

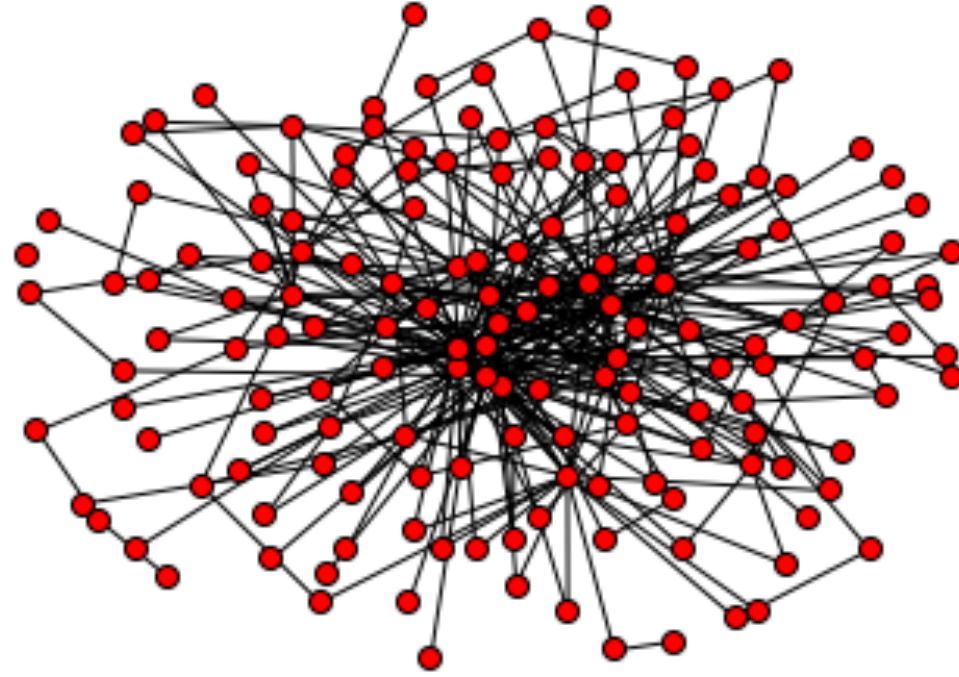


Edge-exchangeable graphs, sparsity, and power laws

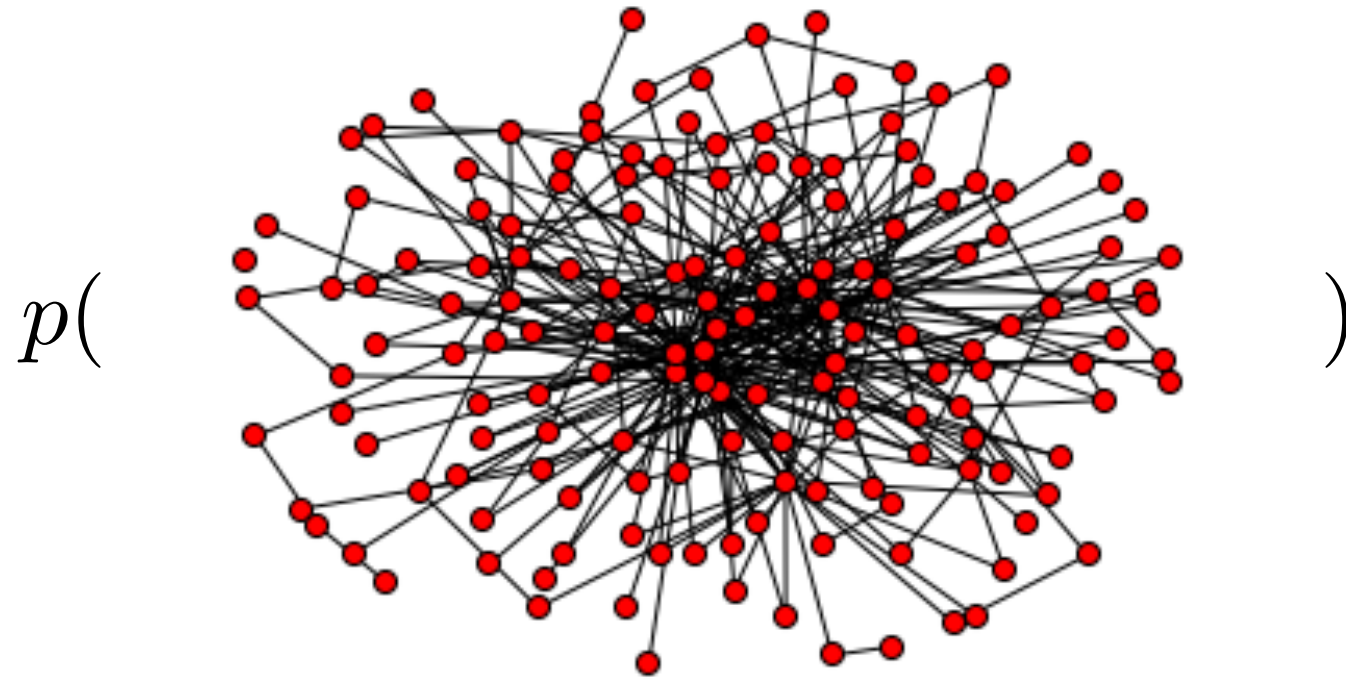
Tamara Broderick
ITT Career Development
Assistant Professor,
MIT

