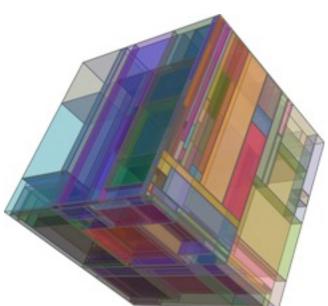


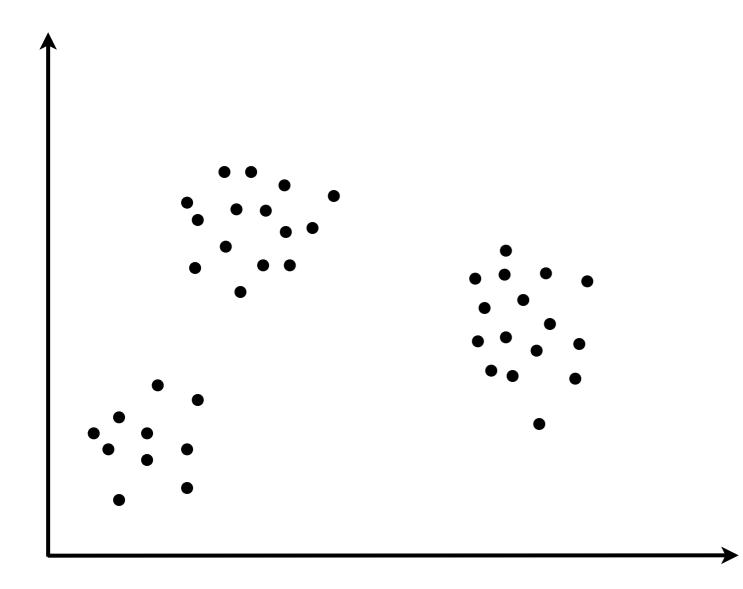


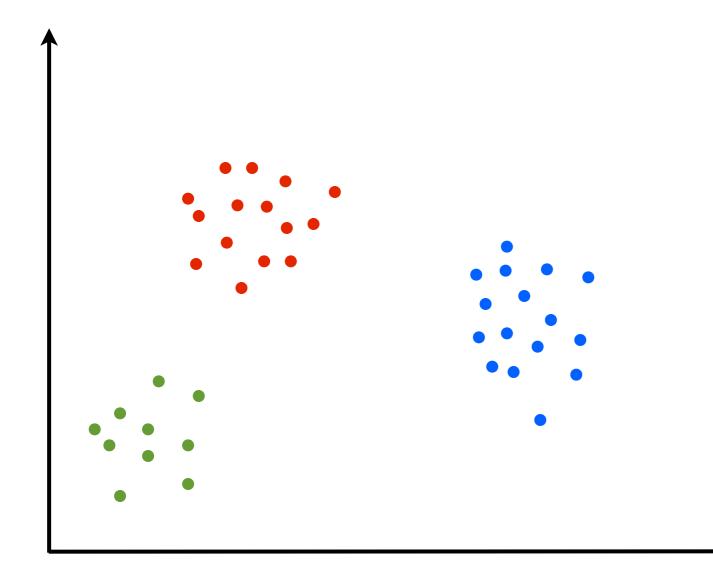
Clusters and features from combinatorial stochastic processes

Tamara Broderick, Michael I. Jordan, Jim Pitman UC Berkeley

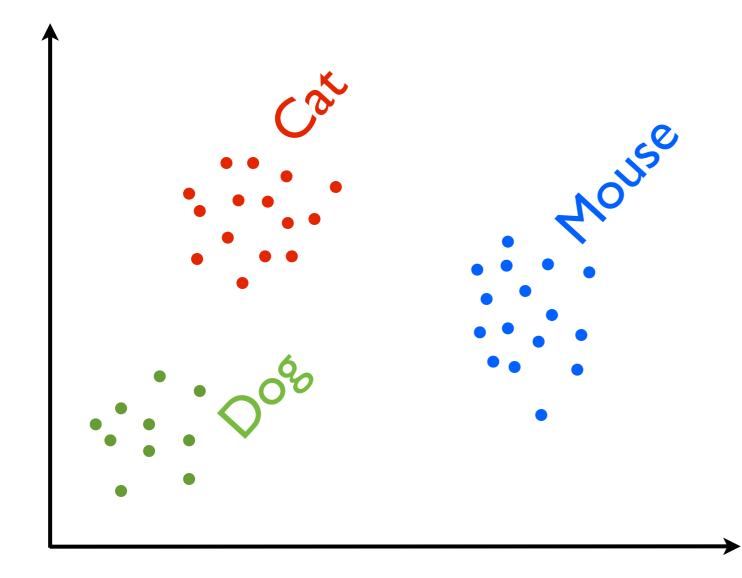




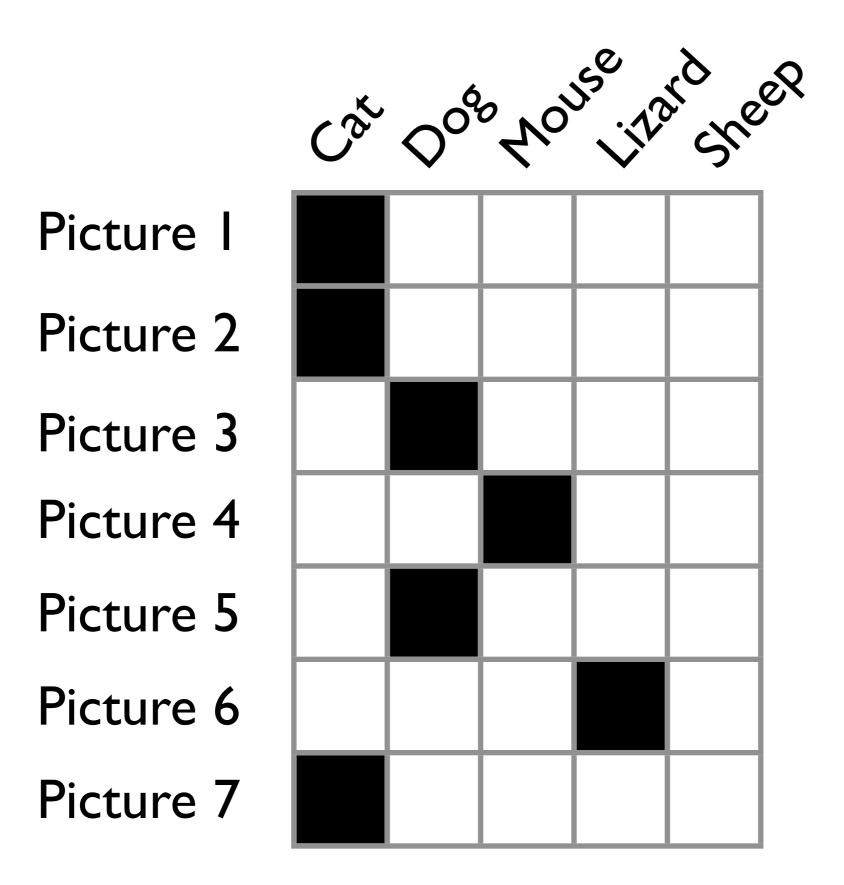




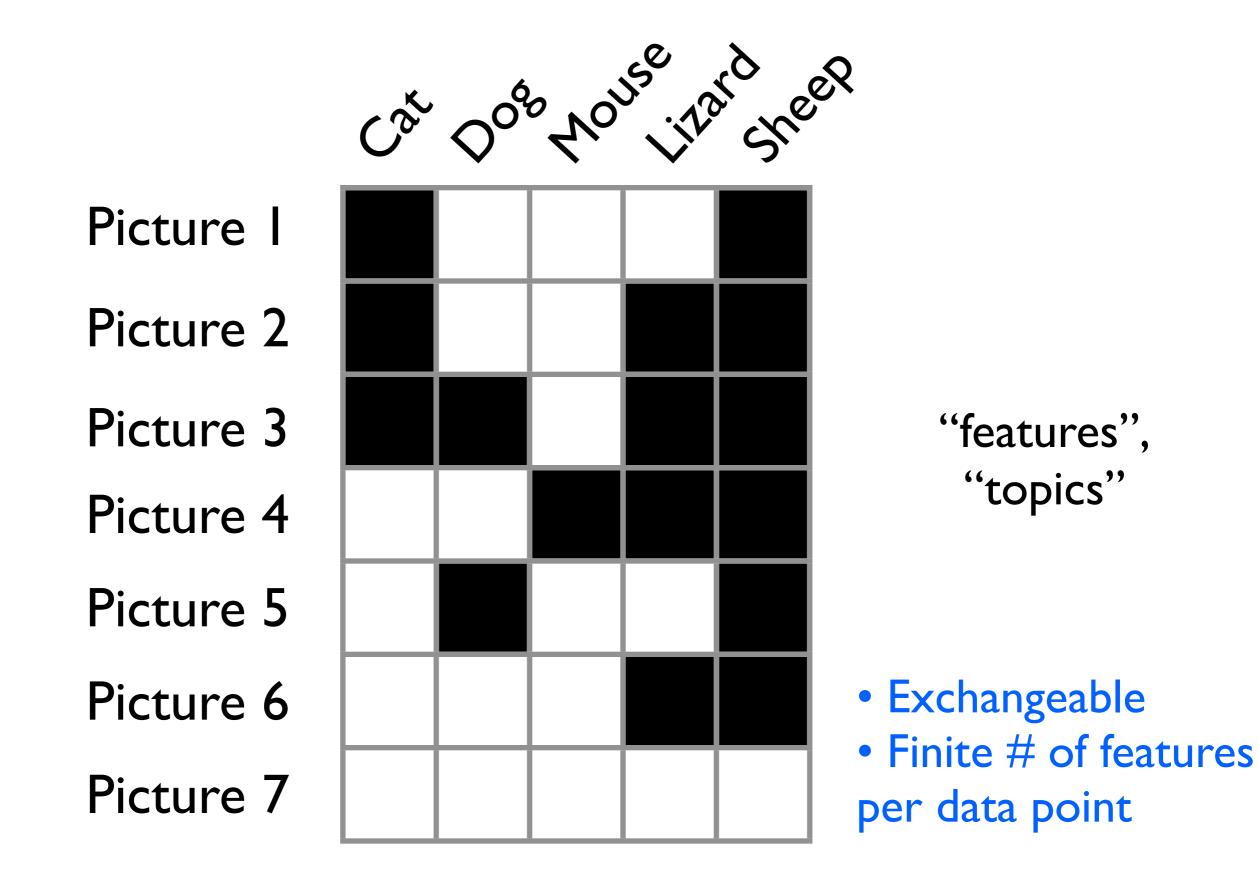
"clusters", "classes", "blocks (of a partition)"



"clusters", "classes", "blocks (of a partition)"

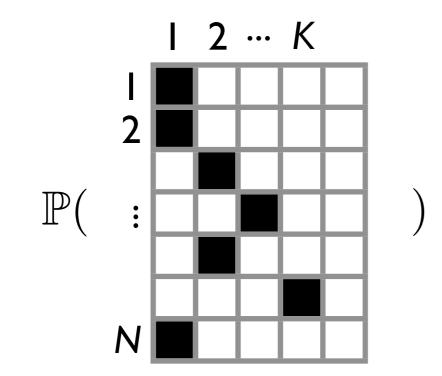


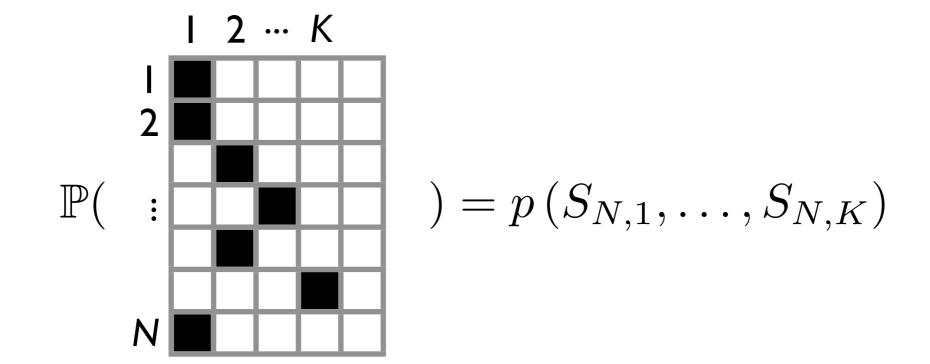
Latent feature allocation

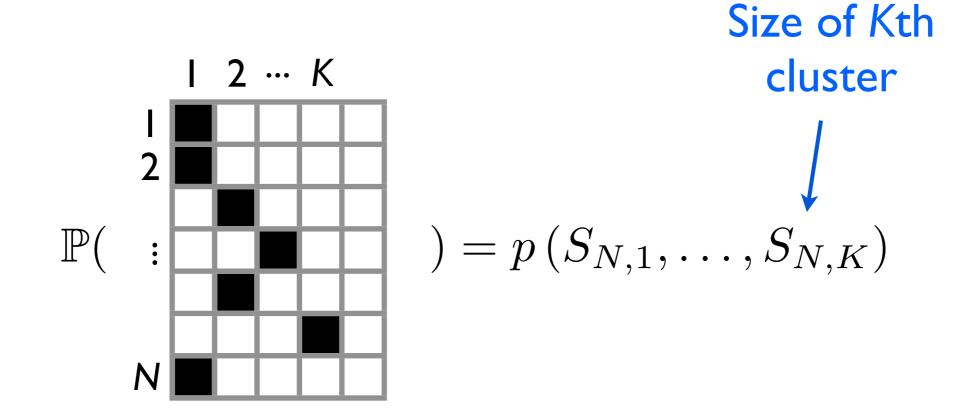


Characterizations

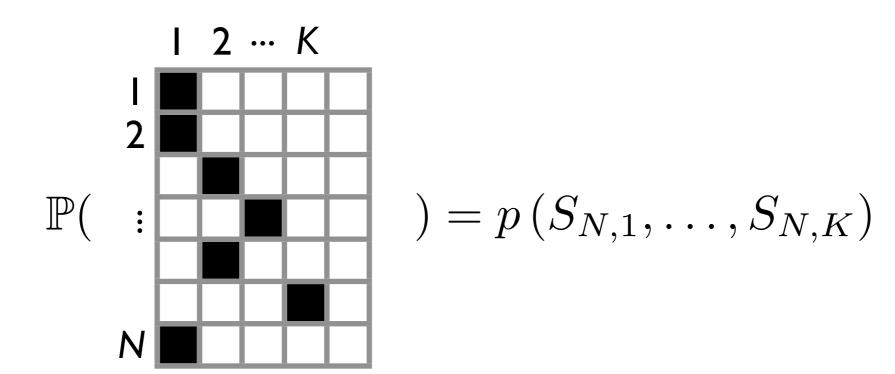
- Exchangeable cluster distributions are characterized
- What about exchangeable feature distributions?





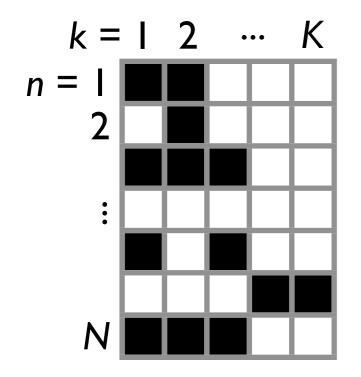


Exchangeable partition probability function (EPPF)

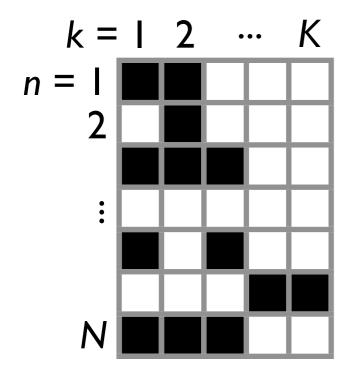


"Exchangeable feature probability function" (EFPF)?

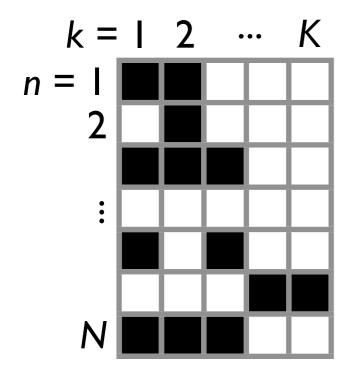
7



7

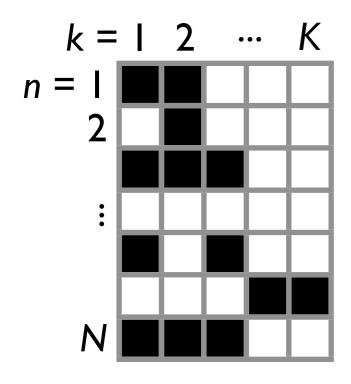


7

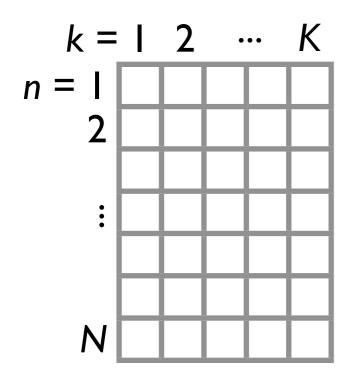


7

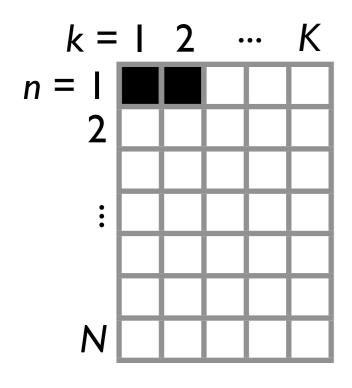
For n = 1, 2, ..., NI. Data point *n* has an existing feature *k* that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$



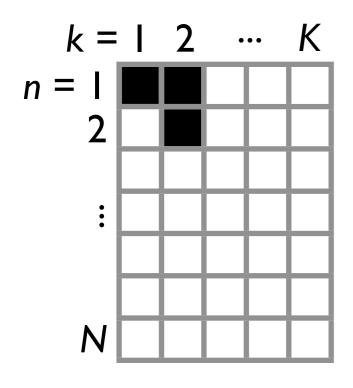
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



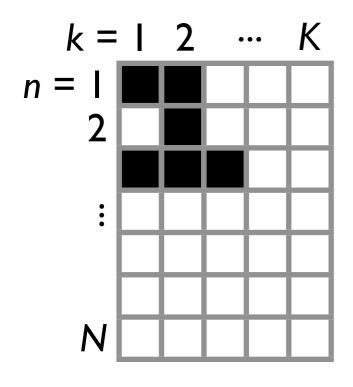
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



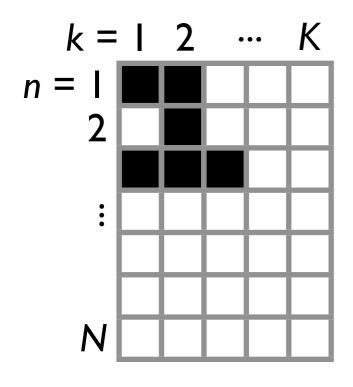
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



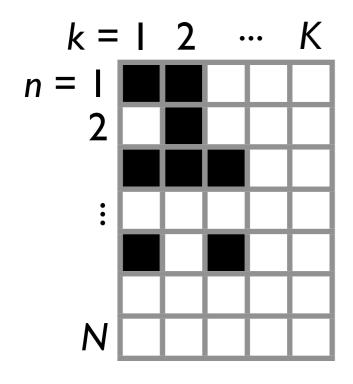
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



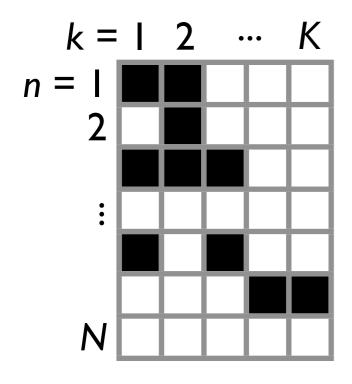
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



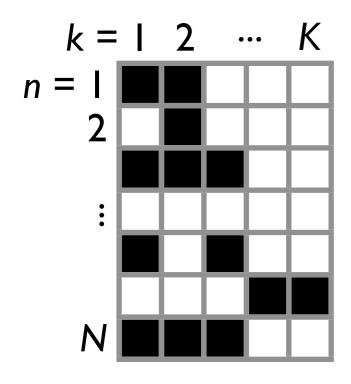
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



For n = 1, 2, ..., NI. 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: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



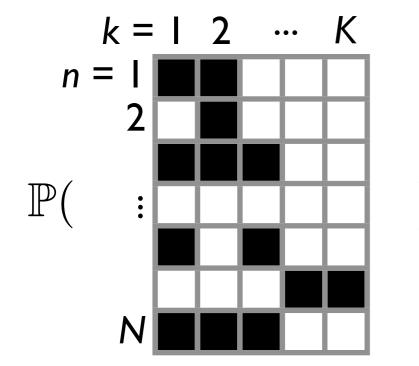
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$



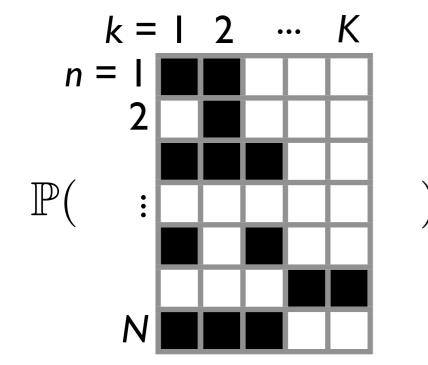
For n = 1, 2, ..., NI. Data point n has an existing feature k that has already occurred $S_{n-1,k}$ times with probability $\frac{S_{n-1,k}}{\theta + n - 1}$ 2. Number of new features for data point n: $K_n^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + n - 1}\right)$

"Exchangeable feature probability function" (EFPF)?

"Exchangeable feature probability function" (EFPF)?

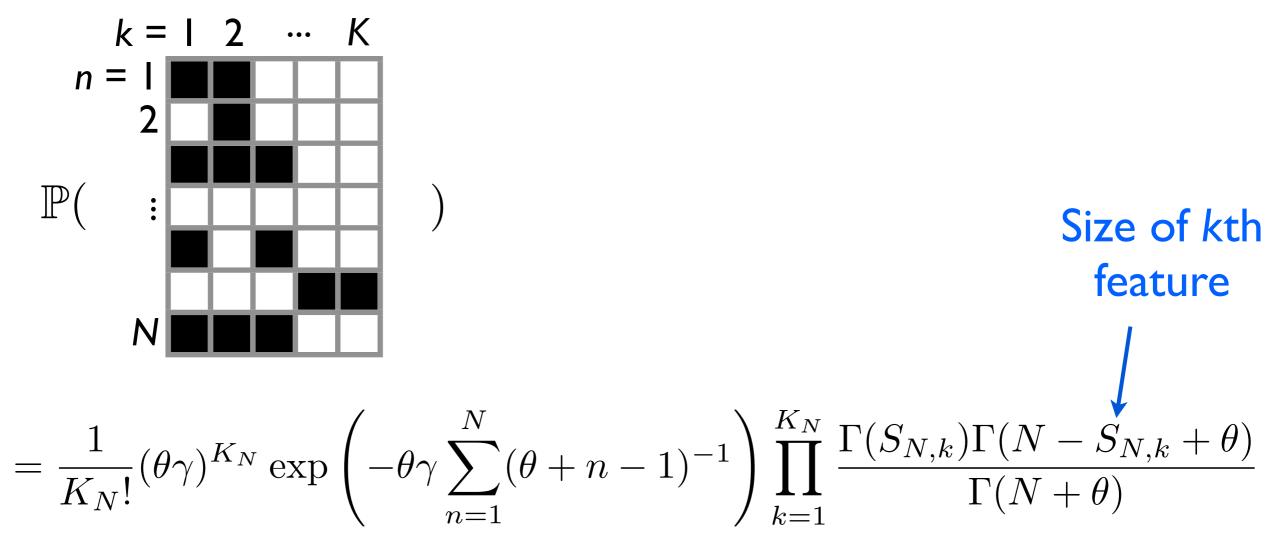


"Exchangeable feature probability function" (EFPF)?

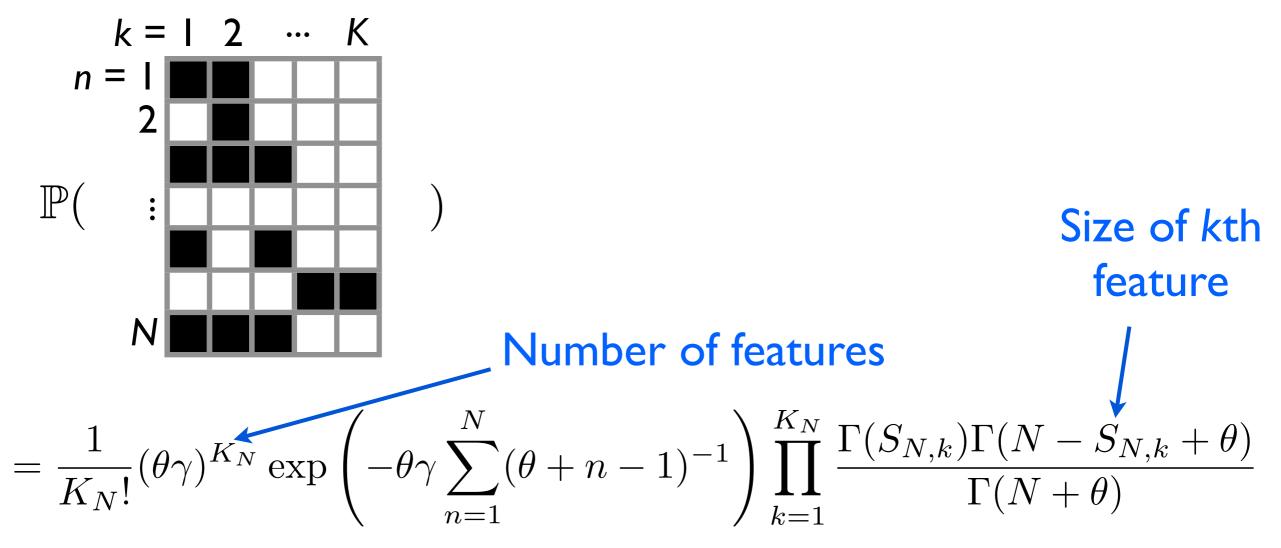


$$= \frac{1}{K_N!} (\theta \gamma)^{K_N} \exp\left(-\theta \gamma \sum_{n=1}^N (\theta + n - 1)^{-1}\right) \prod_{k=1}^{K_N} \frac{\Gamma(S_{N,k}) \Gamma(N - S_{N,k} + \theta)}{\Gamma(N + \theta)}$$

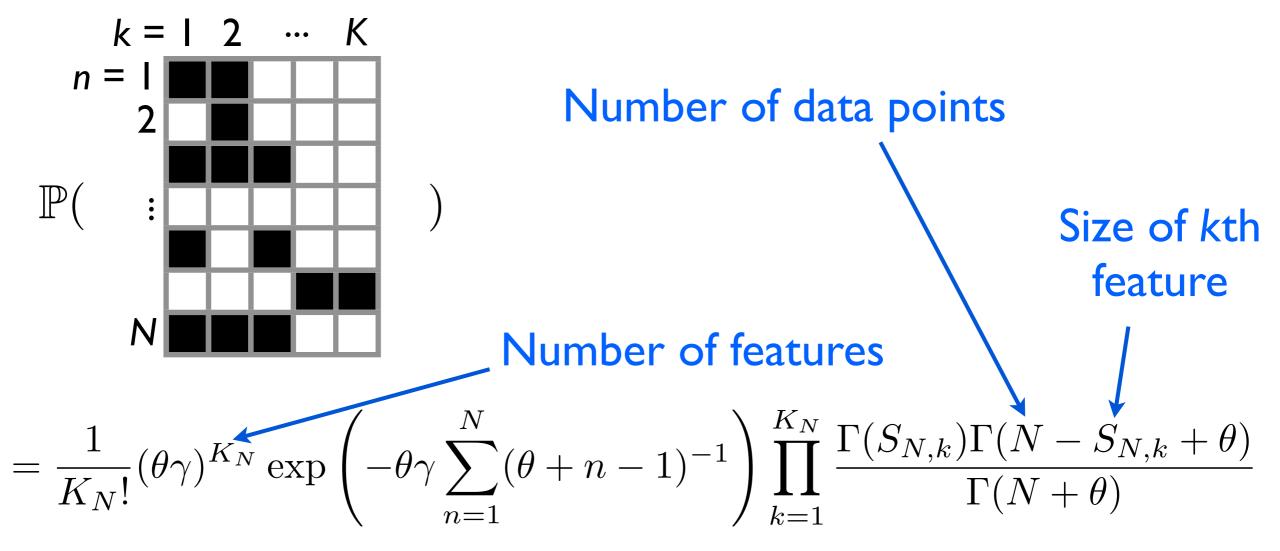
"Exchangeable feature probability function" (EFPF)?



"Exchangeable feature probability function" (EFPF)?

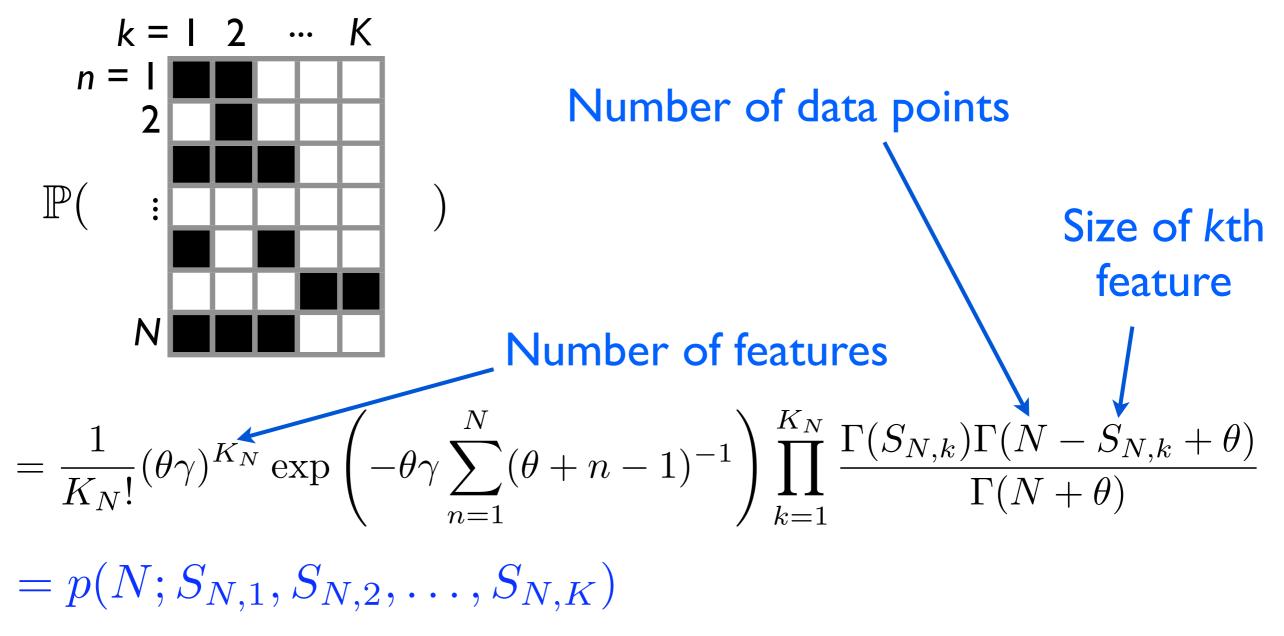


"Exchangeable feature probability function" (EFPF)?



