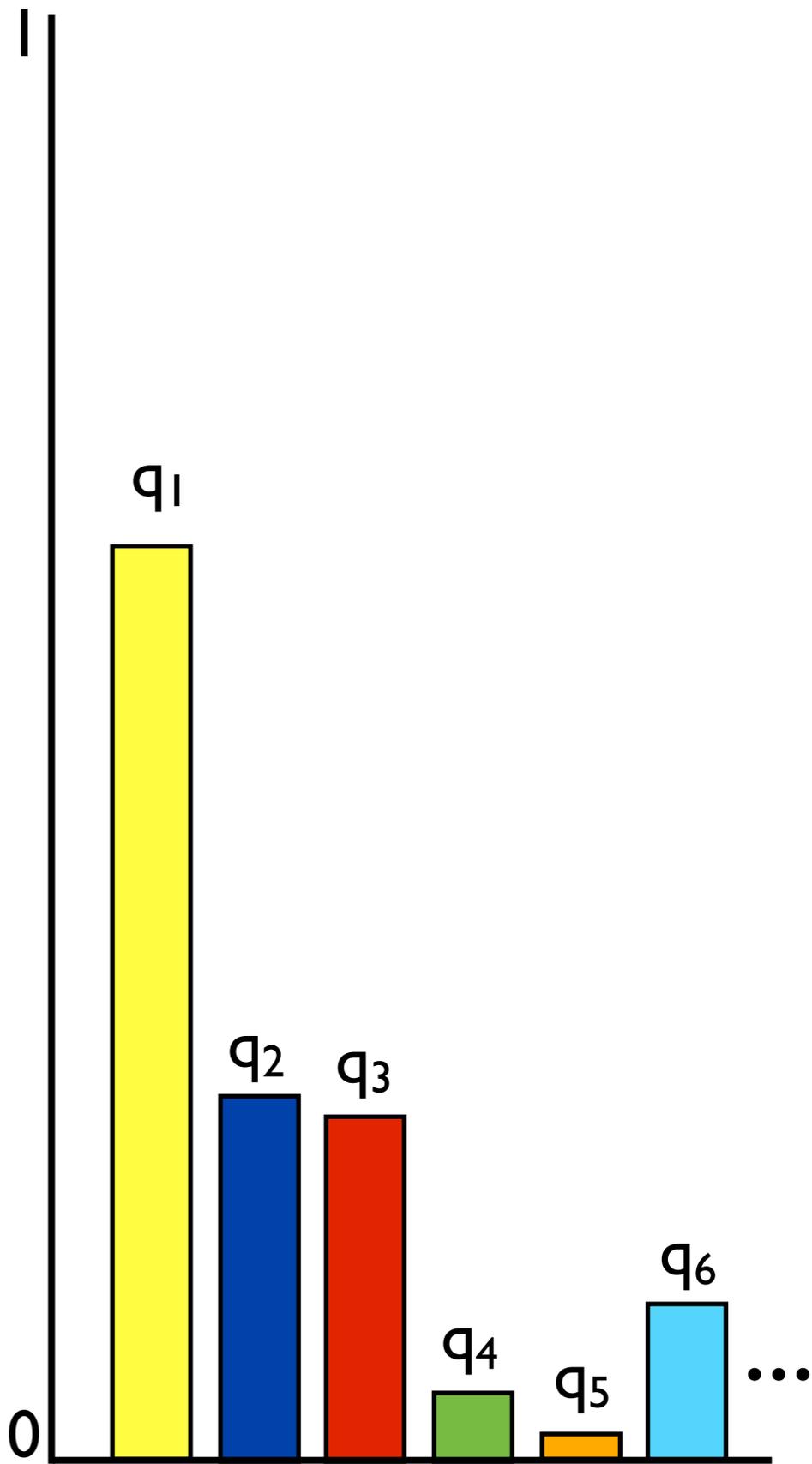
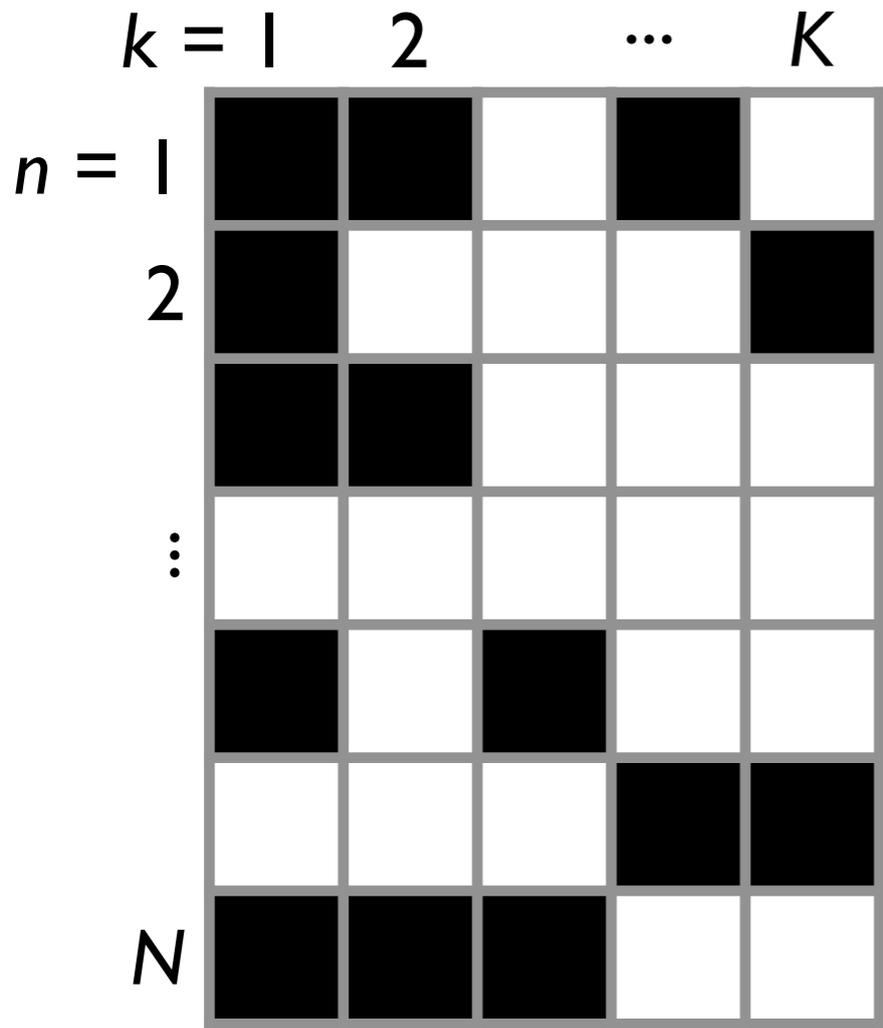
# Feature frequency models: EFPFs?



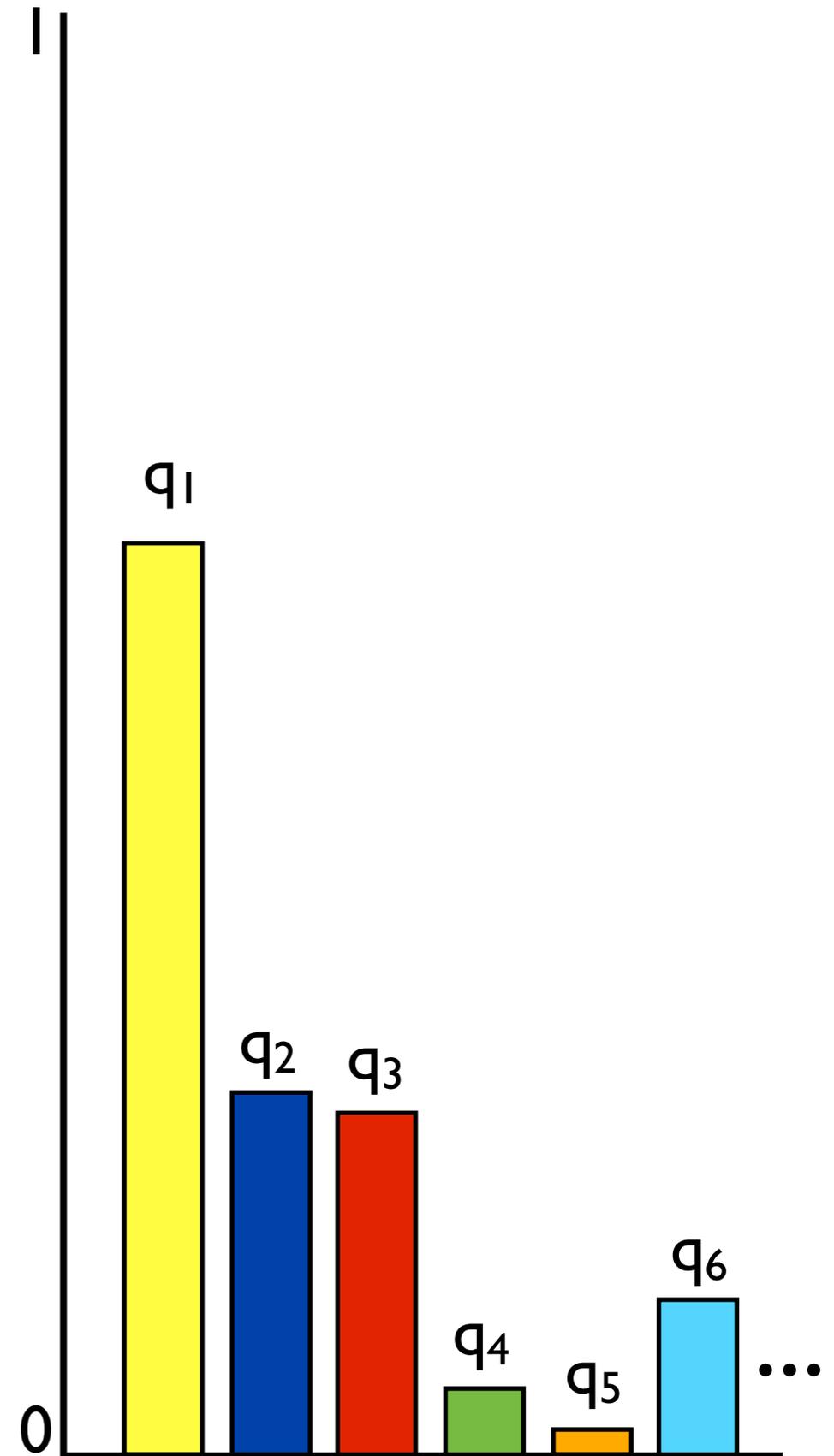
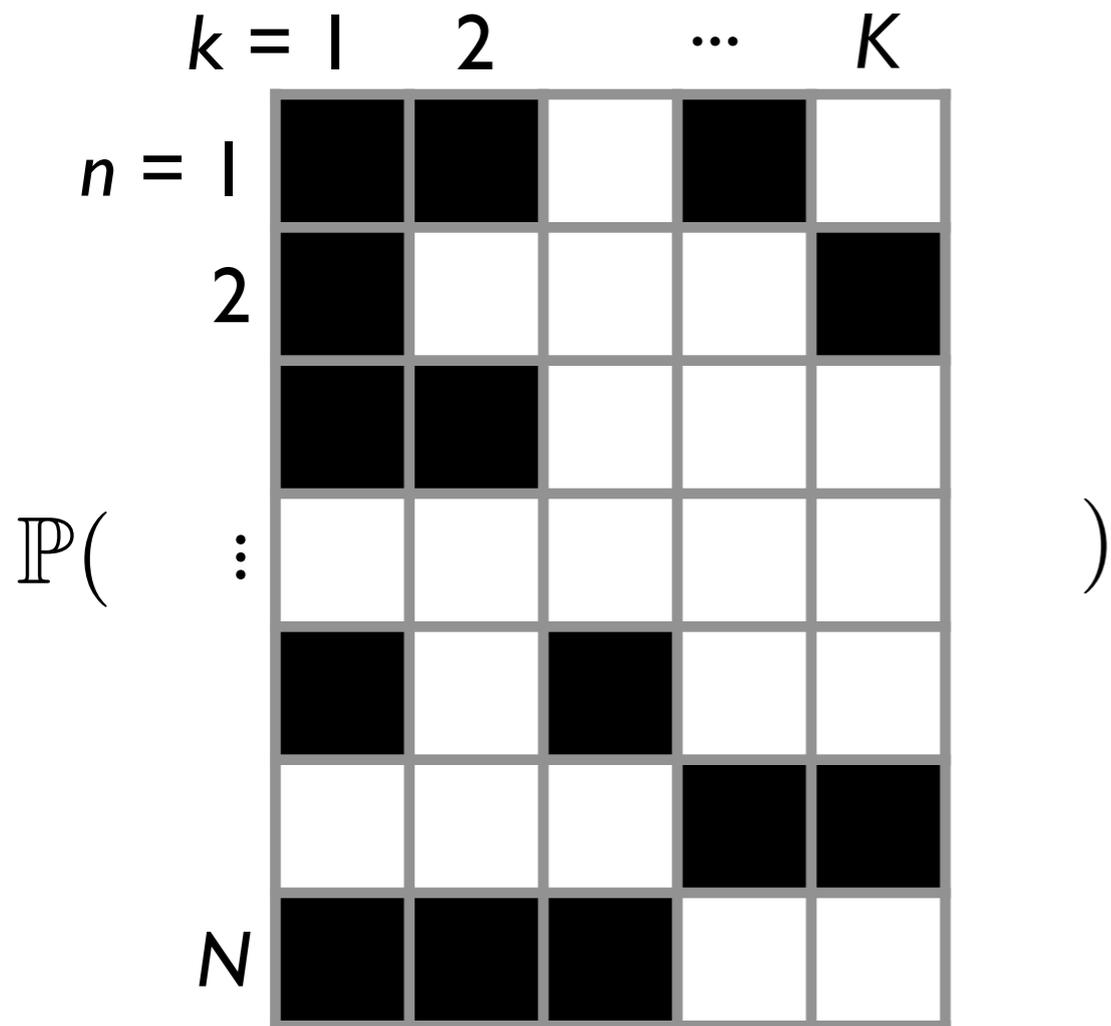
# Feature frequency models: EFPFs?



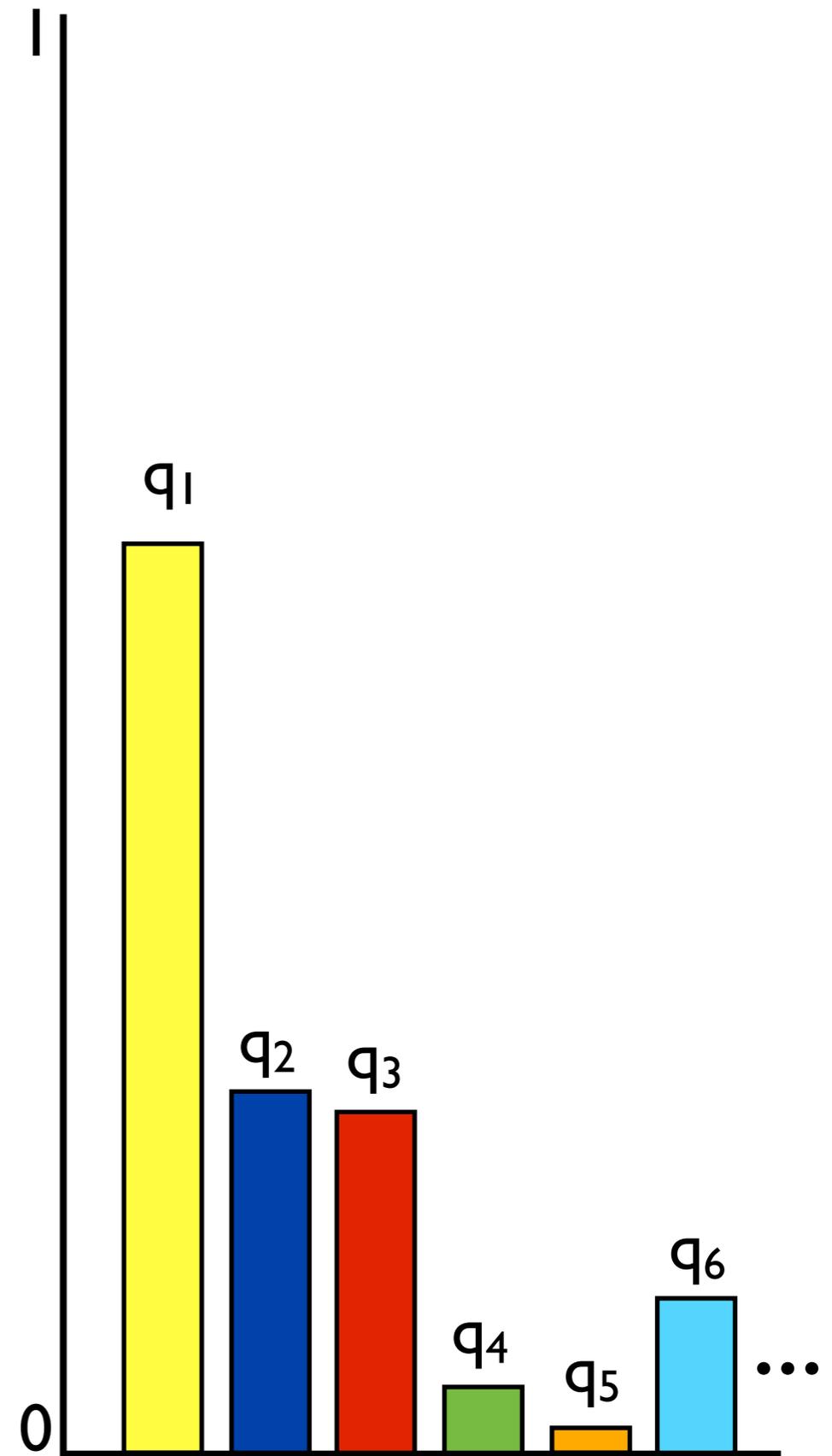
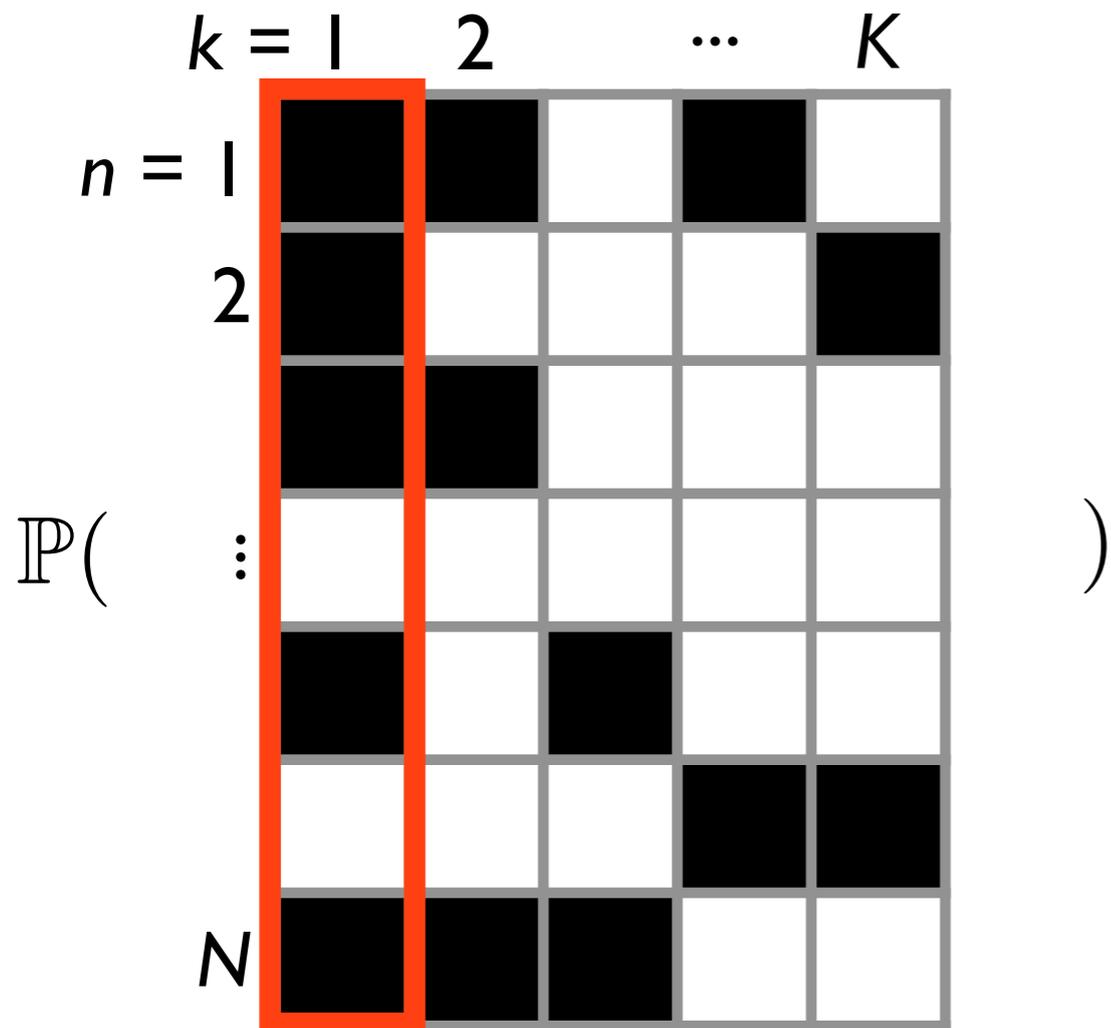
# Feature frequency models: EFPFs?