Joint work with: Diana Cai, Trevor Campbell

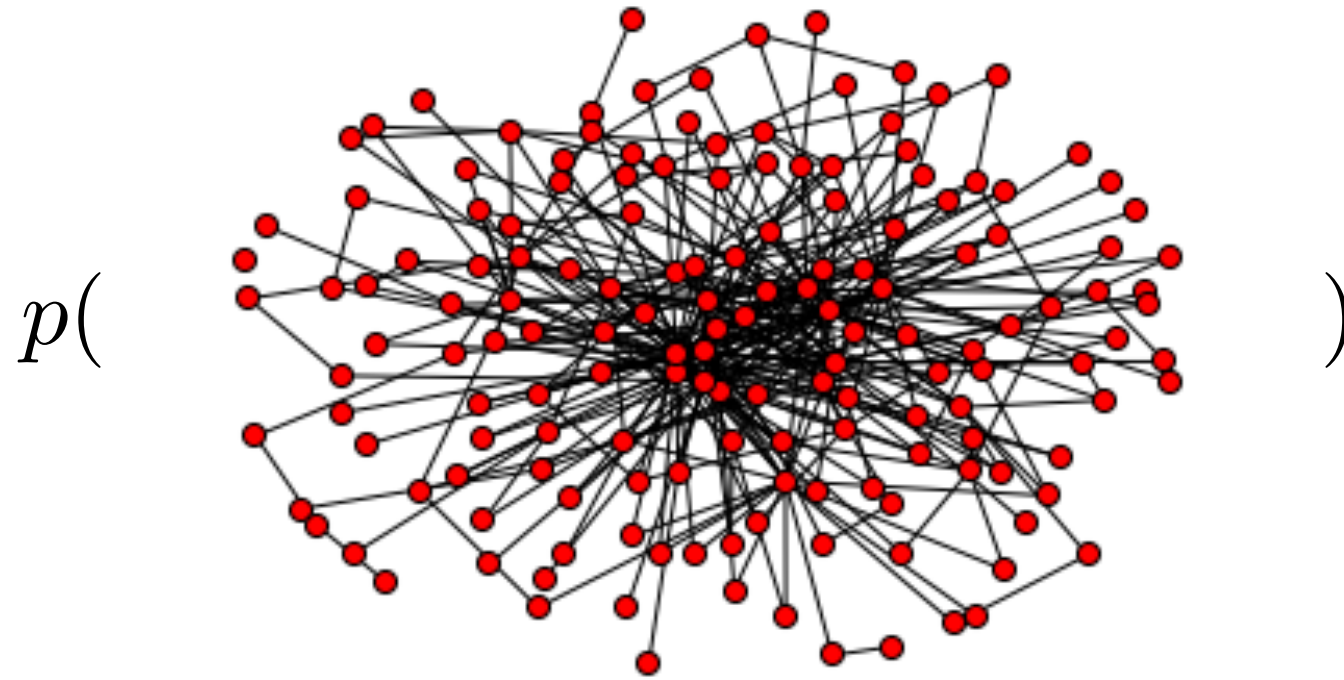
Probabilistic models for graphs



Probabilistic models for graphs

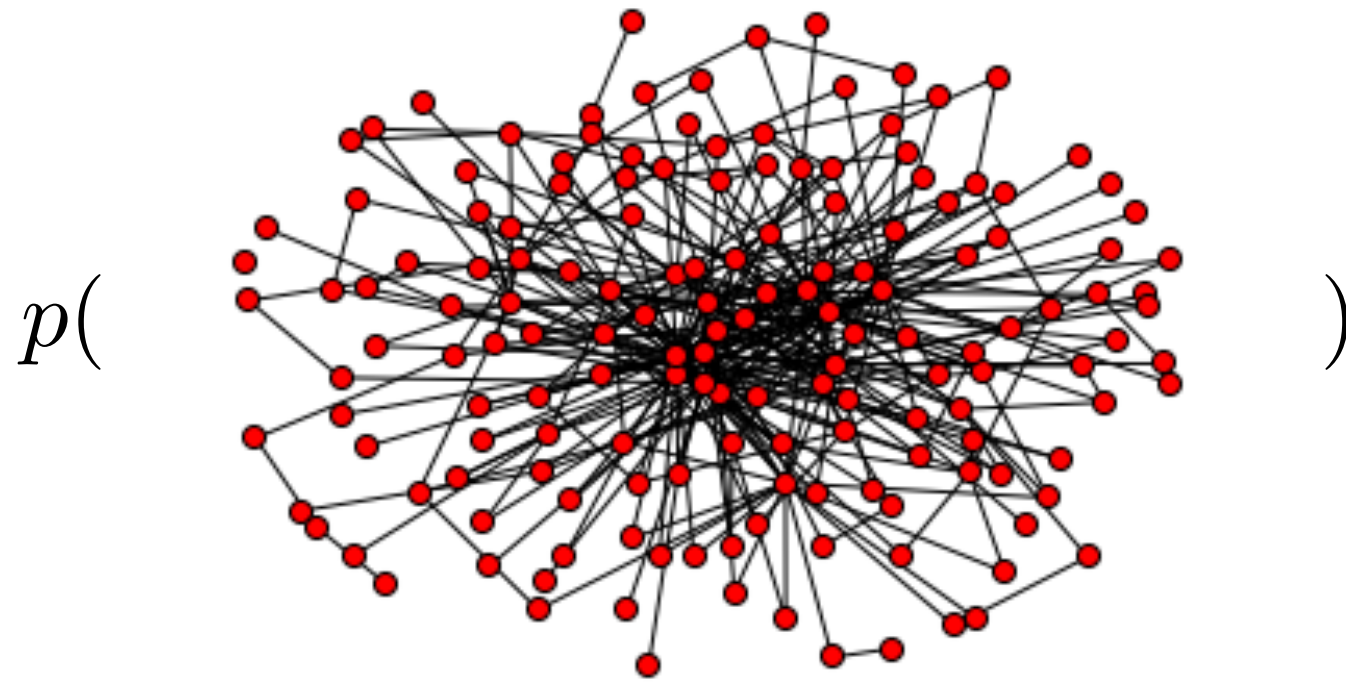