"Exchangeable feature probability function" (EFPF)?

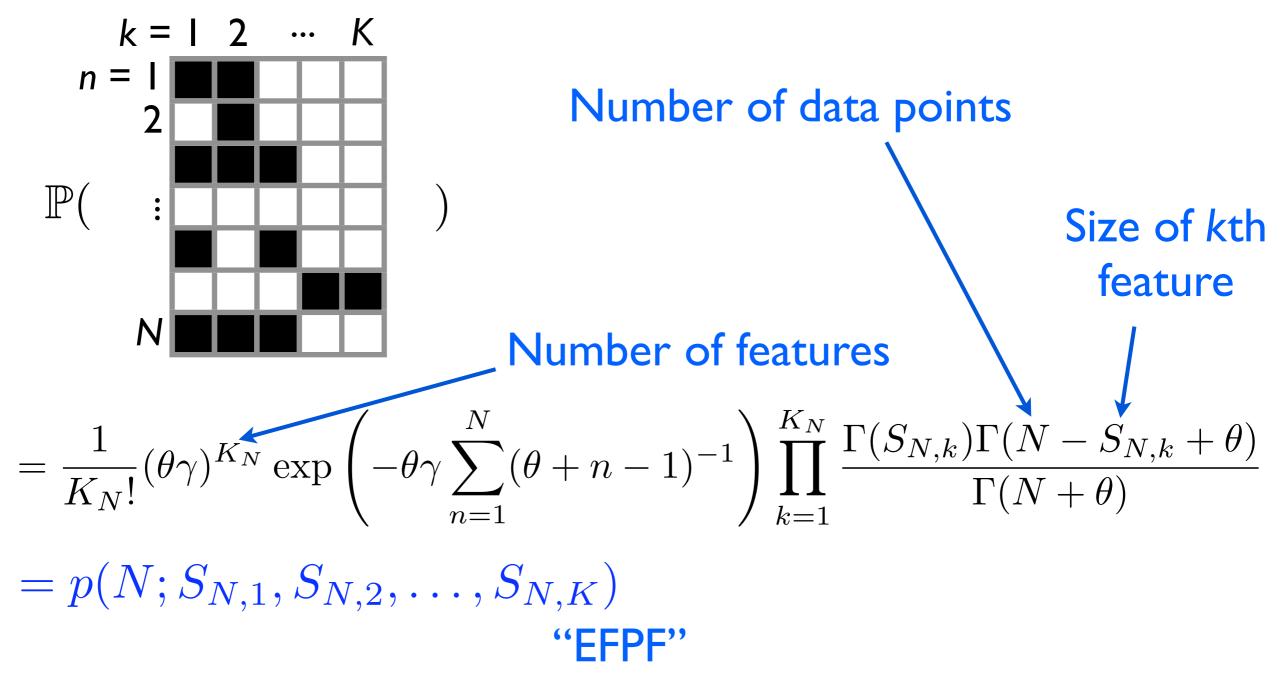
Example: Indian buffet process (IBP)



[Broderick, Jordan, Pitman 2012]

"Exchangeable feature probability function" (EFPF)?

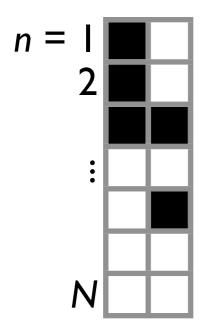
Example: Indian buffet process (IBP)



[Broderick, Jordan, Pitman 2012]

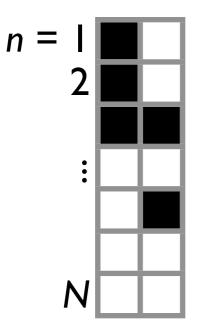
"Exchangeable feature probability function" (EFPF)?

Counterexample



"Exchangeable feature probability function" (EFPF)?

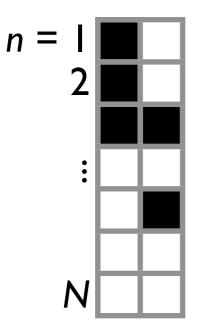
Counterexample



$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$

"Exchangeable feature probability function" (EFPF)?

Counterexample



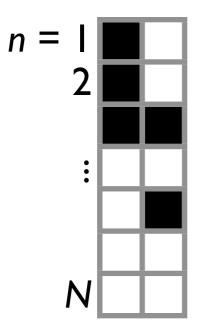
$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$



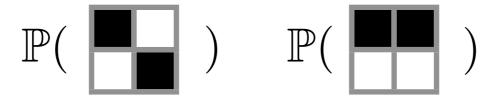
[Broderick, Jordan, Pitman 2012]

"Exchangeable feature probability function" (EFPF)?

Counterexample

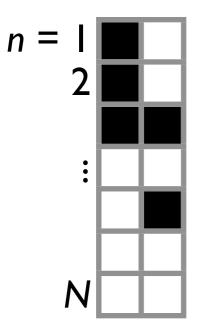


$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$

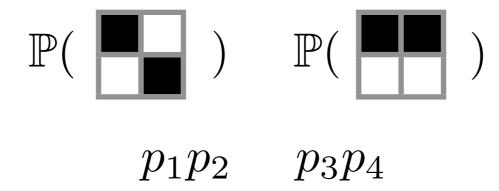


"Exchangeable feature probability function" (EFPF)?

Counterexample

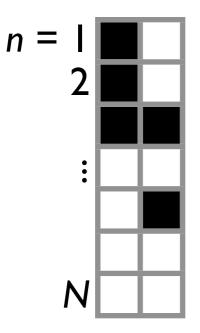


$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$



"Exchangeable feature probability function" (EFPF)?

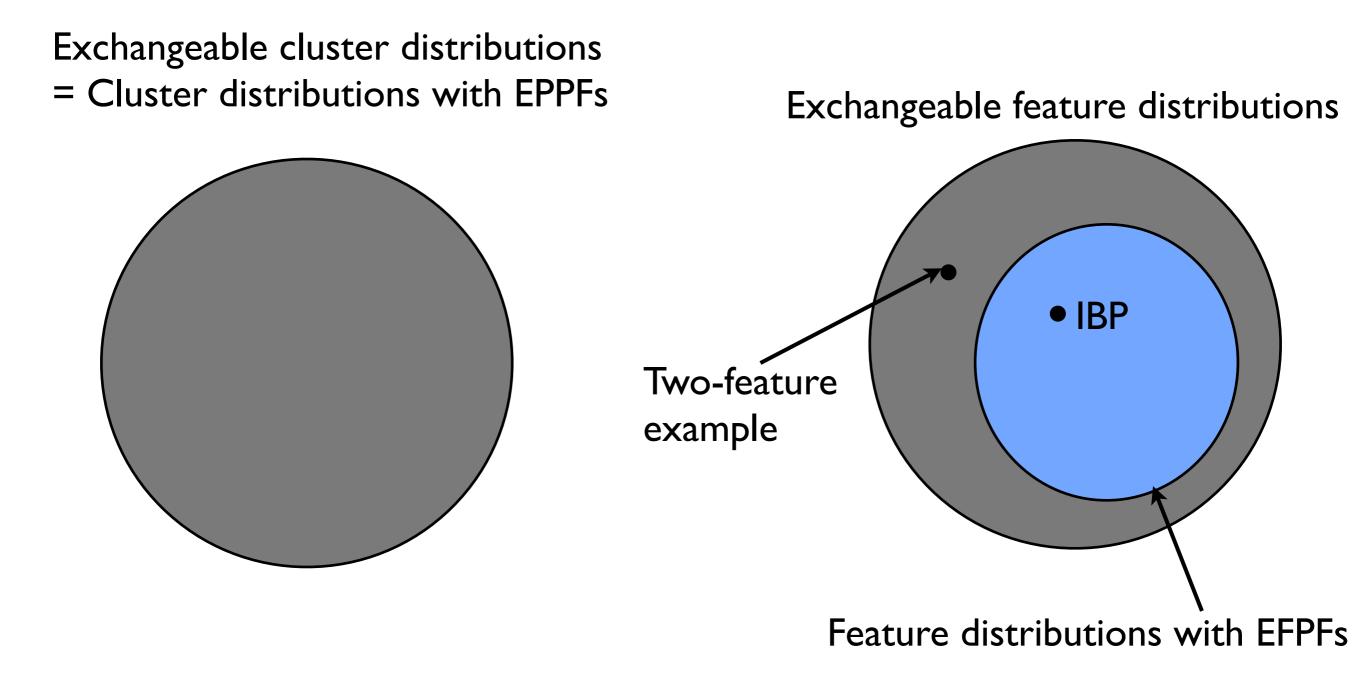
Counterexample



$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$

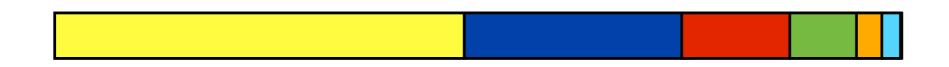
$$\mathbb{P}(\square) \neq \mathbb{P}(\square)$$

$$p_1 p_2 \neq p_3 p_4$$



Exchangeable partition: Kingman paintbox

Exchangeable partition: Kingman paintbox

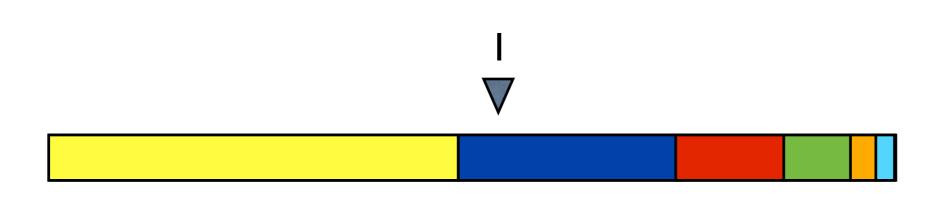


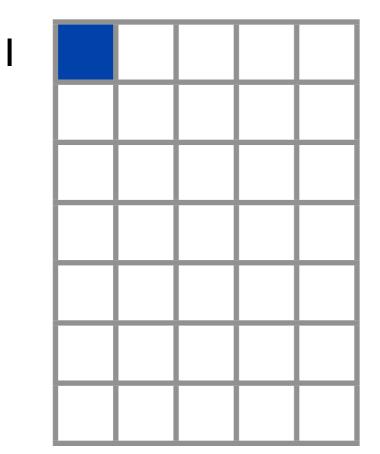
Exchangeable partition: Kingman paintbox



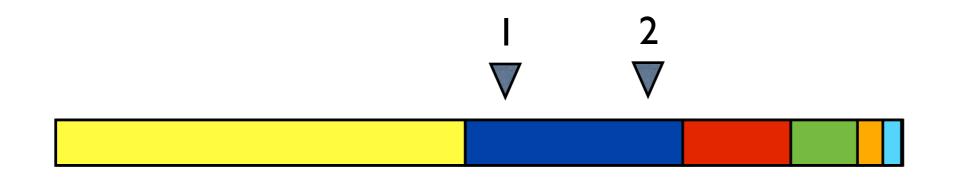


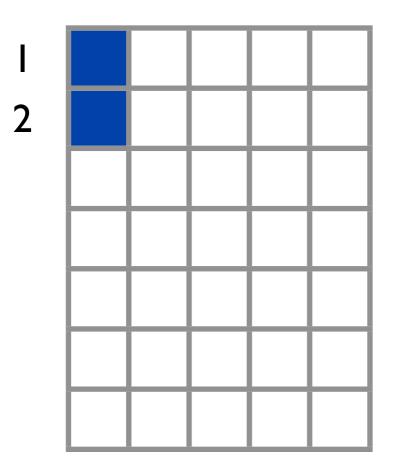
Exchangeable partition: Kingman paintbox



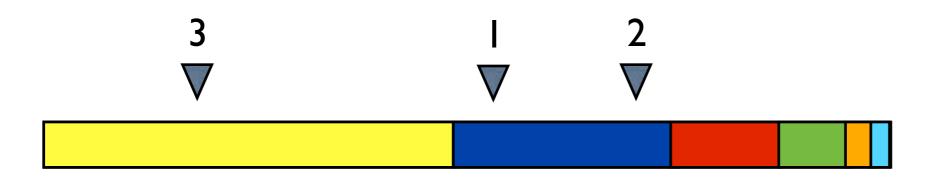


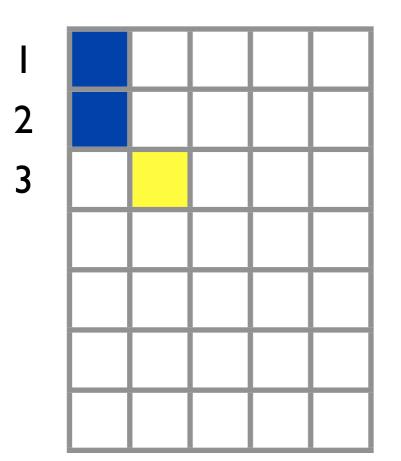
Exchangeable partition: Kingman paintbox



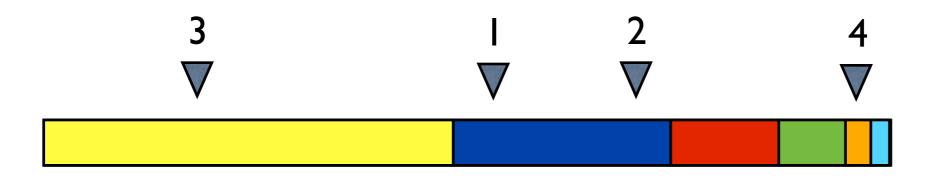


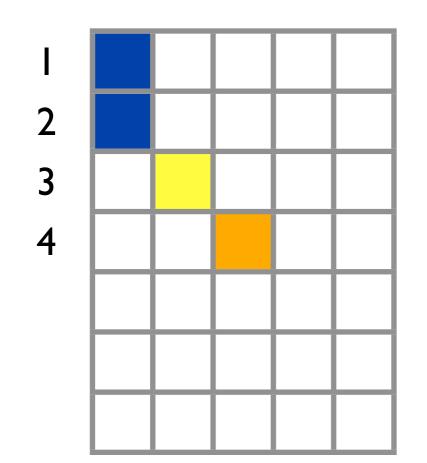
Exchangeable partition: Kingman paintbox



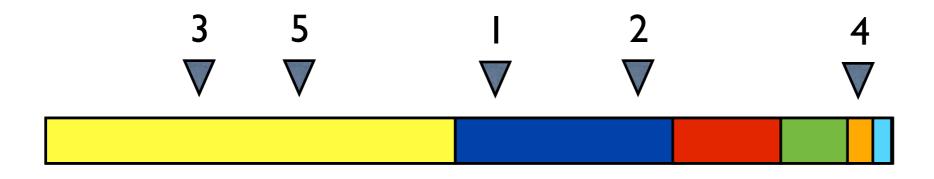


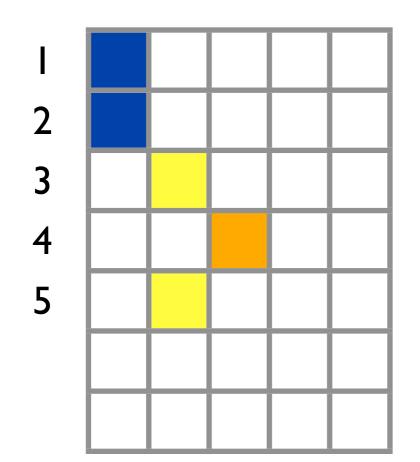
Exchangeable partition: Kingman paintbox



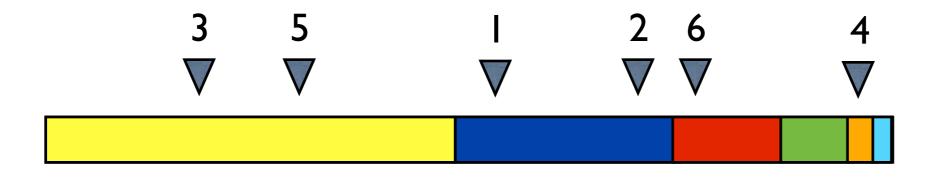


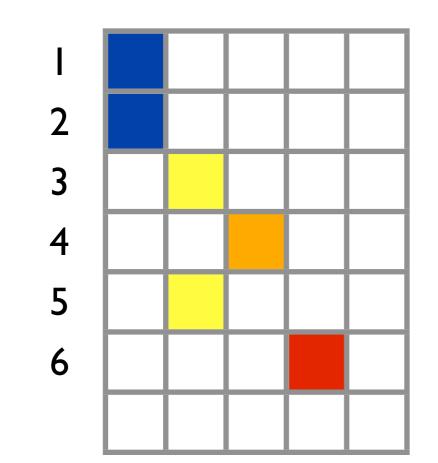
Exchangeable partition: Kingman paintbox



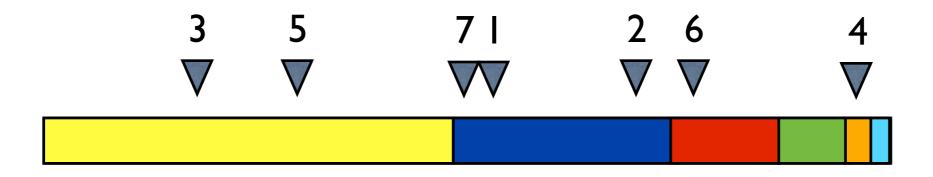


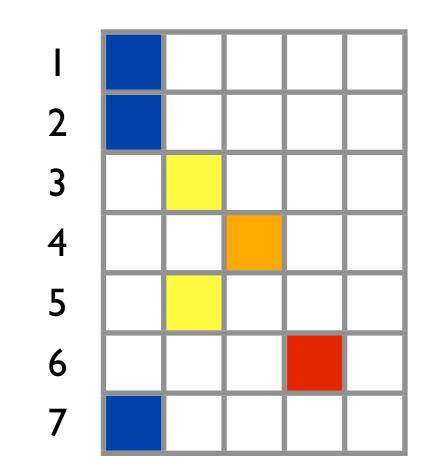
Exchangeable partition: Kingman paintbox



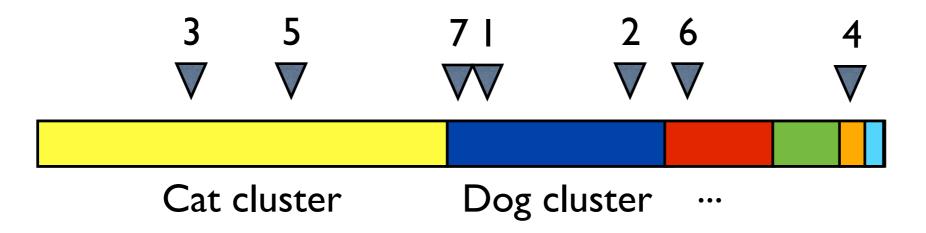


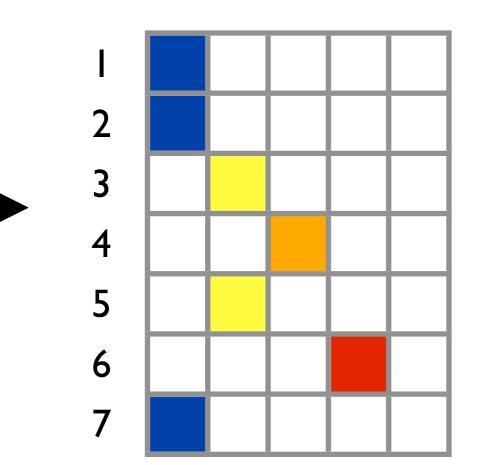
Exchangeable partition: Kingman paintbox



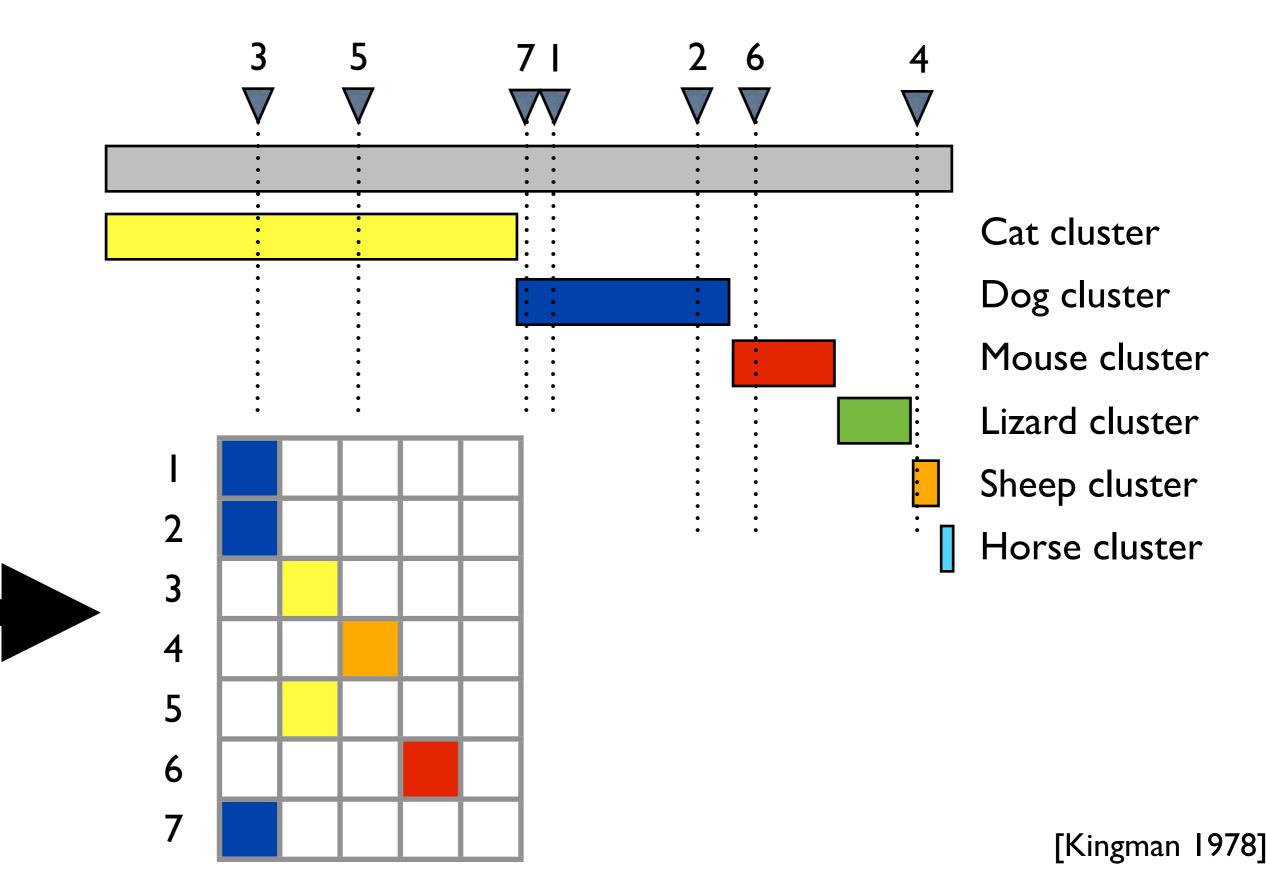


Exchangeable partition: Kingman paintbox

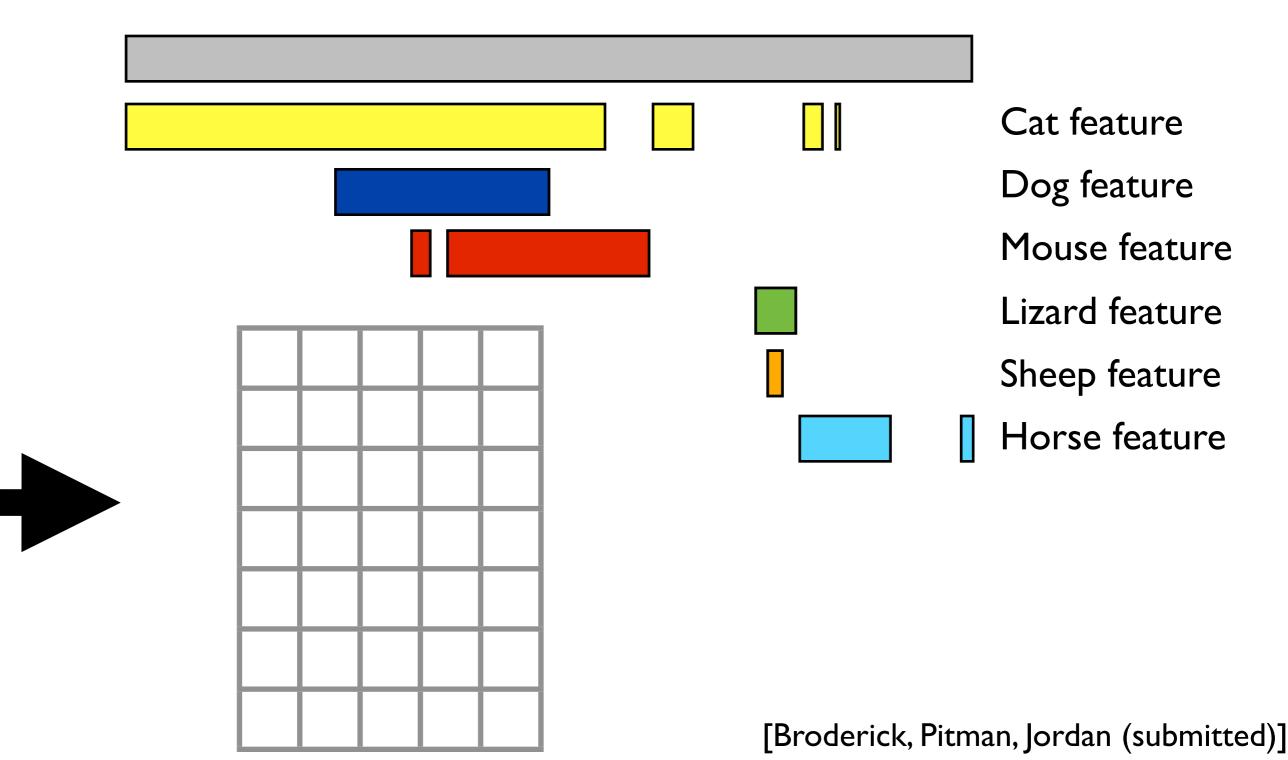


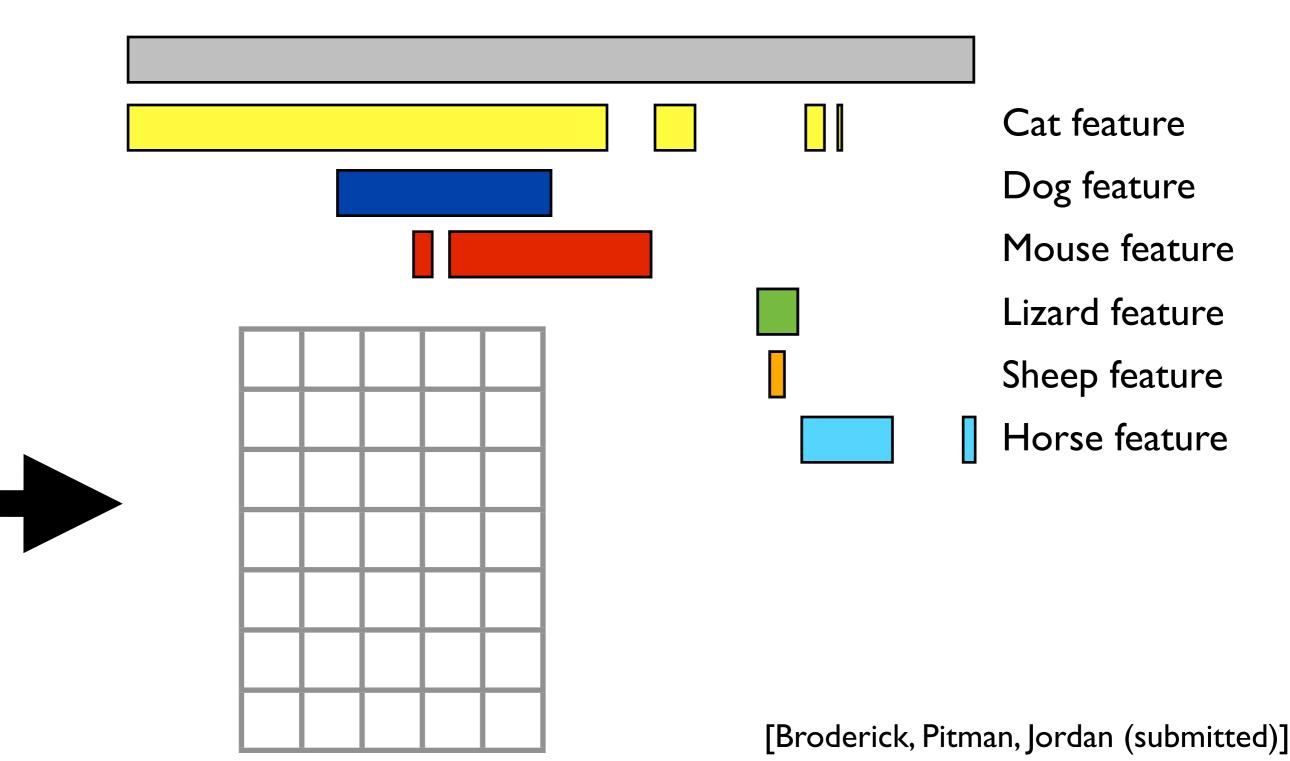


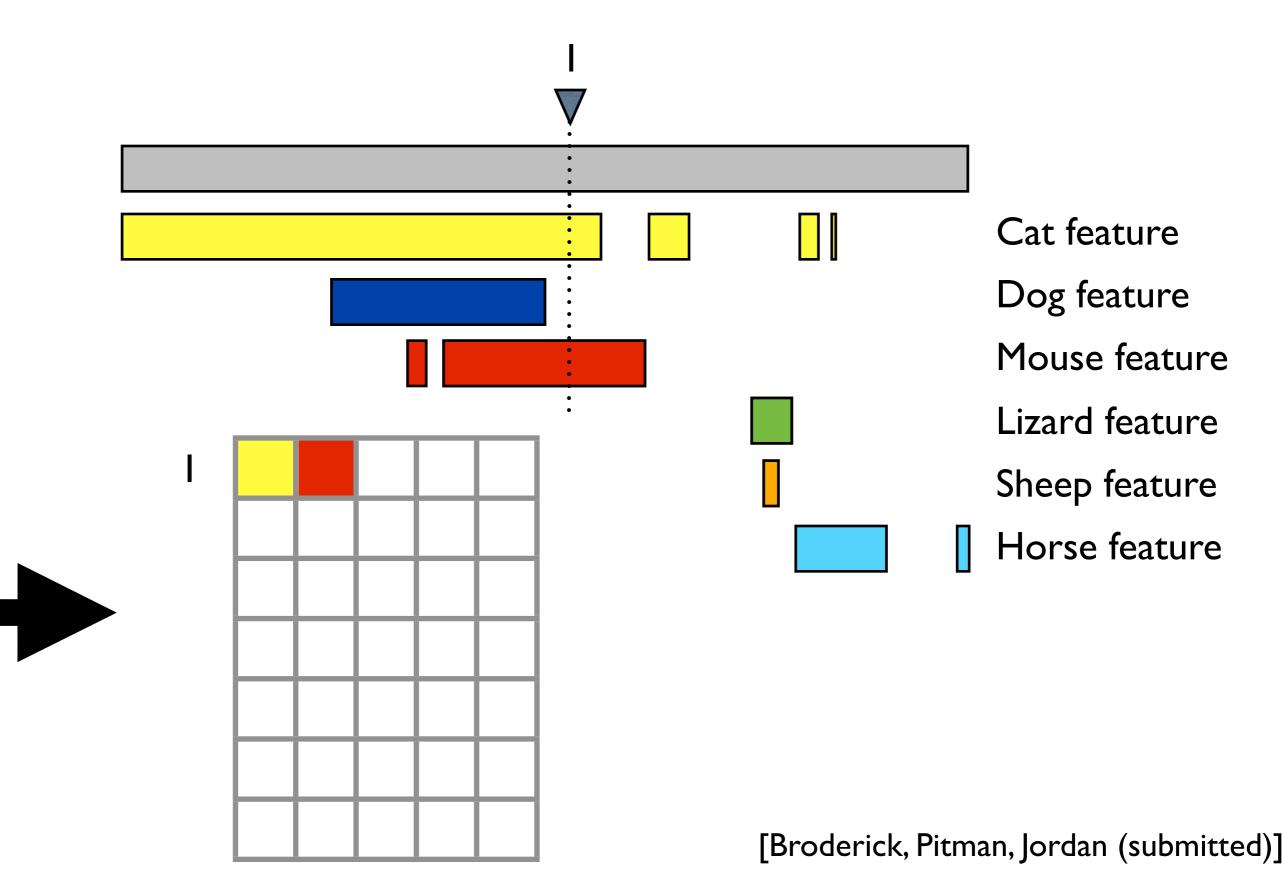
Exchangeable partition: Kingman paintbox