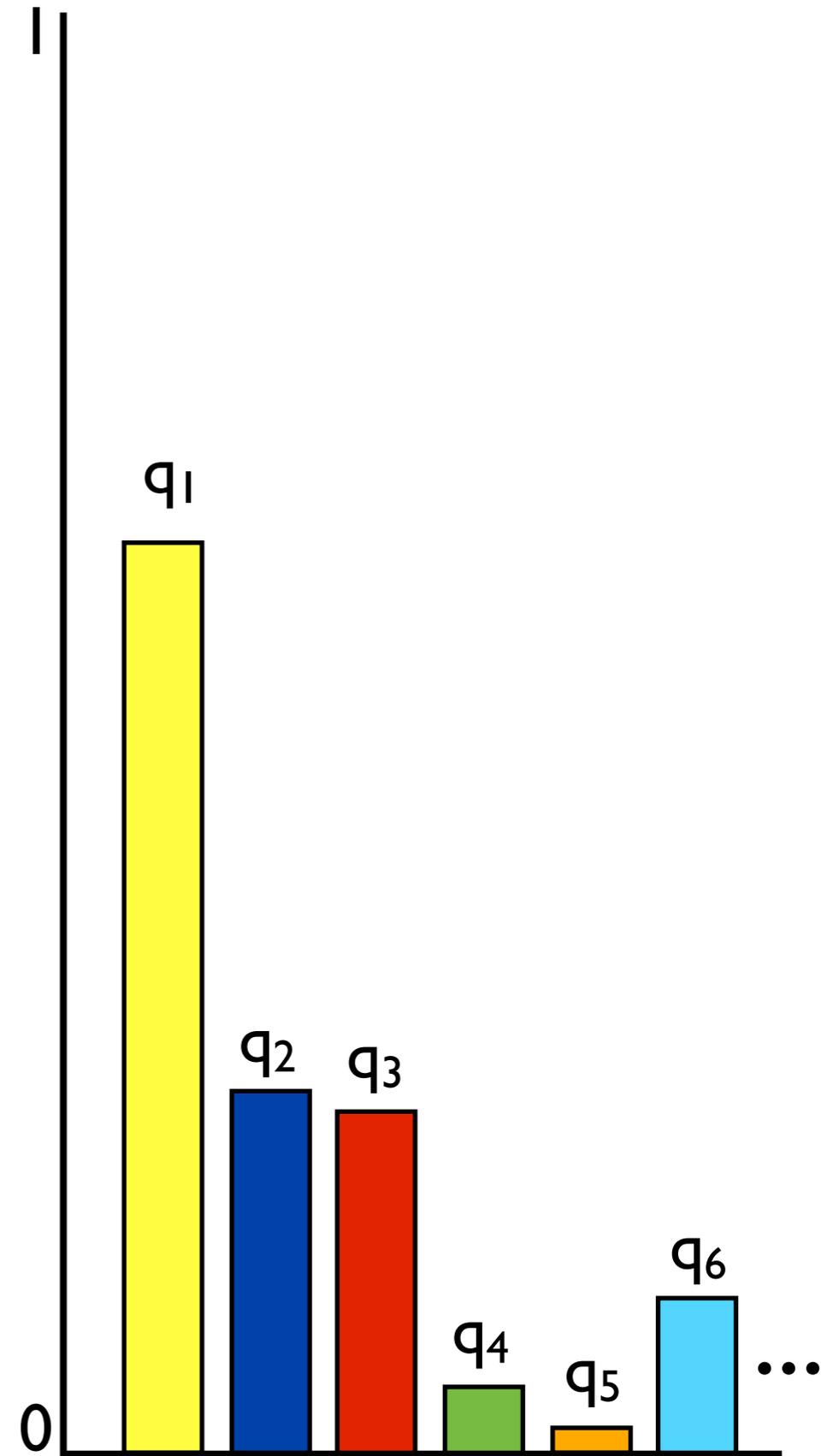
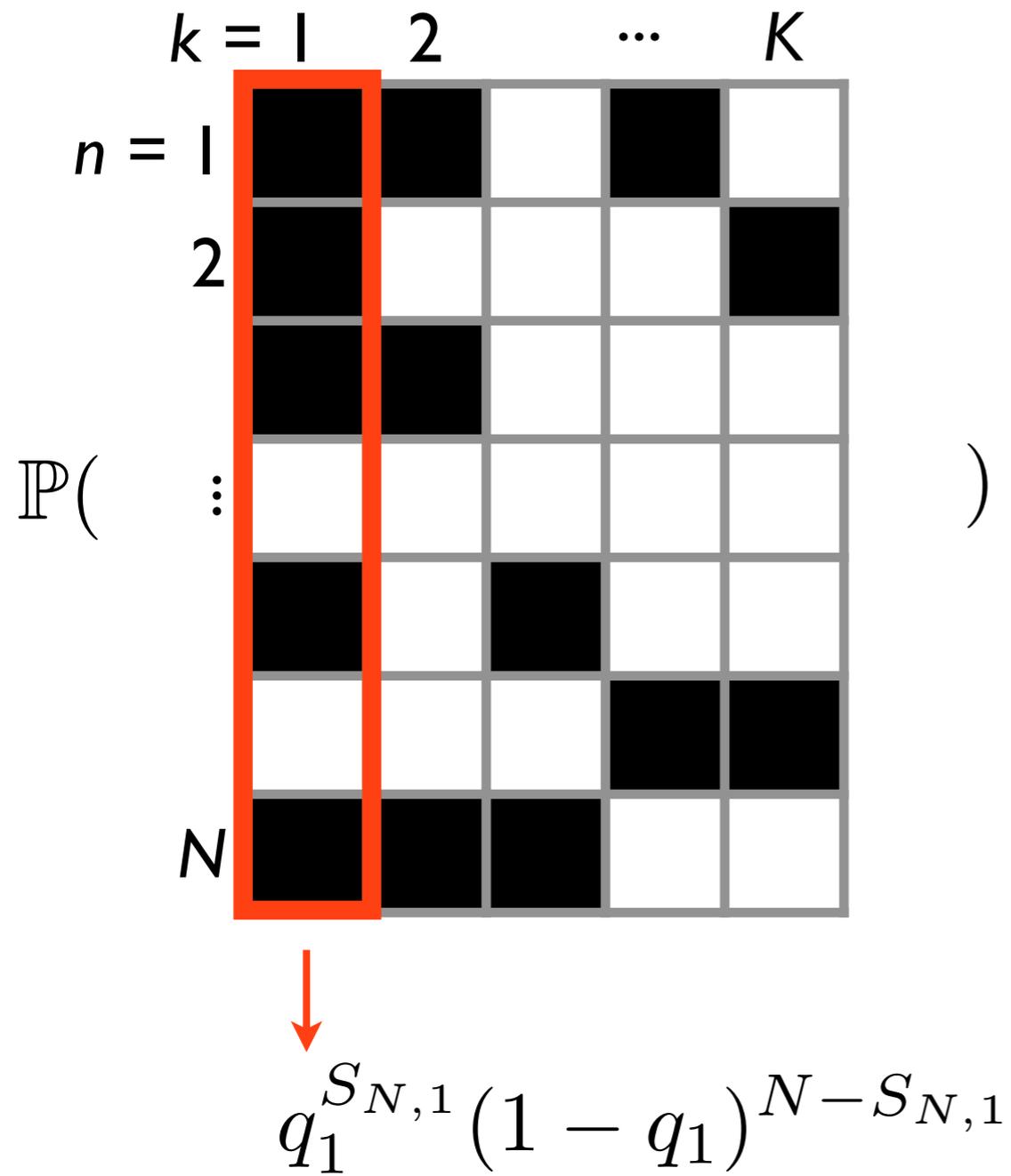
# Feature frequency models: EFPFs?



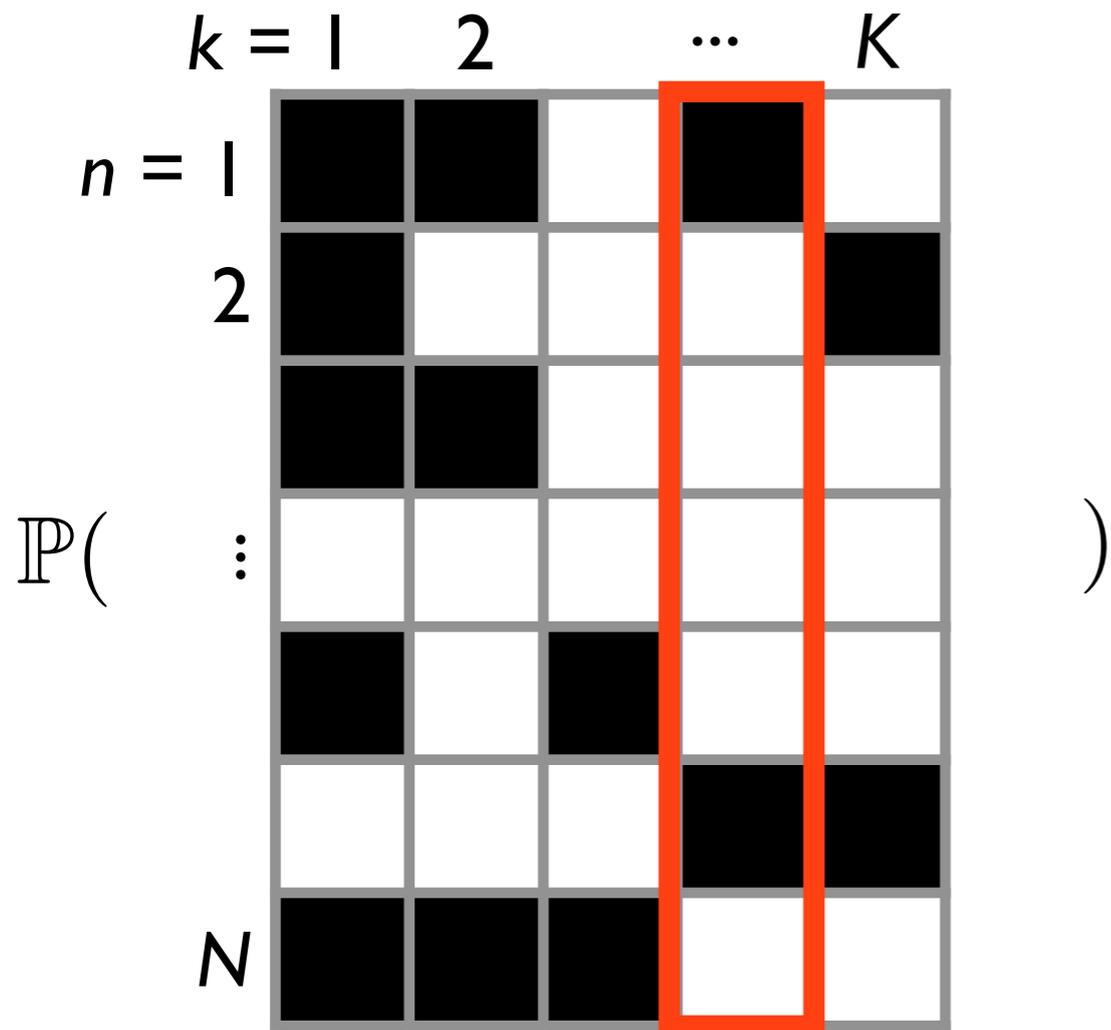
# Feature frequency models: EFPFs?



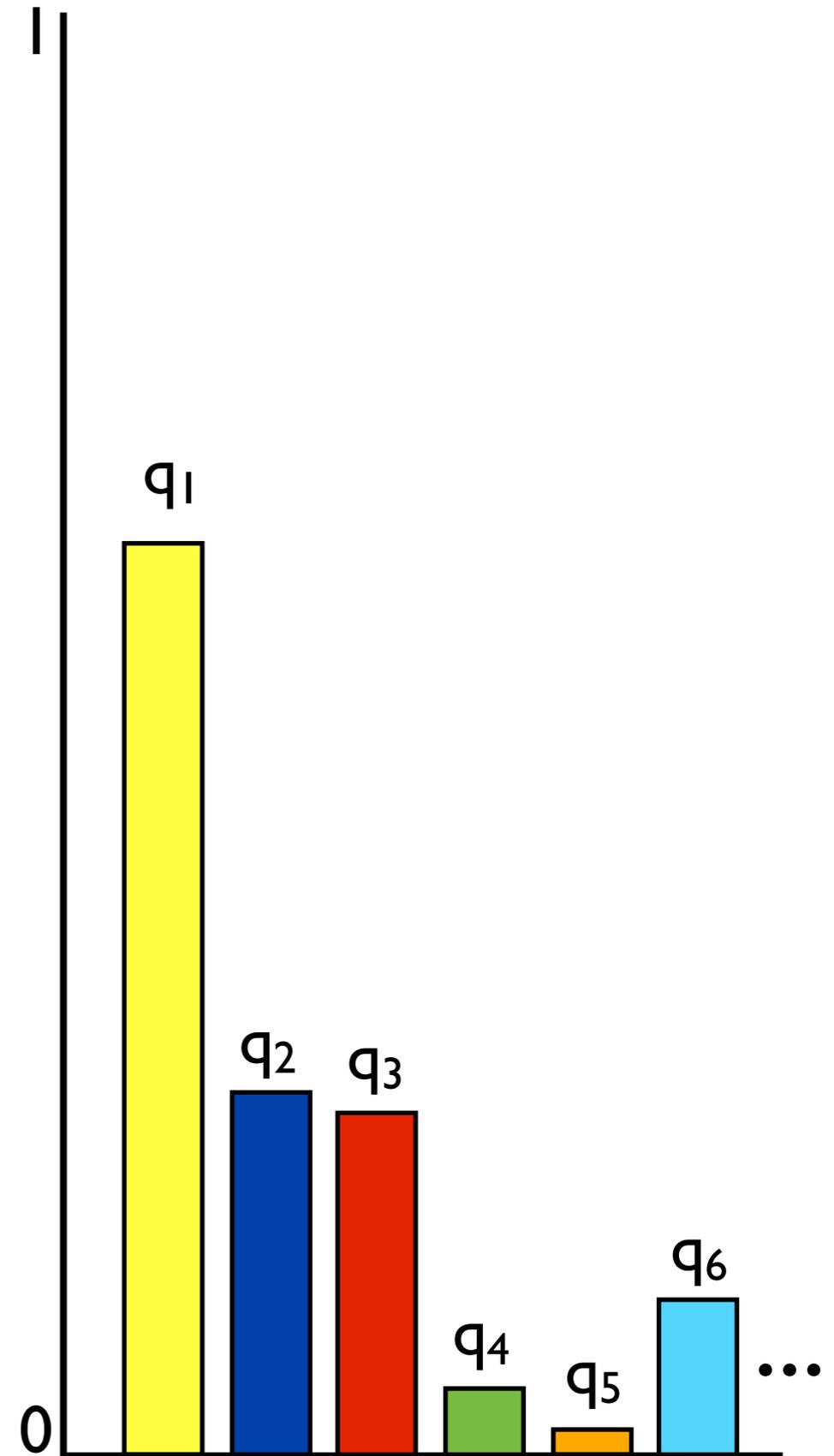
# Feature frequency models: EFPFs?



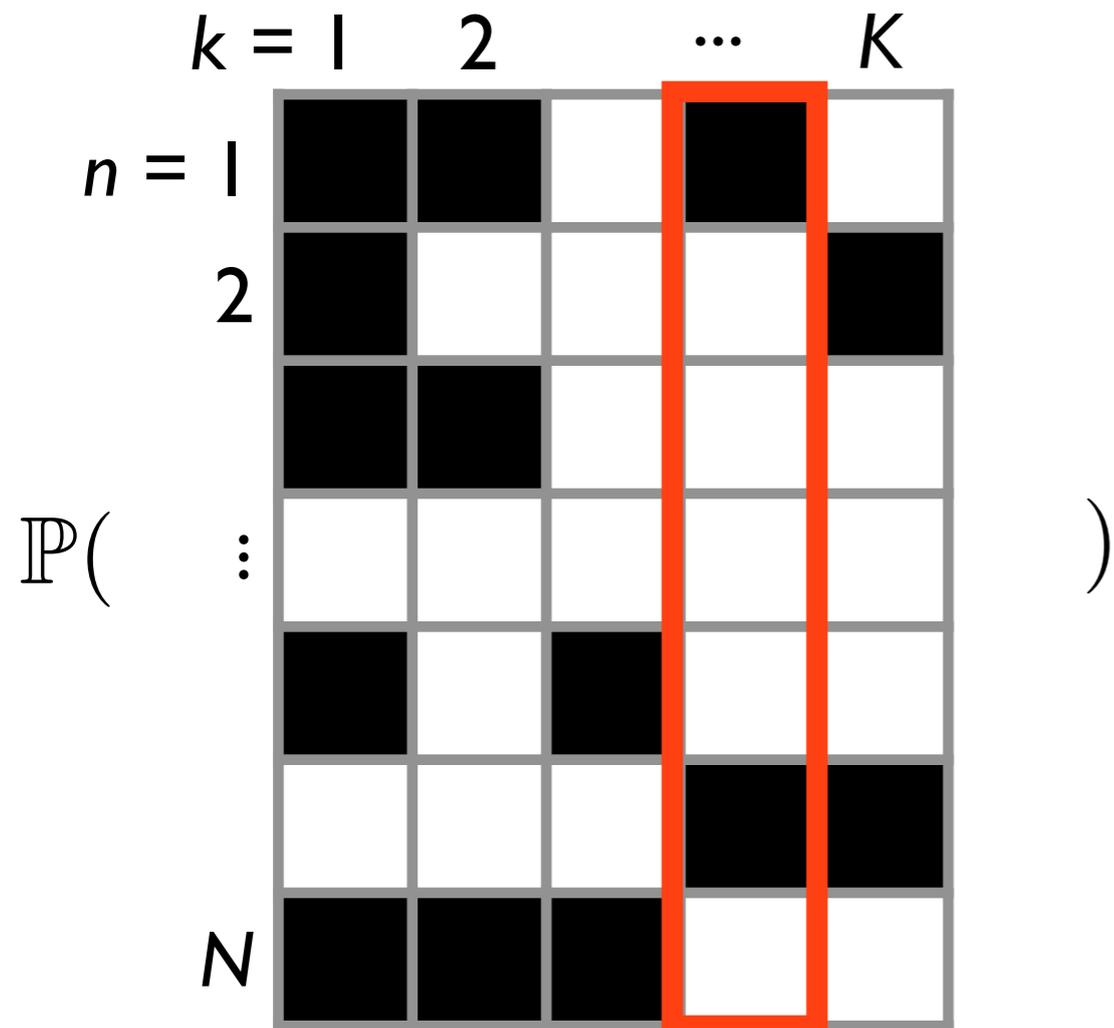
# Feature frequency models: EFPFs?