Probabilistic models for graphs



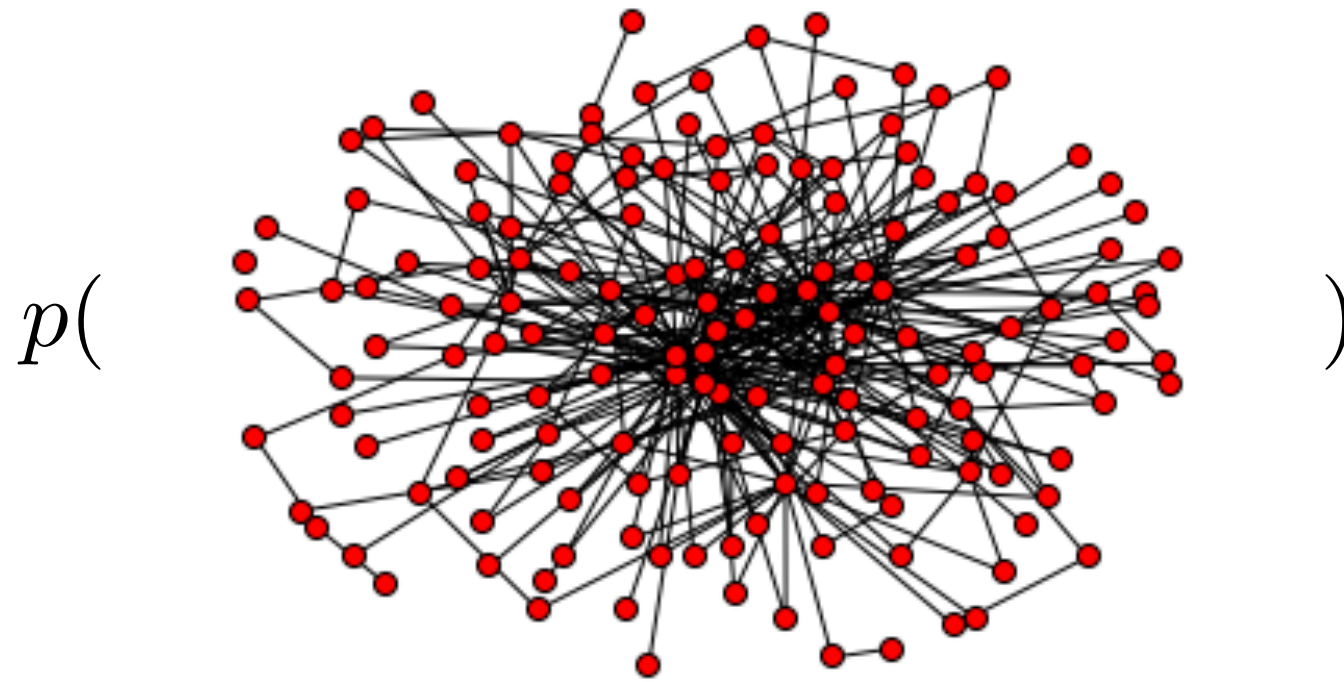
- Stochastic block model, mixed membership stochastic block model, infinite relational model, etc