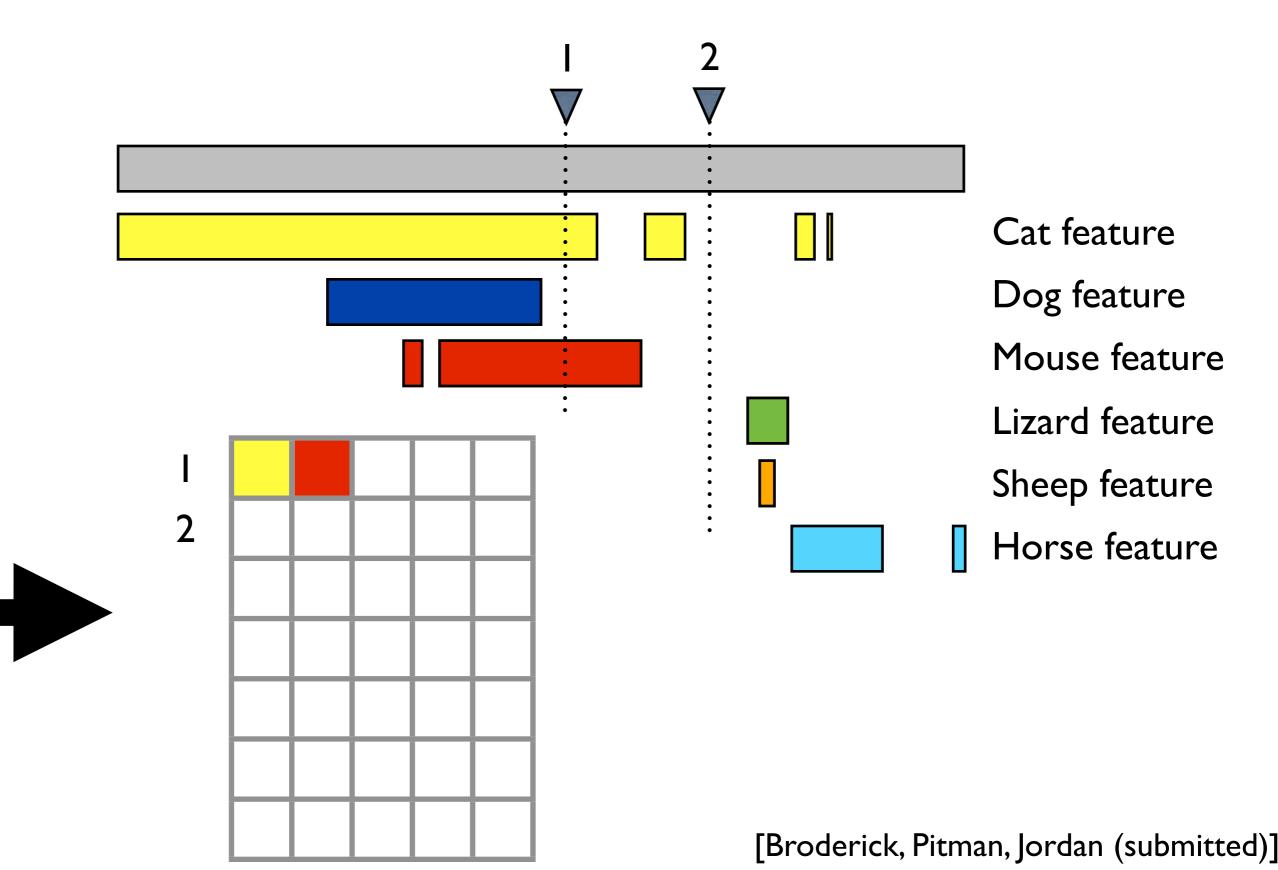


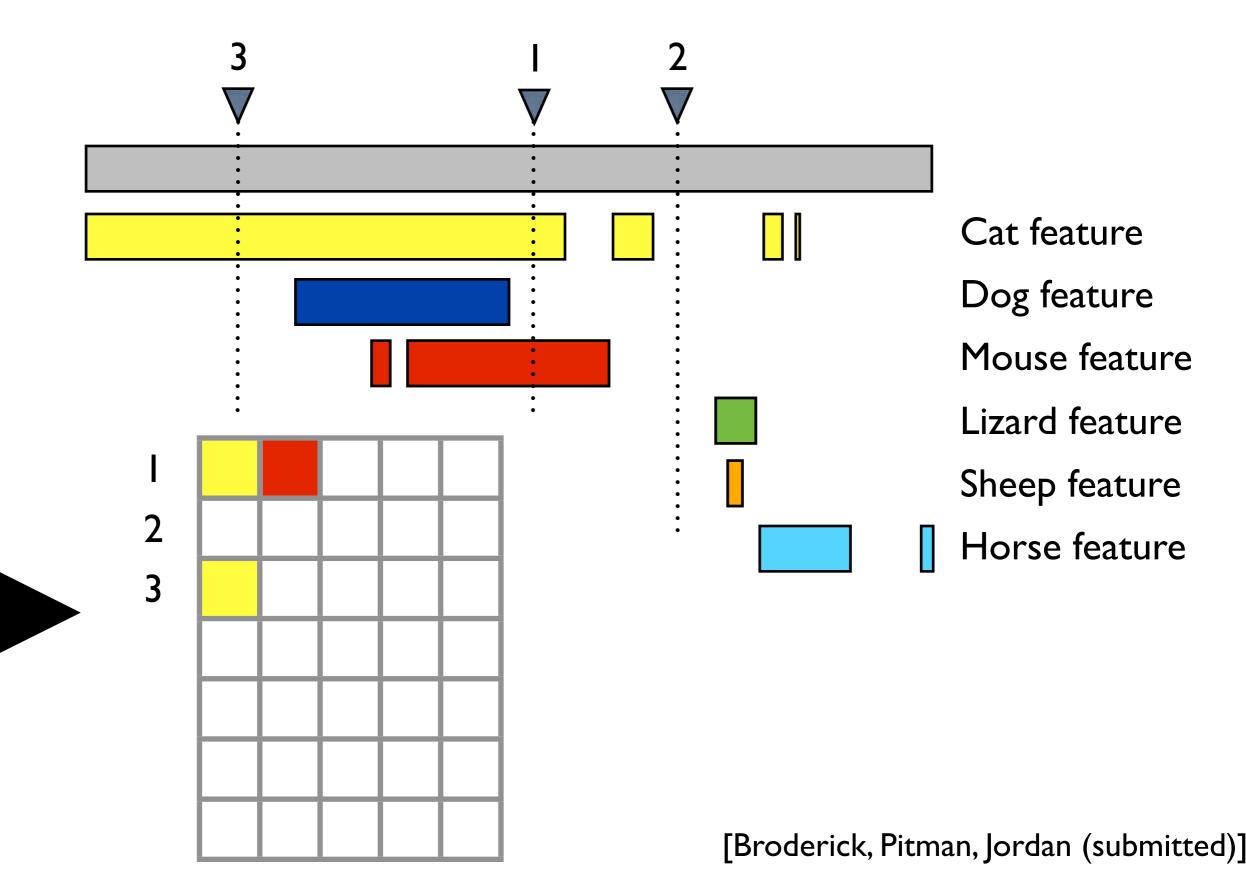
12

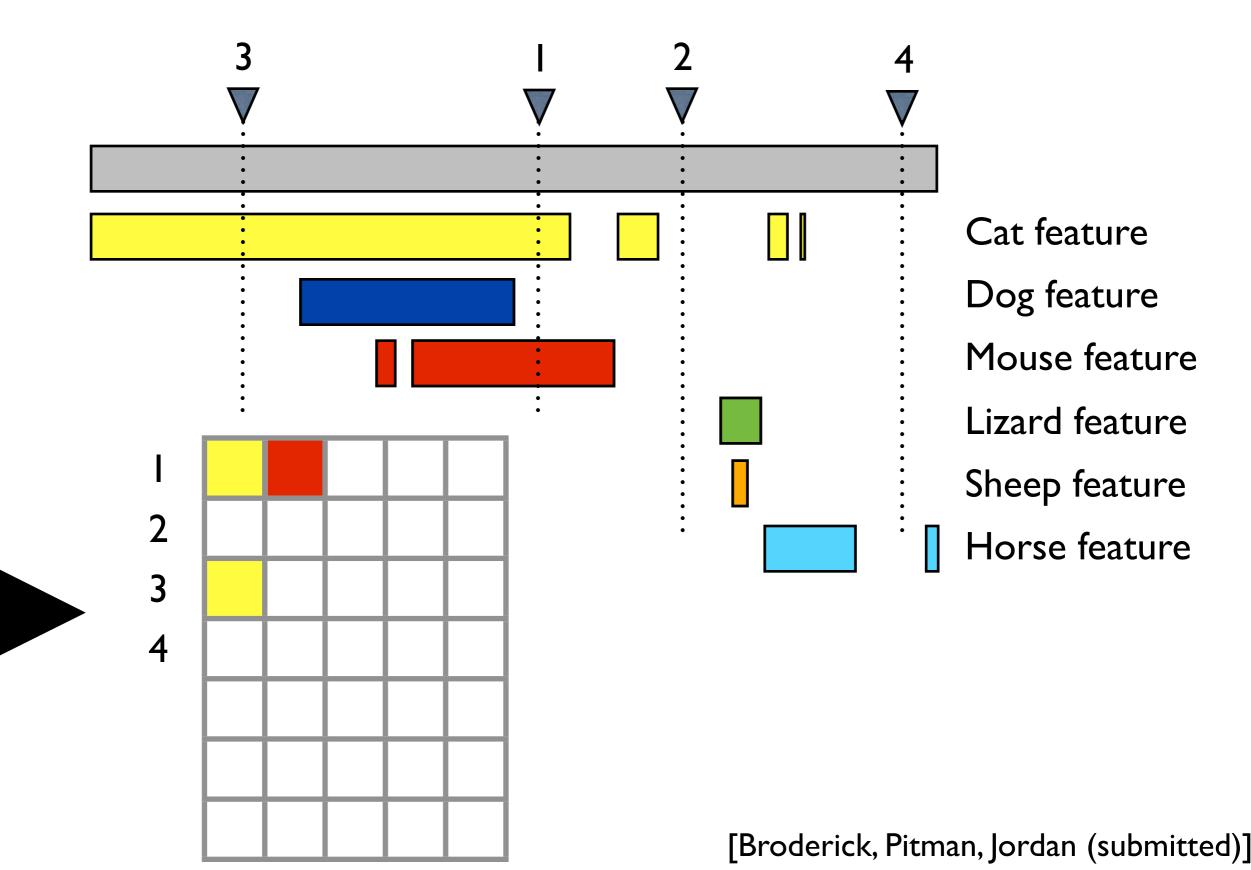


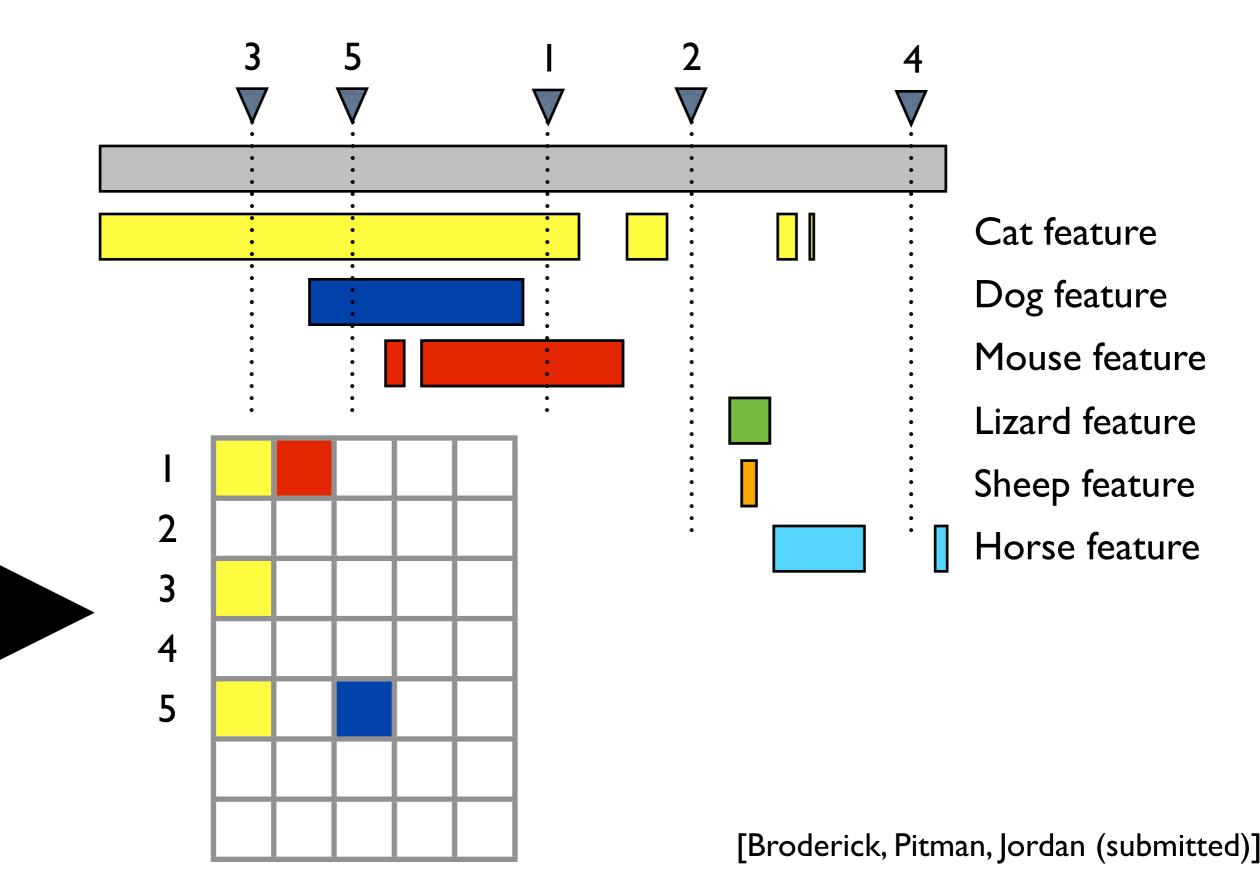


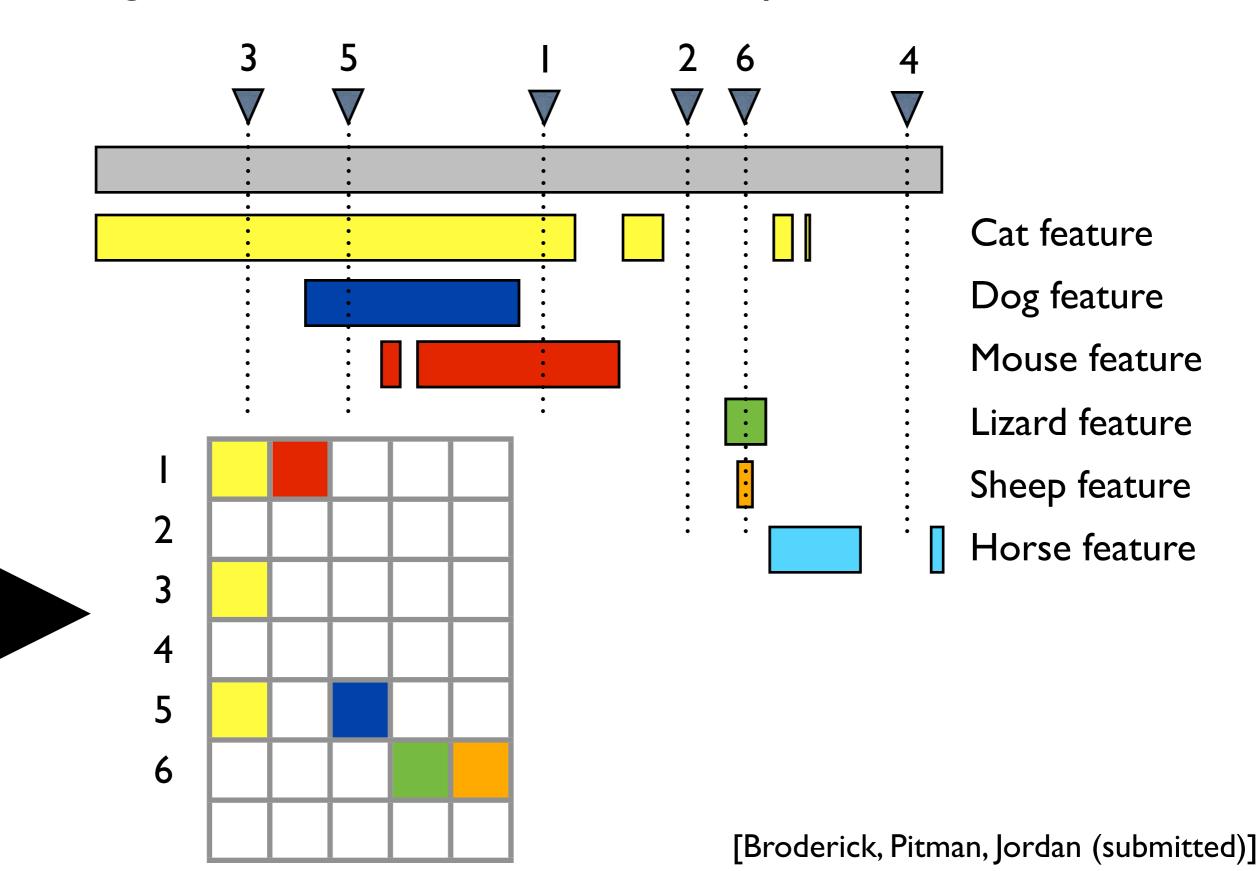


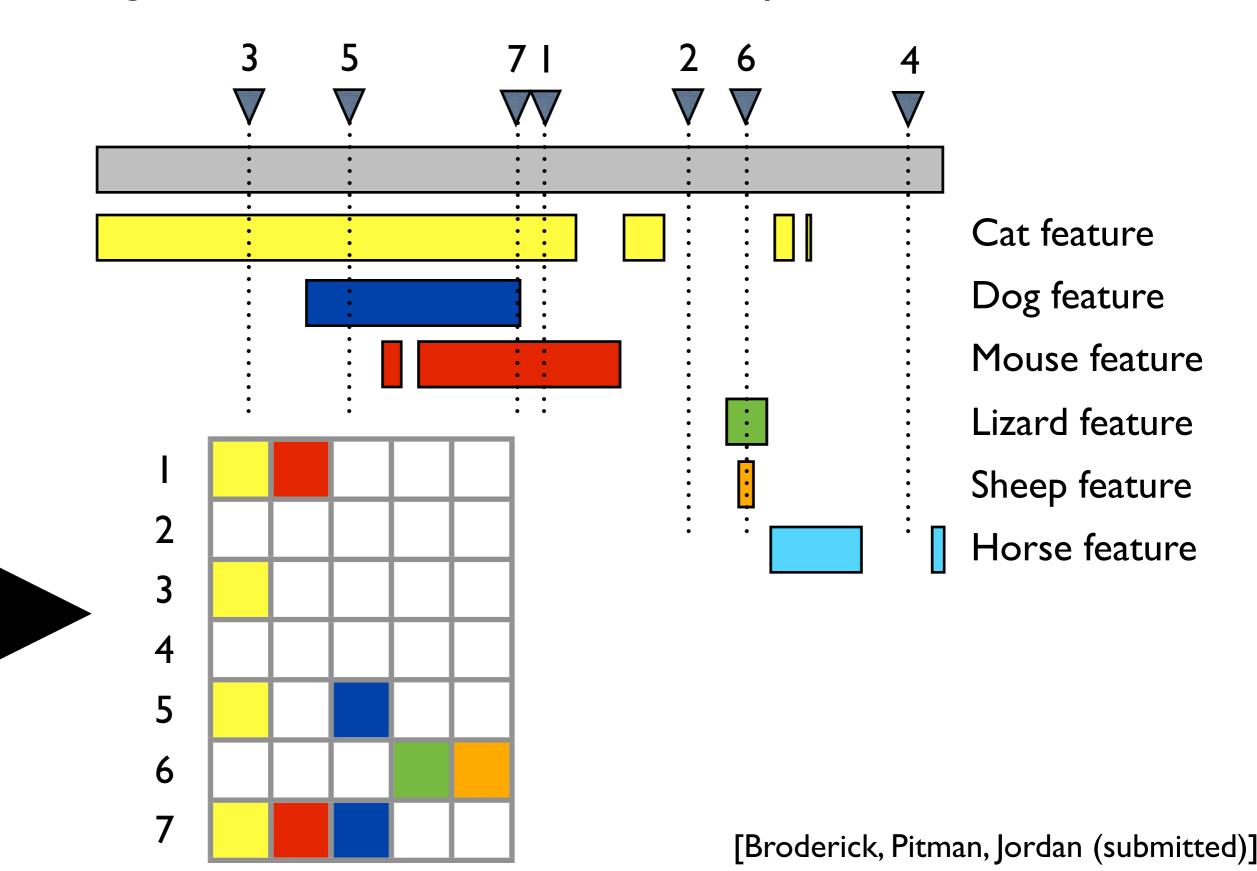




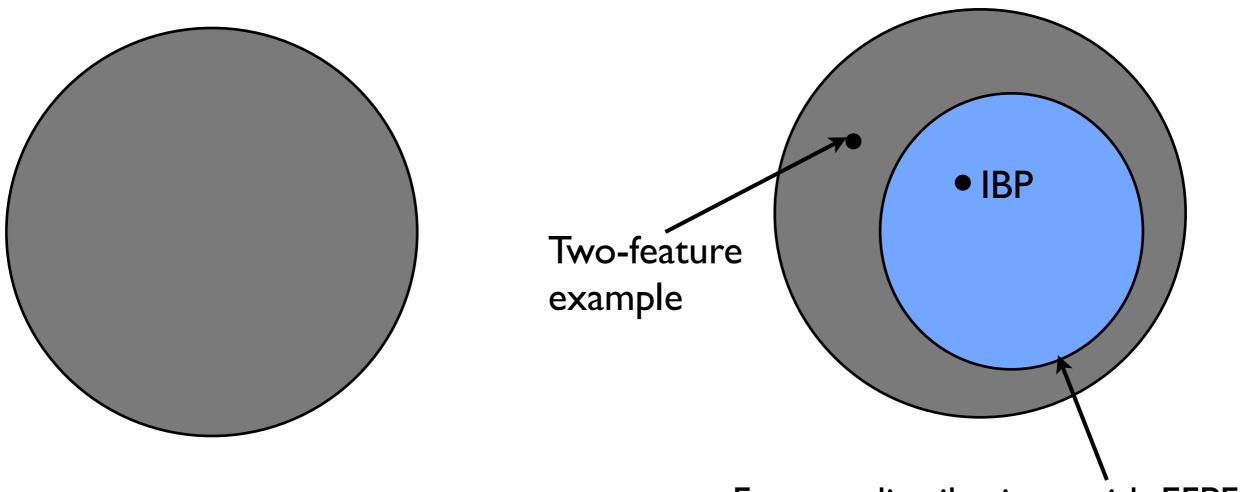








Exchangeable cluster distributions = Cluster distributions with EPPFs



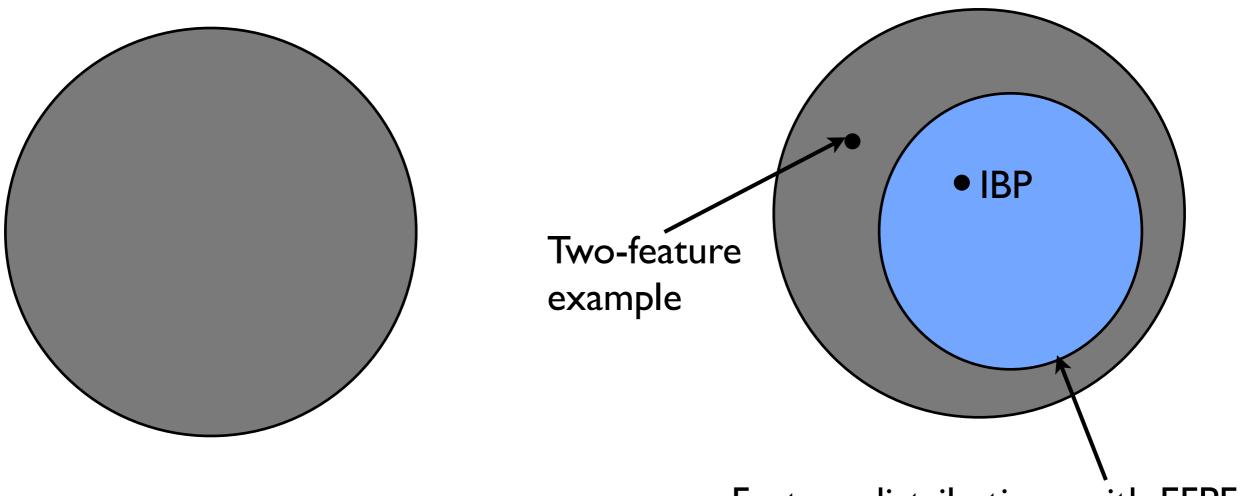
Feature distributions with EFPFs

Exchangeable feature distributions

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

= Kingman paintbox partitions

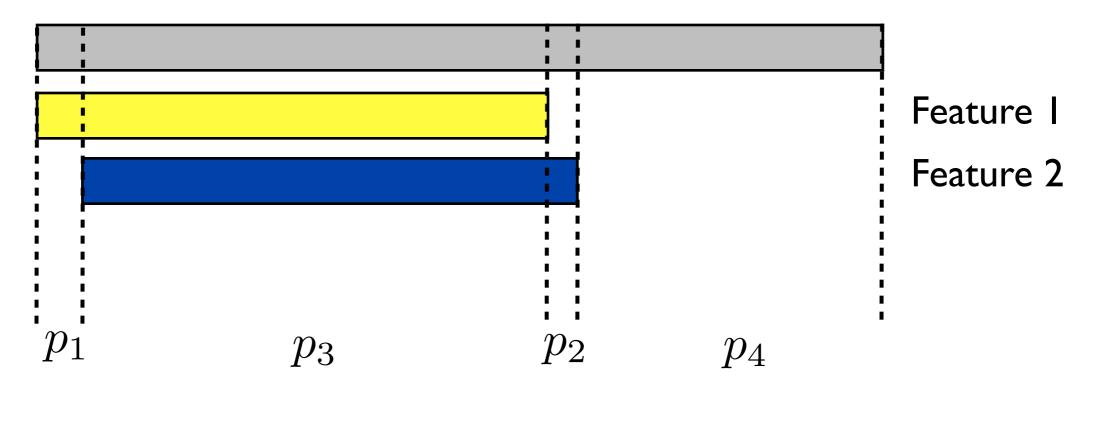
Exchangeable feature distributions = Feature paintbox allocations



Feature distributions with EFPFs

[Broderick, Pitman, Jordan (submitted)]

Two feature example



$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$

Indian buffet process: beta feature frequencies

[Thibaux, Jordan 2007]

Indian buffet process: beta feature frequencies

For
$$m = 1, 2, ...$$

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

Indian buffet process: beta feature frequencies

For
$$m = 1, 2, ...$$

1. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$
Set $K_m = \sum_{j=1}^m K_m^+$
2. For $k = K_{m-1}, \dots, K_m$
Draw a frequency of size
 $q_k \sim \text{Beta}(1, \theta + m - 1)$

Indian buffet process: beta feature frequencies

For
$$m = 1, 2, ...$$

1. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$
Set $K_m = \sum_{j=1}^m K_m^+$
2. For $k = K_{m-1}, ..., K_m$
Draw a frequency of size
 $q_k \sim \text{Beta}(1, \theta + m - 1)$

[Thibaux, Jordan 2007]

0

Indian buffet process: beta feature frequencies For m = 1, 2, ...I. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$ ٩ı Set $K_m = \sum K_m^+$ j=1**2.** For $k = K_{m-1}, \ldots, K_m$ Draw a frequency of size $q_k \sim \text{Beta}(1, \theta + m - 1)$

[Thibaux, Jordan 2007]

q₂

Indian buffet process: beta feature frequencies For m = 1, 2, ...I. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$ ٩ı Set $K_m = \sum K_m^+$ j=1**2.** For $k = K_{m-1}, \ldots, K_m$ Draw a frequency of size $q_k \sim \text{Beta}(1, \theta + m - 1)$

[Thibaux, Jordan 2007]

q₂

q₃

Indian buffet process: beta feature frequencies For m = 1, 2, ...I. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$ ٩ı Set $K_m = \sum K_m^+$ j=1**2.** For $k = K_{m-1}, \ldots, K_m$ Draw a frequency of size $q_k \sim \text{Beta}(1, \theta + m - 1)$ **q**₂

[Thibaux, Jordan 2007]

q₃

q₄

q5

q₆

Indian buffet process: beta feature frequencies For m = 1, 2, ...I. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$ ٩ı Set $K_m = \sum K_m^+$ j=1**2.** For $k = K_{m-1}, \ldots, K_m$ Draw a frequency of size $q_k \sim \text{Beta}(1, \theta + m - 1)$ **q**₂ **q**₃