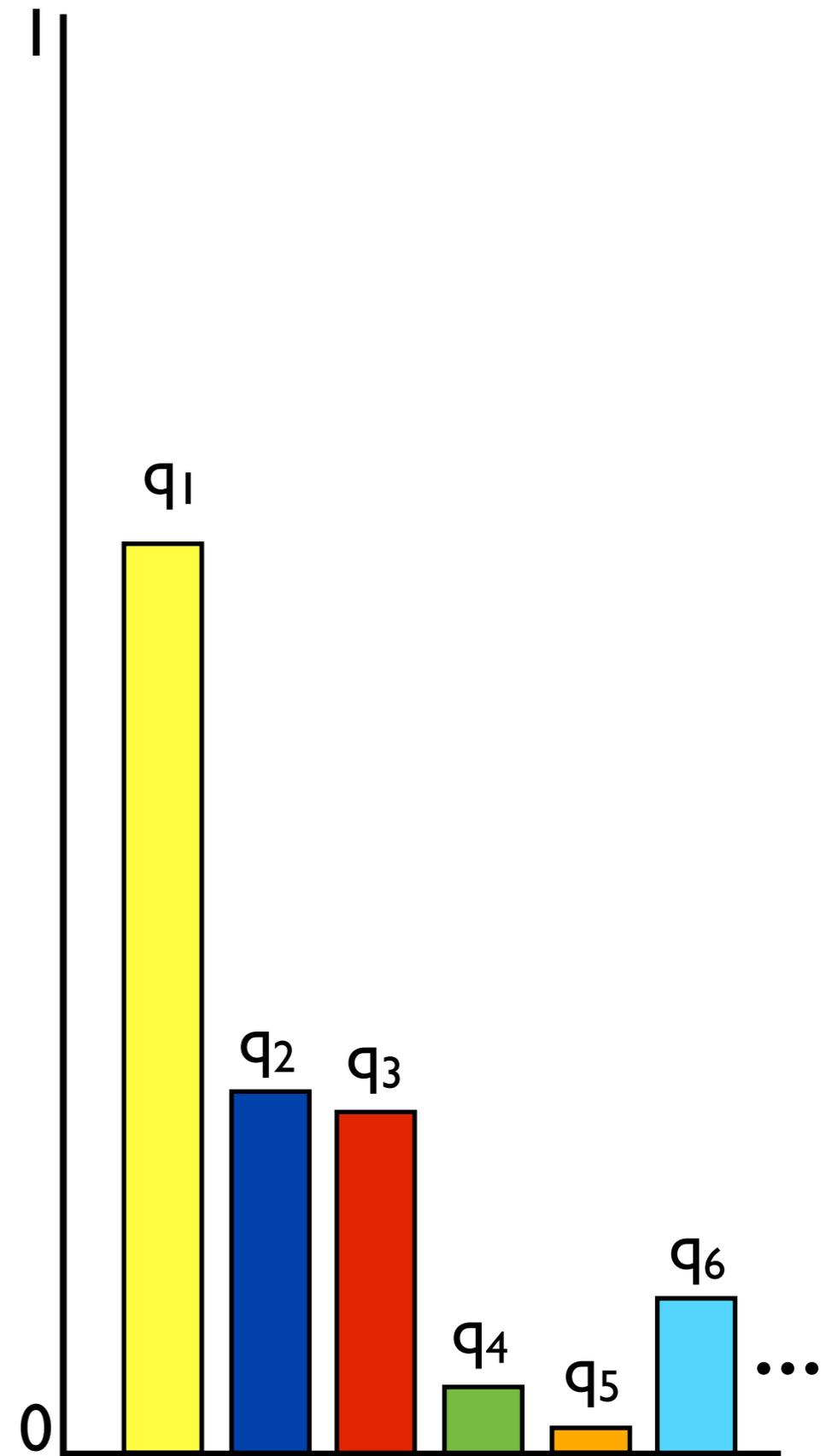
$$q_k^{S_{N,k}} (1 - q_k)^{N - S_{N,k}}$$



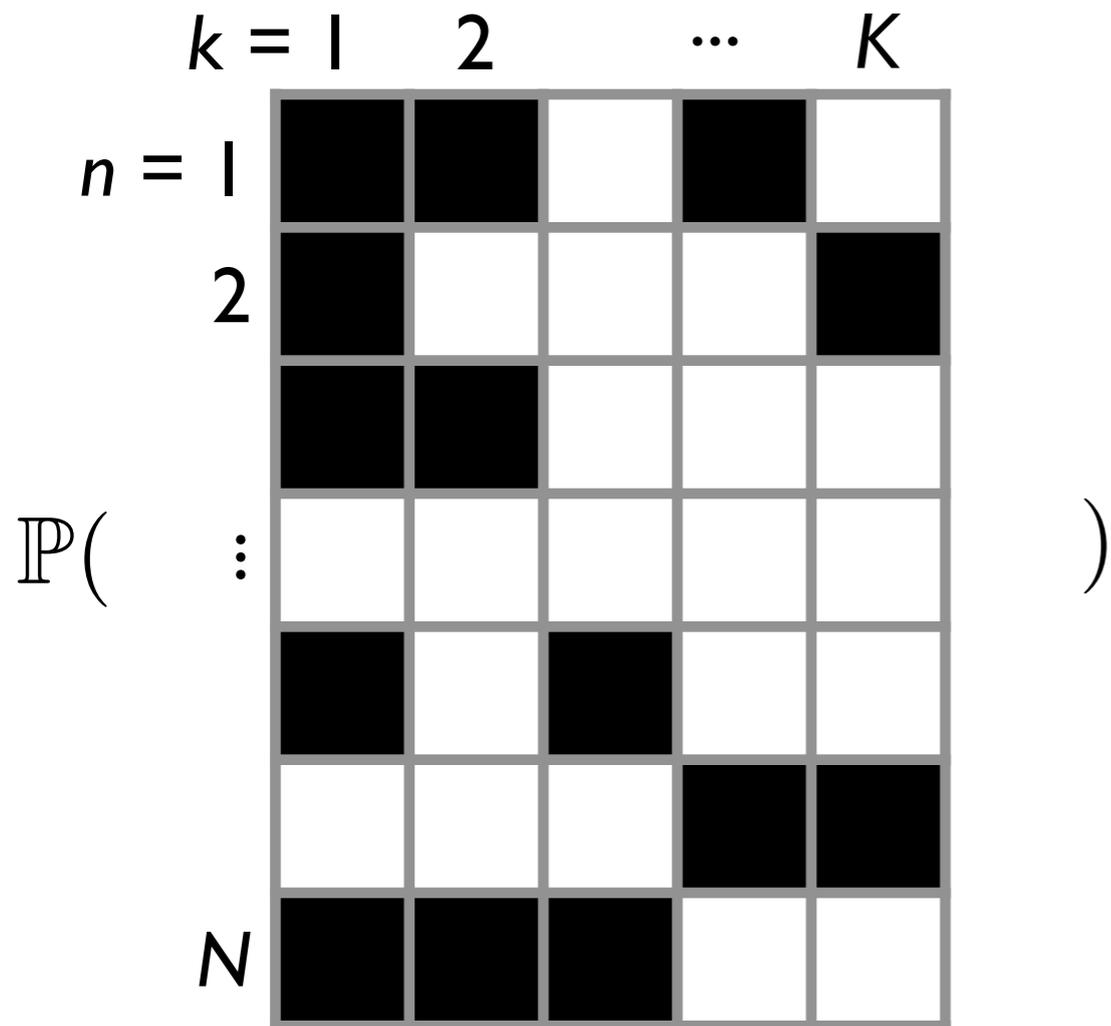
# Feature frequency models: EFPFs?



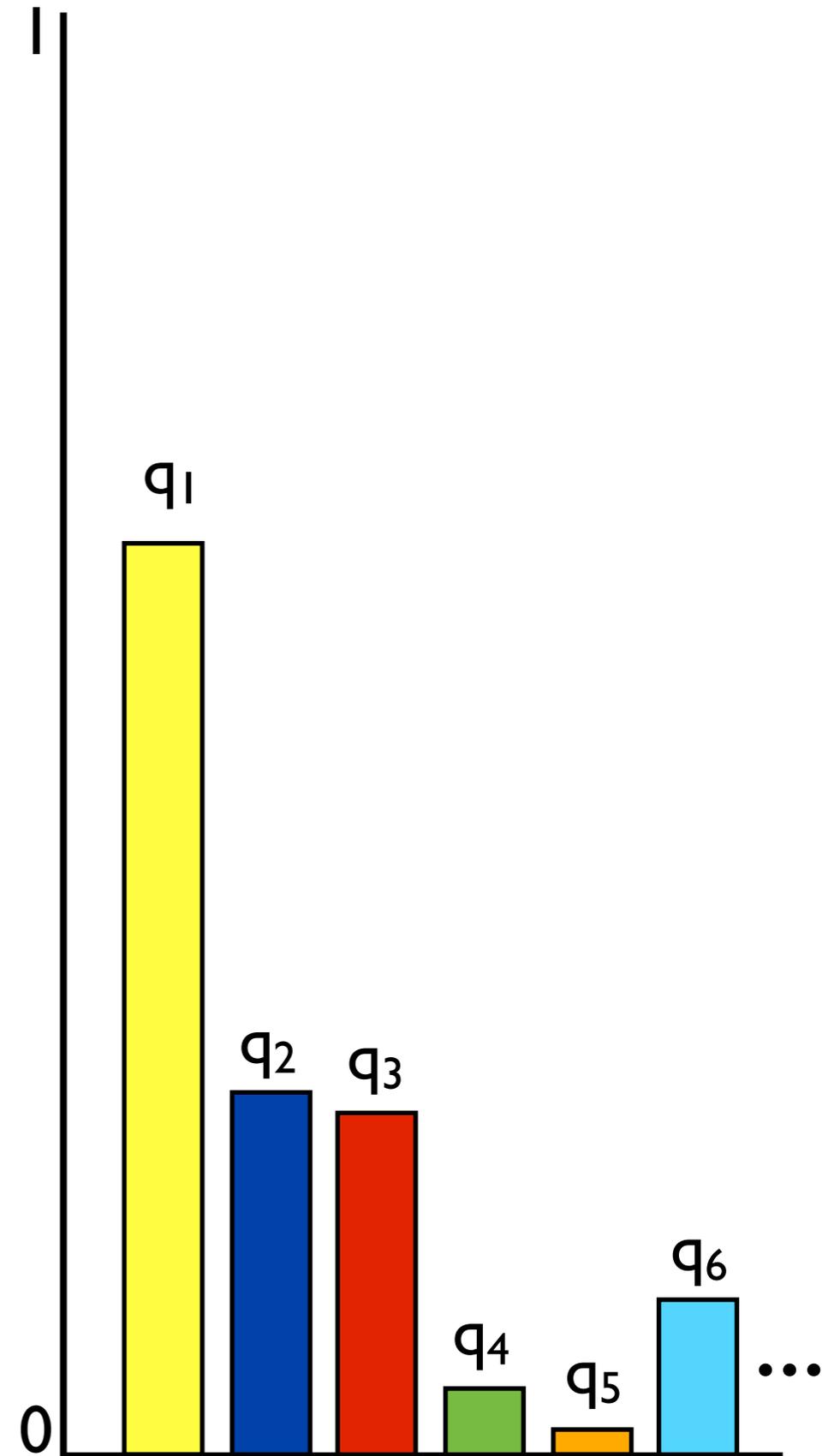
$\downarrow$   
 $q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}}$



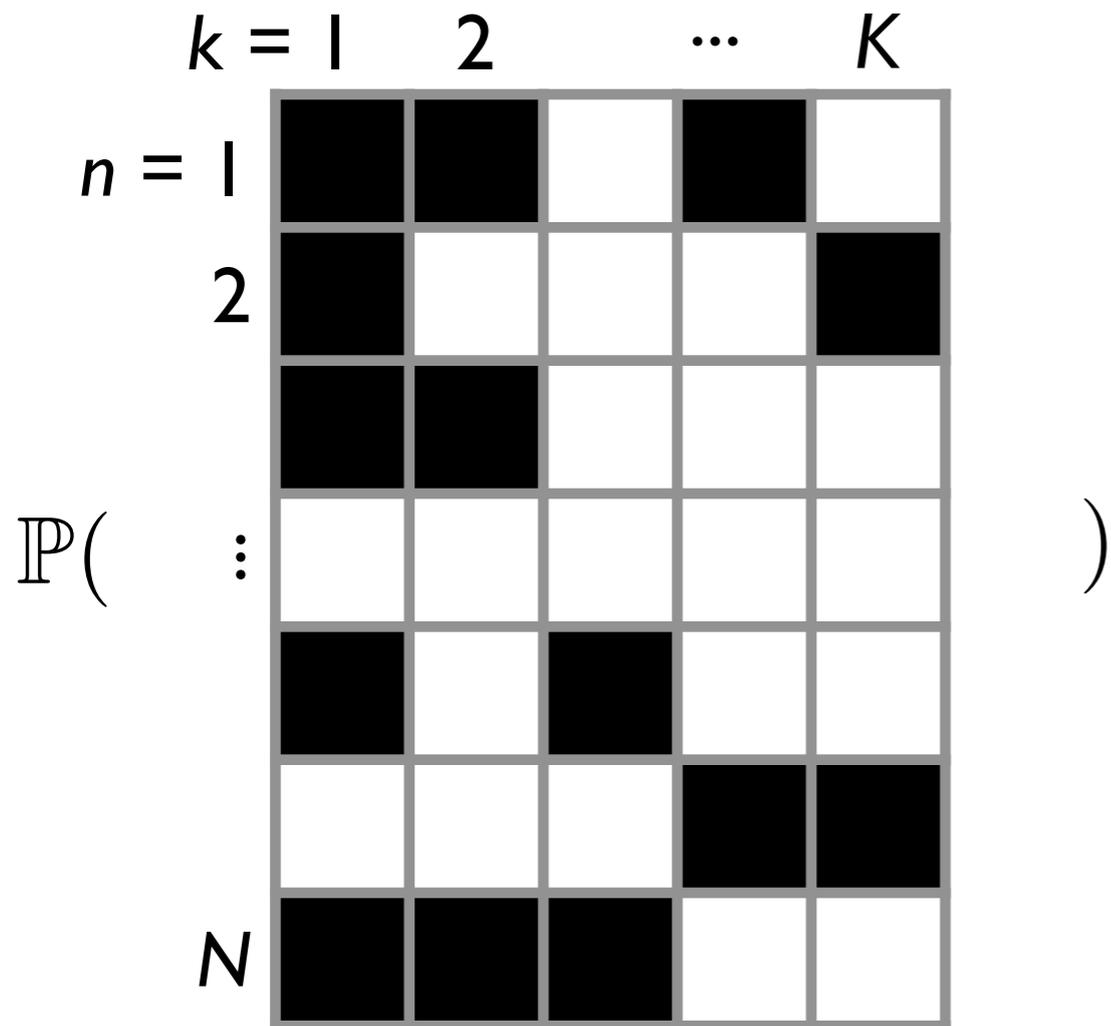
# Feature frequency models: EFPFs?