Probabilistic models for graphs



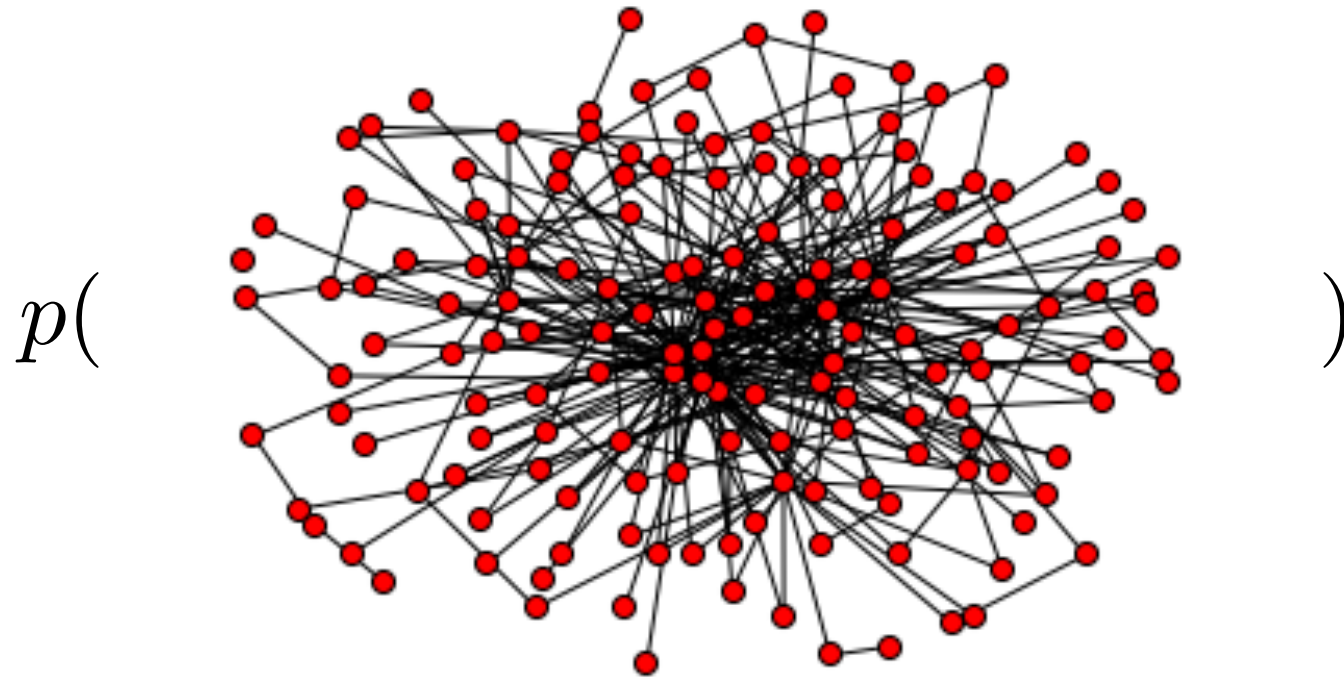
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Probabilistic models for graphs



- Stochastic block model, mixed membership stochastic block model, infinite relational model, etc
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- Problem: model misspecification, dense graphs

Probabilistic models for graphs



- Stochastic block model, mixed membership stochastic block model, infinite relational model, etc
- Learn hidden structure, uncertainties, modularity
- Problem: model misspecification, dense graphs
- Solution: a new set of models for sparse graphs

De Finetti

- A data sequence X_1, X_2, \dots

De Finetti

- A data sequence is *infinitely exchangeable* if the distribution of any N data points doesn't change when permuted: $p(X_1, \dots, X_N) = p(X_{\sigma(1)}, \dots, X_{\sigma(N)})$

De Finetti

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- *De Finetti's Theorem* (roughly): A sequence X_1, X_2, \dots is infinitely exchangeable if and only if, for all N and some distribution P :

$$p(X_1, \dots, X_N) = \int_{\theta} \prod_{n=1}^N p(X_n | \theta) P(d\theta)$$

De Finetti

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- Motivates:

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- Motivates:
 - Parameters and likelihoods

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- Motivates:
 - Parameters and likelihoods
 - Priors