[Thibaux, Jordan 2007]

q₆

q₄

q₅

Indian buffet process: beta feature frequencies

For
$$m = 1, 2, ...$$

I. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$
Set $K_m = \sum_{j=1}^m K_m^+$
2. For $k = K_{m-1}, \dots, K_m$
Draw a frequency of size
 $q_k \sim \text{Beta}(1, \theta + m - 1)$

q₆

q₄

()

q5

[Thibaux, Jordan 2007]

Indian buffet process: beta feature frequencies

For
$$m = 1, 2, ...$$

I. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$
Set $K_m = \sum_{j=1}^m K_m^+$
2. For $k = K_{m-1}, \dots, K_m$
Draw a frequency of size
 $q_k \sim \text{Beta}(1, \theta + m - 1)$

[Thibaux, Jordan 2007]

q₆

q₄

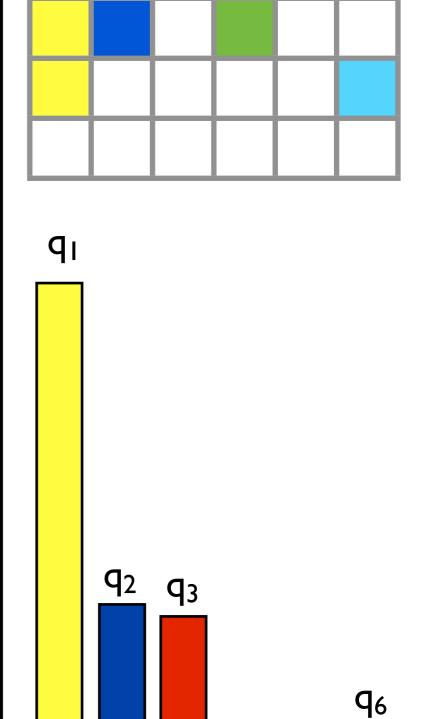
0

q5

Indian buffet process: beta feature frequencies

For
$$m = 1, 2, ...$$

1. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$
Set $K_m = \sum_{j=1}^m K_m^+$
2. For $k = K_{m-1}, ..., K_m$
Draw a frequency of size
 $q_k \sim \text{Beta}(1, \theta + m - 1)$



q₄

0

q5

[Thibaux, Jordan 2007]

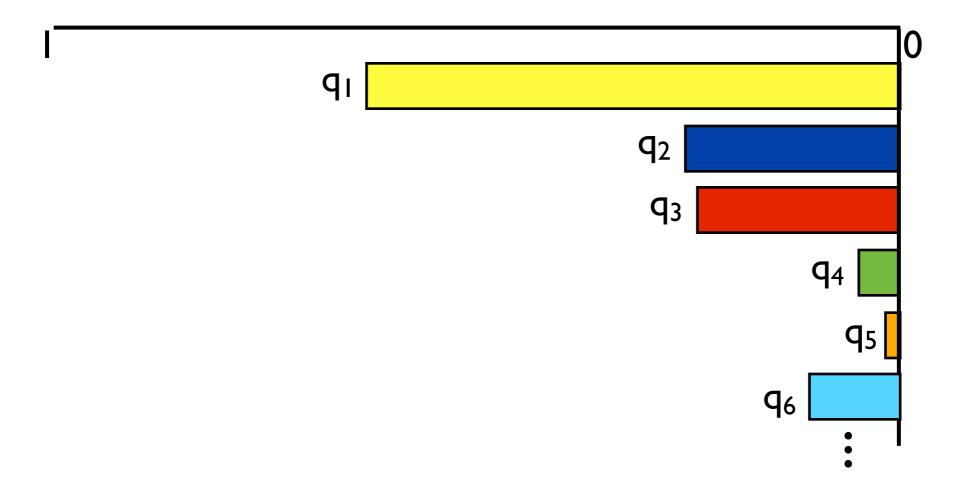
Indian buffet process: beta feature frequencies

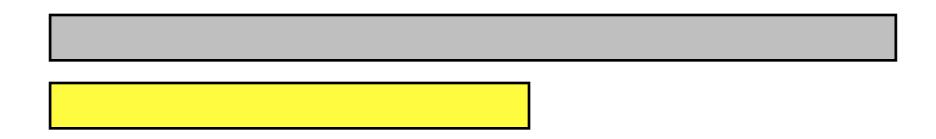
For
$$m = 1, 2, ...$$

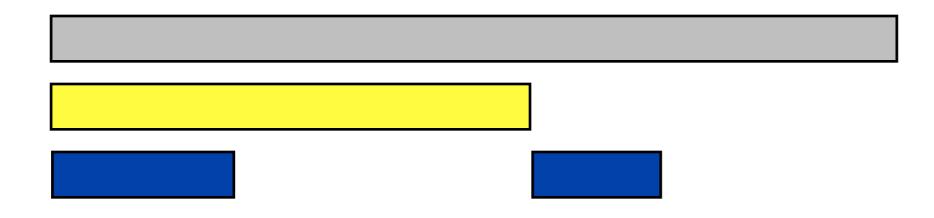
1. Draw $K_m^+ = \text{Poisson}\left(\gamma \frac{\theta}{\theta + m - 1}\right)$
Set $K_m = \sum_{j=1}^m K_m^+$
2. For $k = K_{m-1}, ..., K_m$
Draw a frequency of size
 $q_k \sim \text{Beta}(1, \theta + m - 1)$

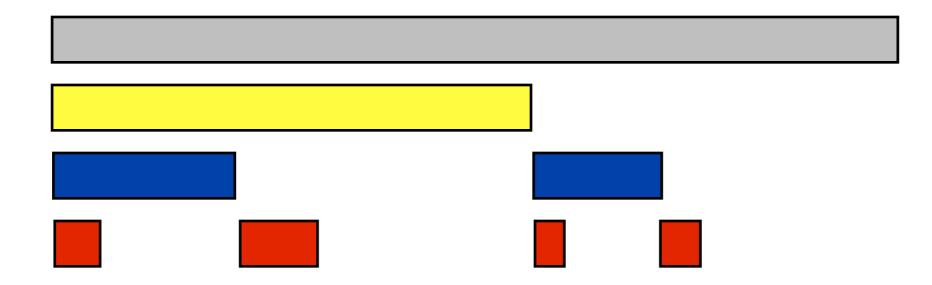
٩ı **q**₂ **q**₃ **q**₆ **q**₄ **q**5 0

[Thibaux, Jordan 2007]

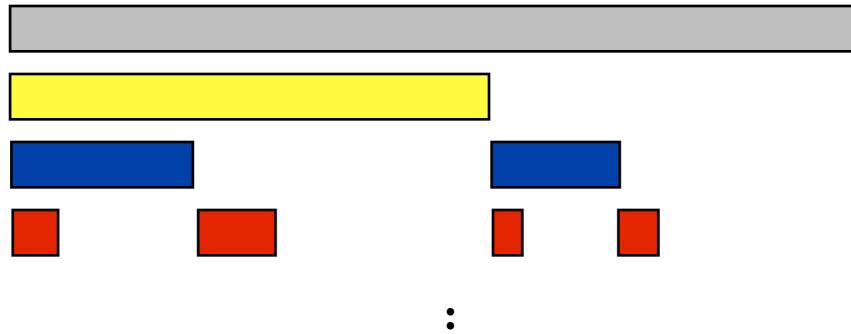




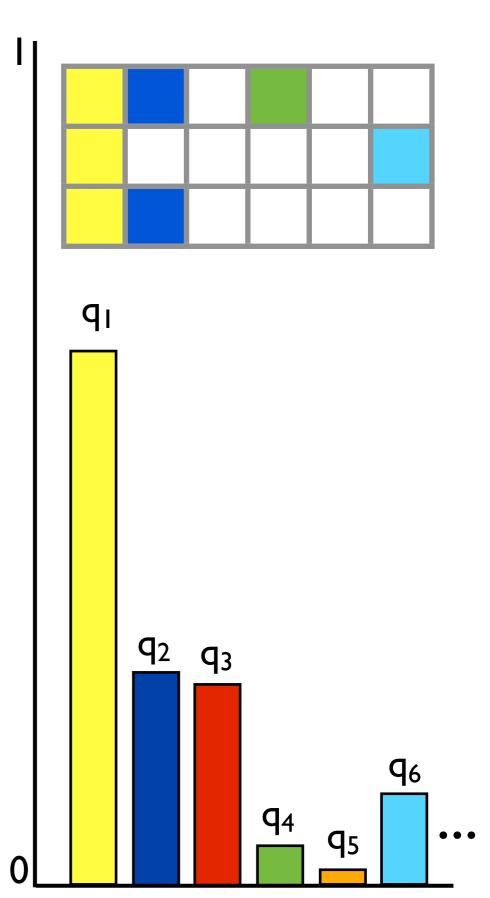




Indian buffet process: beta feature frequencies



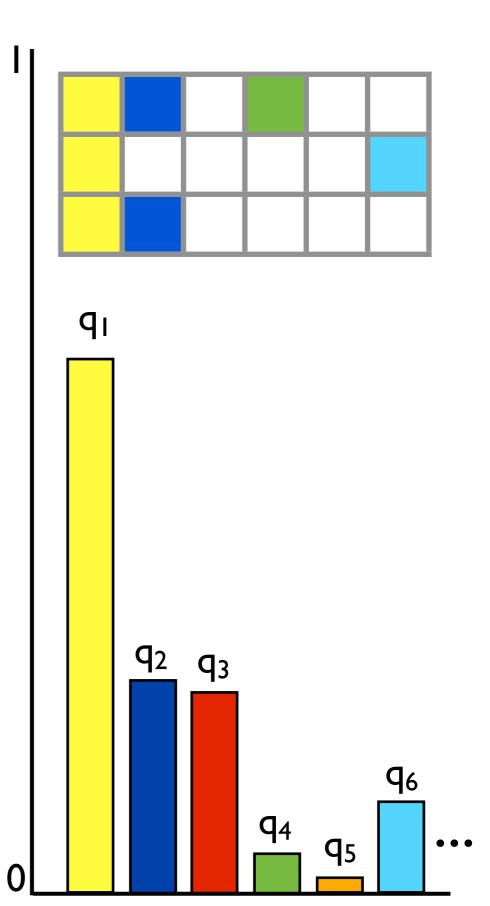
•



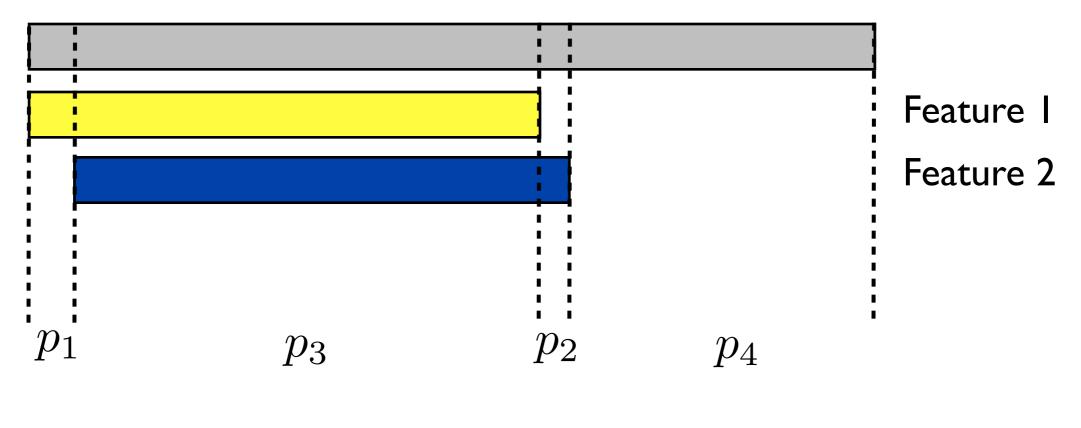
19

"Frequency models"

[Broderick, Pitman, Jordan (submitted)]

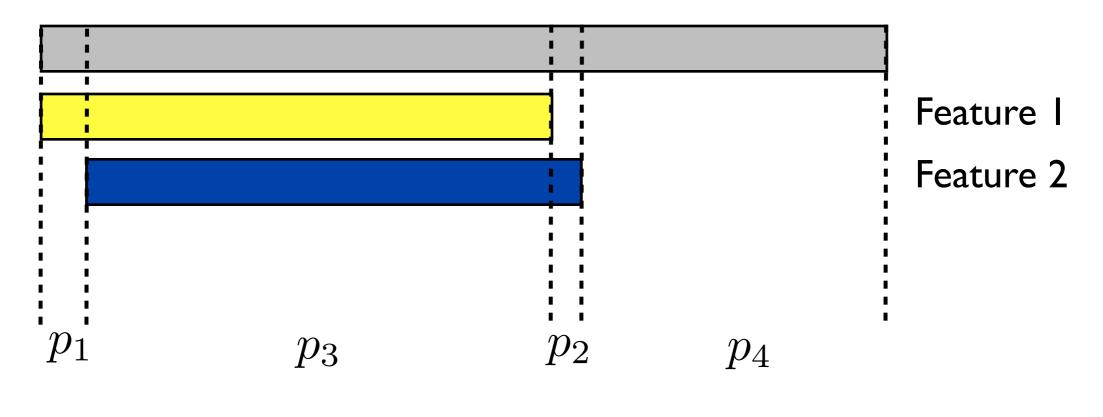


Two feature example



$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$

Two feature example Not a frequency model

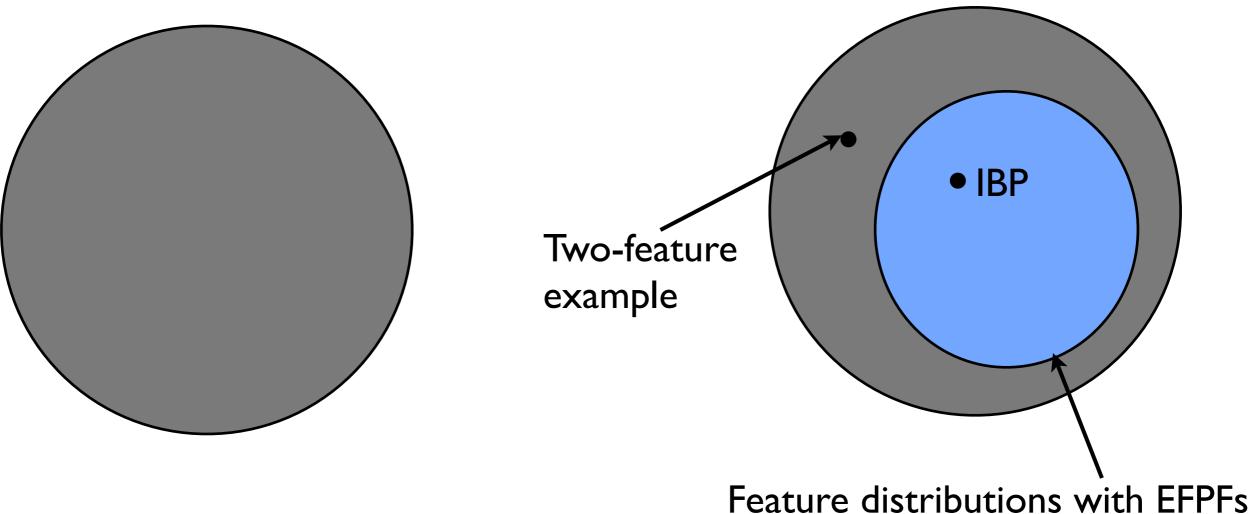


$$\mathbb{P}(\text{row} = \blacksquare) = p_1$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_2$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_3$$
$$\mathbb{P}(\text{row} = \blacksquare) = p_4$$

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

= Kingman paintbox partitions

Exchangeable feature distributions = Feature paintbox allocations



[Broderick, Pitman, Jordan (submitted)]

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

• IBP Two-feature example

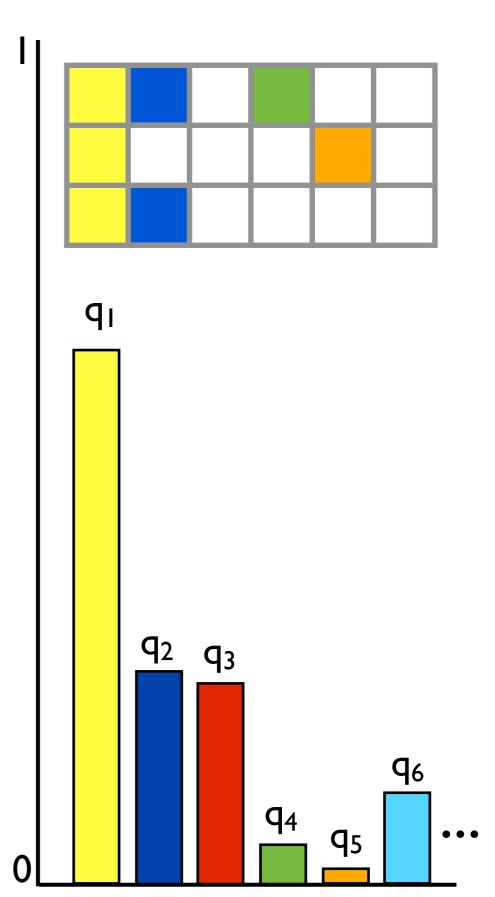
Exchangeable feature distributions

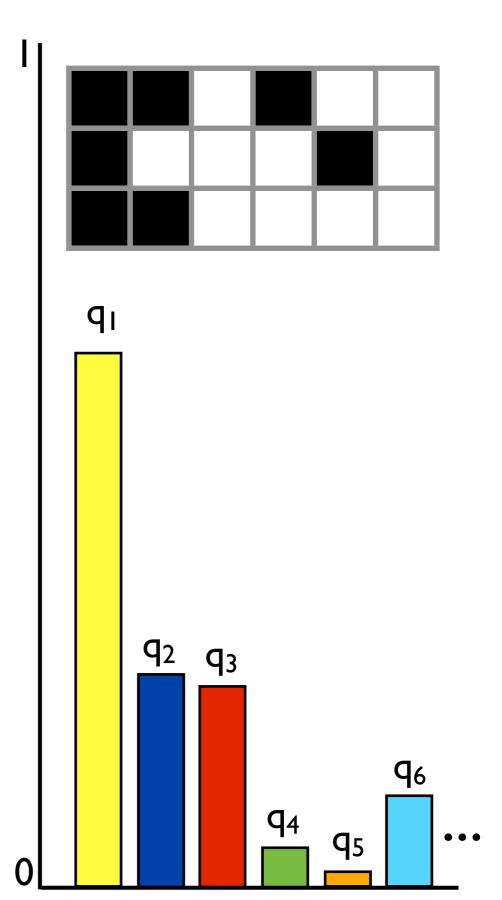
= Feature paintbox allocations

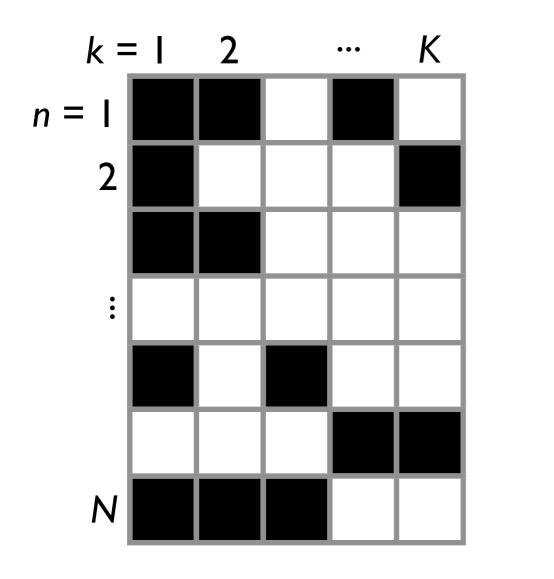
Frequency models

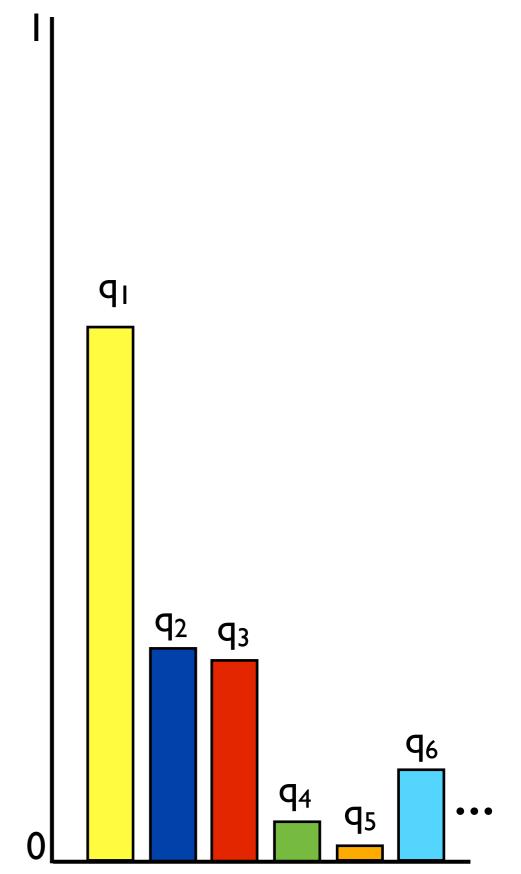
[Broderick, Pitman, Jordan (submitted)]

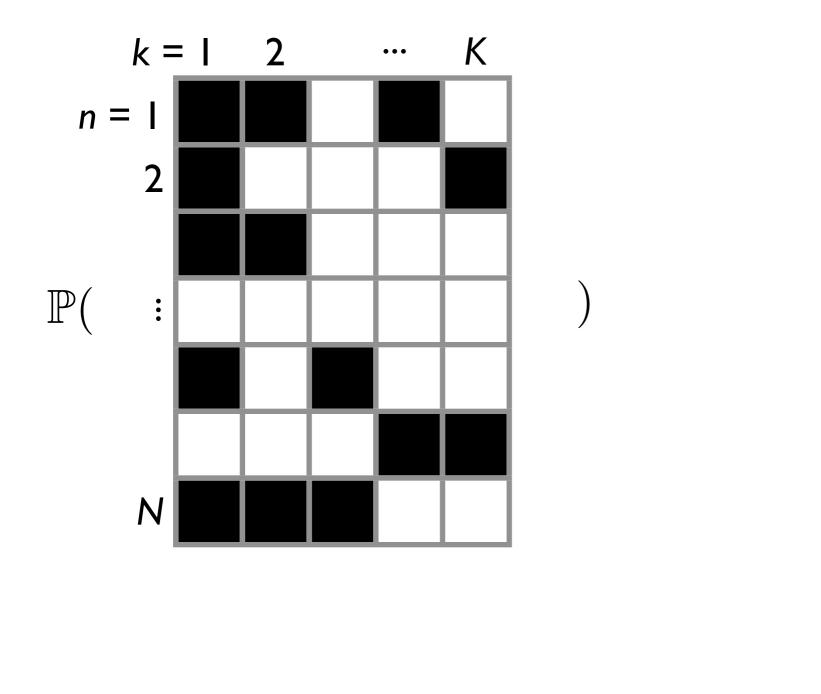
٩ı $\underline{q_2}$ q_3 **q**₆ **q**₄ **q**5 . 0