$$\prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}}$$

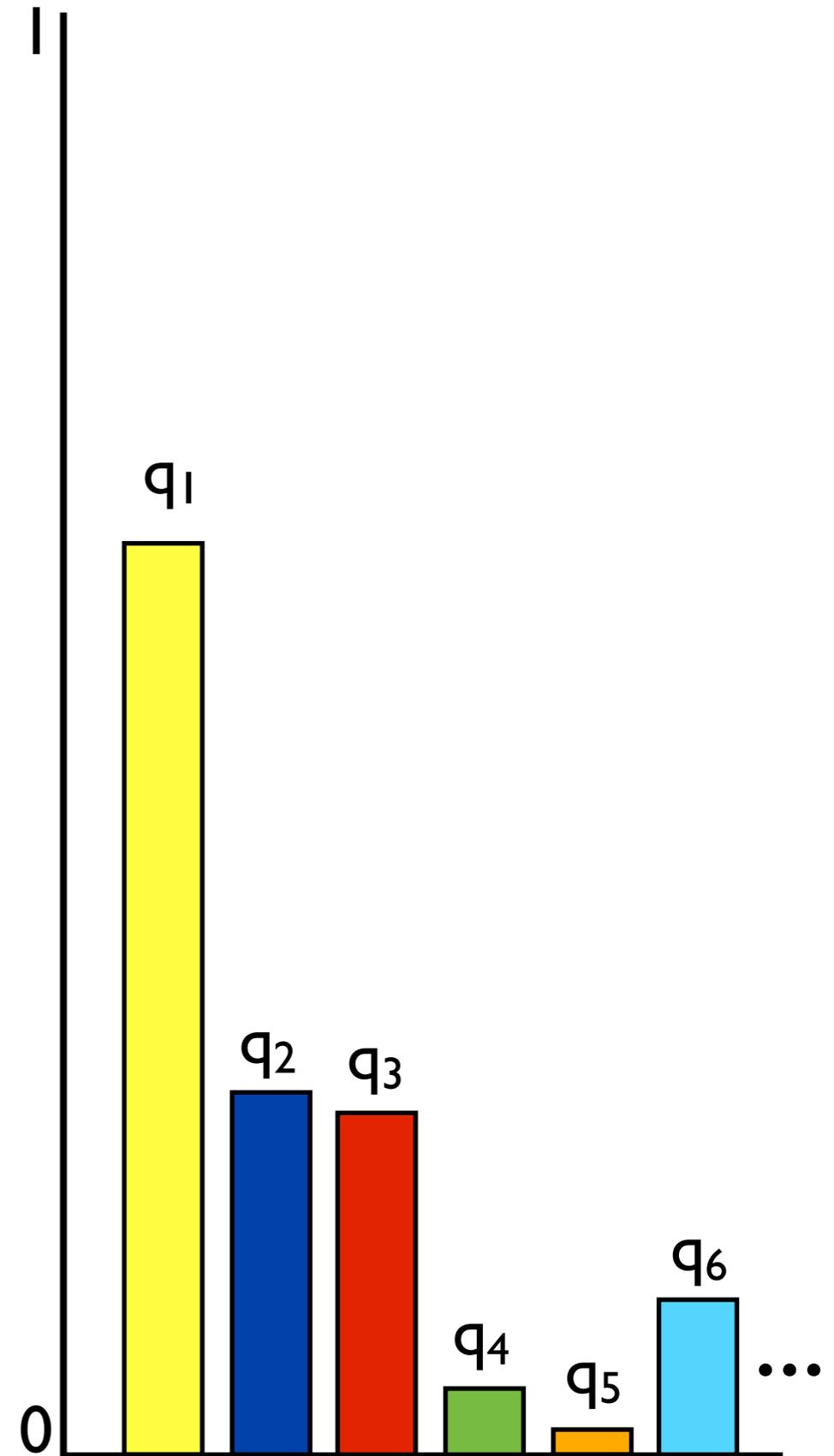


# Feature frequency models: EFPFs?

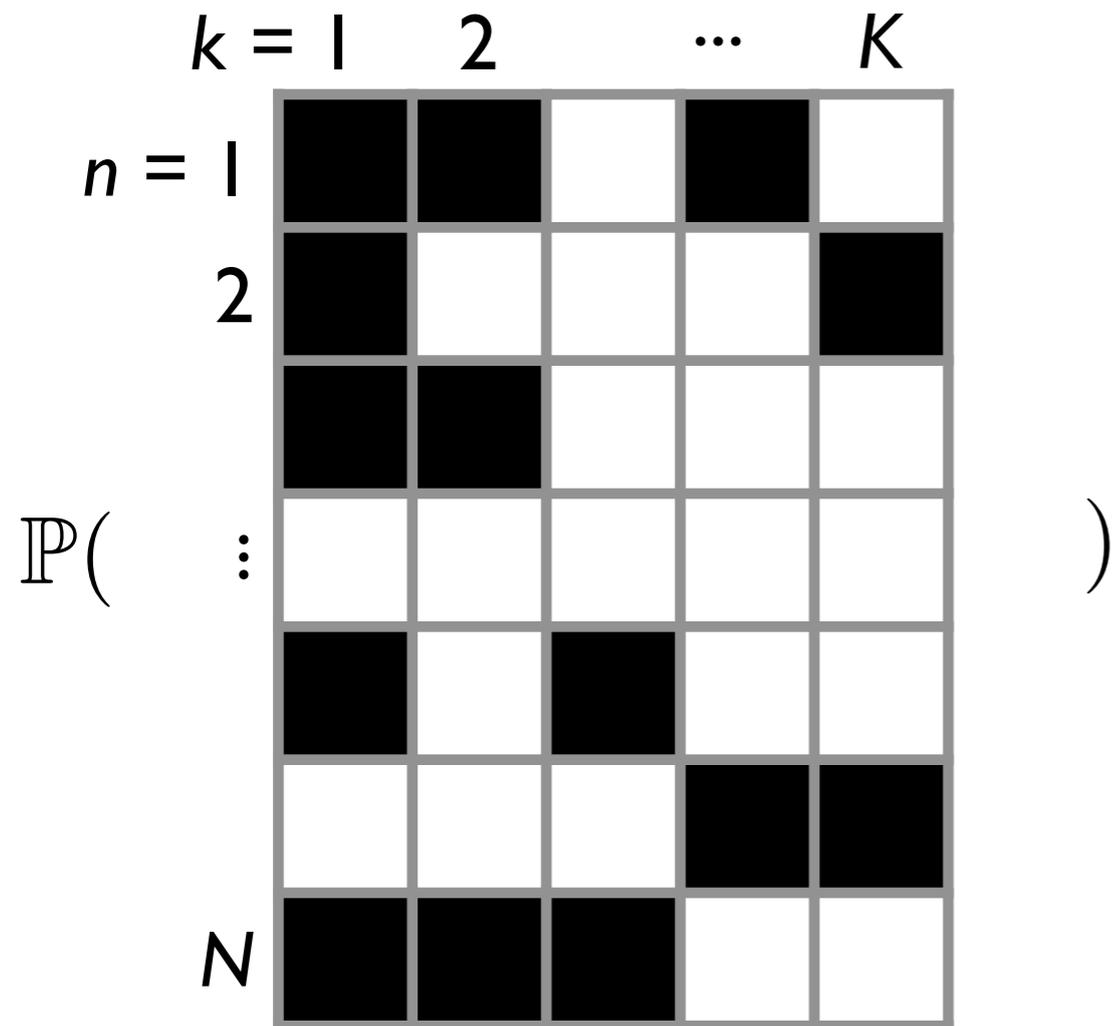


$$\prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}}$$

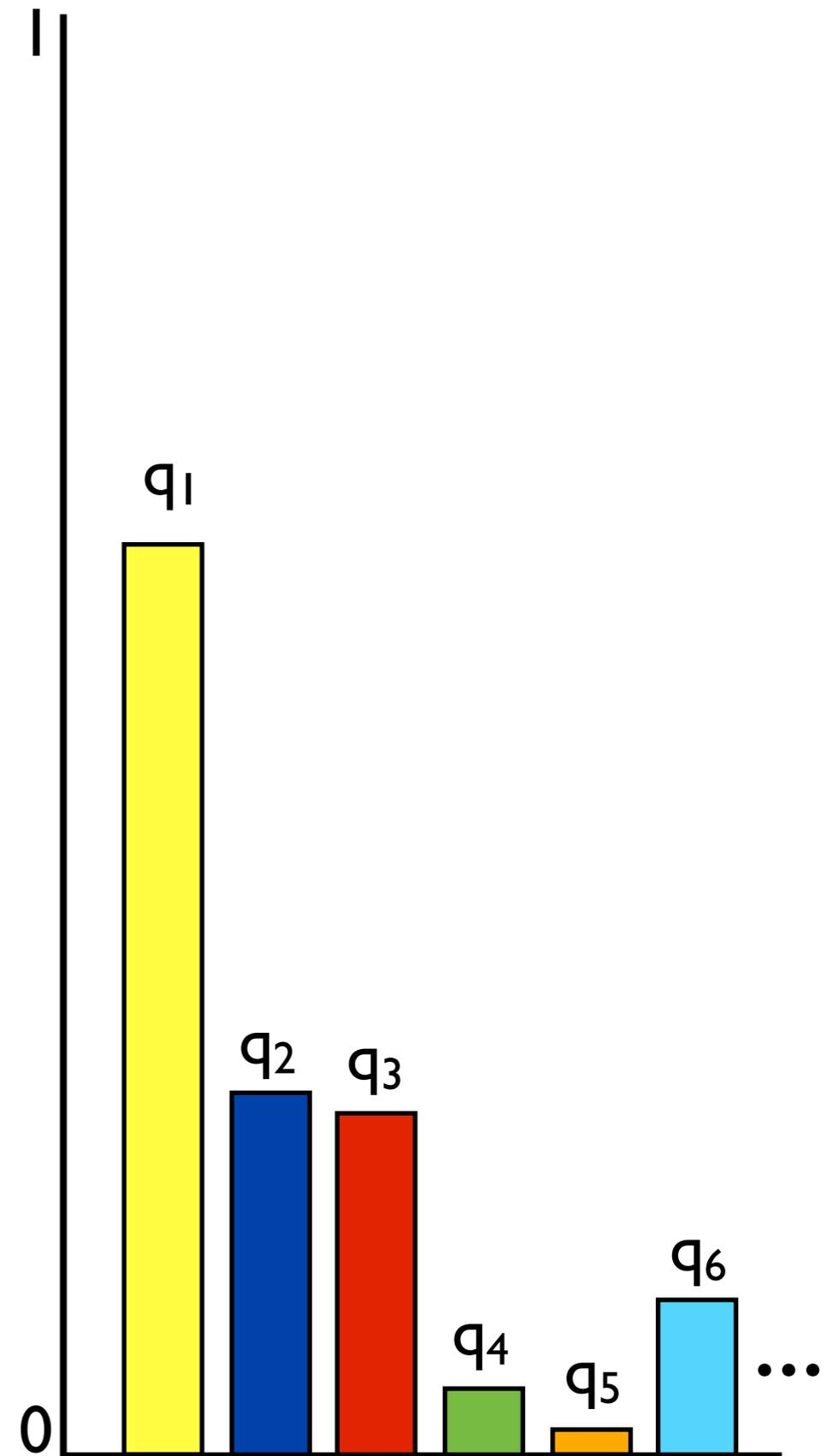
$$\cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N$$



# Feature frequency models: EFPFs?



$$= \mathbb{E} \left[ \sum_{\text{distinct } i_k} \frac{1}{K!} \prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}} \cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N \right]$$



# Feature frequency models: EFPFs?

	$k = 1$	$2$	$\dots$	$K$
$n = 1$				
$2$				
$\vdots$				
$N$				

$\mathbb{P}( \quad )$

$$\begin{aligned}
 &= \mathbb{E} \left[ \sum_{\text{distinct } i_k} \frac{1}{K!} \prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}} \right. \\
 &\quad \left. \cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N \right]
 \end{aligned}$$

# Feature frequency models: EFPFs?

	$k = 1$	2	...	$K$
$n = 1$				
2				
$\vdots$				
$N$				

$\mathbb{P}(\quad)$

$$= \mathbb{E} \left[ \sum_{\text{distinct } i_k} \frac{1}{K!} \prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}} \cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N \right]$$

Size of  $k$ th feature

# Feature frequency models: EFPFs?

	$k = 1$	2	...	$K$
$n = 1$	■	■	□	■
2	■	□	□	■
⋮	■	■	□	□
⋮	□	□	□	□
⋮	■	□	■	□
⋮	□	□	■	■
$N$	■	■	■	□

$\mathbb{P}(\quad)$

Number of features

Size of  $k$ th feature

$$= \mathbb{E} \left[ \sum_{\text{distinct } i_k} \frac{1}{K!} \prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}} \cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N \right]$$

# Feature frequency models: EFPFs?

$\mathbb{P}(\begin{matrix} & k=1 & 2 & \dots & K \\ n=1 & \blacksquare & \blacksquare & \square & \blacksquare & \square \\ 2 & \blacksquare & \square & \square & \square & \blacksquare \\ \vdots & & & & & \\ N & \blacksquare & \blacksquare & \blacksquare & \square & \square \end{matrix})$

Number of features

Number of data points

Size of  $k$ th feature

$$= \mathbb{E} \left[ \sum_{\text{distinct } i_k} \frac{1}{K!} \prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}} \cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N \right]$$

# Feature frequency models: EFPFs?

$\mathbb{P}(\dots)$

	$k = 1$	2	...	$K$
$n = 1$	■	■	□	■
2	■	□	□	■
⋮				
$N$	■	■	■	□

Number of features

Number of data points

Size of  $k$ th feature

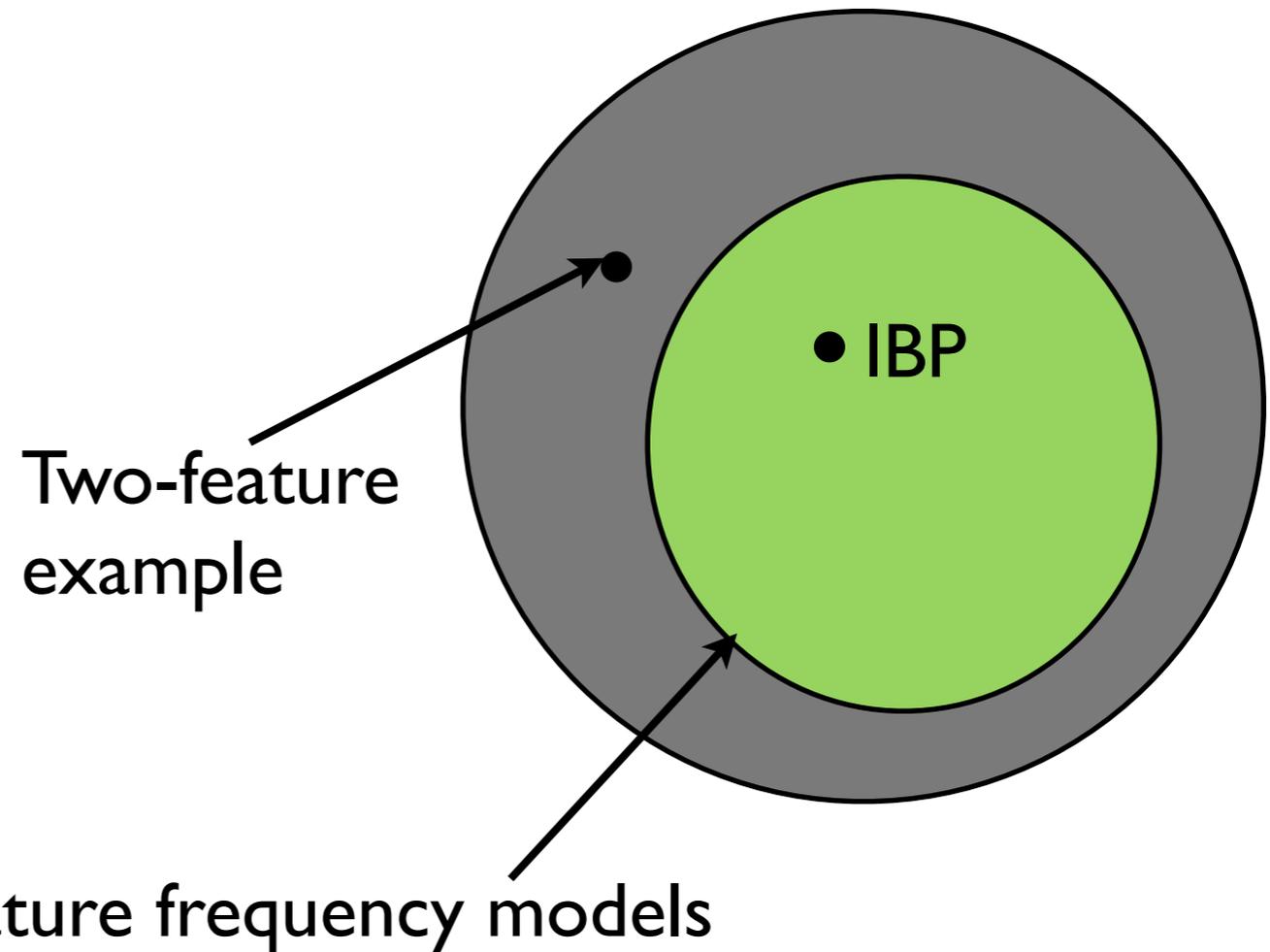
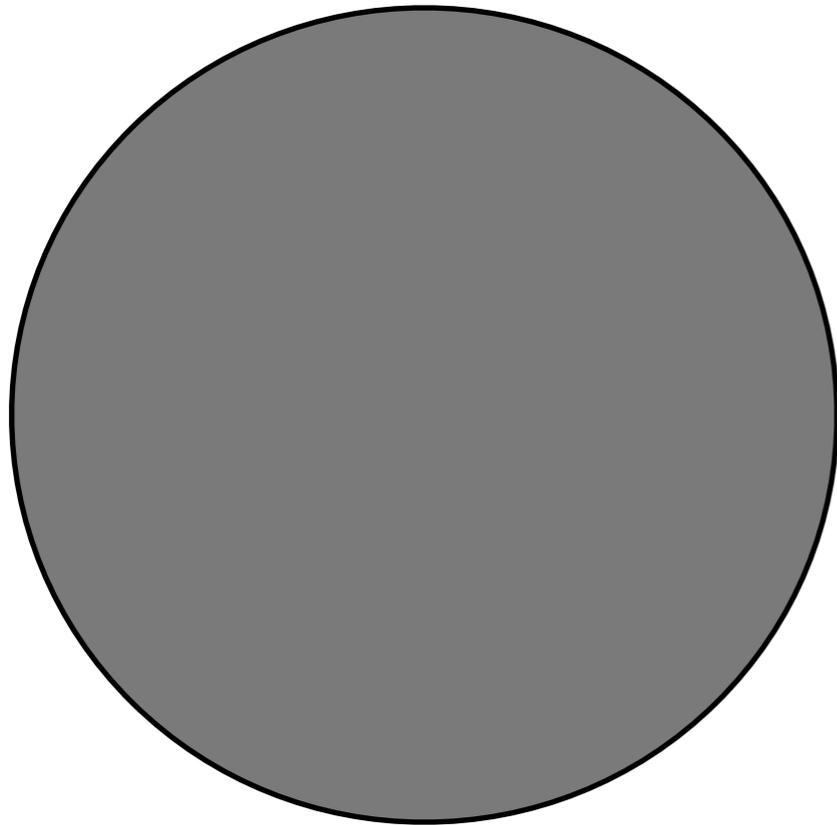
$$= \mathbb{E} \left[ \sum_{\text{distinct } i_k} \frac{1}{K!} \prod_{k=1}^K q_{i_k}^{S_{N,k}} (1 - q_{i_k})^{N - S_{N,k}} \cdot \prod_{j \notin \{i_k\}_{k=1}^K} (1 - q_j)^N \right] = p(N; S_{N,1}, S_{N,2}, \dots, S_{N,K})$$

**EFPF**

# Feature frequency models: EFPFs?

Exchangeable cluster distributions  
= Cluster distributions with EPPFs  
= Kingman paintbox partitions

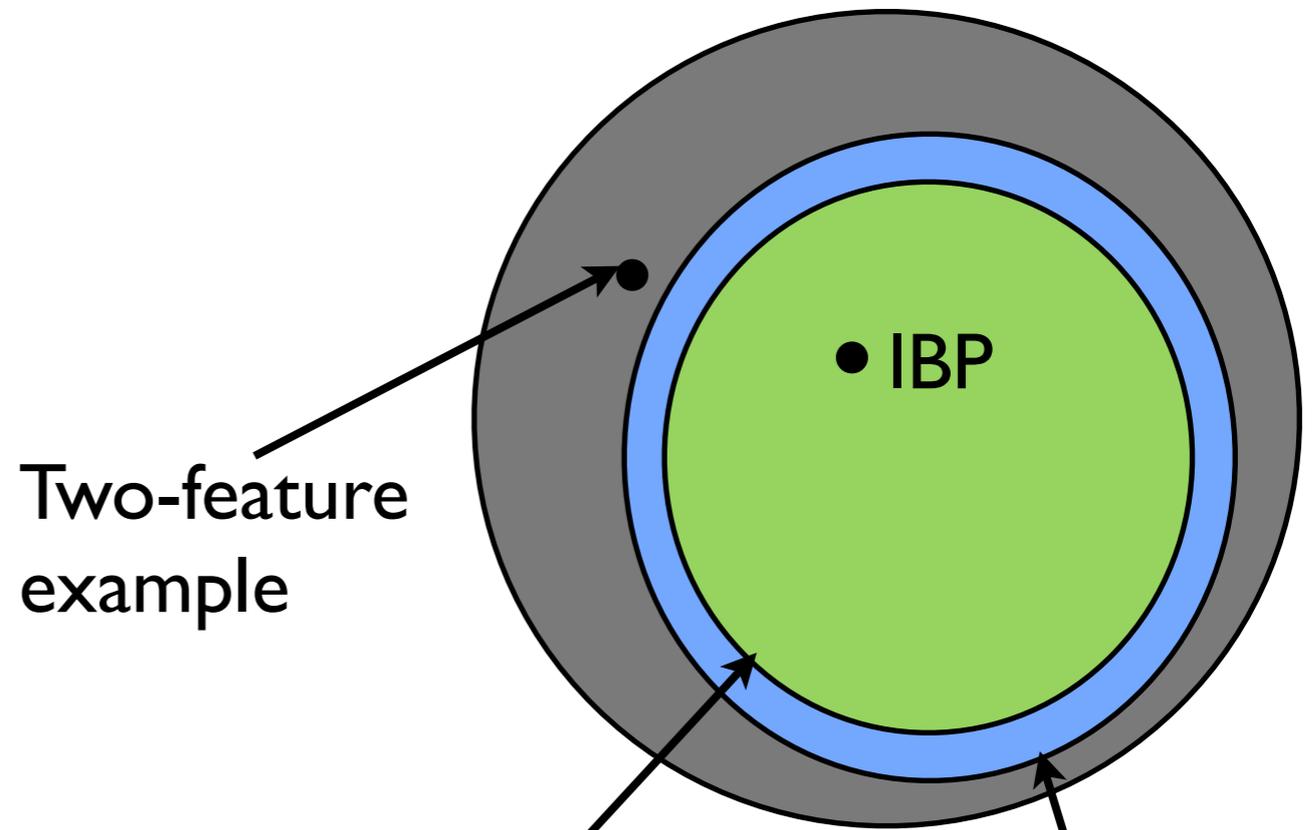
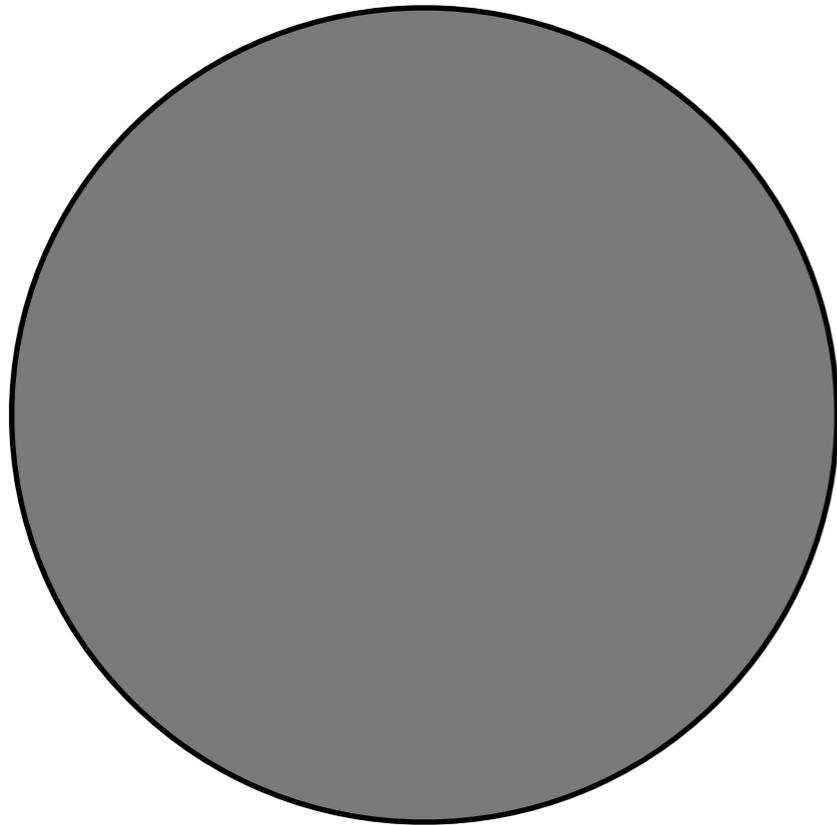
Exchangeable feature distributions  
= Feature paintbox allocations