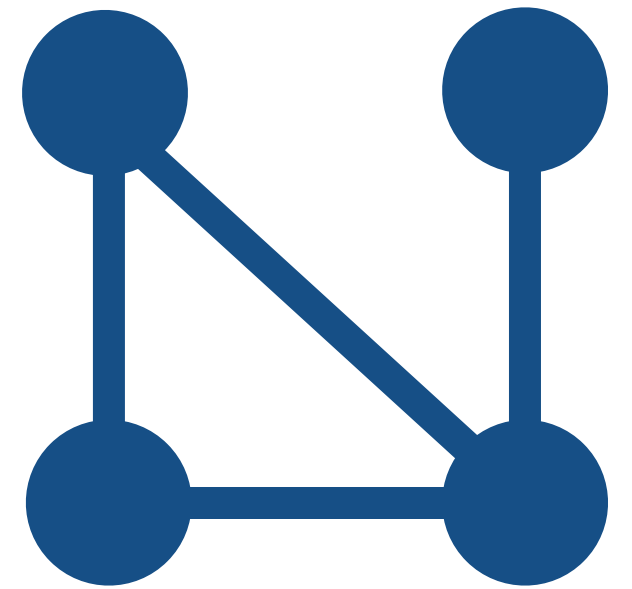
De Finetti

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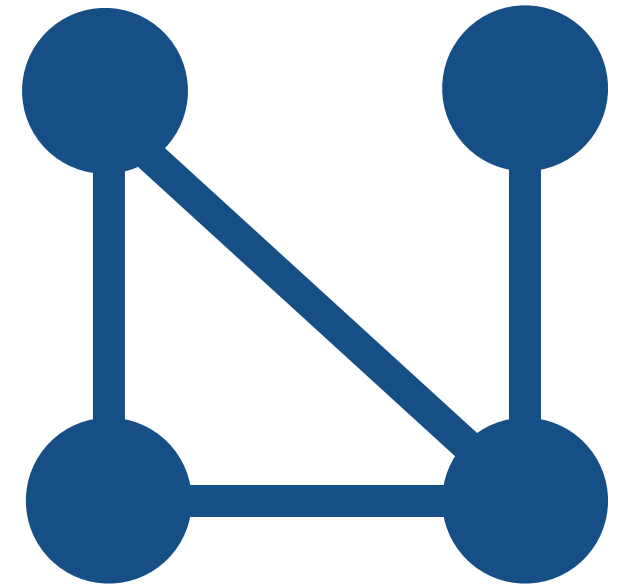
- Motivates:
 - Parameters and likelihoods
 - Priors
 - *Nonparametric Bayesian* priors