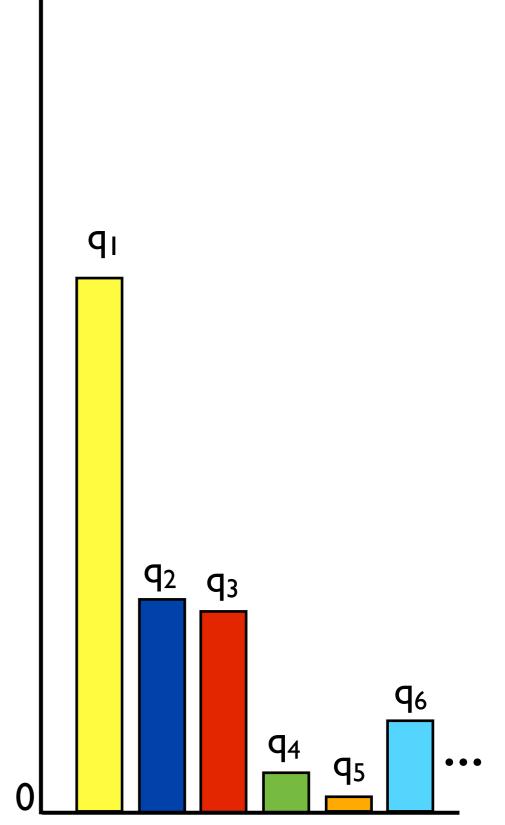


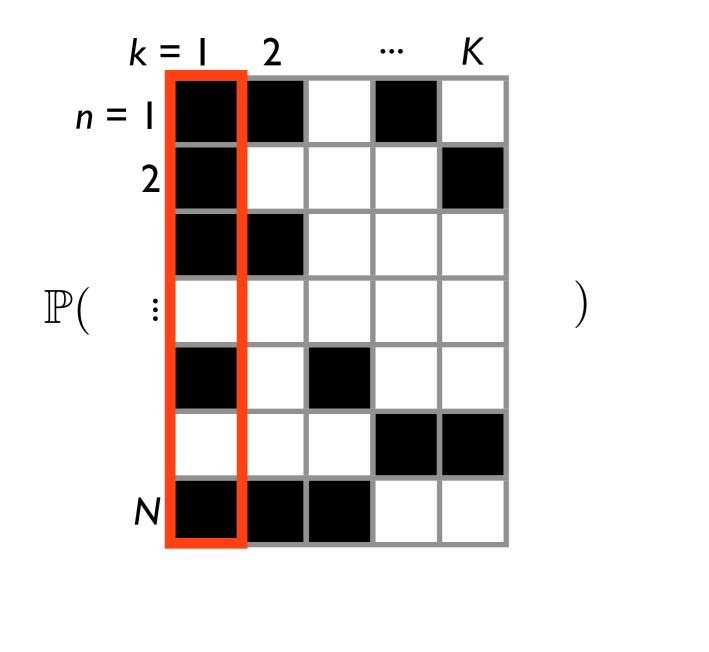


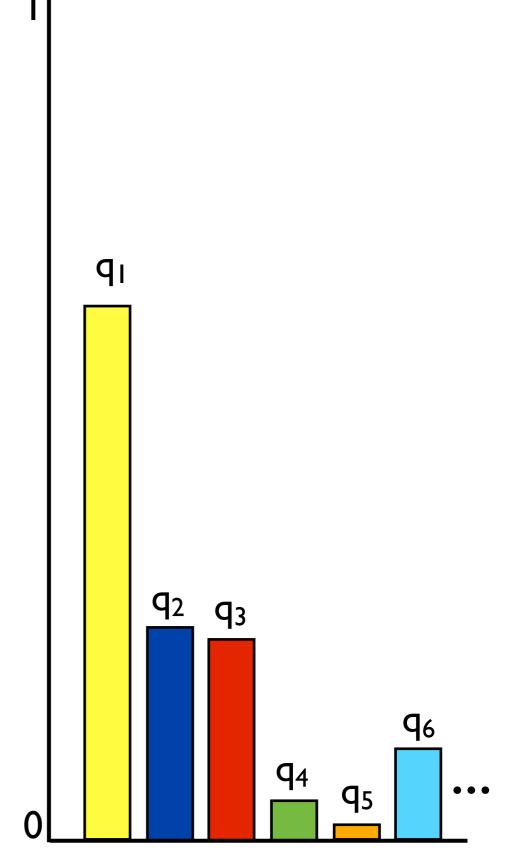


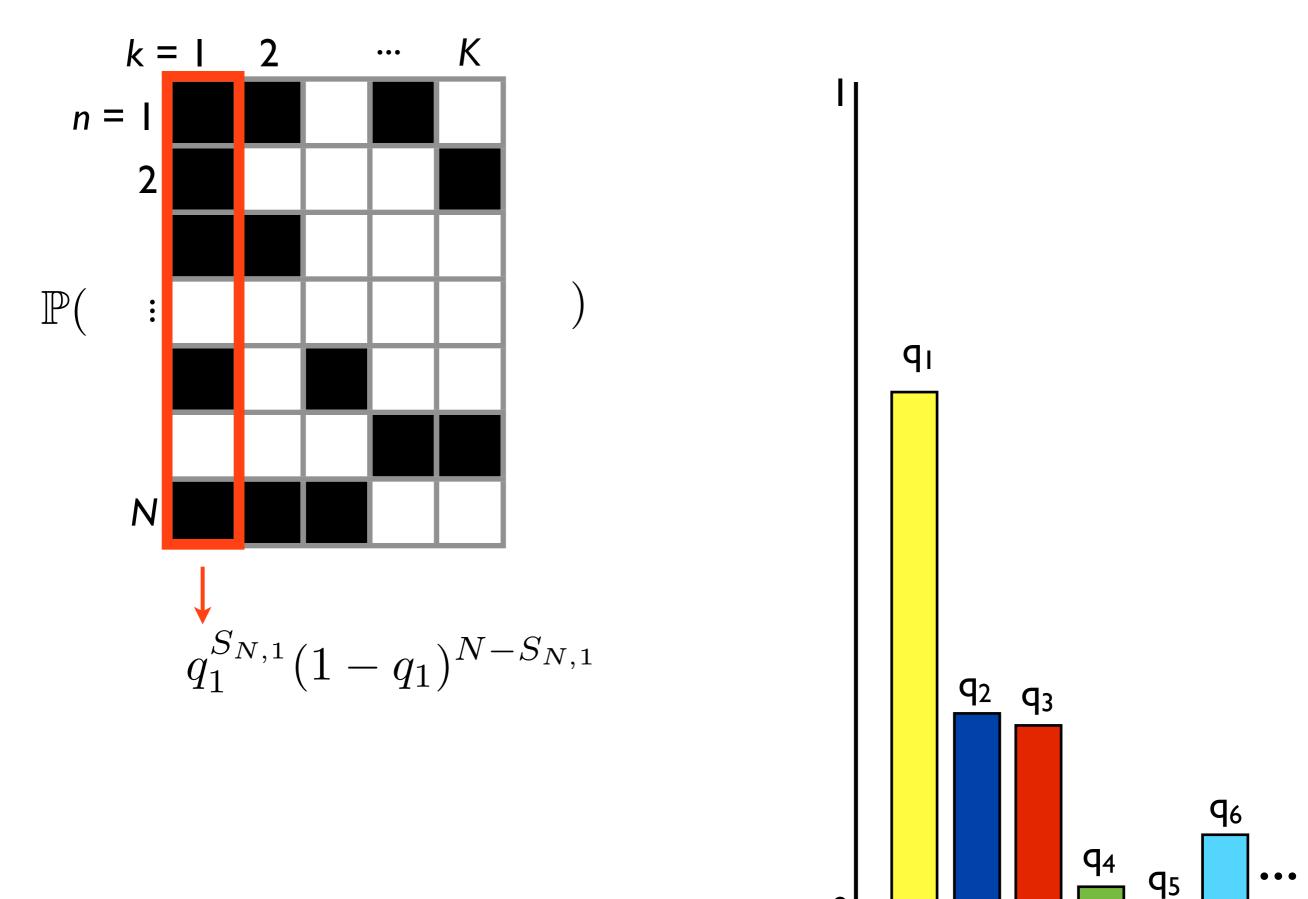


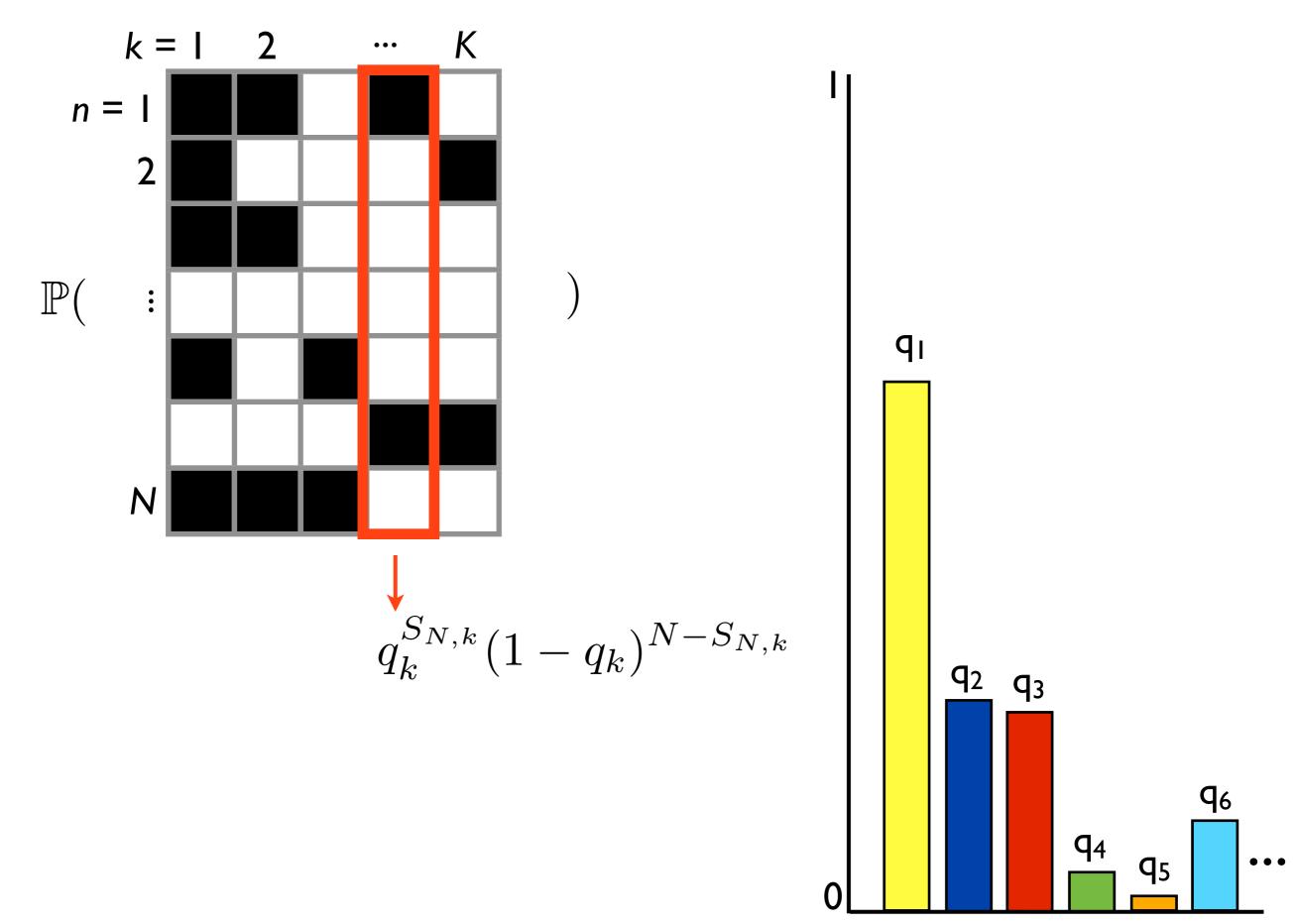


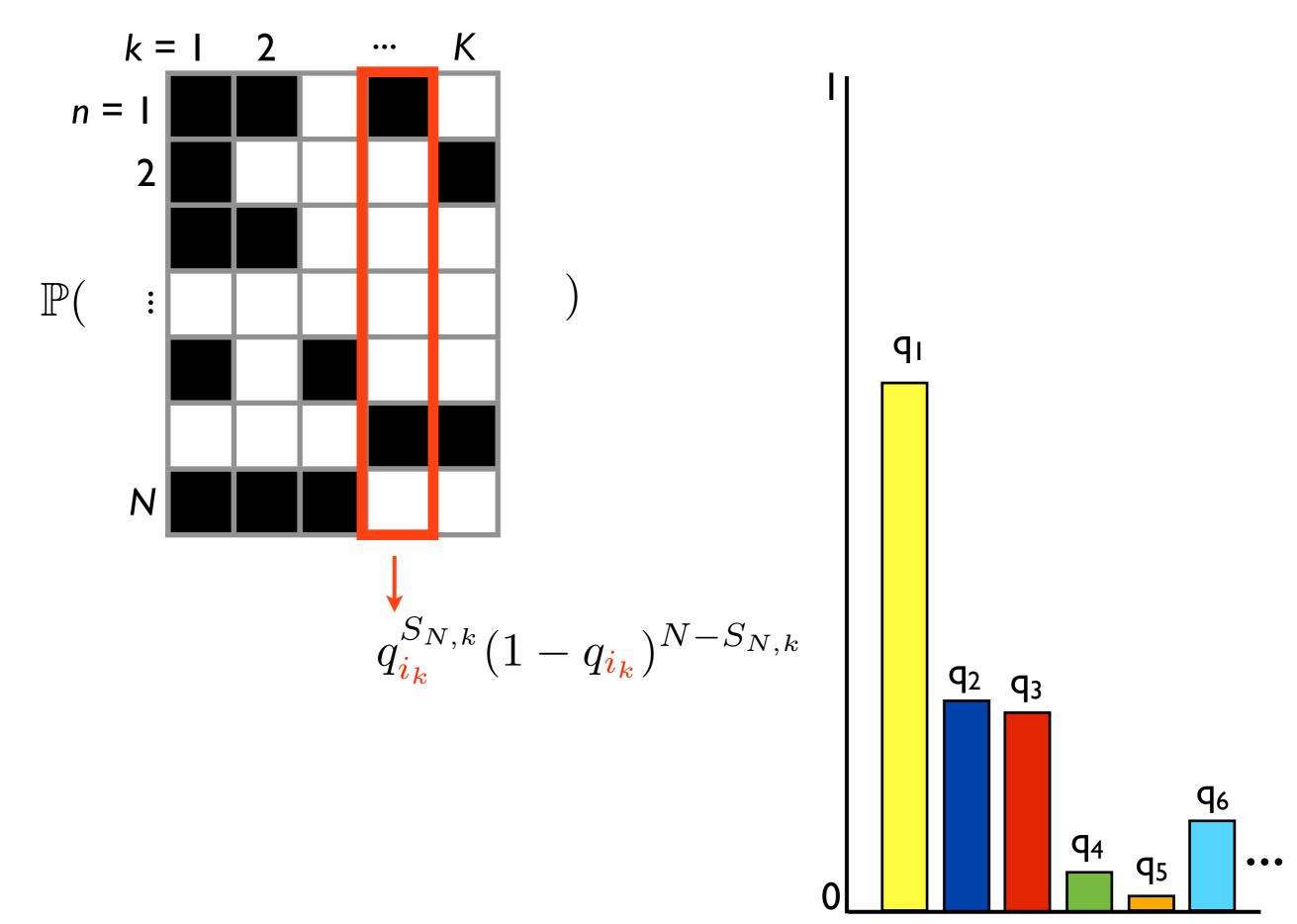


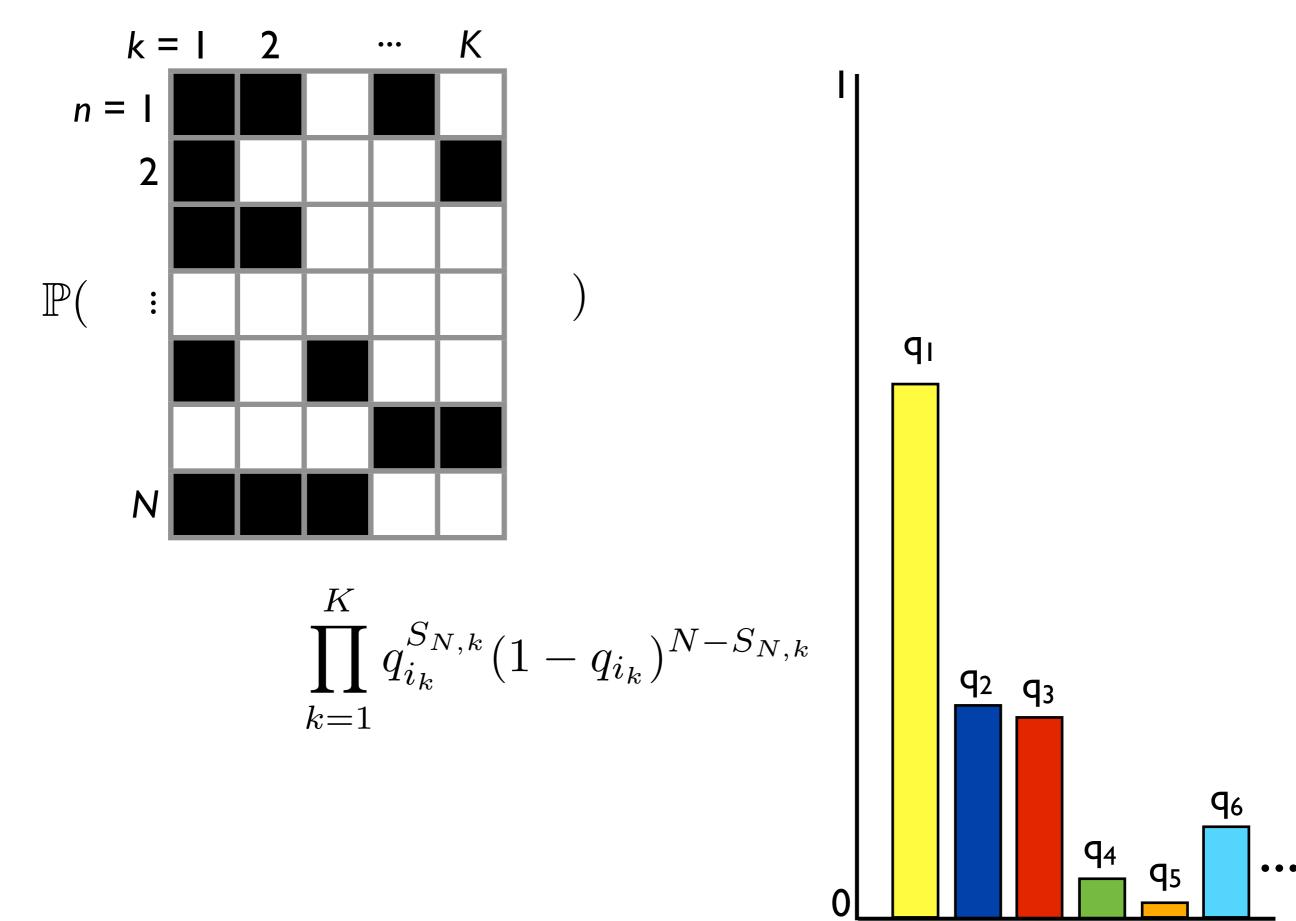


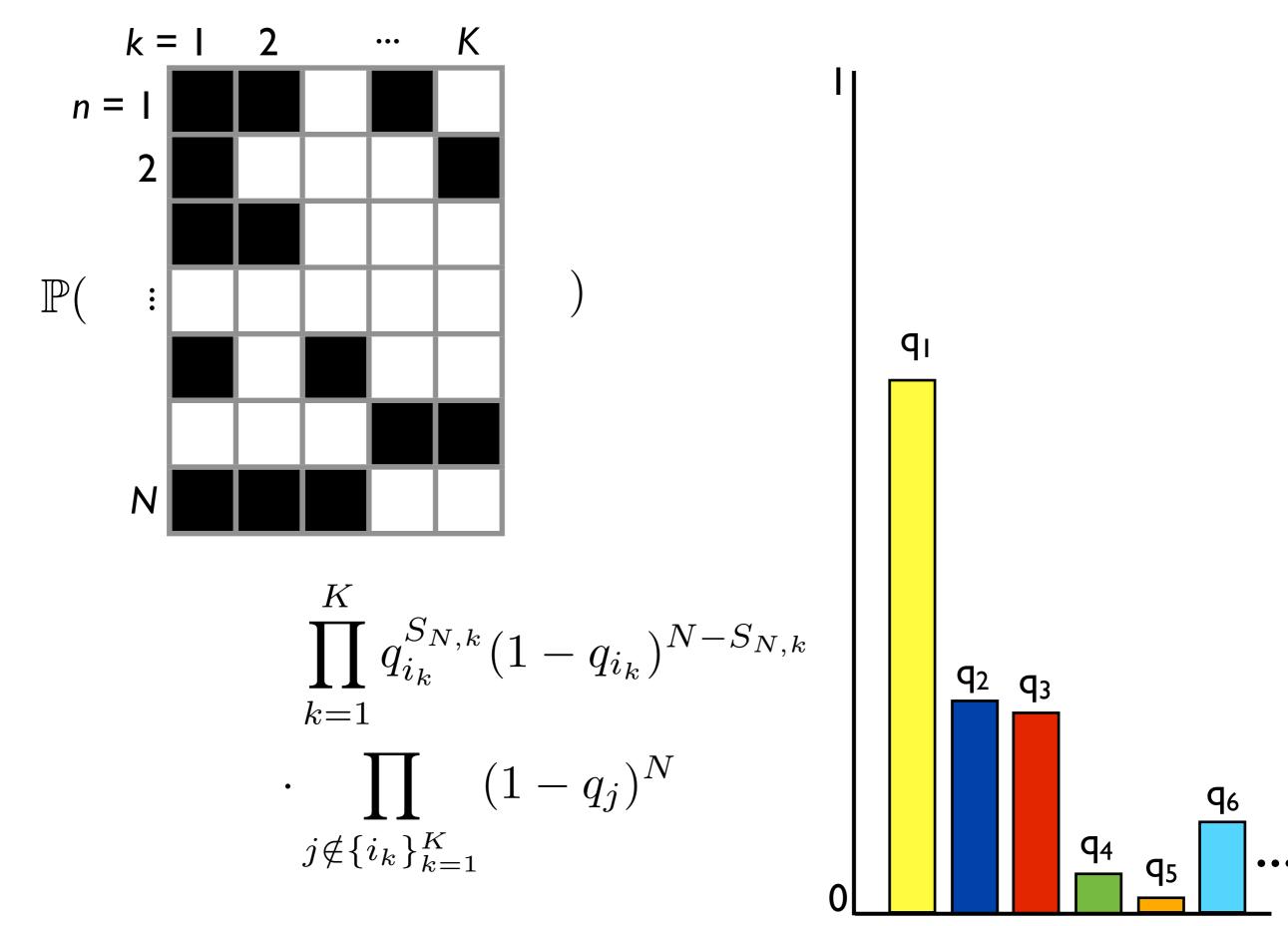


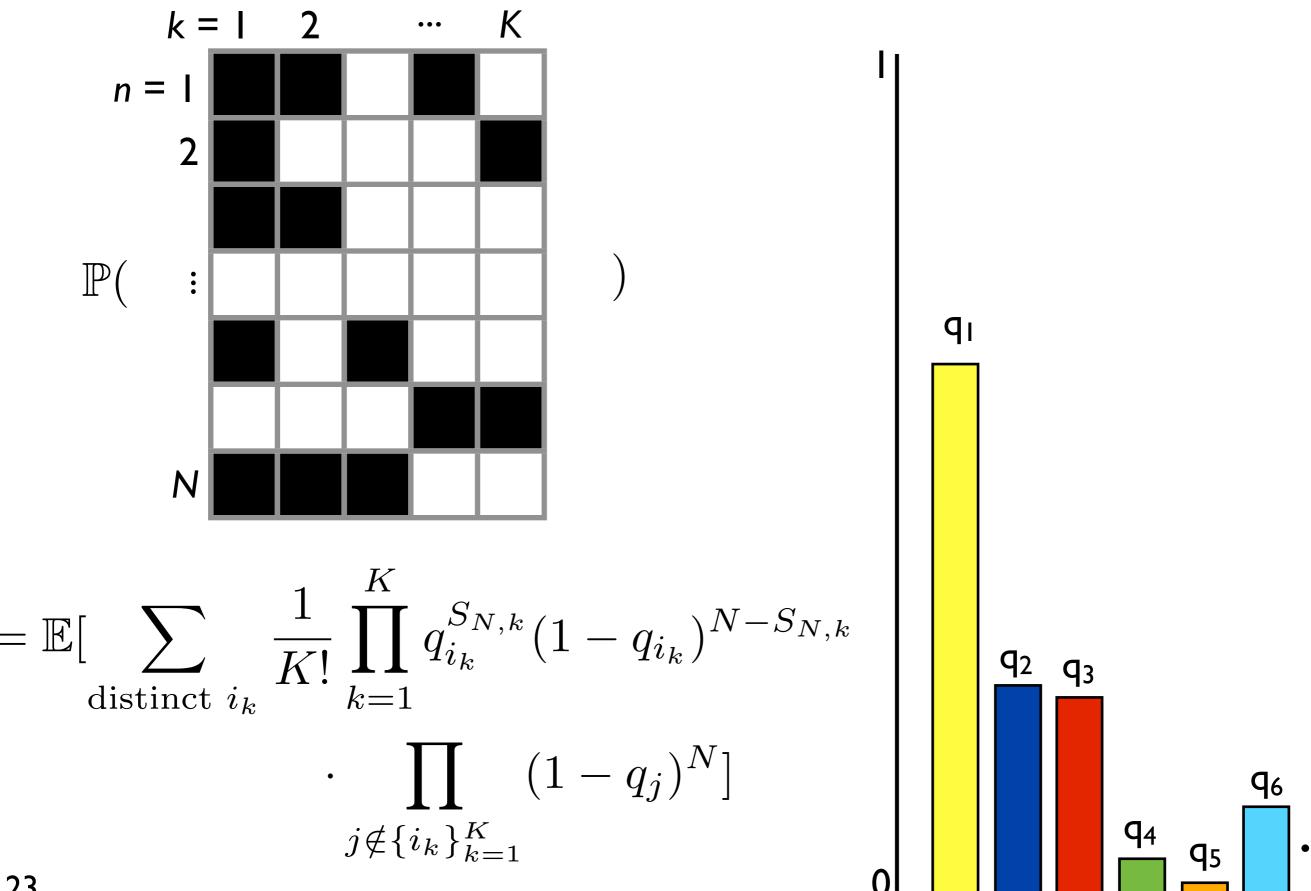


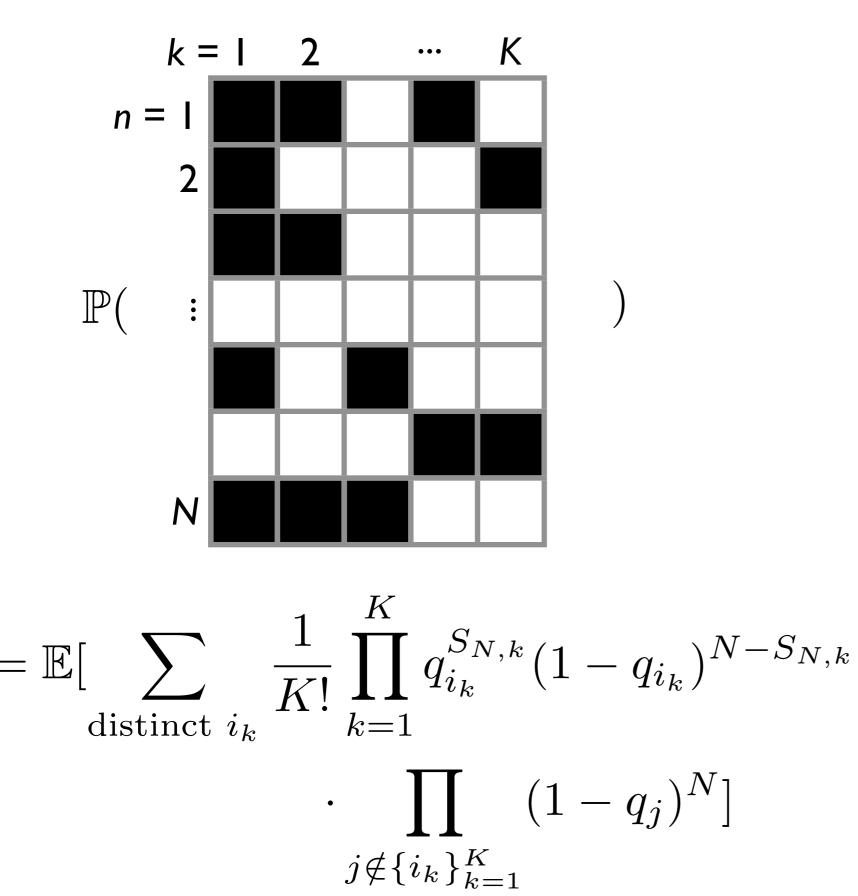






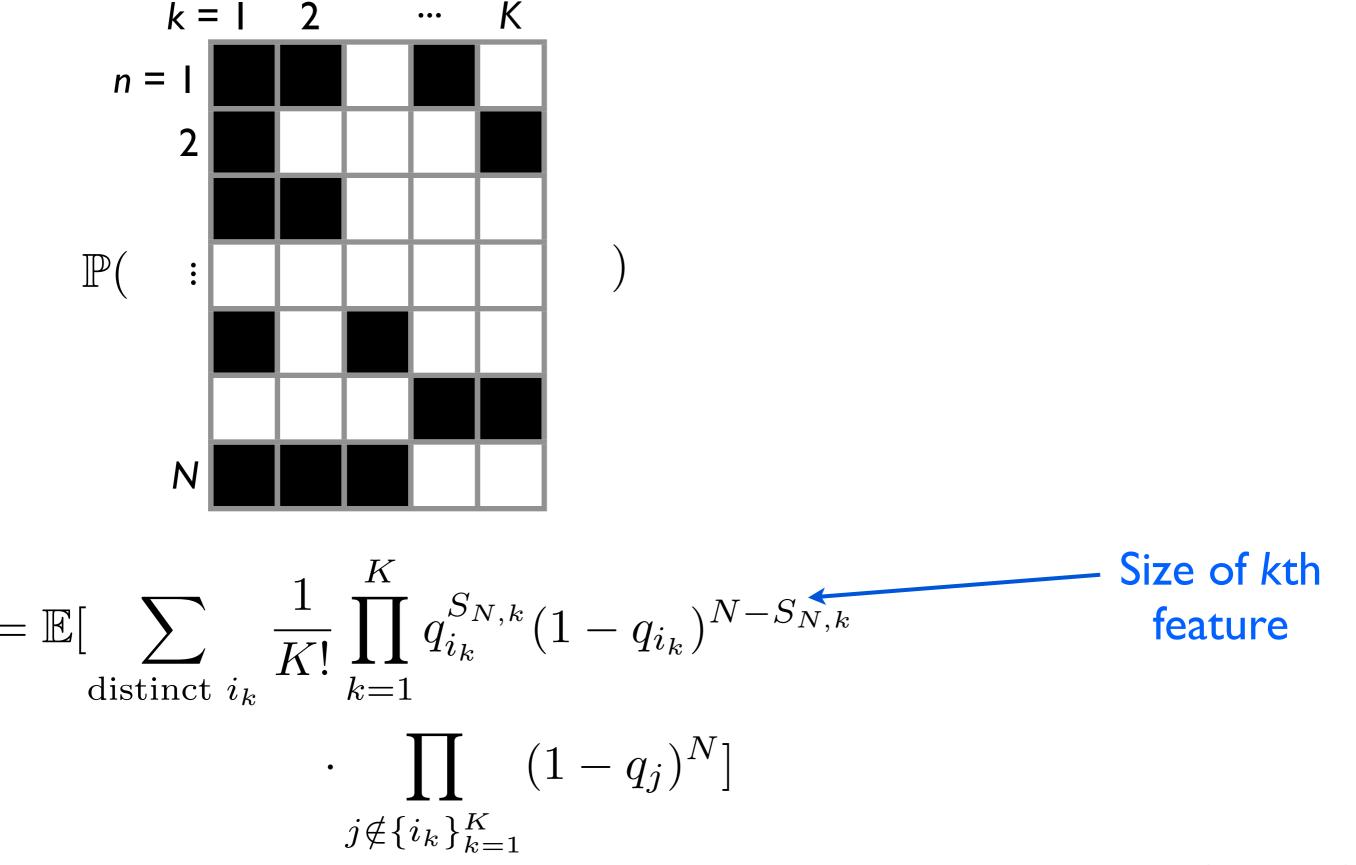


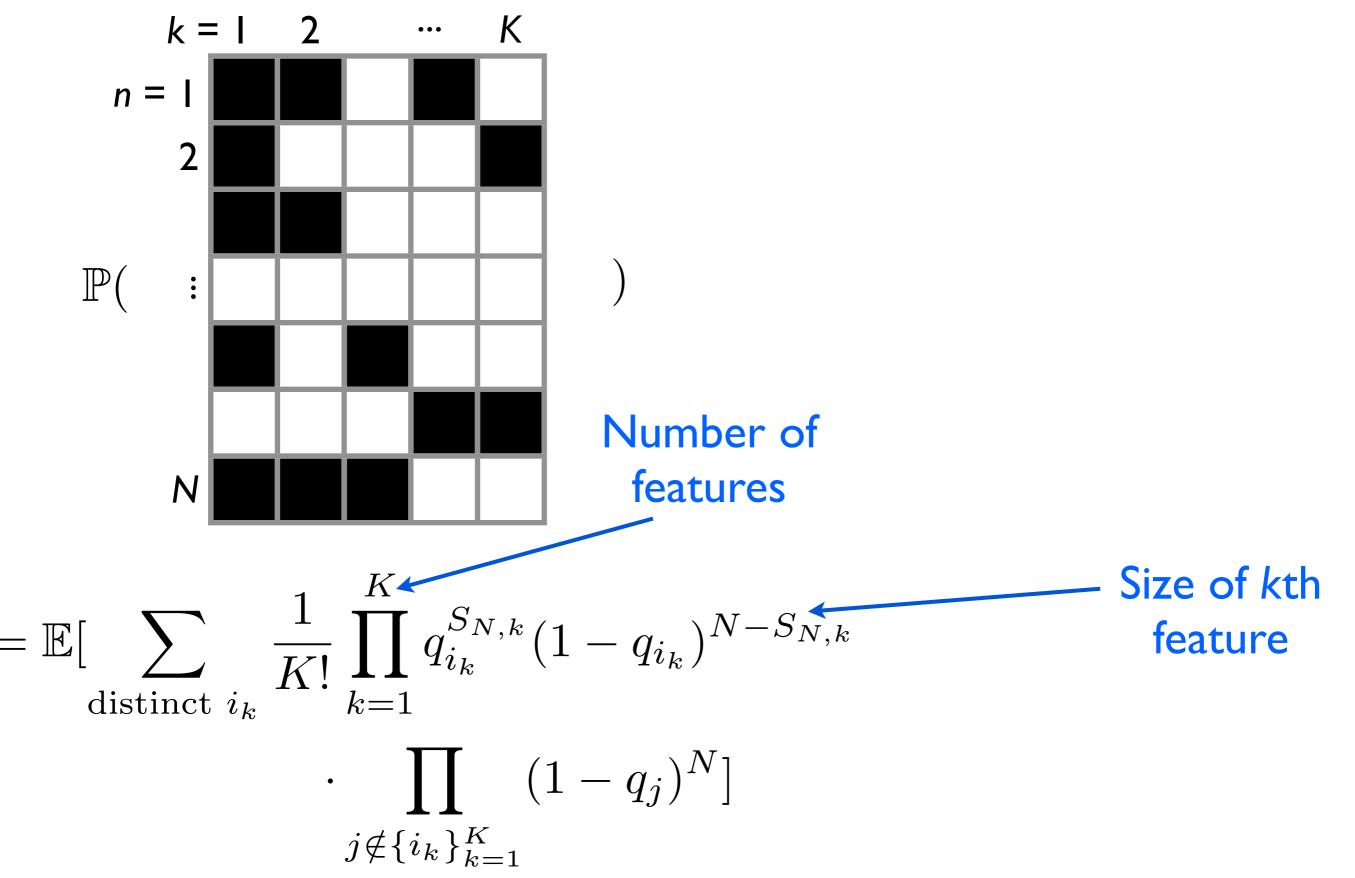


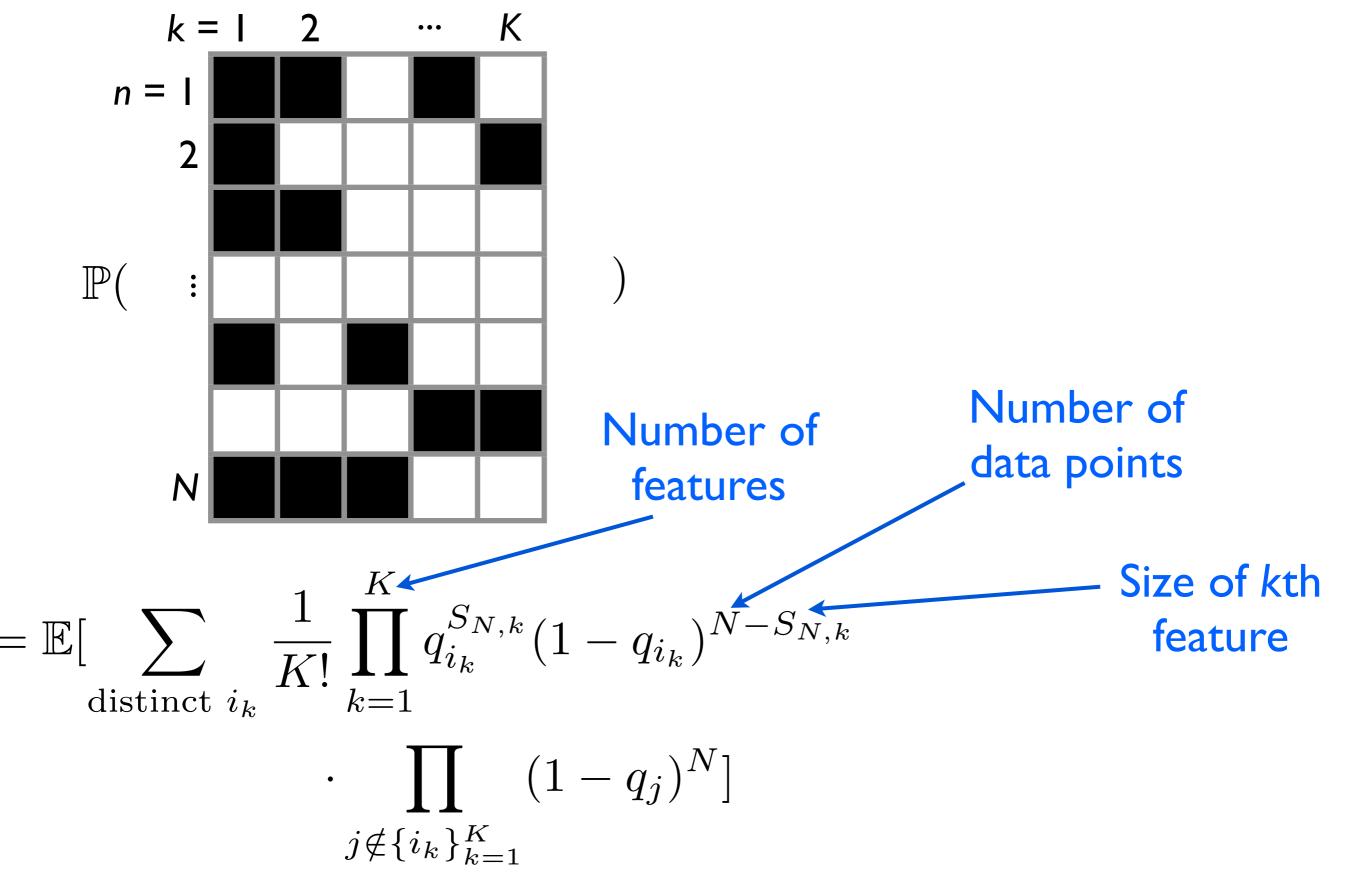


[Broderick, Pitman, Jordan (submitted)]