# Feature frequency models: EFPFs?

Exchangeable cluster distributions  
= Cluster distributions with EPPFs  
= Kingman paintbox partitions

Exchangeable feature distributions  
= Feature paintbox allocations



Two-feature  
example

Feature frequency models

Feature distributions with EFPFs

# Distributions with EFPFs: frequencies?

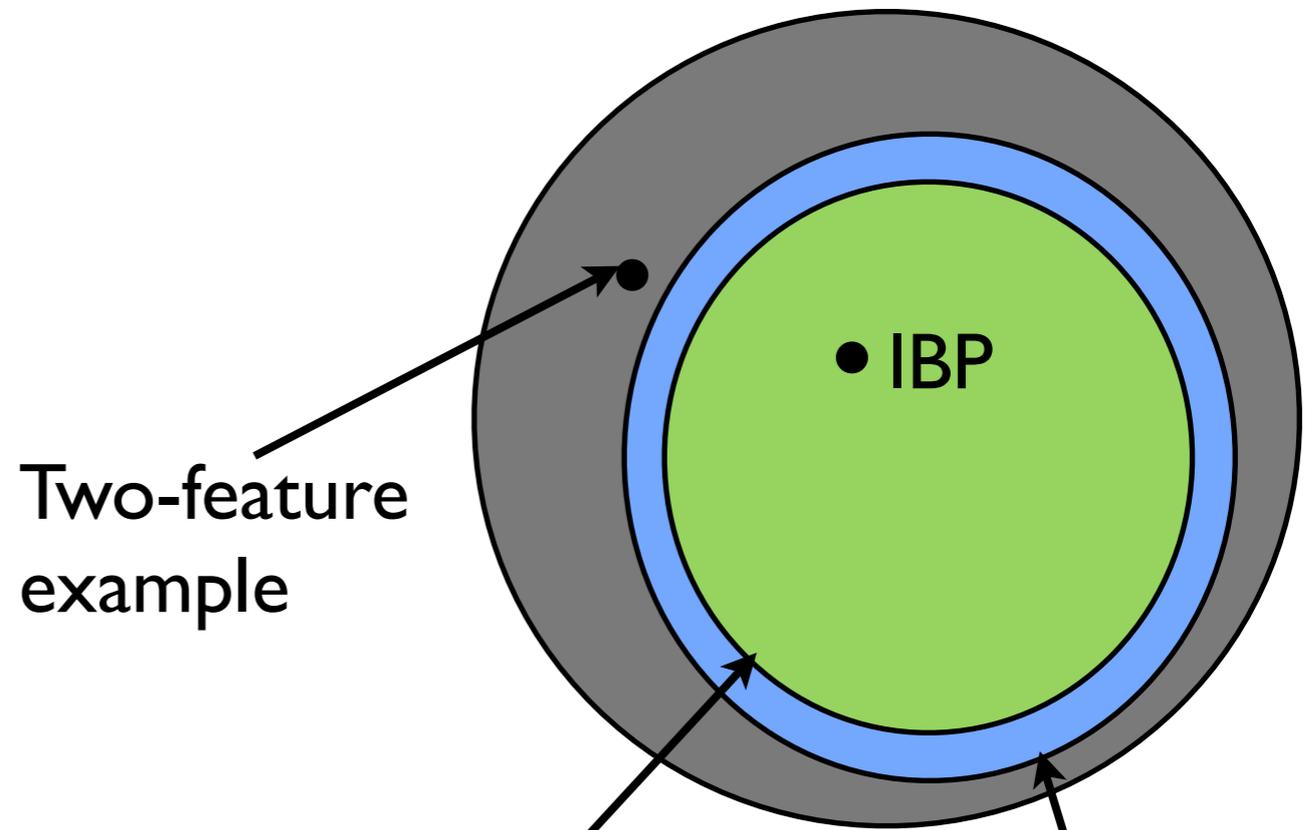
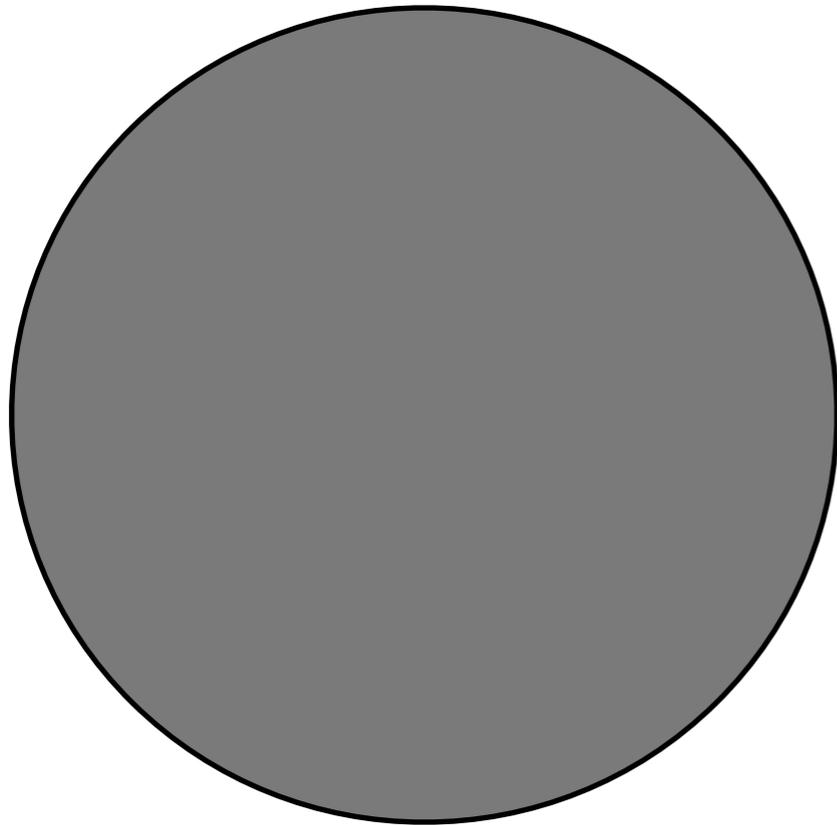
# Distributions with EFPFs: frequencies?

- ✓ • Any number  
(+unbounded case) of  
features

# Distributions with EFPFs: frequencies?

Exchangeable cluster distributions  
= Cluster distributions with EPPFs  
= Kingman paintbox partitions

Exchangeable feature distributions  
= Feature paintbox allocations



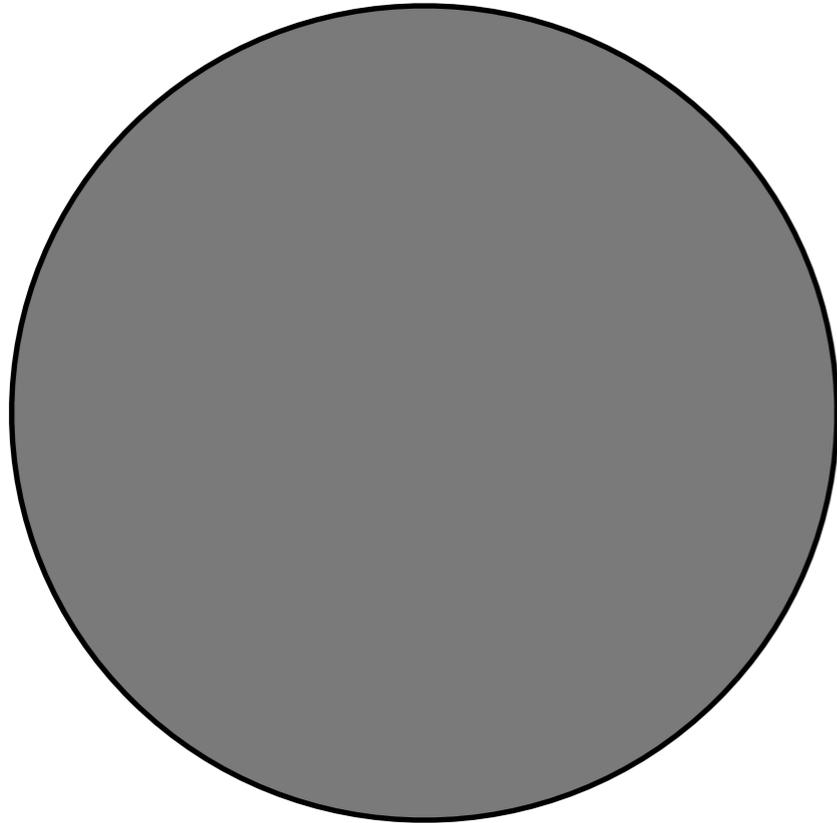
Two-feature  
example

Feature frequency models

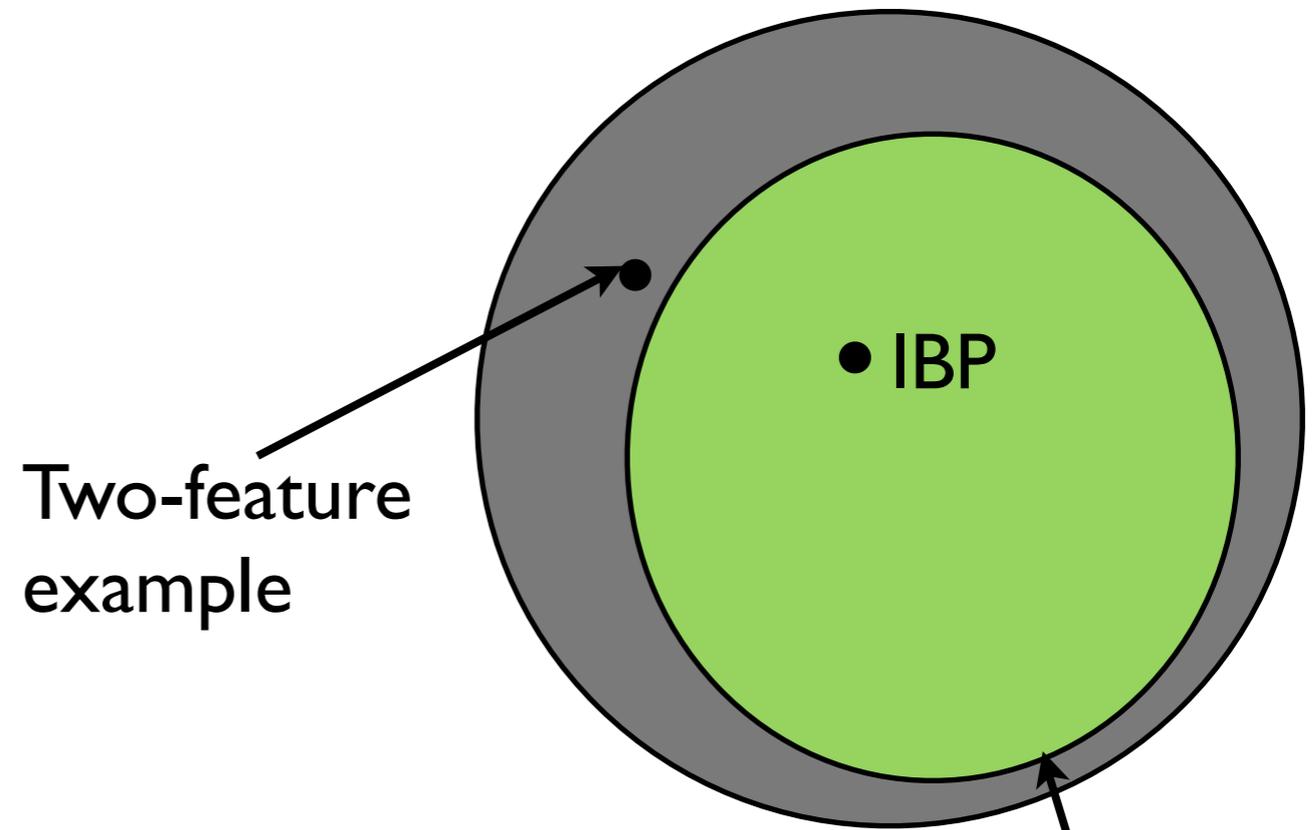
Feature distributions with EFPFs

# Distributions with EFPFs: frequencies?

Exchangeable cluster distributions  
= Cluster distributions with EPPFs  
= Kingman paintbox partitions

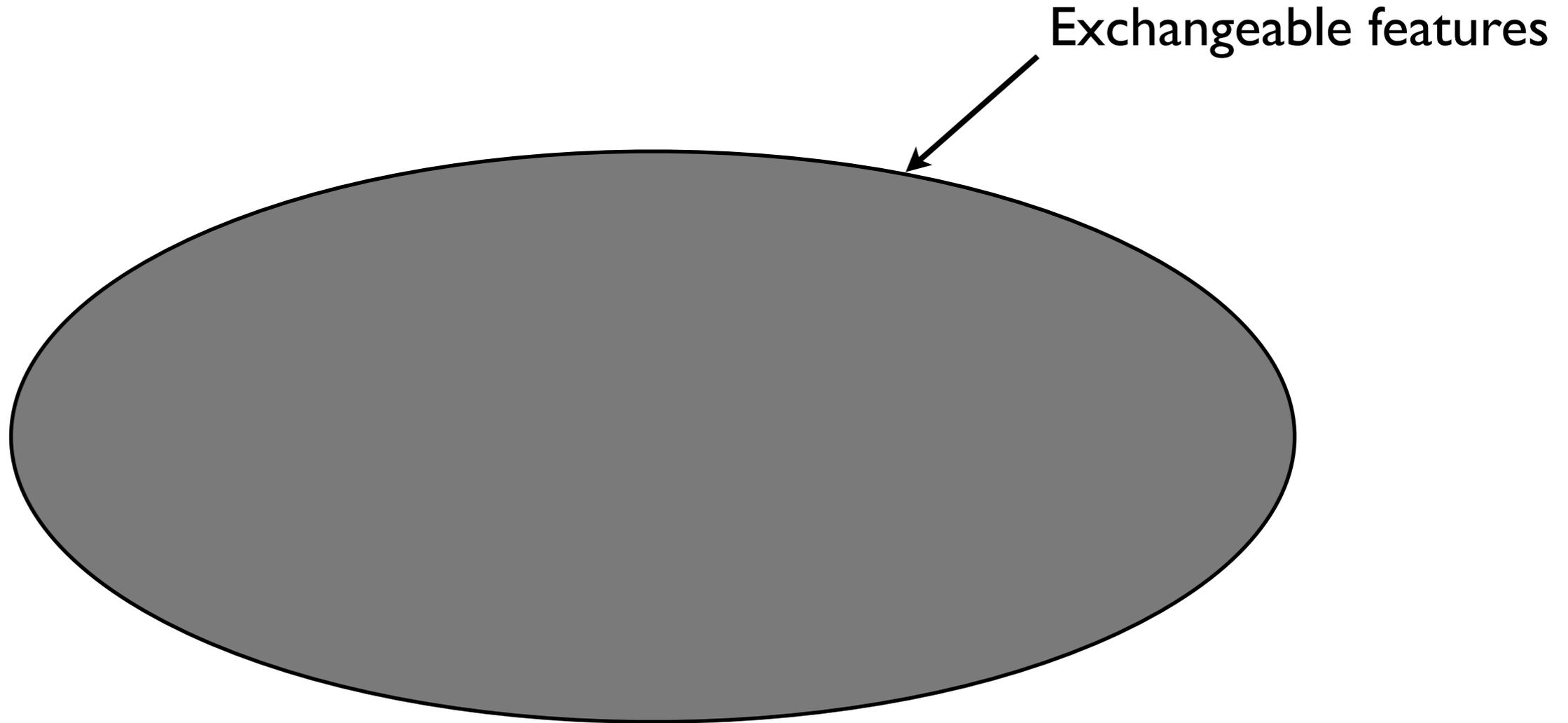


Exchangeable feature distributions  
= Feature paintbox allocations



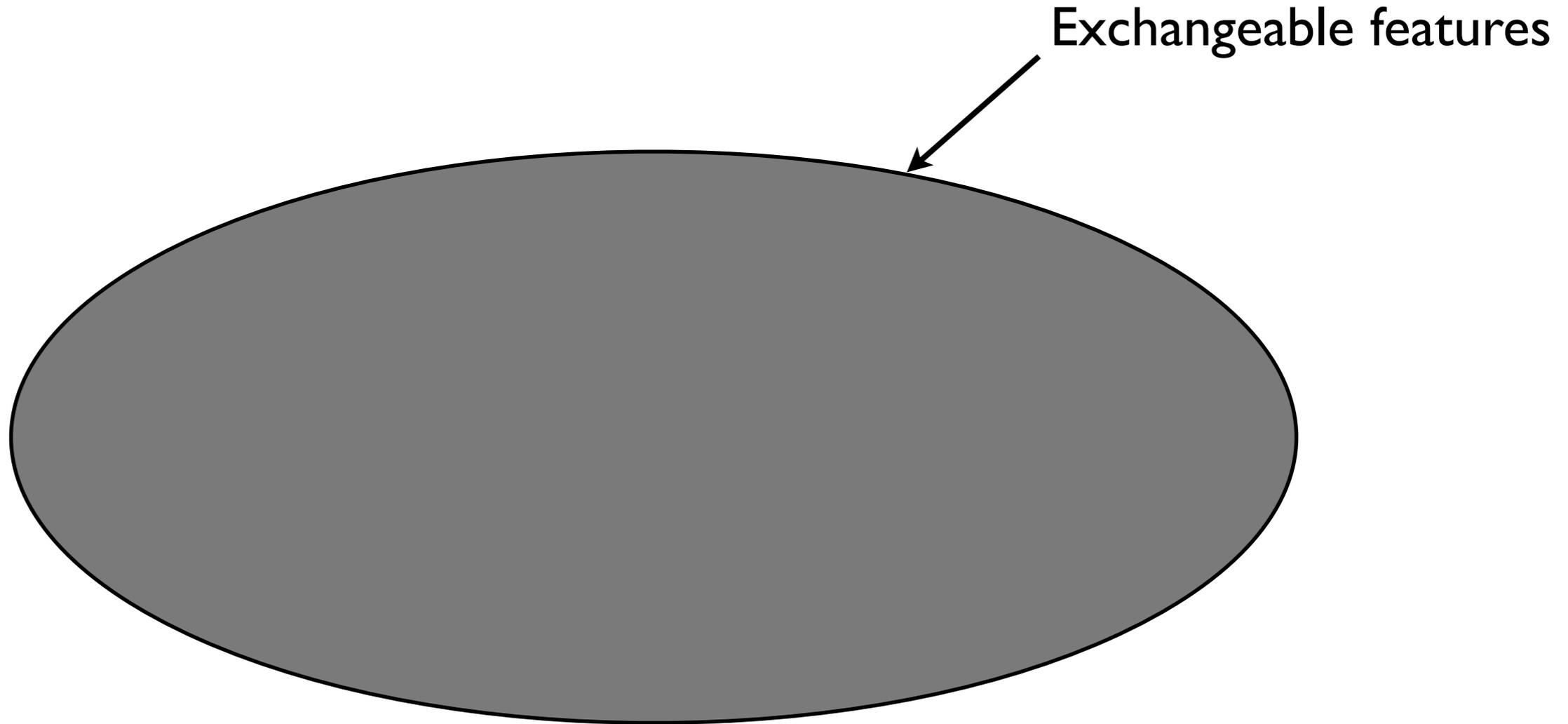
Feature distributions with EFPFs  
= Feature frequency models