Sequence of graphs



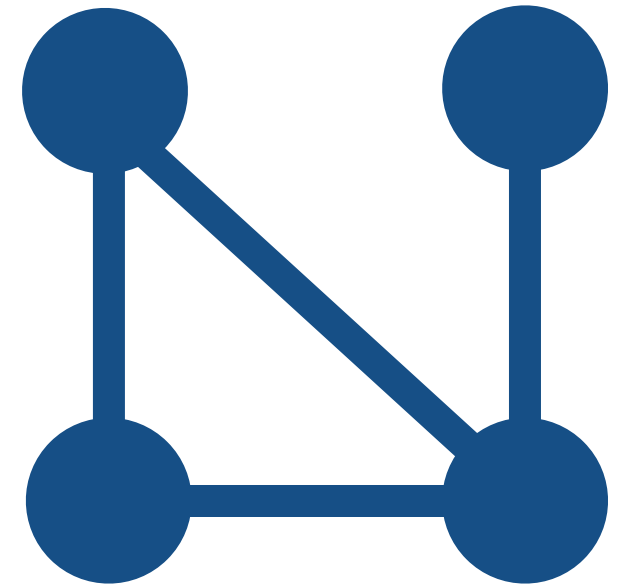
G

Sequence of graphs



- Nodes/vertices

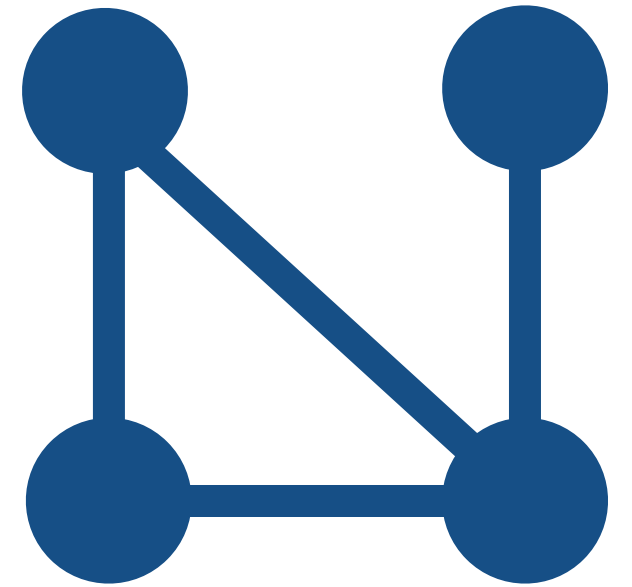
Sequence of graphs



G

- Nodes/vertices
- Edges

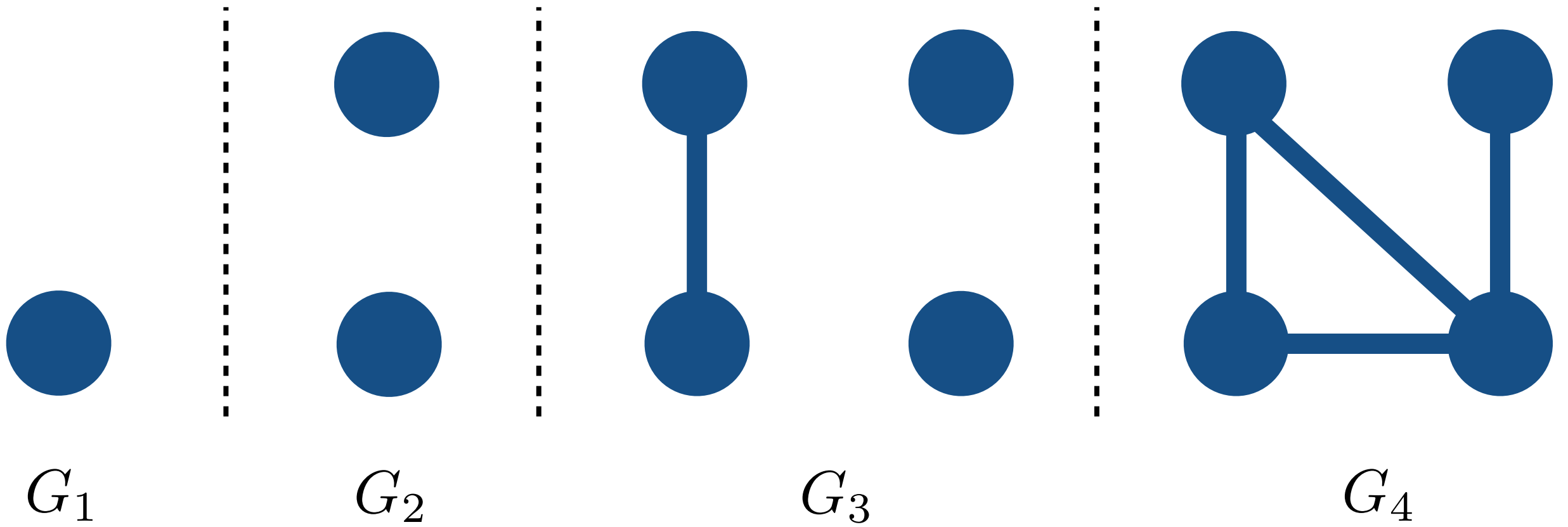
Sequence of graphs



G

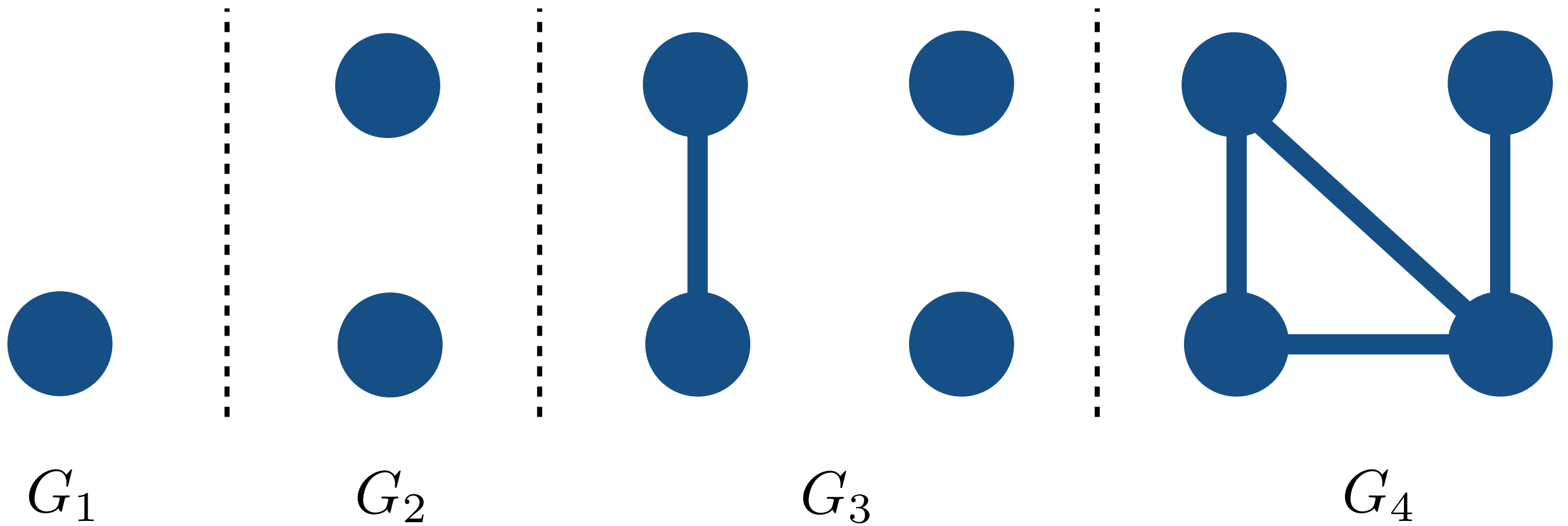