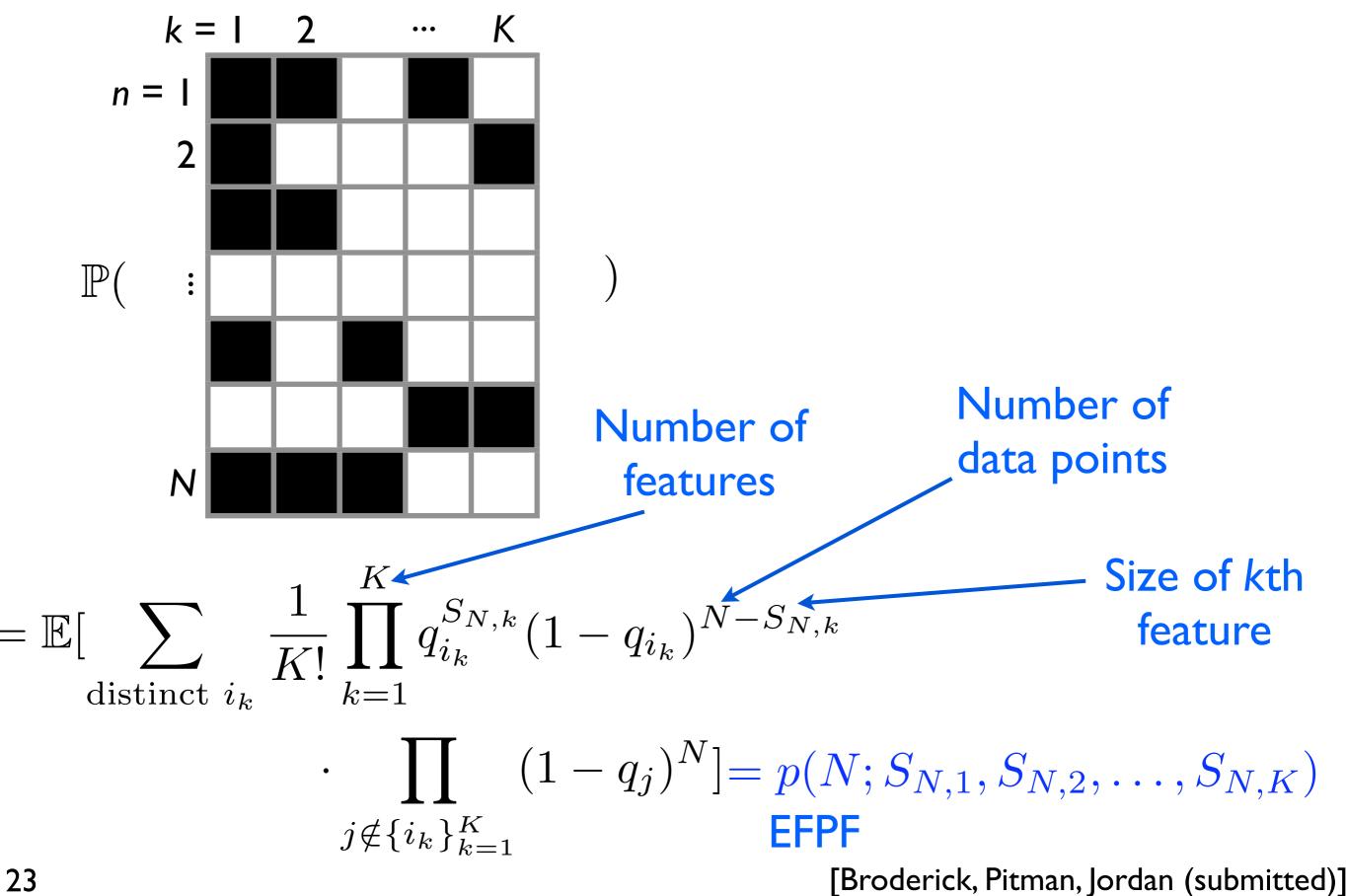
23







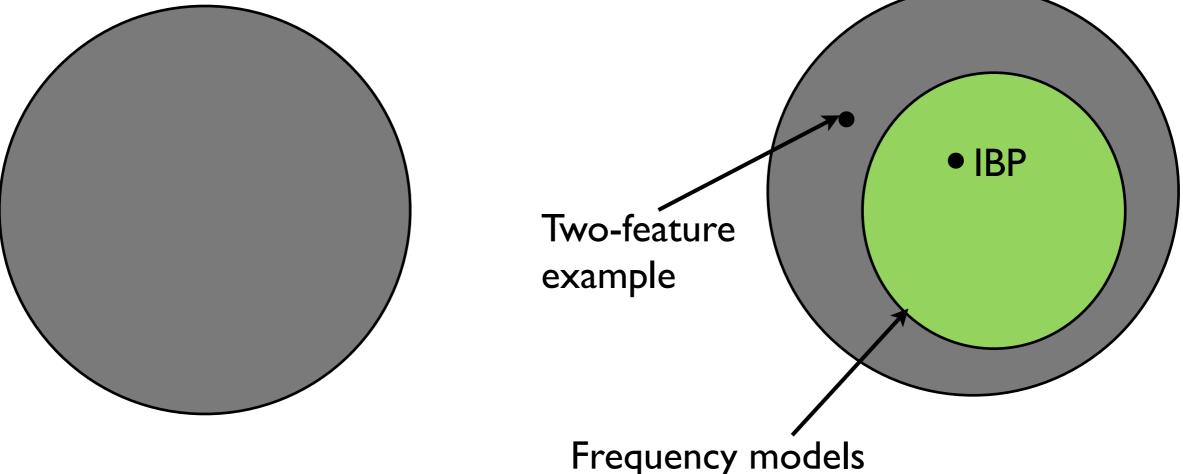
[Broderick, Pitman, Jordan (submitted)]



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

= Kingman paintbox partitions

PFs Exchangeable feature distributions = Feature paintbox allocations



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

Two-feature example Frequency models

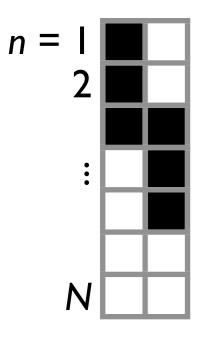
Feature distributions with EFPFs

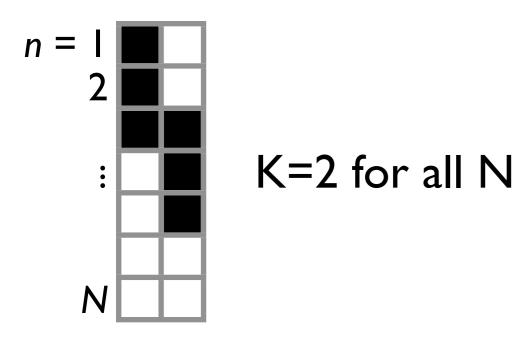
Exchangeable feature distributions

= Feature paintbox allocations

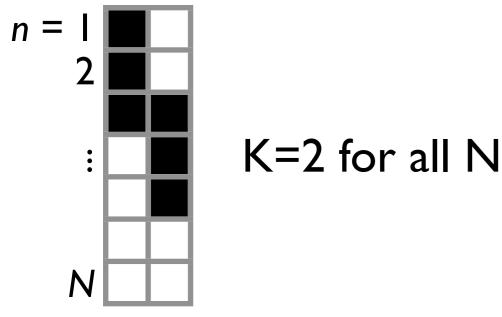
[Broderick, Pitman, Jordan (submitted)]

Distributions with EFPFs: frequencies?

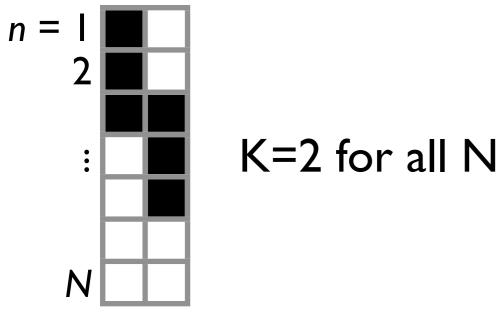




Feature allocation



Feature allocation

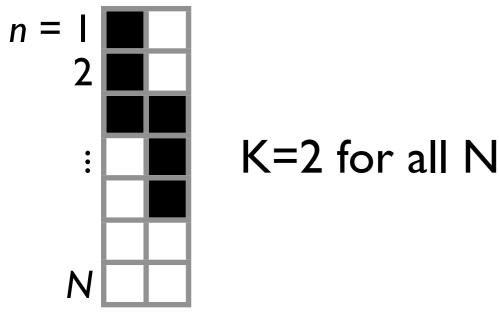


Assume EFPF $p(N; S_{N,1}, S_{N,2})$

Want to show:

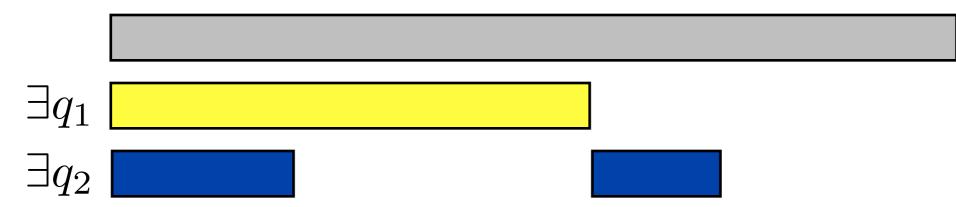
 $\exists q_1 \\ \exists q_2$

Feature allocation

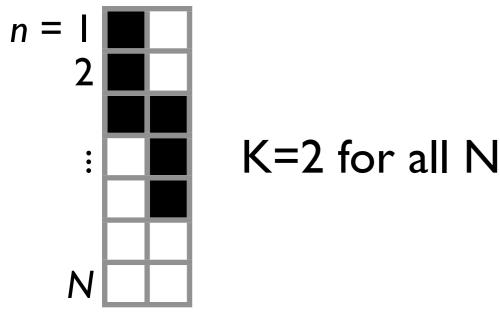


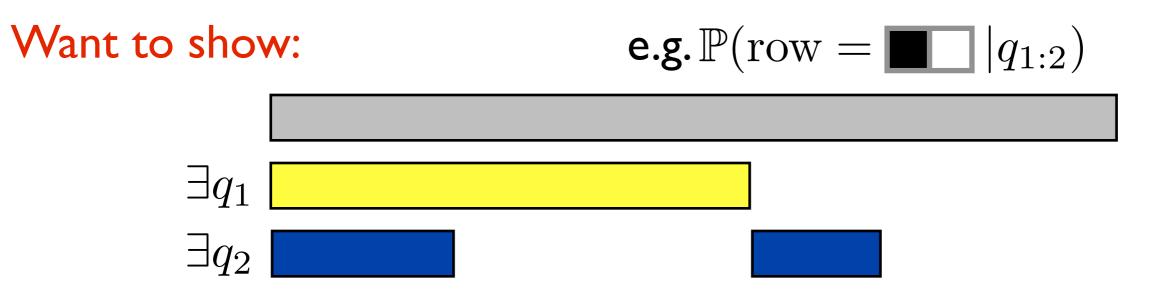
Assume EFPF $p(N; S_{N,1}, S_{N,2})$

Want to show:

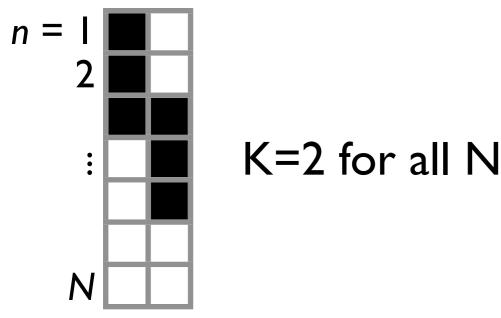


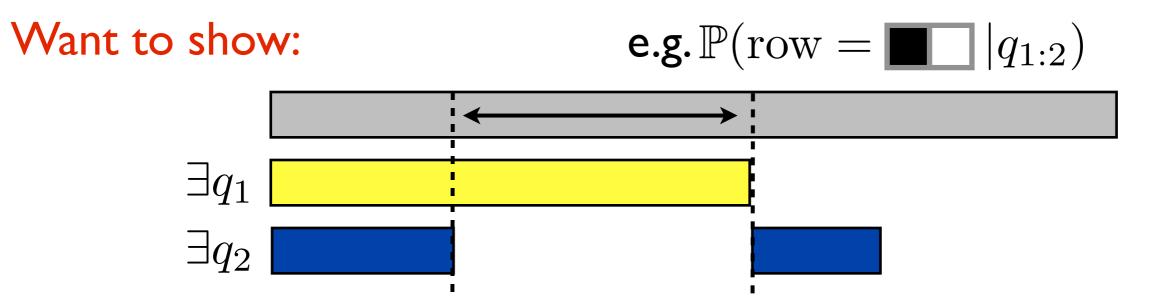
Feature allocation



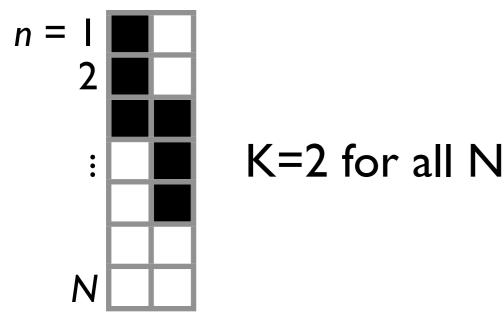


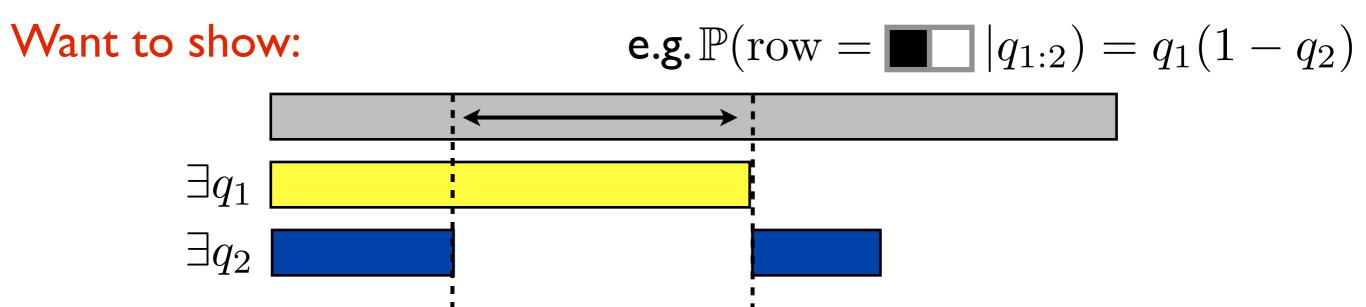
Feature allocation



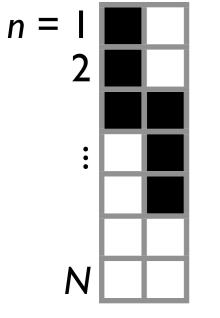


Feature allocation



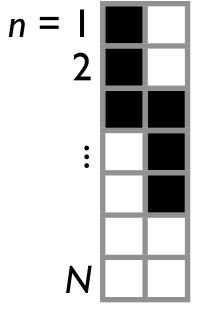


Feature allocation



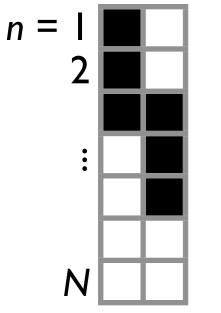
Feature allocation

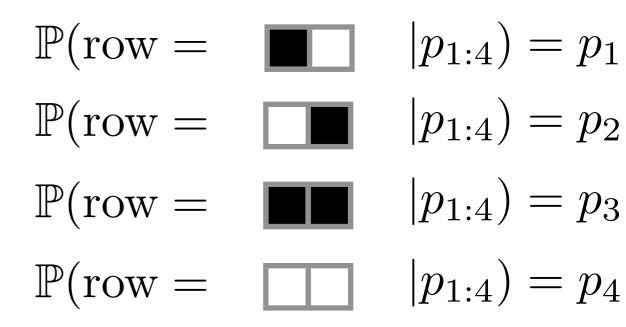


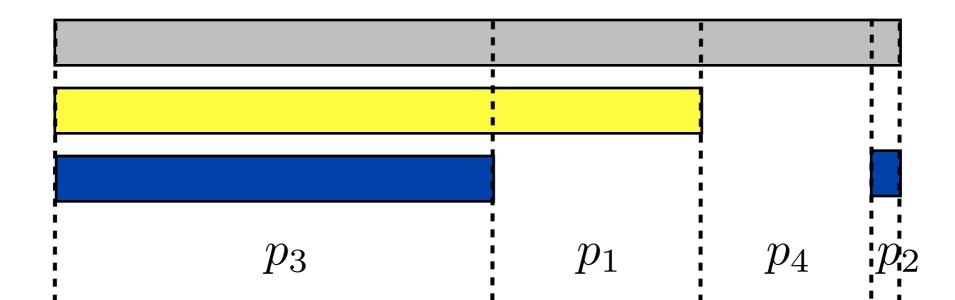


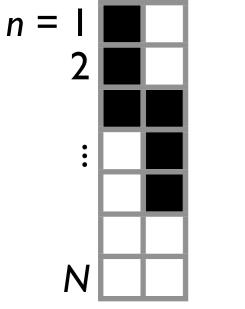
$\mathbb{P}(\mathrm{row} =$	$ p_{1:4}) = p_1$
$\mathbb{P}(\mathrm{row} =$	$ p_{1:4}) = p_2$
$\mathbb{P}(\mathrm{row} =$	$ p_{1:4}) = p_3$
$\mathbb{P}(\mathrm{row} =$	$ p_{1:4}) = p_4$

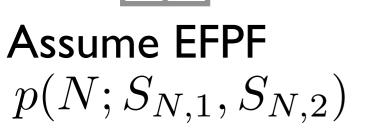
Feature allocation

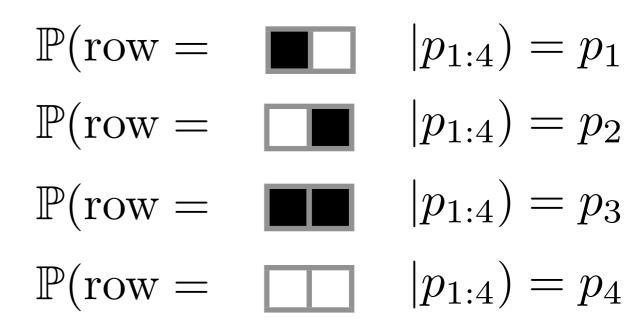


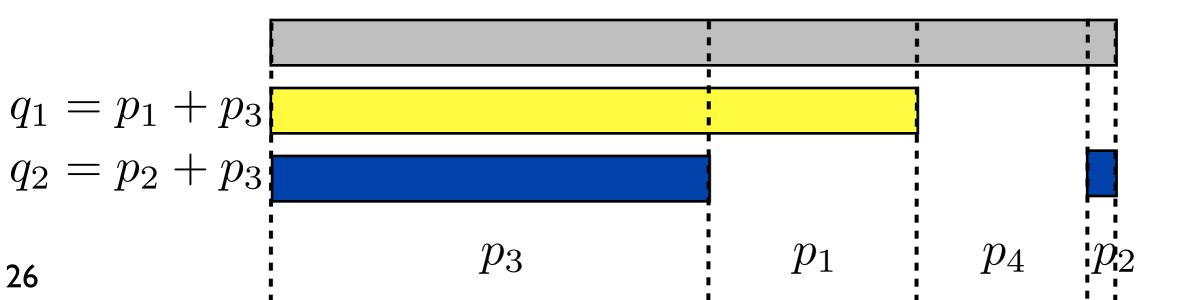




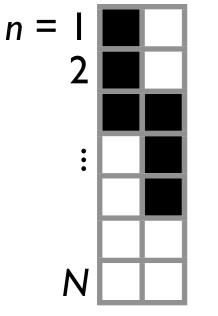


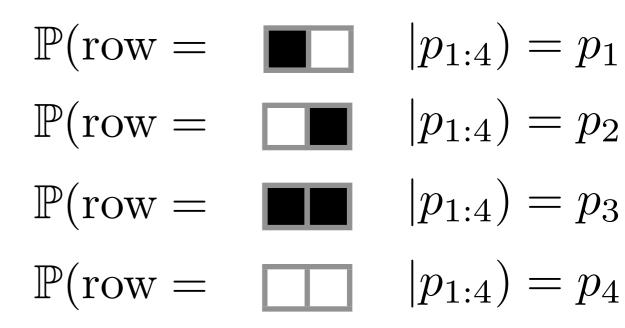




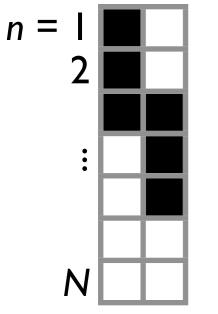


Feature allocation





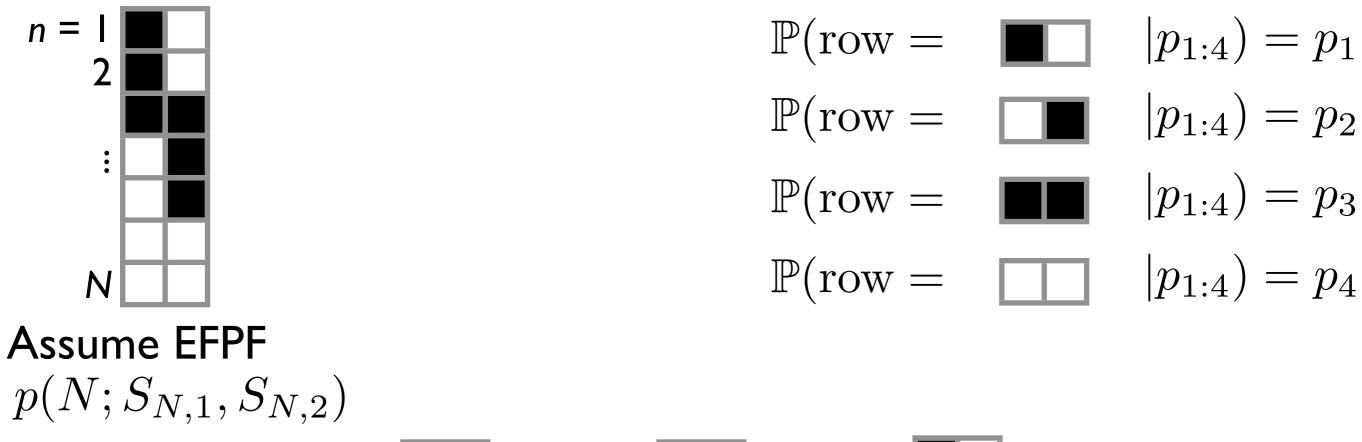
Feature allocation

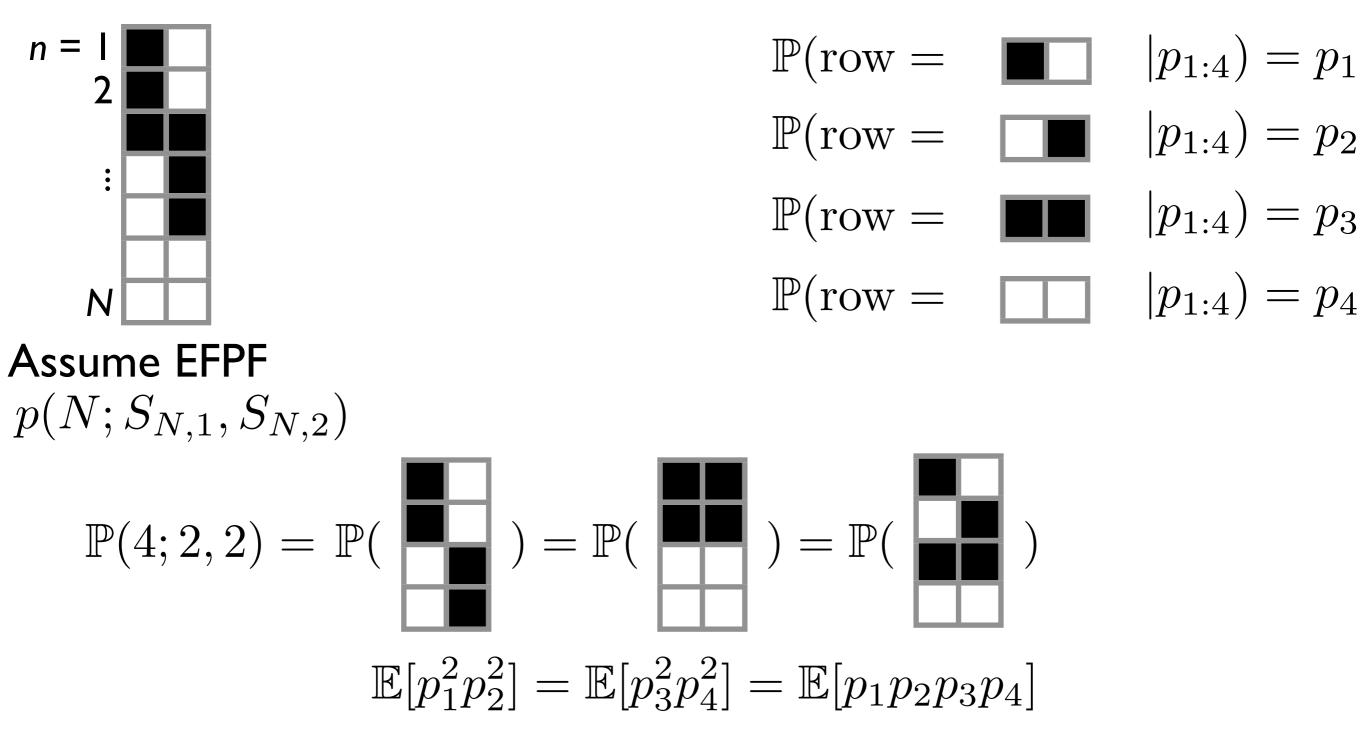


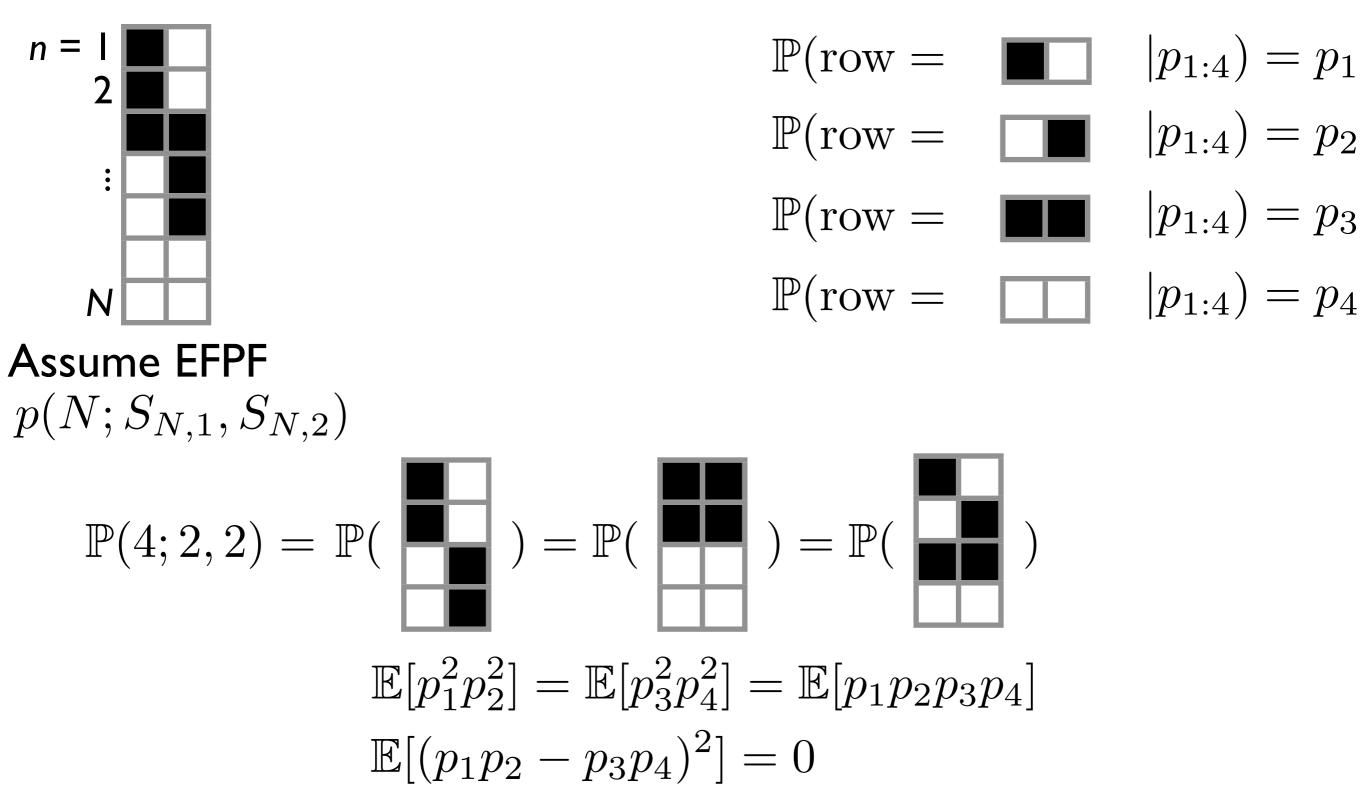
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_1$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_2$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_3$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_4$$