# Theory conclusions



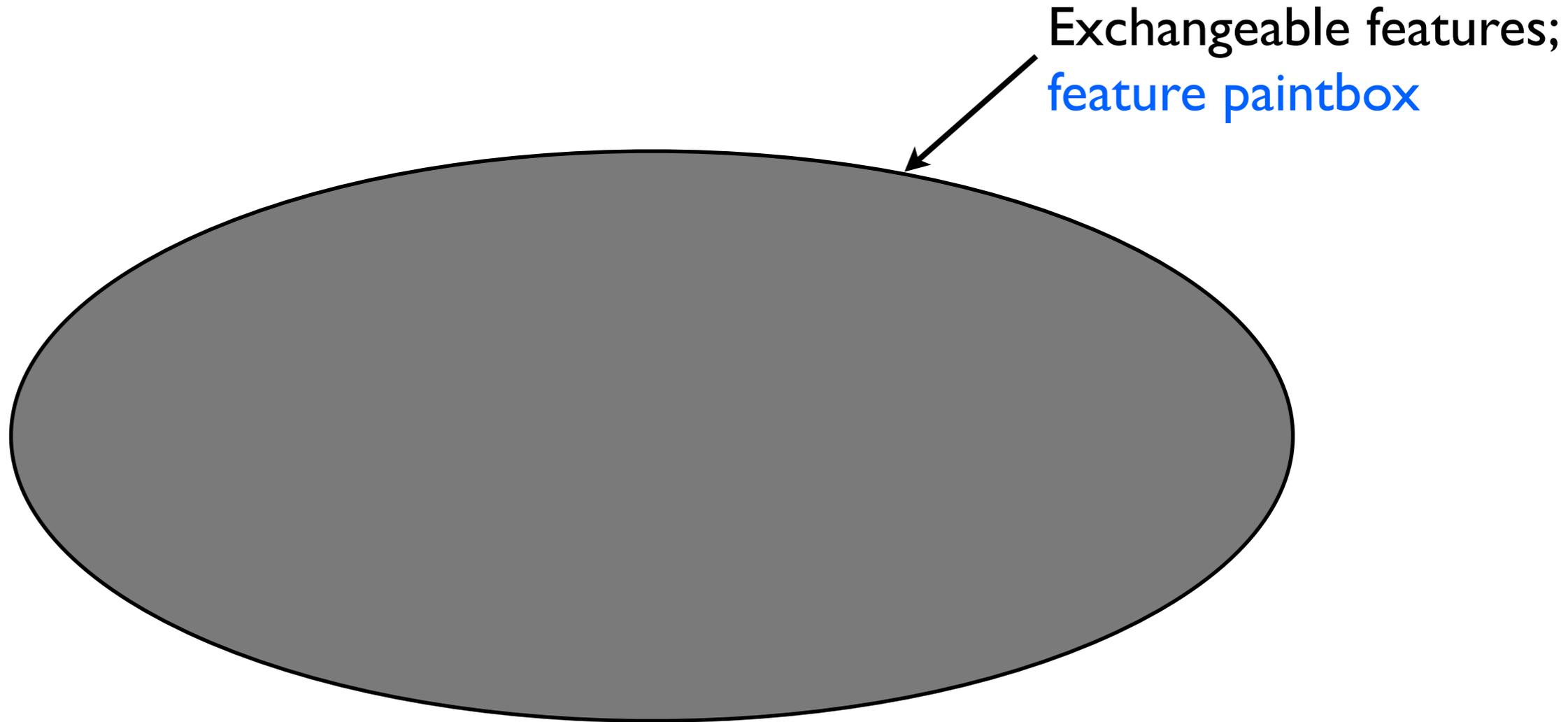
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models



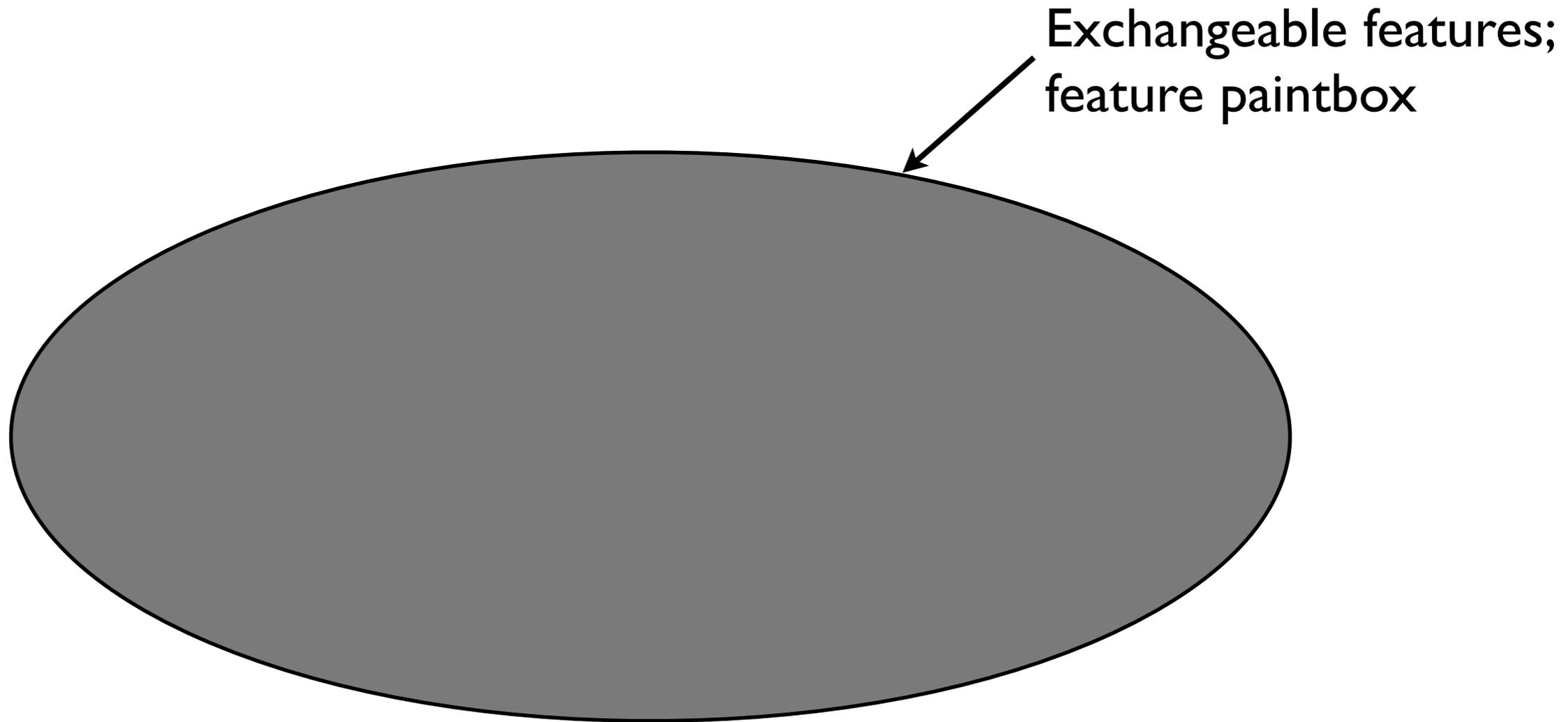
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models



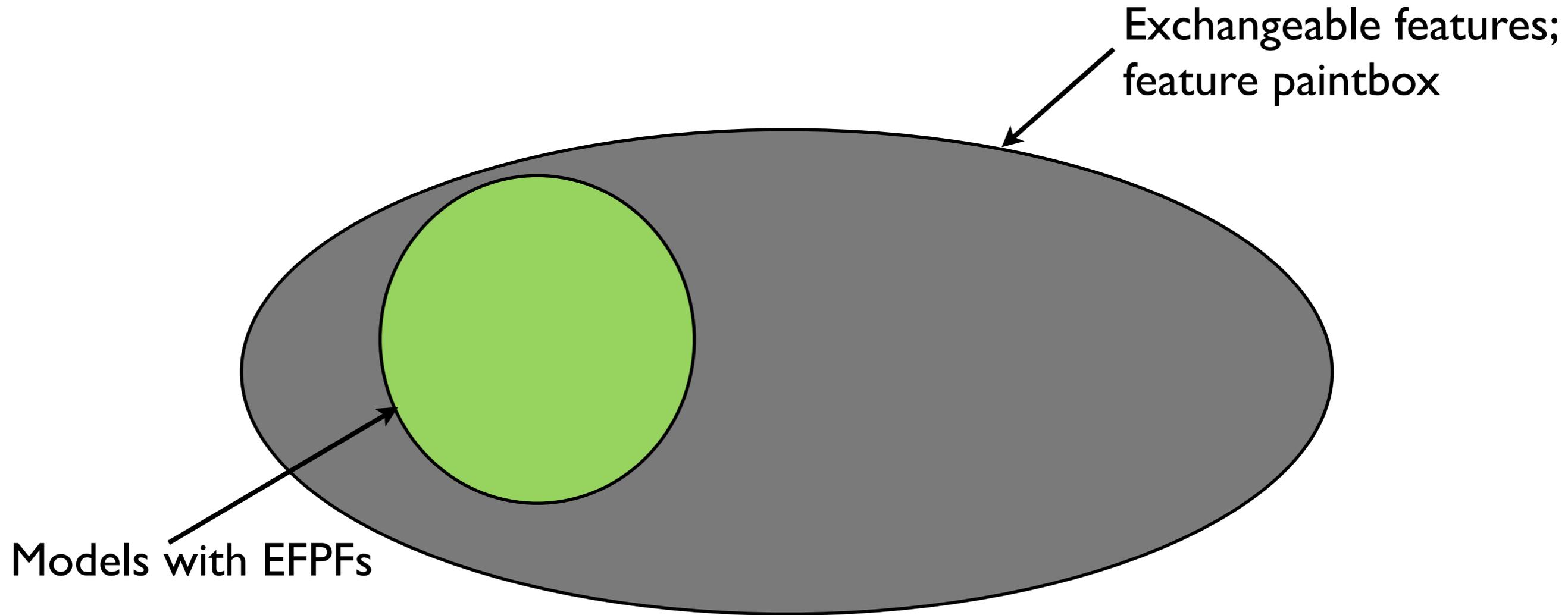
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



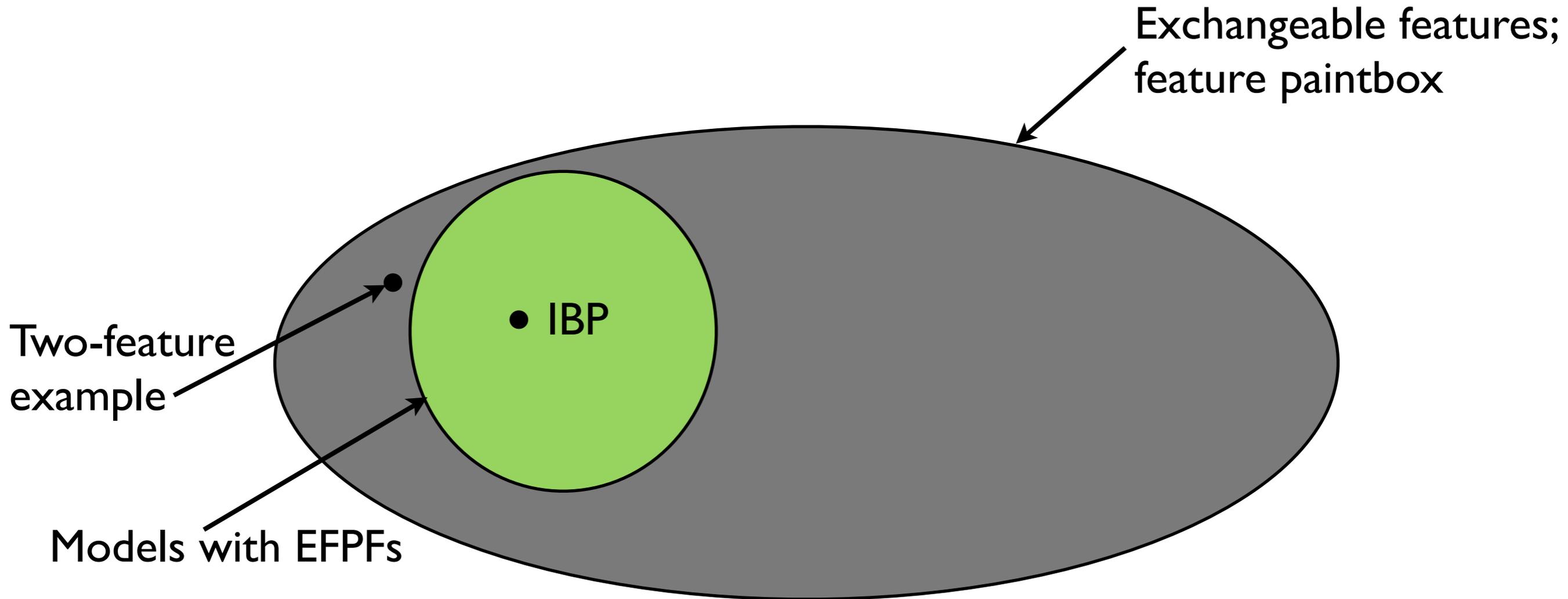
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



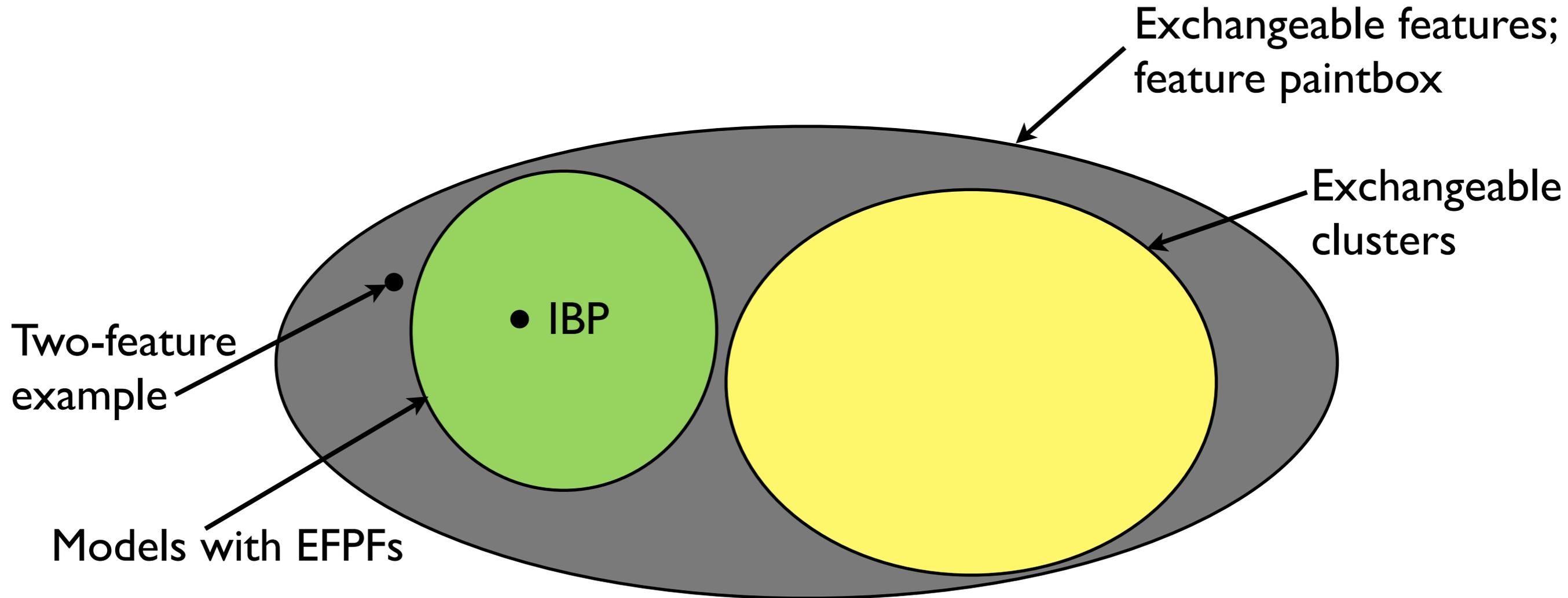
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