- Nodes/vertices
- Edges
- Active nodes

Sequence of graphs



- Nodes/vertices
- Edges
- Active nodes

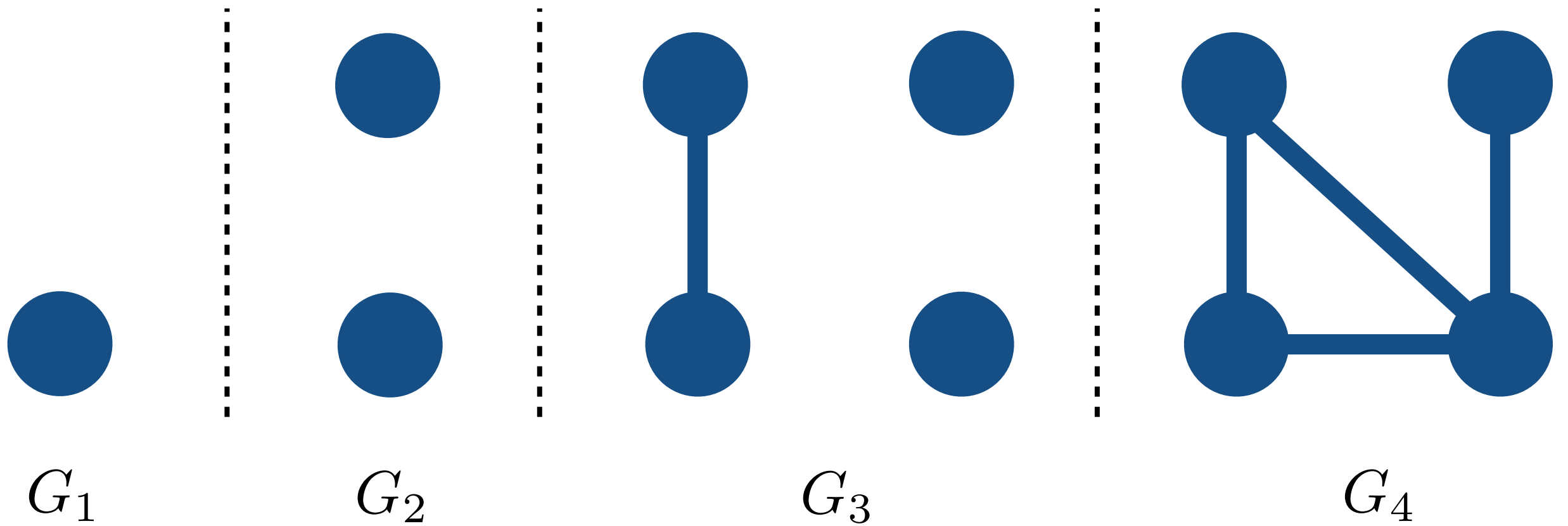
Sequence of graphs



- Nodes/vertices
- Edges
- Active nodes

- *Dense* graph sequence $\#edges(G_n) \geq c \cdot [\#nodes(G_n)]^2$