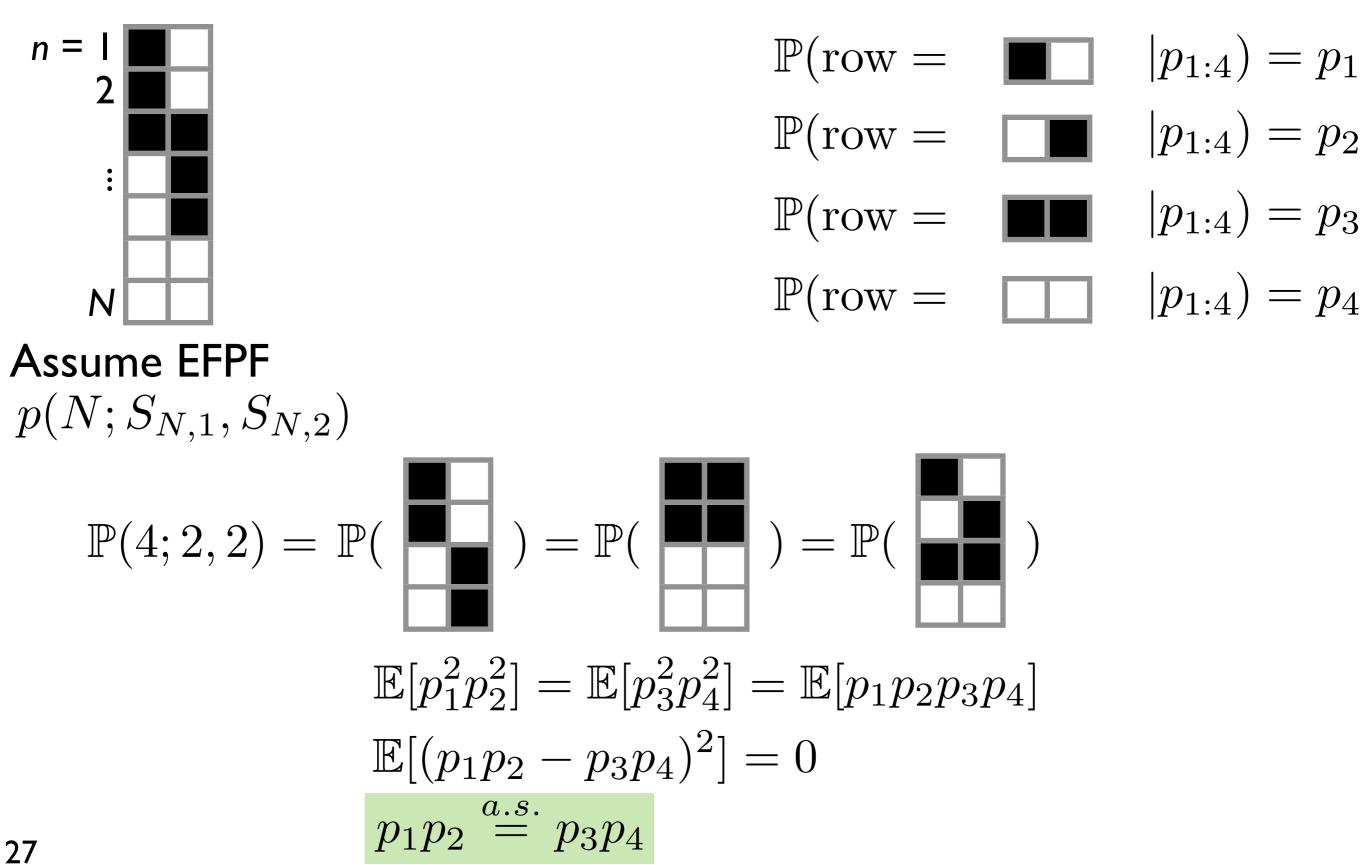
Assume EFPF $p(N; S_{N,1}, S_{N,2})$

 $\mathbb{P}(4;2,2)$

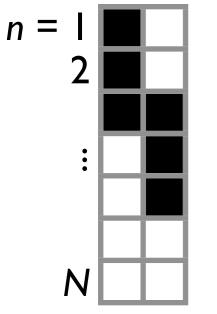








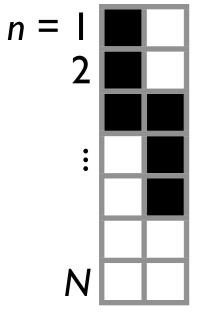
Feature allocation

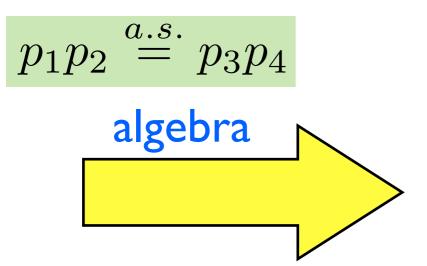


$$p_1p_2 \stackrel{a.s.}{=} p_3p_4$$

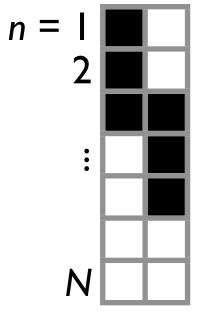
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_1$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_2$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_3$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_4$$

Feature allocation





$$\mathbb{P}(\text{row} = |p_{1:4}) = p_1$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_2$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_3$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_4$$

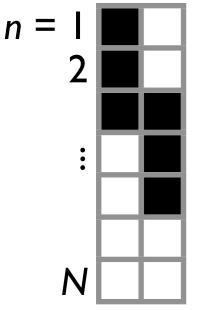


N
Assume EFPF
$$p(N; S_{N,1}, S_{N,2})$$

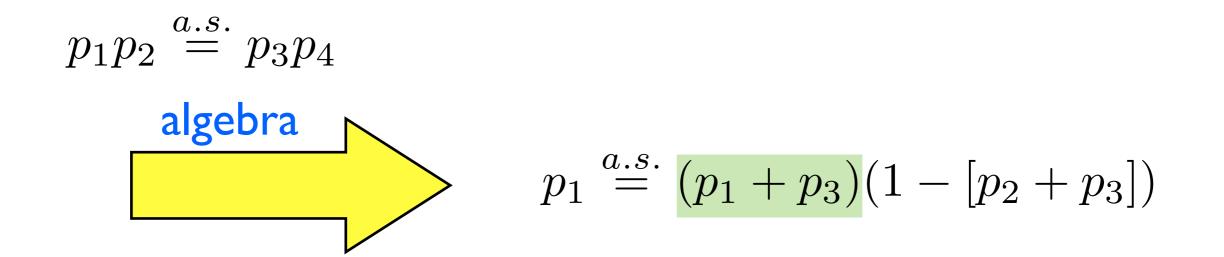
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_1$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_2$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_3$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_4$$

$$p_{1}p_{2} \stackrel{a.s.}{=} p_{3}p_{4}$$
algebra
$$p_{1} \stackrel{a.s.}{=} (p_{1} + p_{3})(1 - [p_{2} + p_{3}])$$

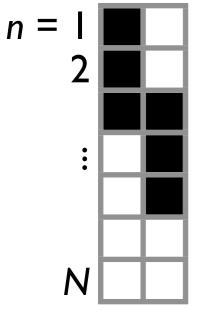
Feature allocation

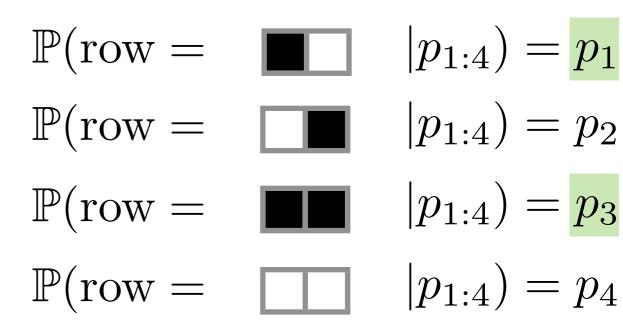


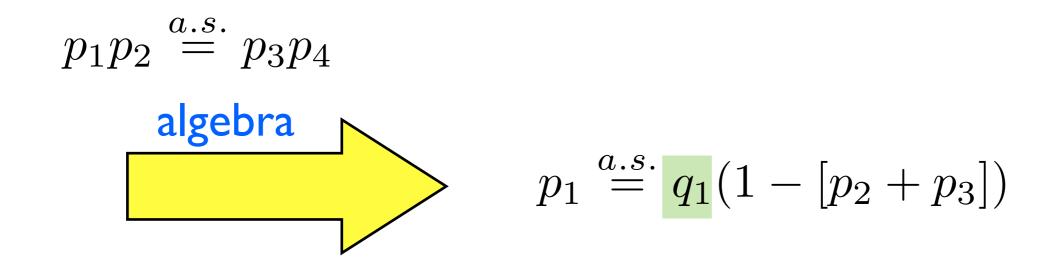
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_1$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_2$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_3$$
$$\mathbb{P}(\text{row} = |p_{1:4}) = p_4$$



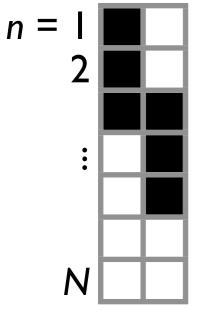
Feature allocation

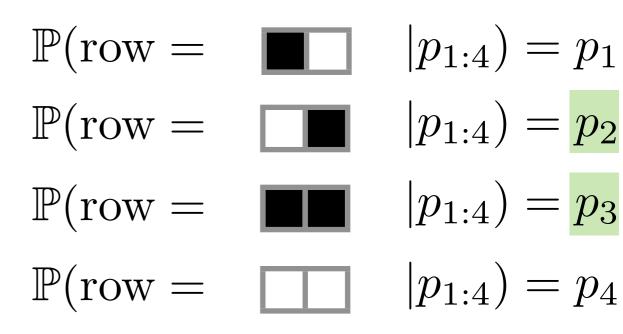


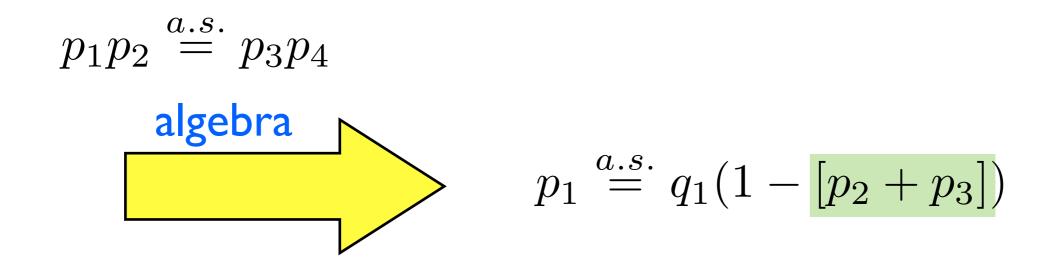




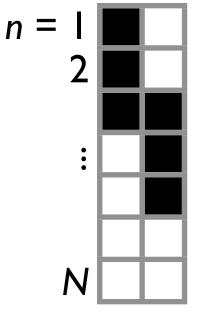
Feature allocation

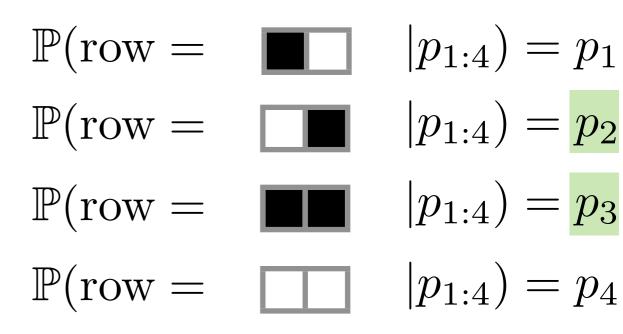


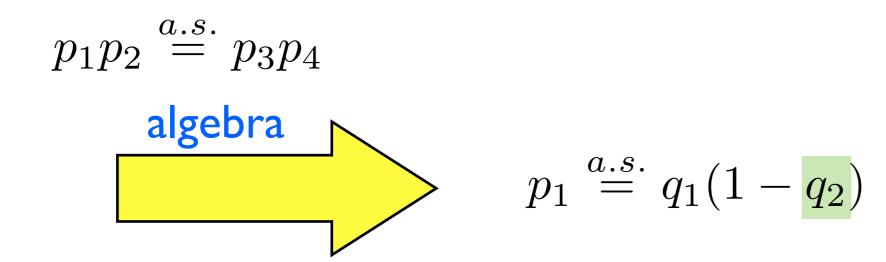




Feature allocation



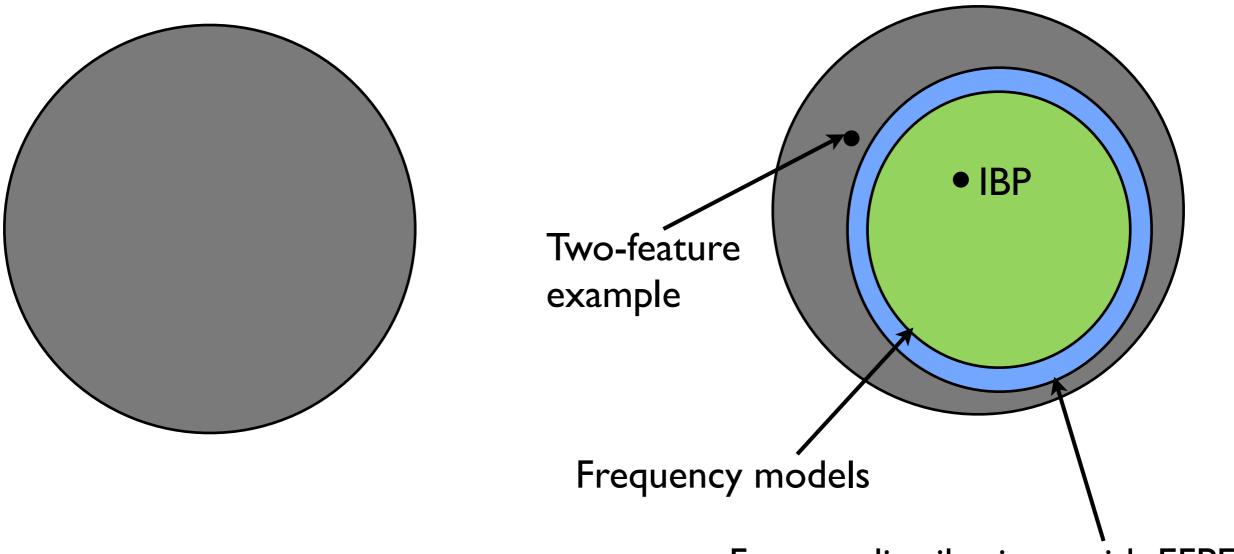




Exchangeable cluster distributions = Cluster distributions with EPPFs = Kingman paintbox partitions

= Kingman paintbox partitions

Exchangeable feature distributions = Feature paintbox allocations



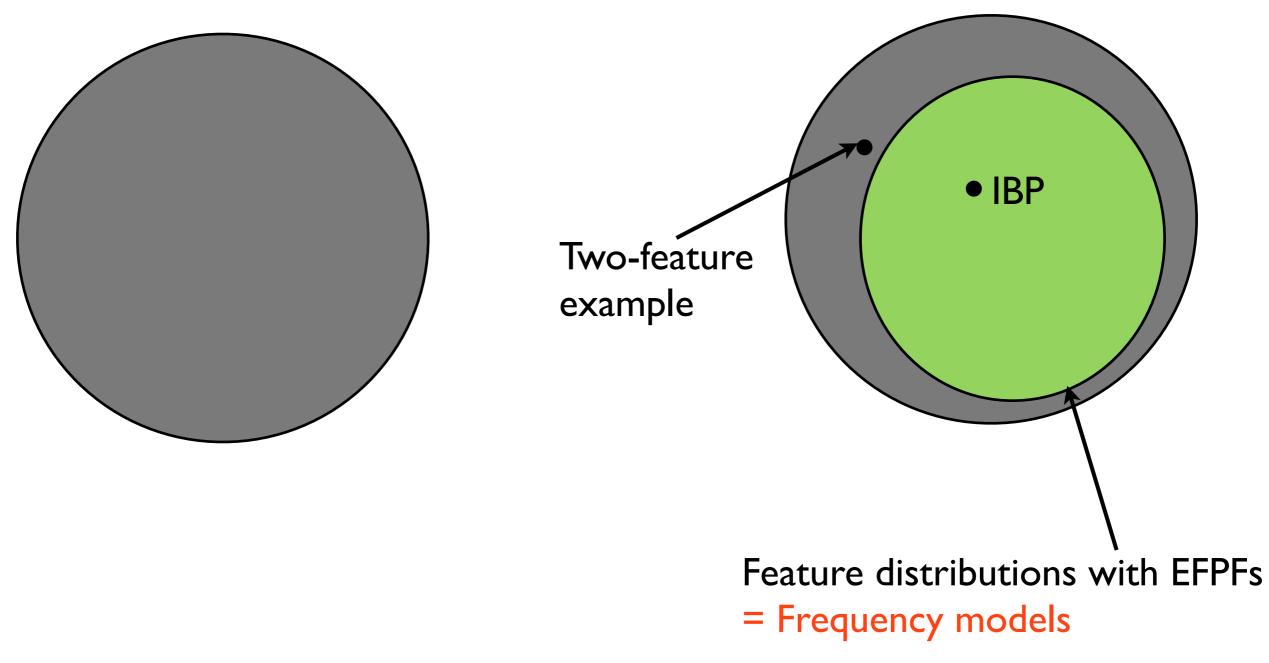
Feature distributions with EFPFs

[Broderick, Pitman, Jordan (submitted)]

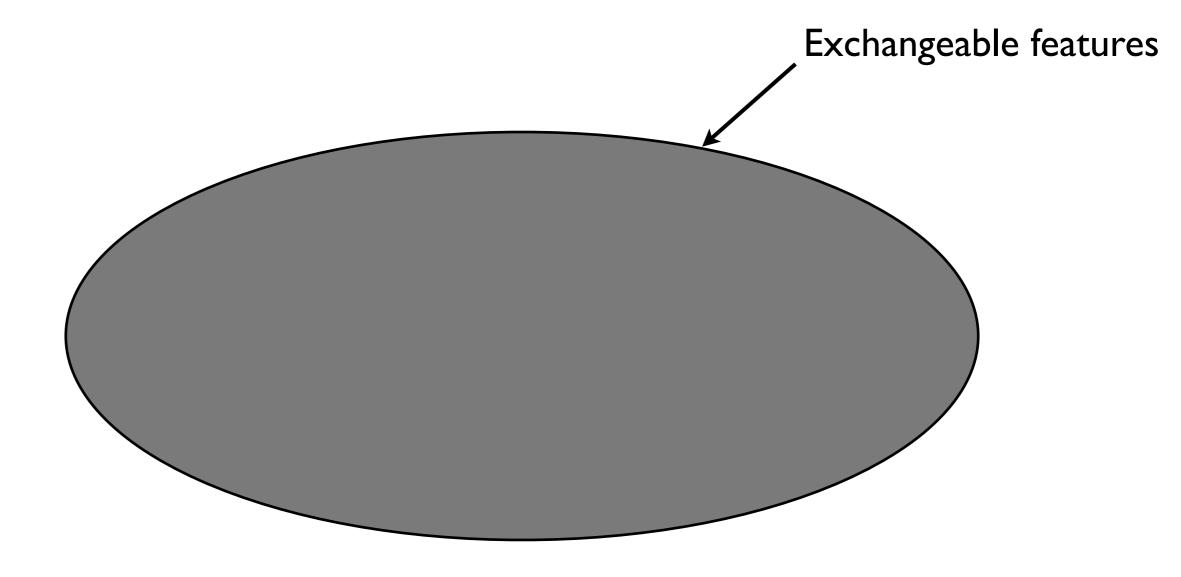
Exchangeable cluster distributions = Cluster distributions with EPPFs = Kingman paintbox partitions

= Kingman paintbox partitions

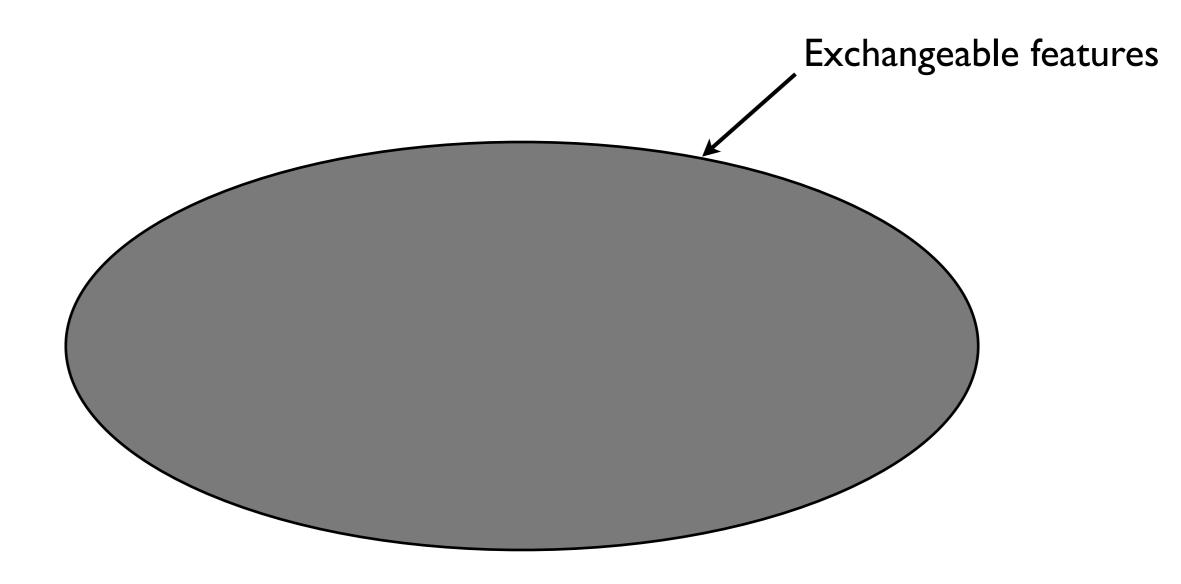
Exchangeable feature distributions = Feature paintbox allocations



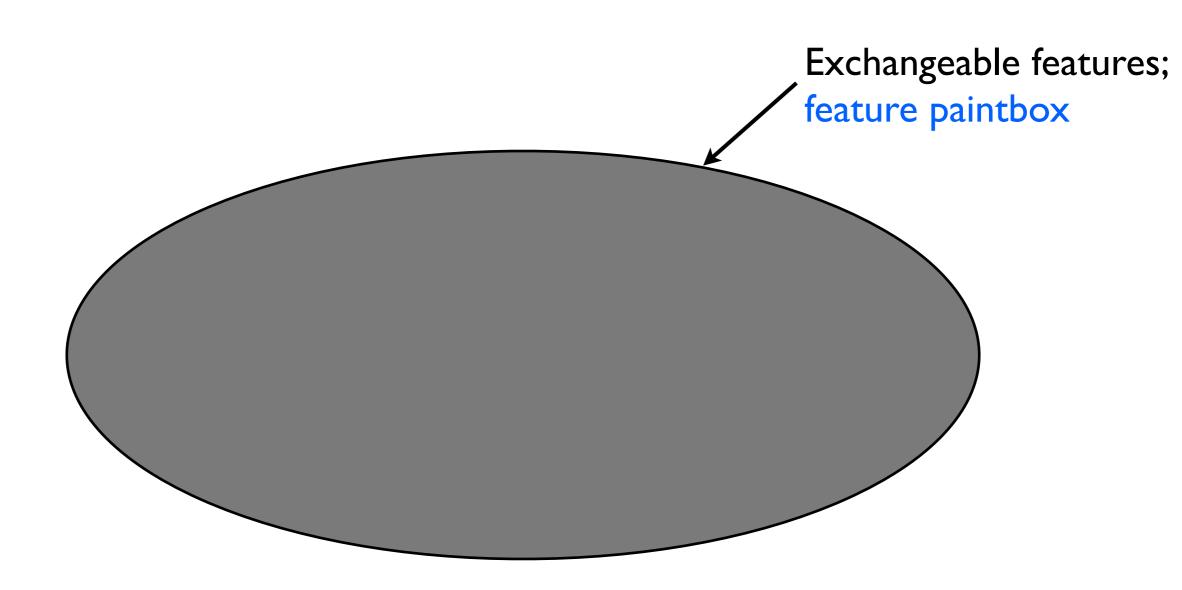
[Broderick, Pitman, Jordan (submitted)]



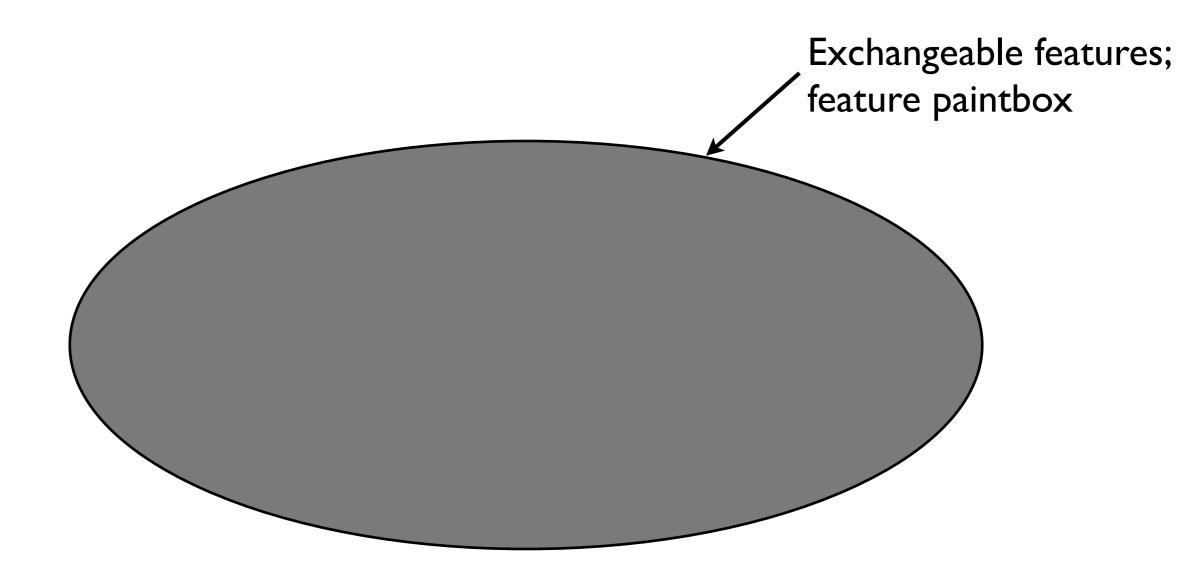
• Feature paintbox: characterization of exchangeable feature models



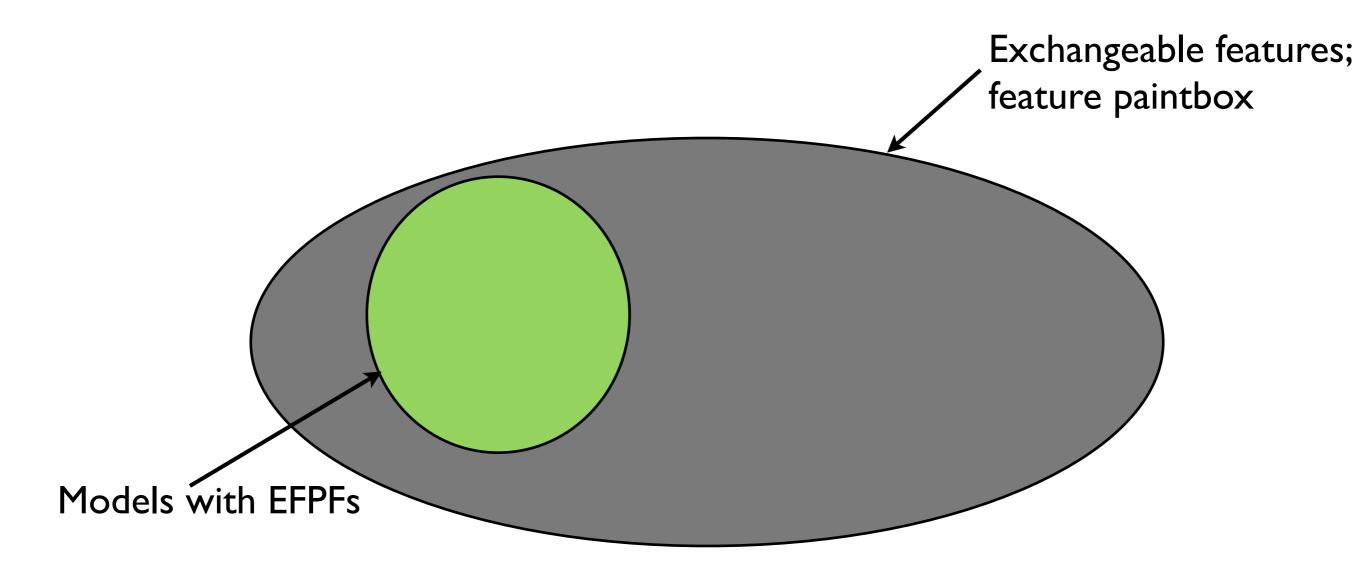
• Feature paintbox: characterization of exchangeable feature models



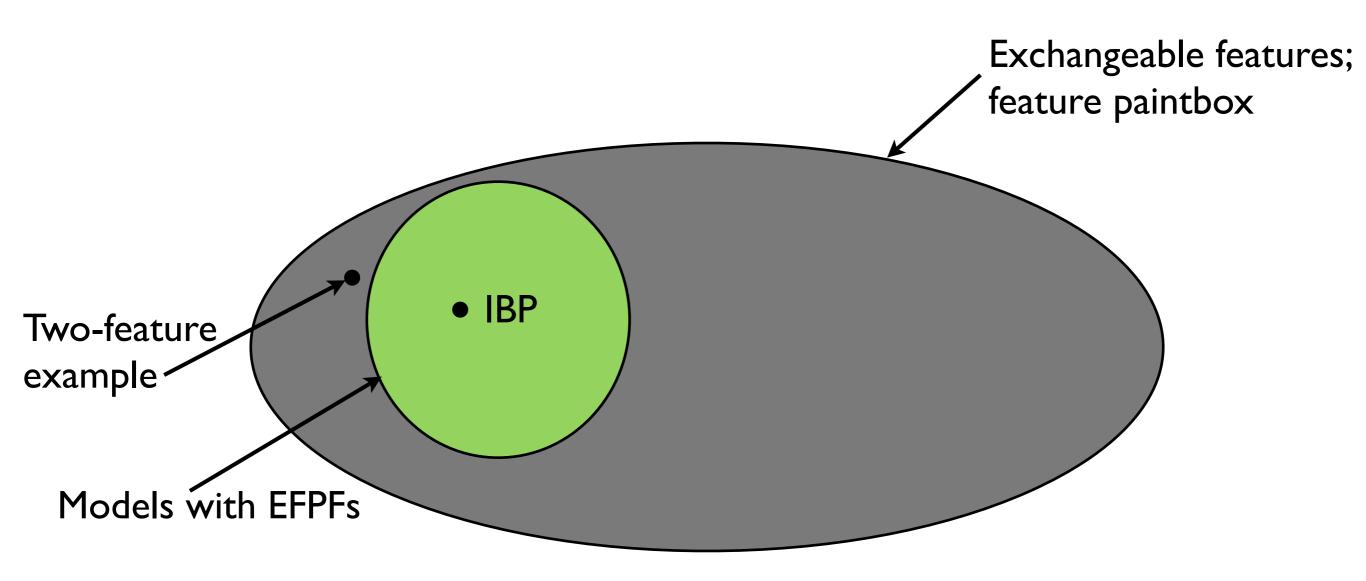
- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