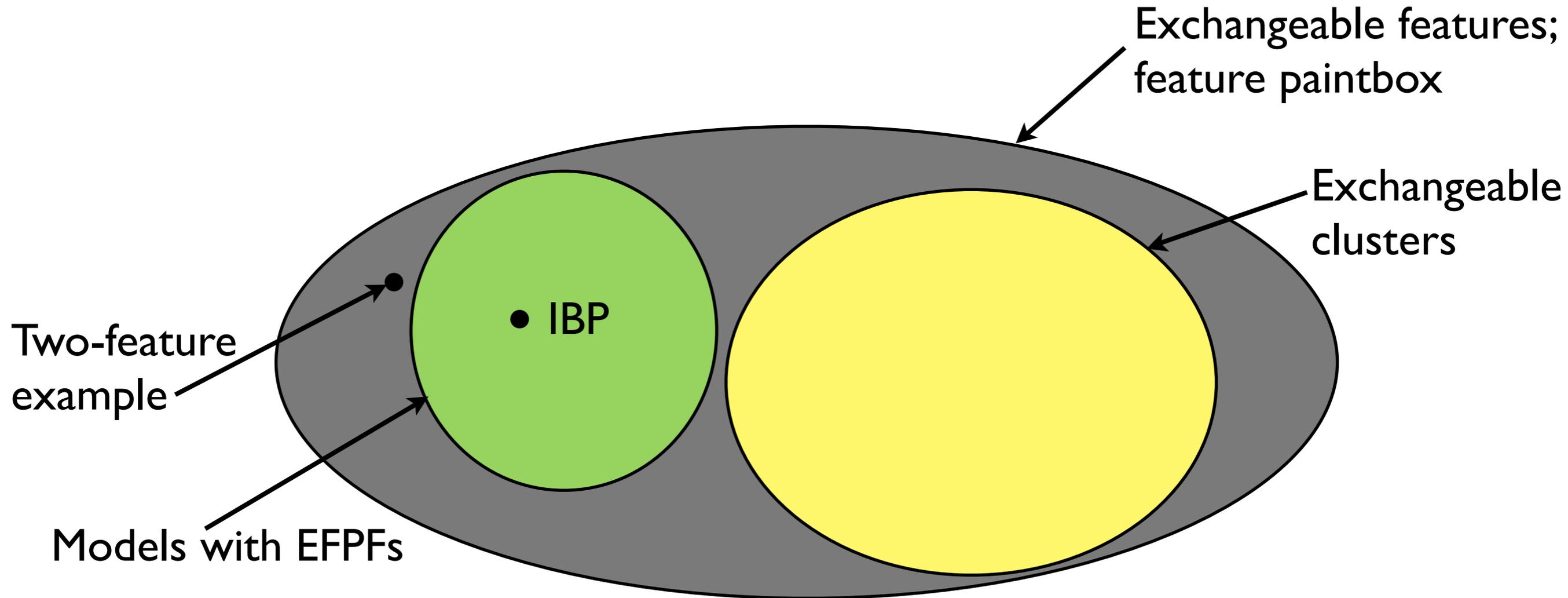
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



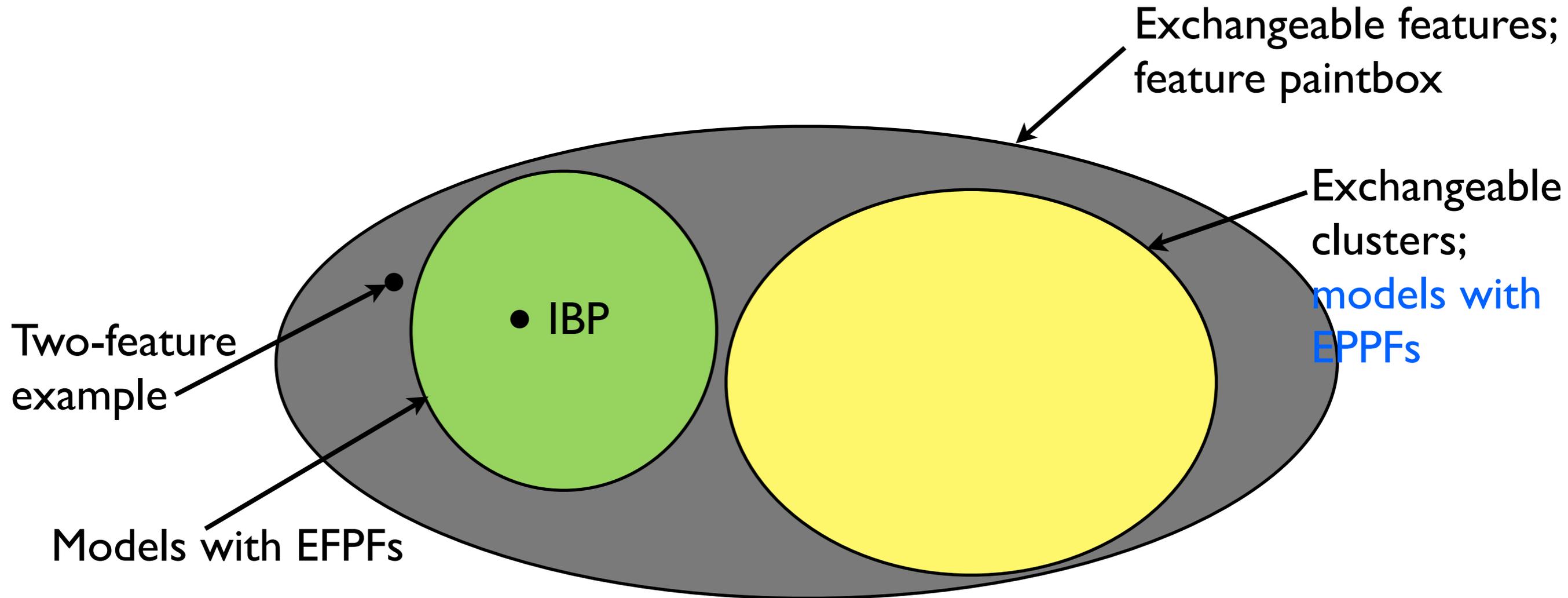
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- **Characterization of alternative correlation structure**



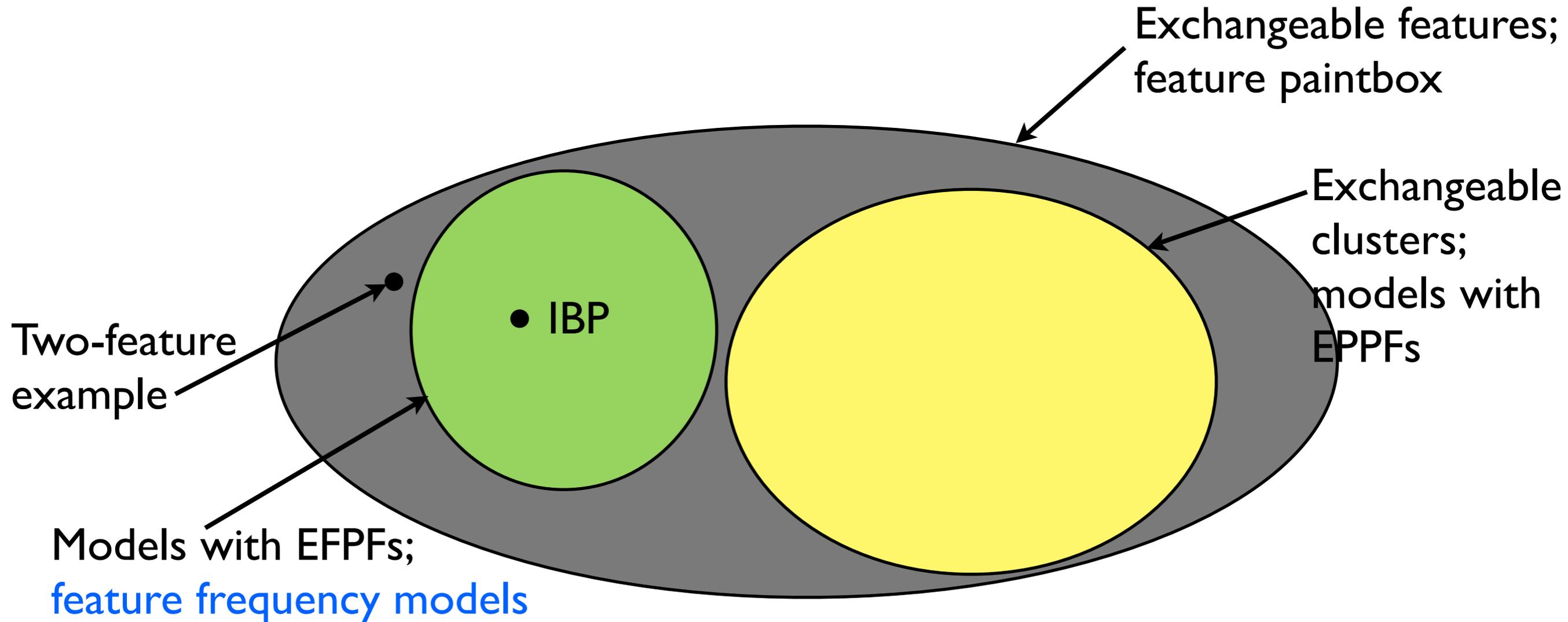
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



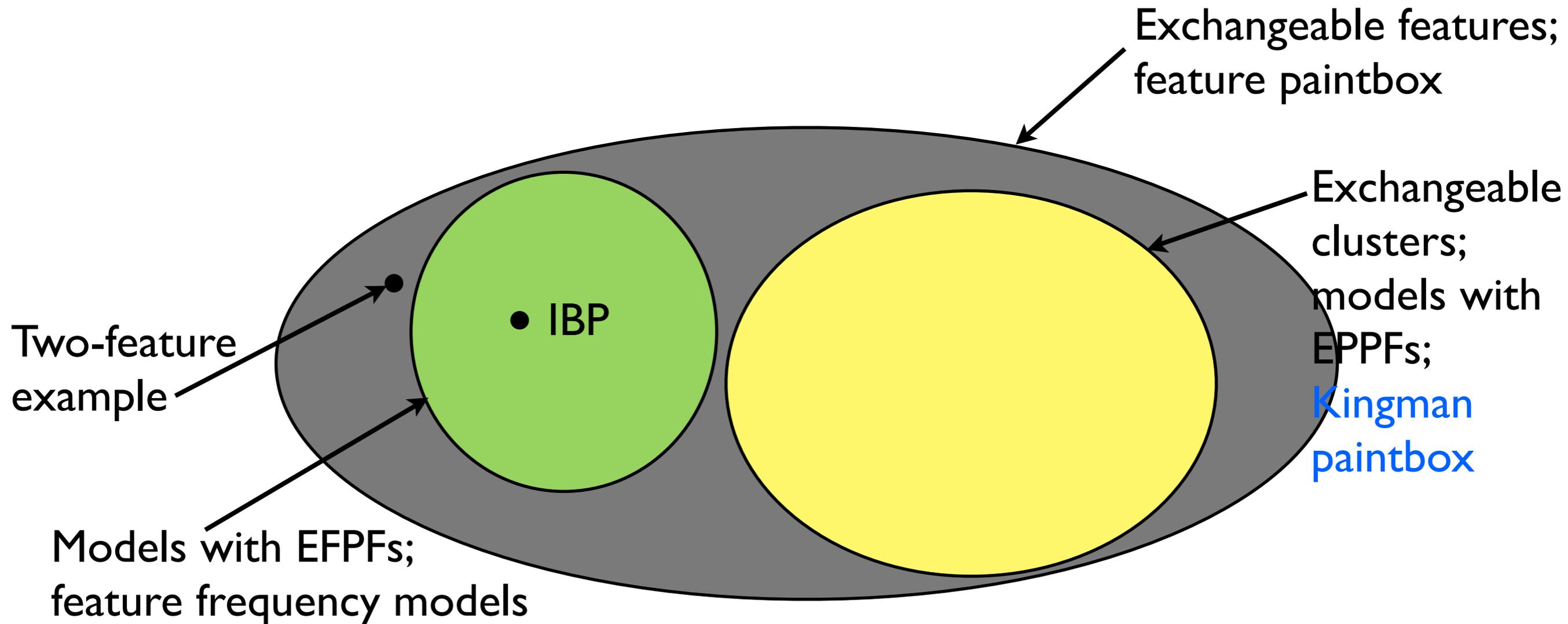
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



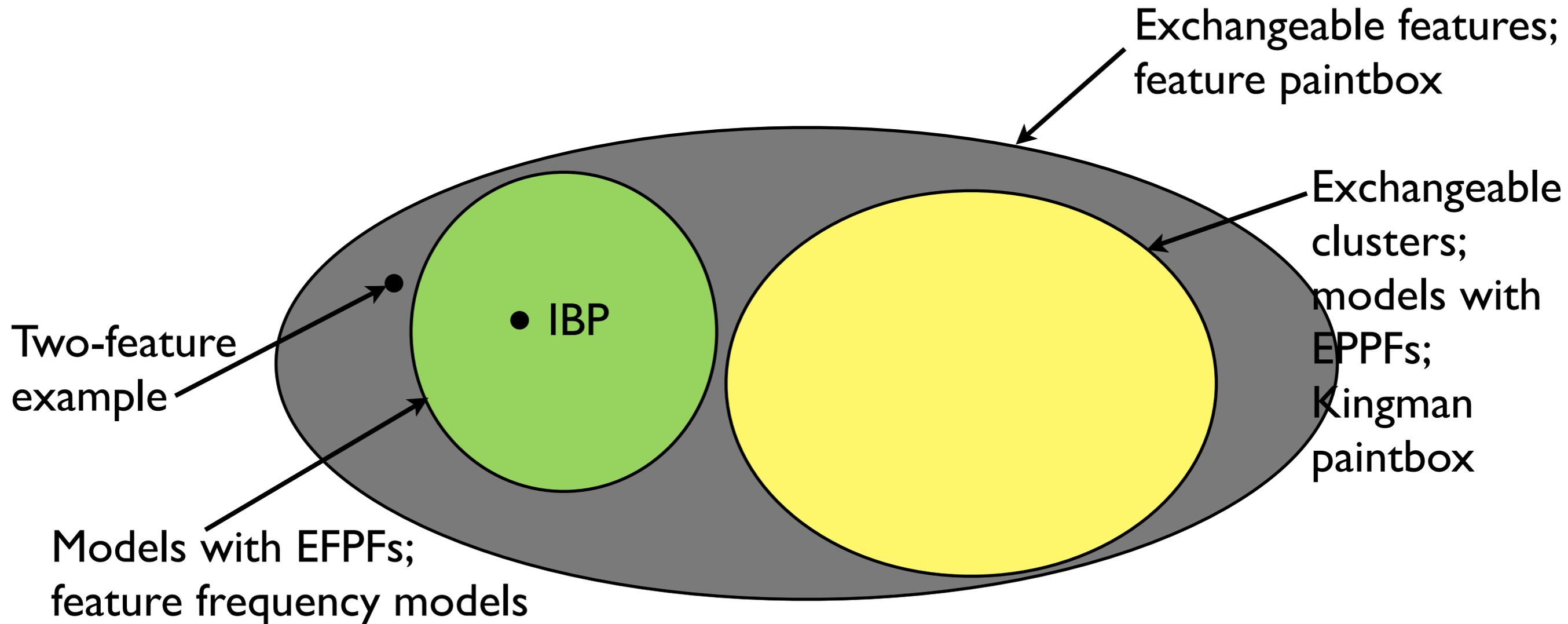
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



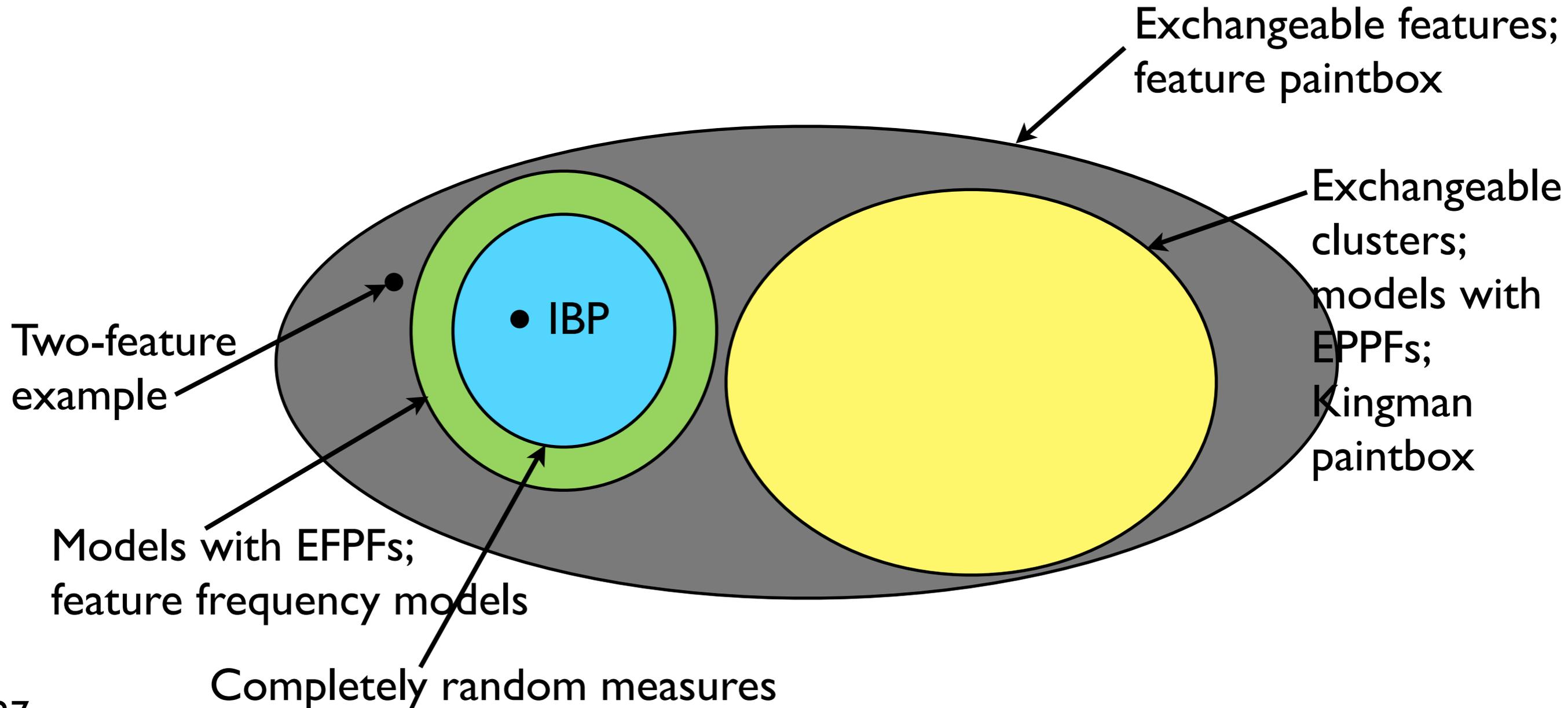
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections



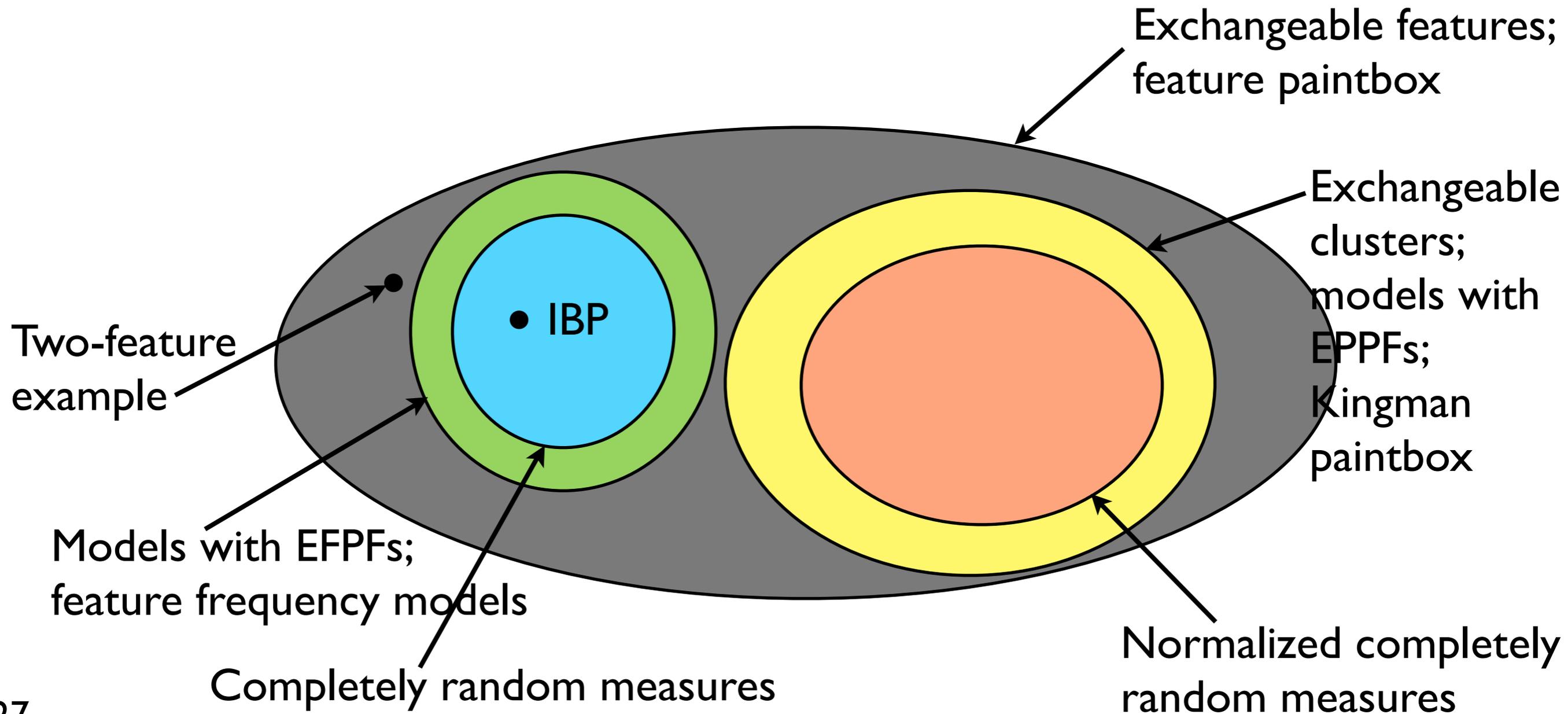
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections (CRMs)