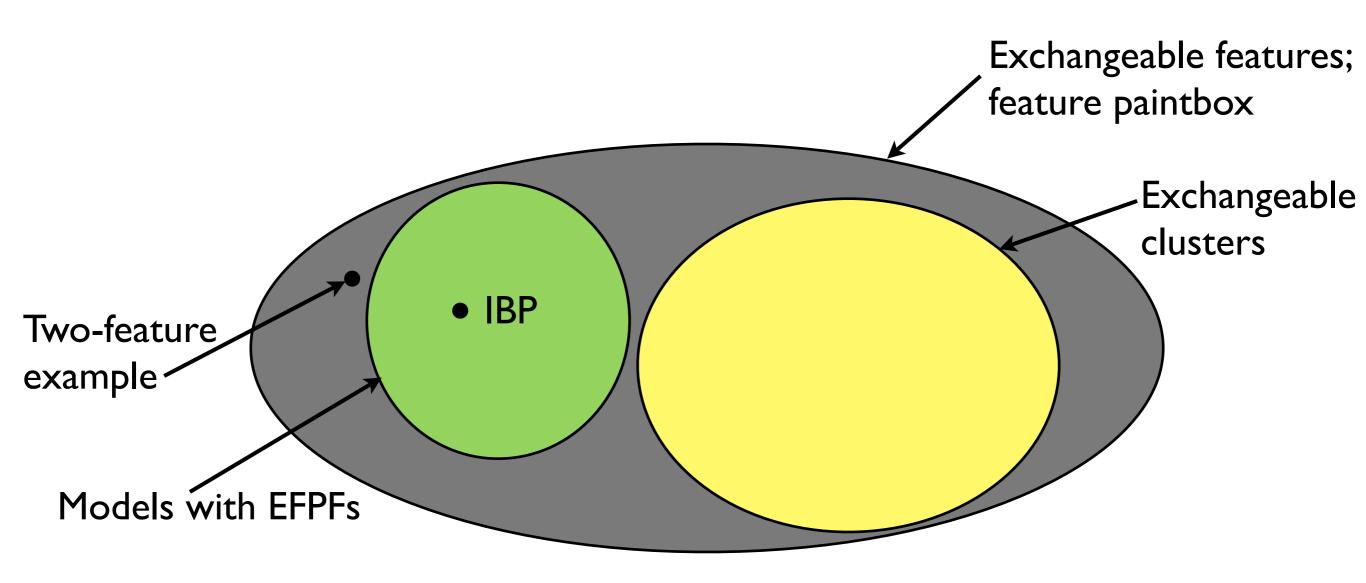
- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



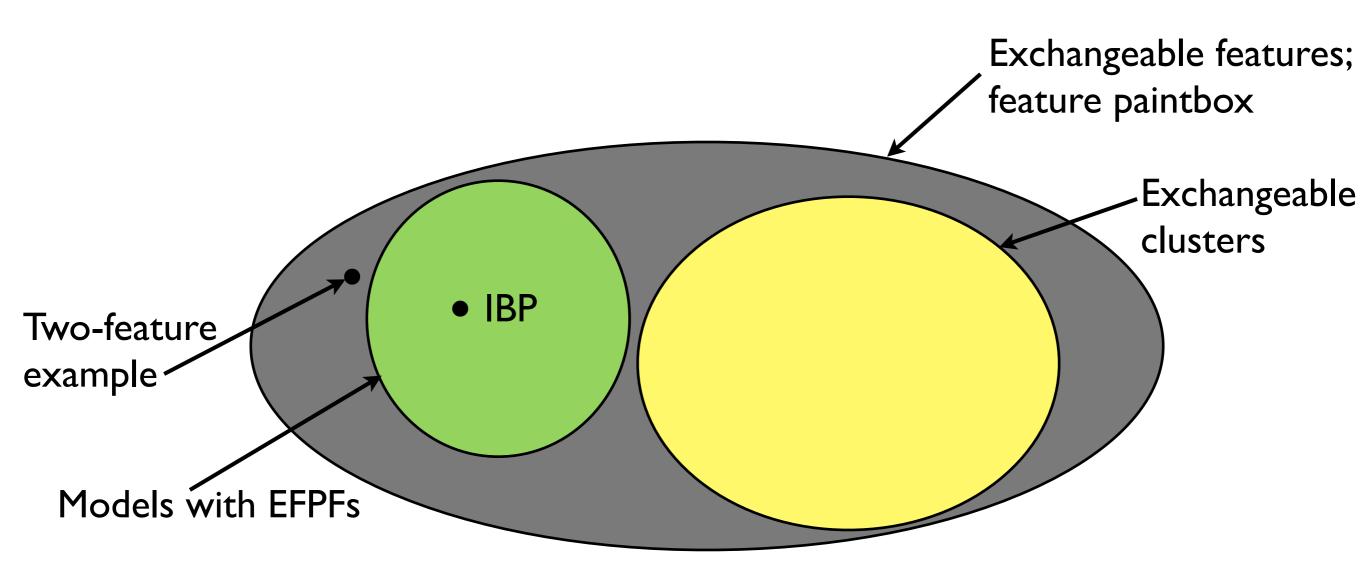
- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



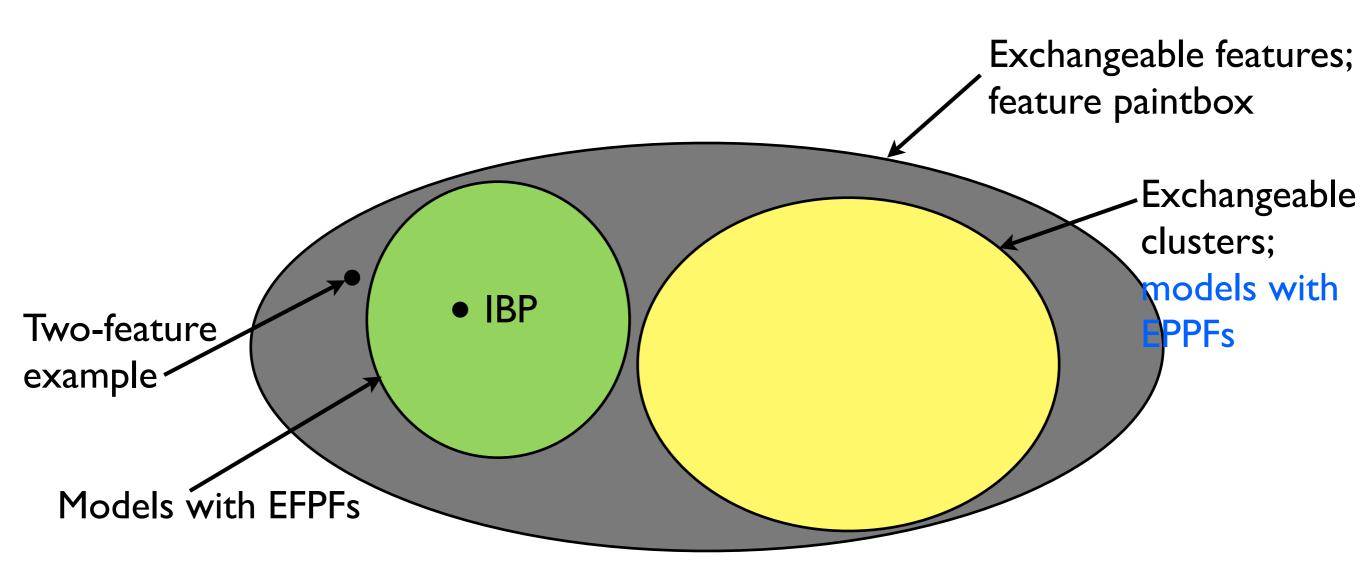
- Feature paintbox: characterization of exchangeable feature models
- Limits of clustering characterizations in feature case?



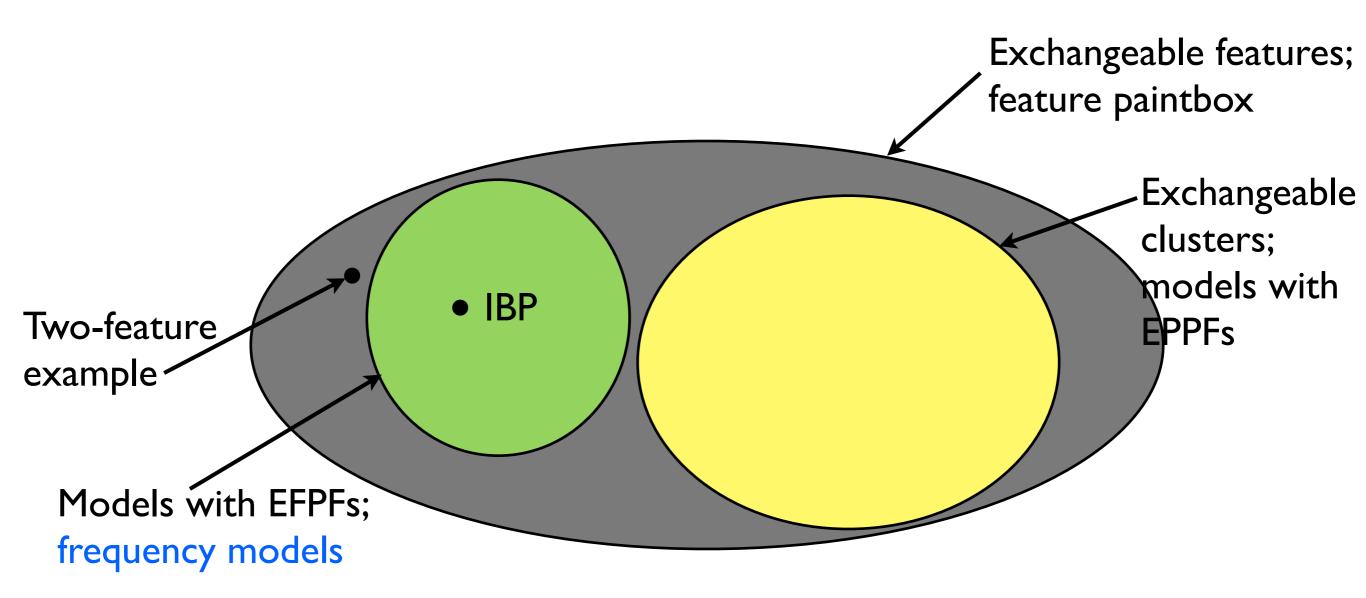
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



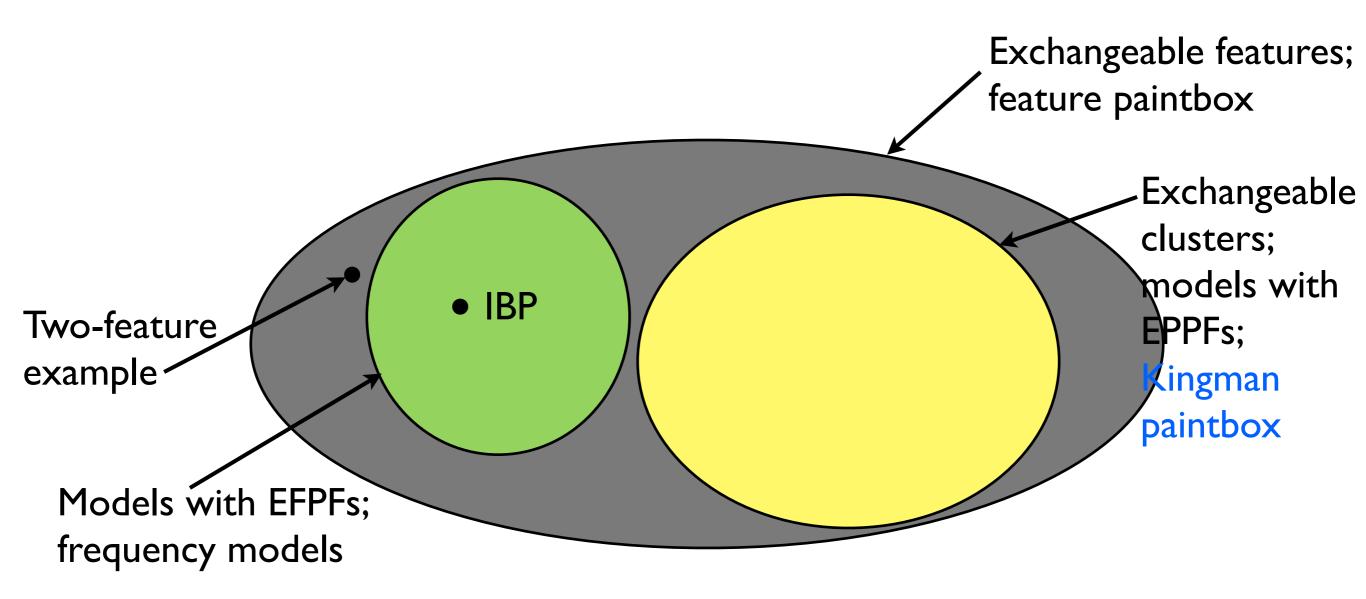
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



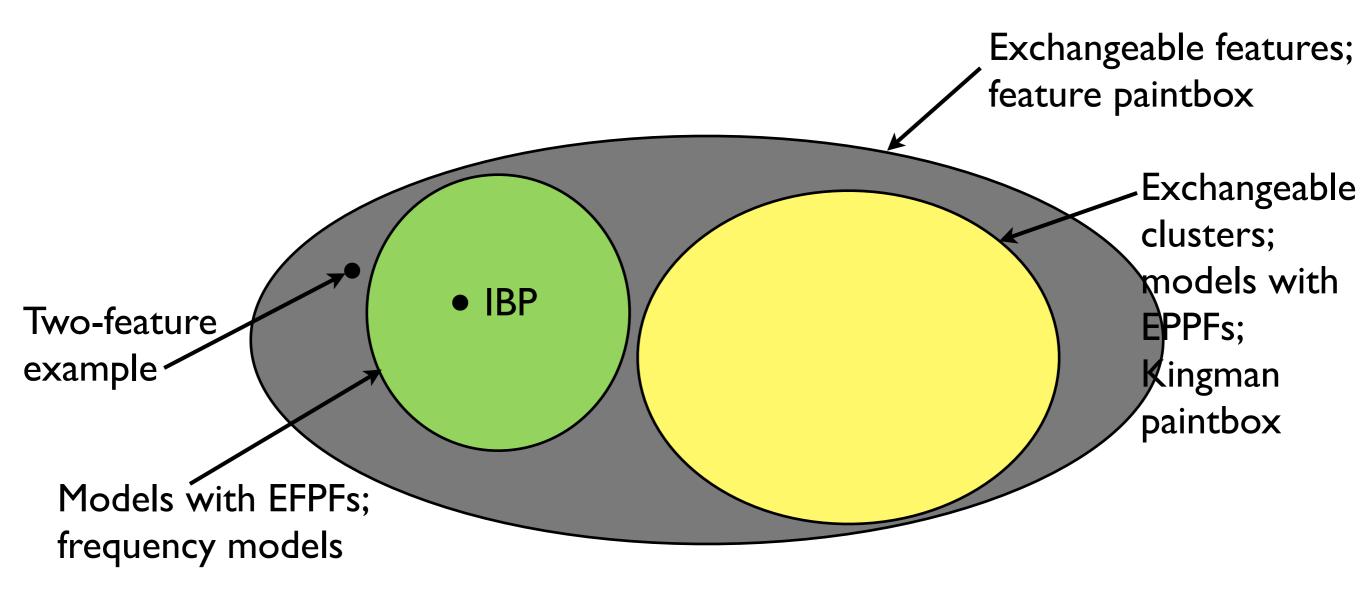
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



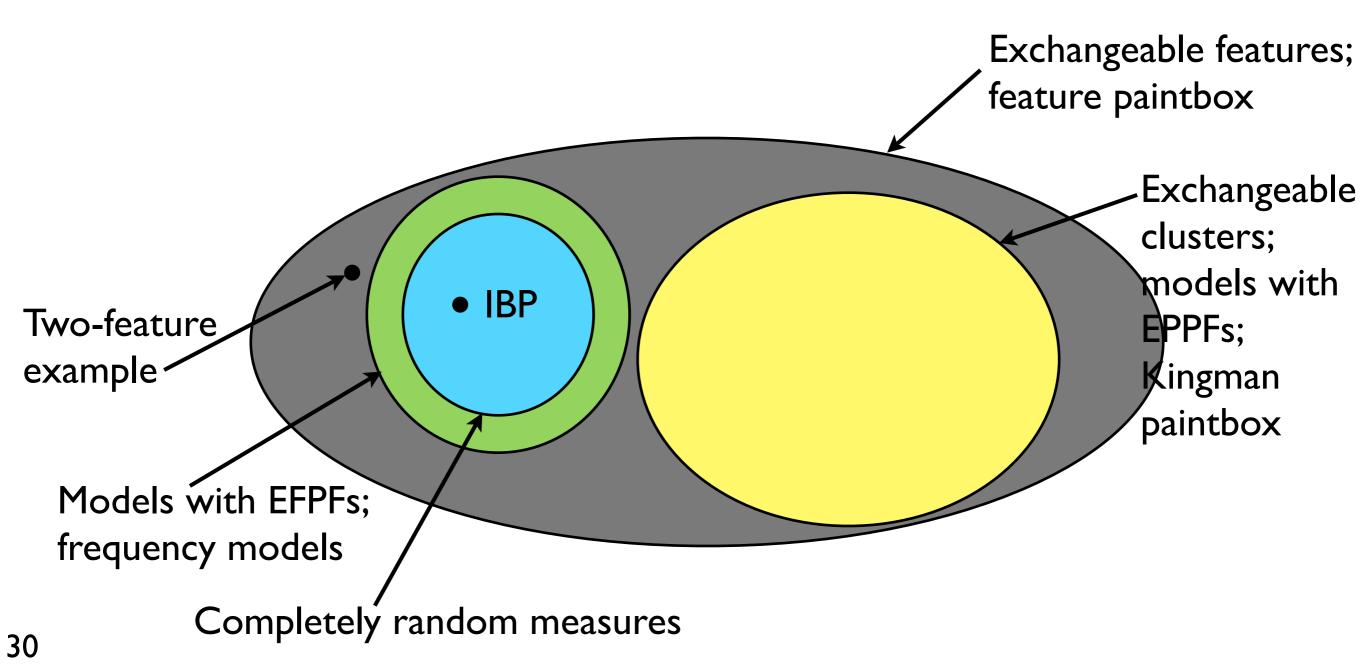
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure



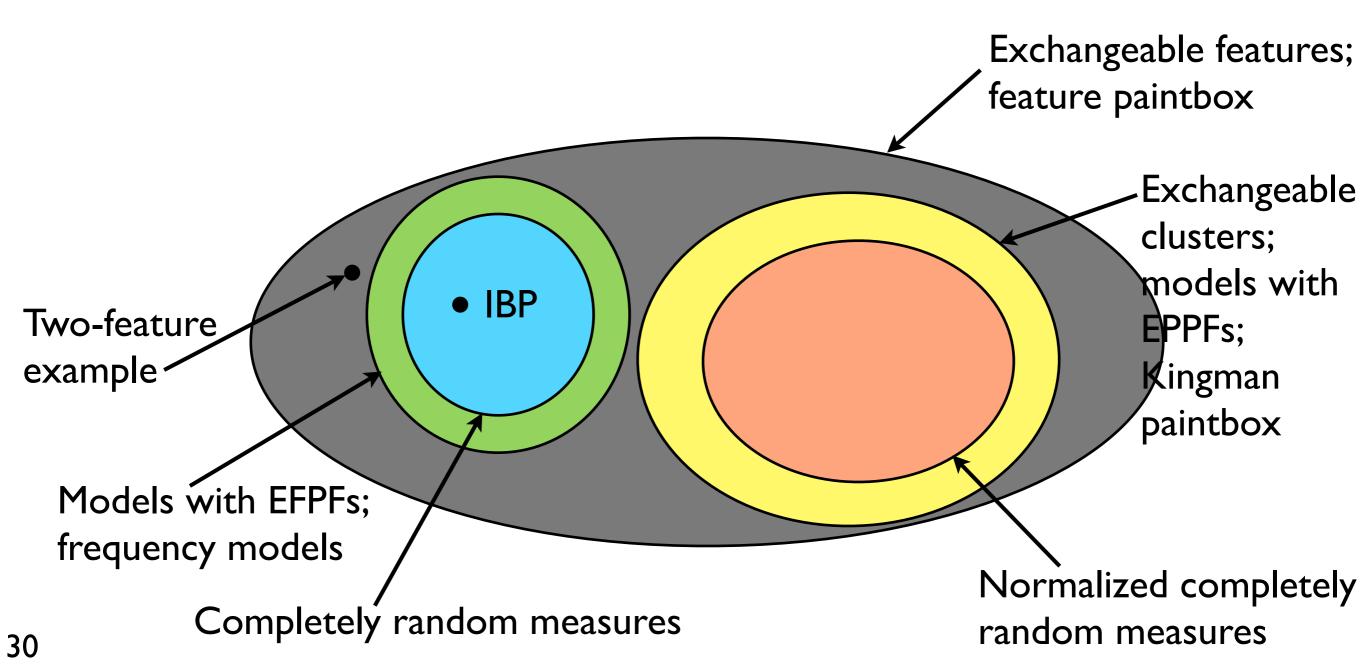
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections to fill in



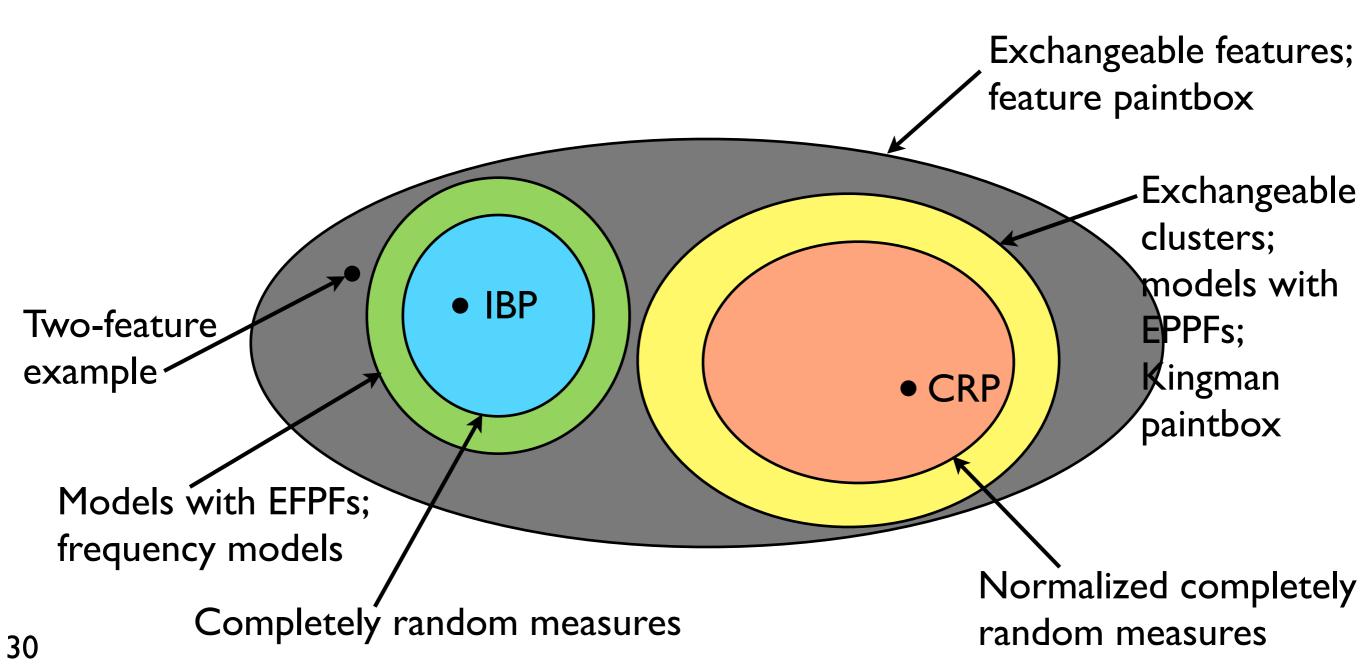
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections to fill in



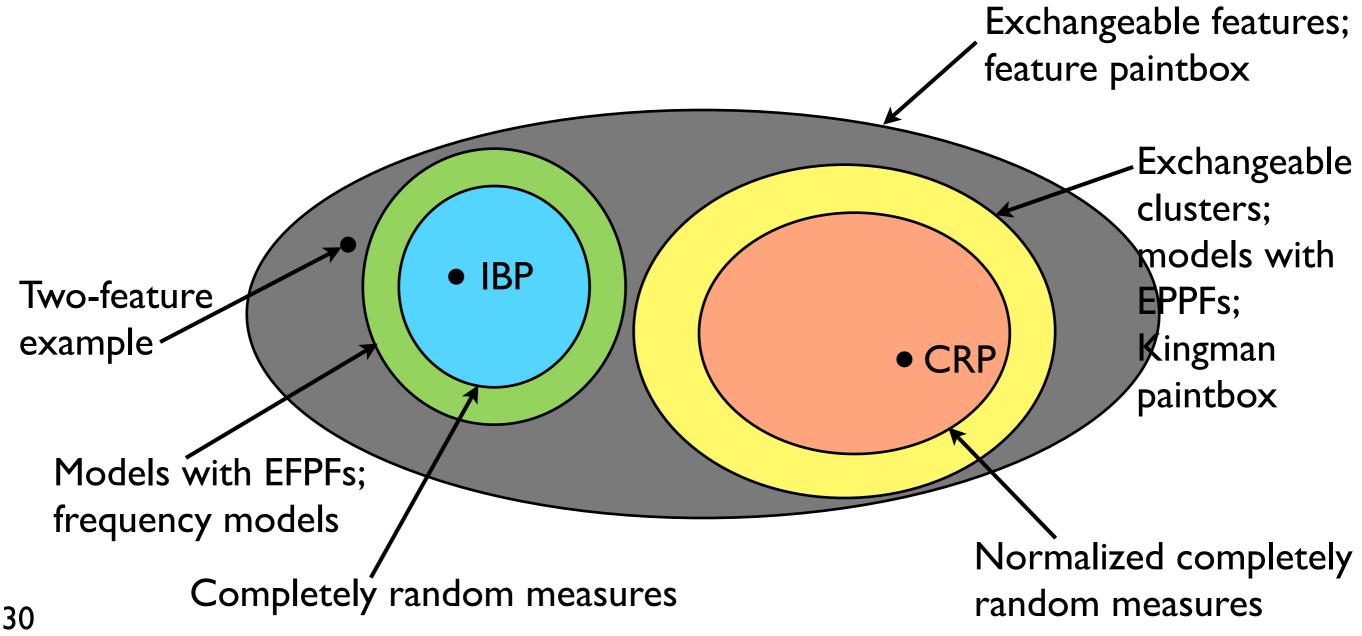
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections to fill in



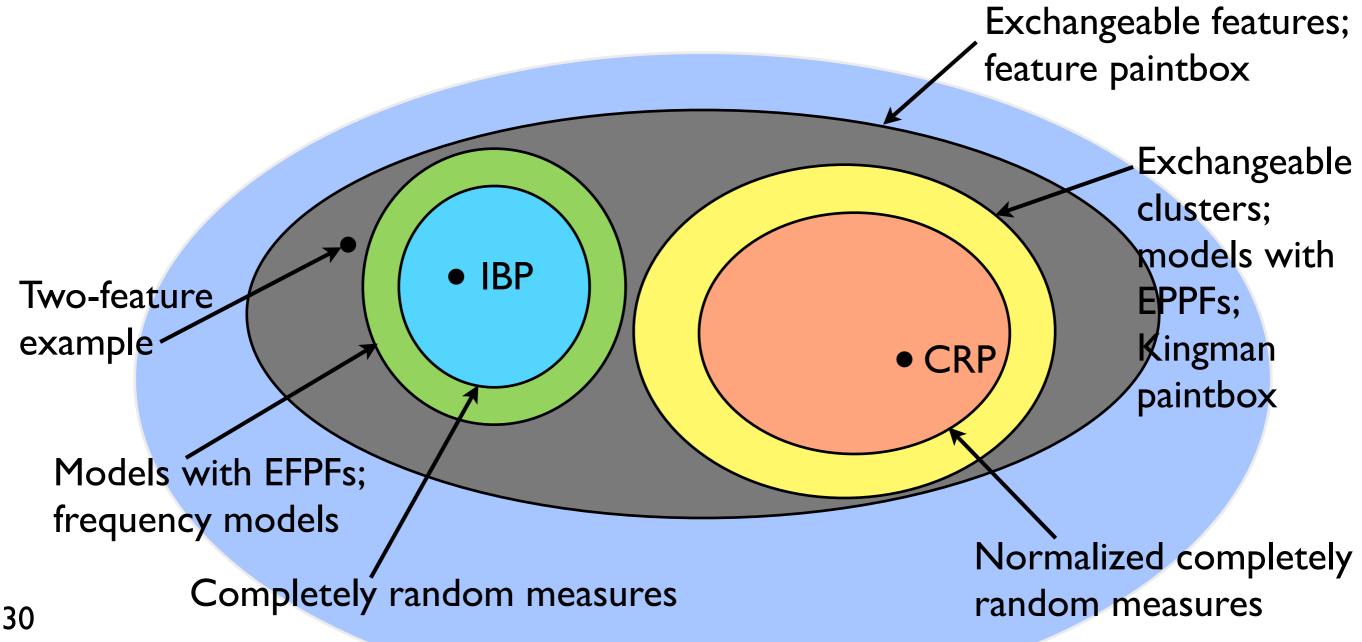
- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections to fill in



- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections to fill in
- Other combinatorial structures



- Feature paintbox: characterization of exchangeable feature models
- Characterization of alternative correlation structure
- Remaining connections to fill in
- Other combinatorial structures



References

T. Broderick, M. I. Jordan, and J. Pitman. Clusters and features from combinatorial stochastic processes. *Arxiv* preprint arXiv:1206.5862, 2012.

T. Broderick, J. Pitman, and M. I. Jordan. Feature allocations, probability functions, and paintboxes. Submitted.

T. Broderick, L. Mackey, J. Paisley, and M. I. Jordan. Combinatorial clustering and the beta negative binomial process. *Arxiv preprint arXiv:1111.1802*, 2011.

T. Griffiths and Z. Ghahramani. Infinite latent feature models and the Indian buffet process. In Y. Weiss, B. Scholkopf, and J. Platt, editors, *Advances in Neural Information Processing Systems 18*, pages 475–482. MIT Press, Cambridge, MA, 2006.

N. L. Hjort. Nonparametric bayes estimators based on beta processes in models for life history data. Annals of Statistics, 18(3):1259–1294, 1990.

Y. Kim. Nonparametric Bayesian estimators for counting processes. Annals of Statistics, 27(2):562–588, 1999.

J. F. C. Kingman. The representation of partition structures. *Journal of the London Mathematical Society*, 2(2):374, 1978.

J. Pitman. Exchangeable and partially exchangeable random partitions. *Probability Theory and Related Fields*, 102(2):145–158, 1995.

R. Thibaux and M. I. Jordan. Hierarchical beta processes and the Indian buffet process. In *Proceedings of the International Conference on Artificial Intelligence and Statistics*, volume 11, 2007.

M. Zhou, L. Hannah, D. Dunson, and L. Carin. Beta-negative binomial process and Poisson factor analysis. In *Proceedings of the International Conference on Artificial Intelligence and Statistics*, volume 15, 2012.