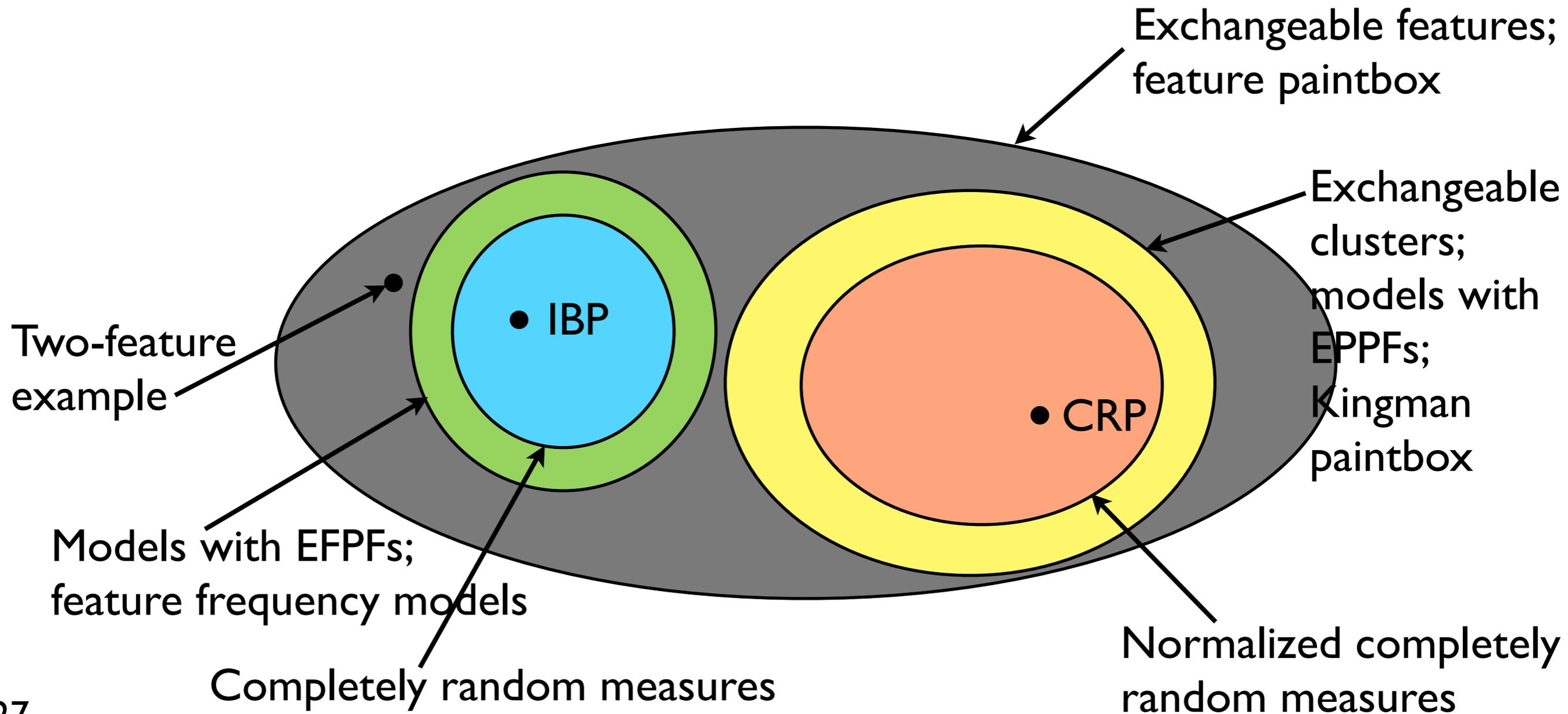
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections (CRMs)



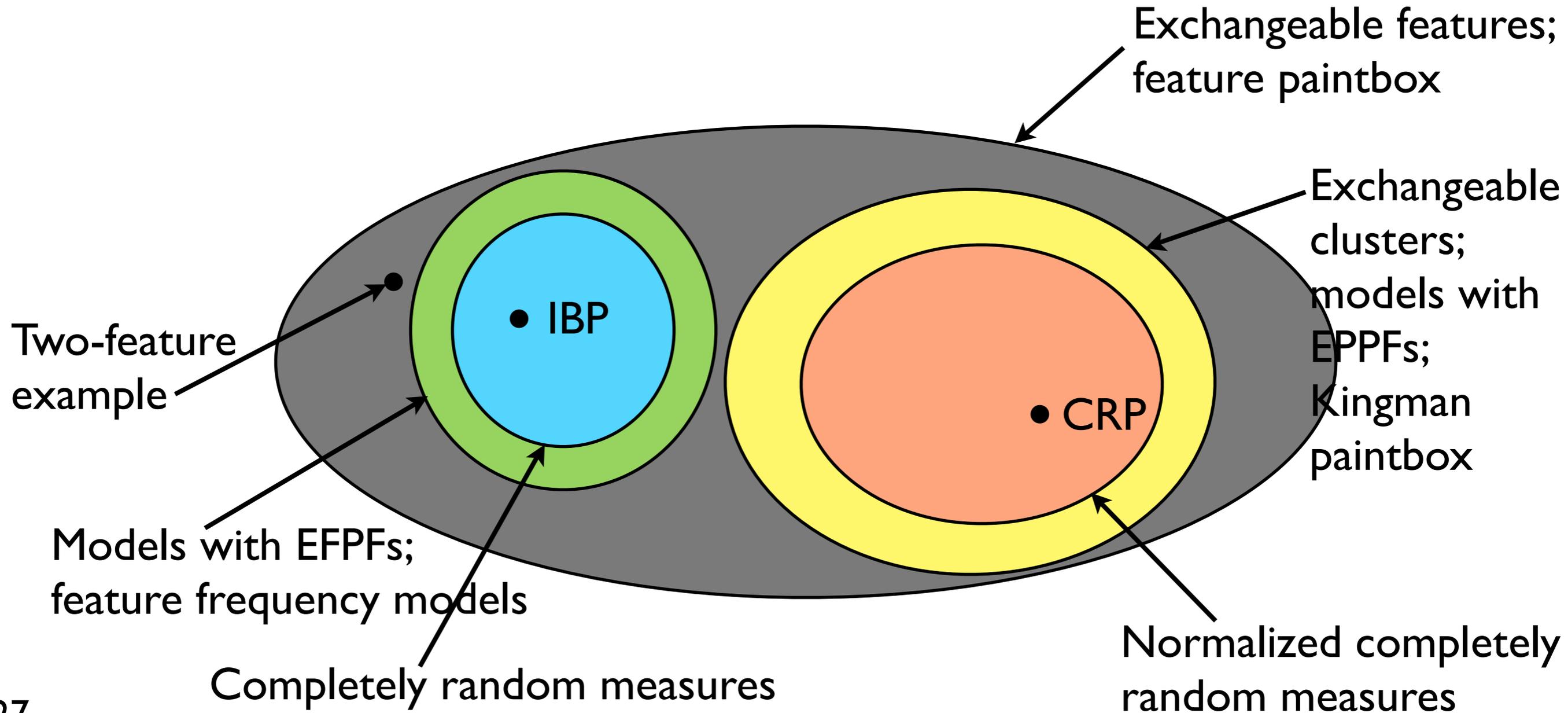
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections (CRMs)



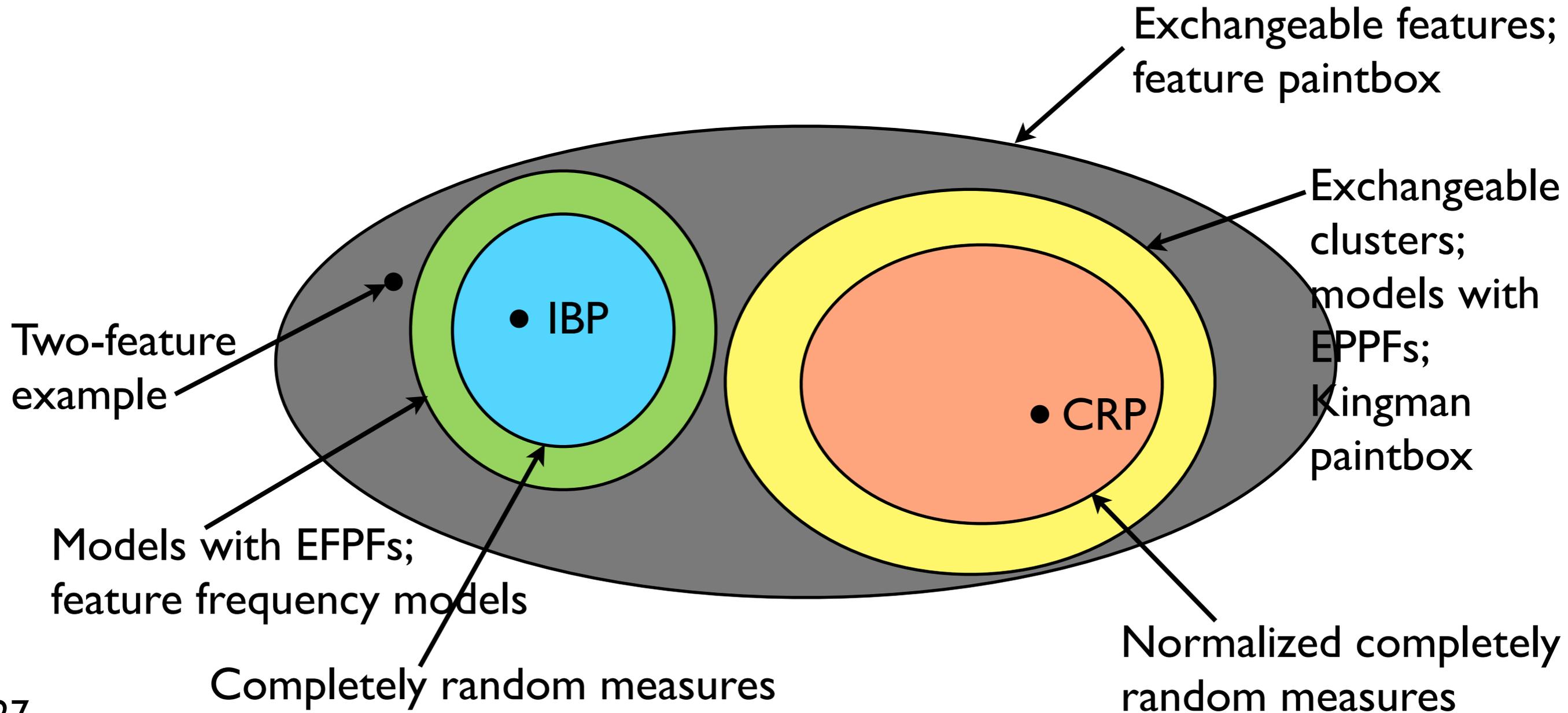
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections (CRMs, dust)



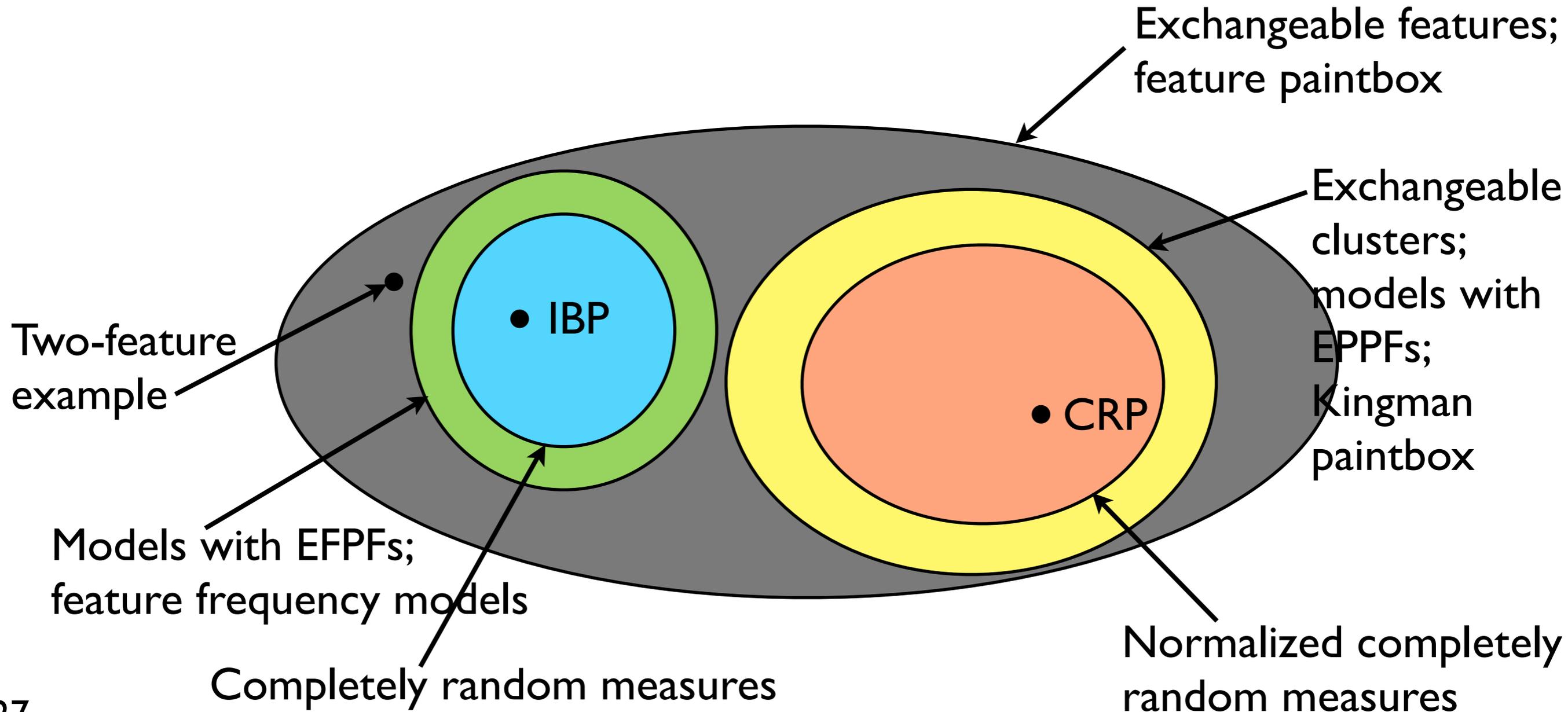
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections (CRMs, dust, etc)



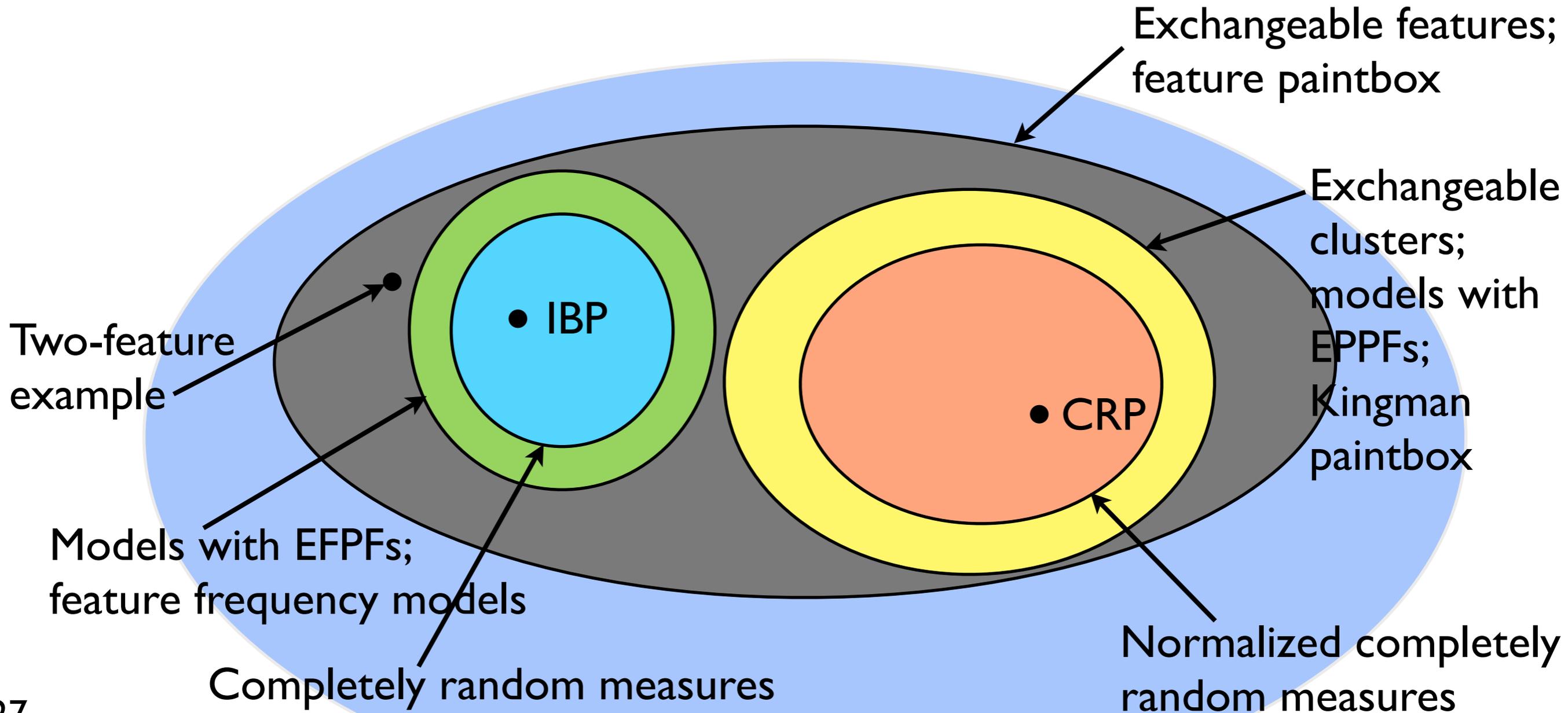
# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections (CRMs, dust, etc)
- Other combinatorial structures



# Theory conclusions

- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
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# References

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