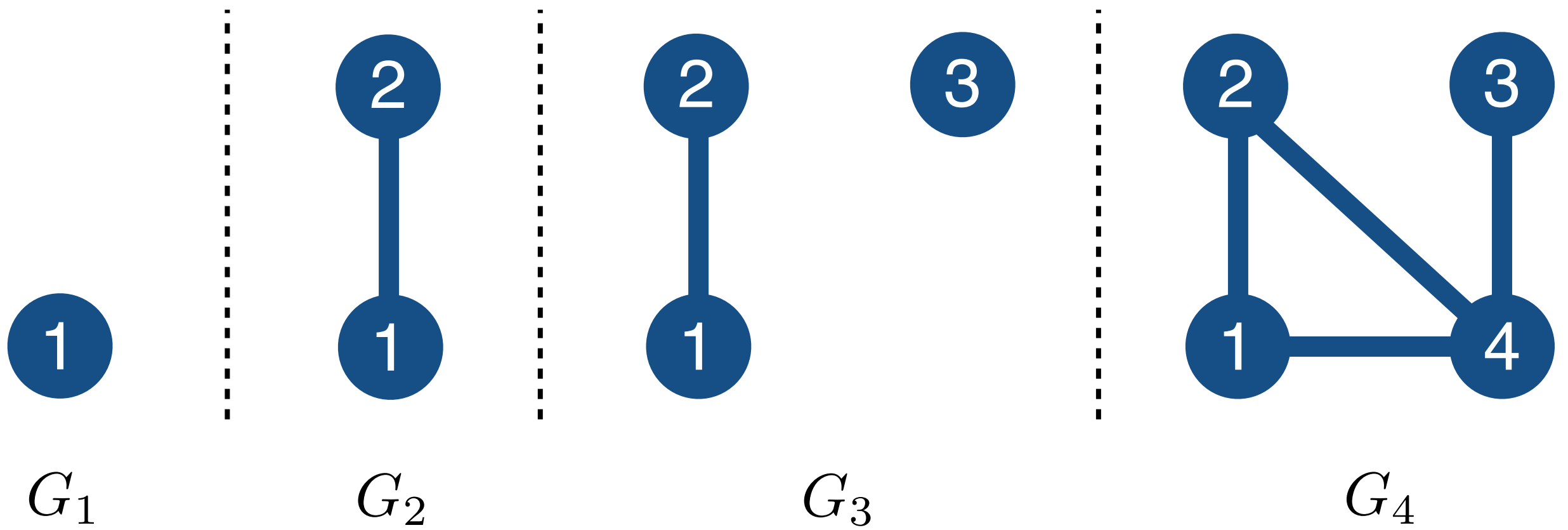
Sequence of graphs



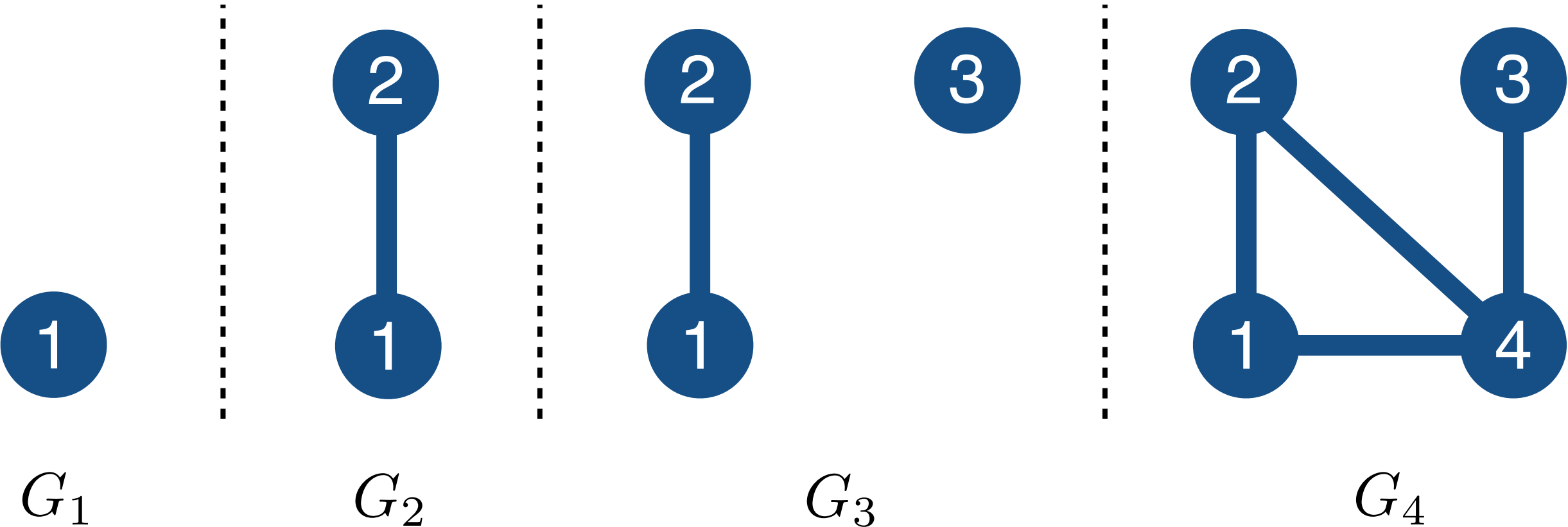
- Nodes/vertices
- Edges
- Active nodes

- *Dense* graph sequence $\#edges(G_n) \geq c \cdot [\#nodes(G_n)]^2$
- *Sparse* graph sequence $\#edges(G_n) \in o([\#nodes(G_n)]^2)$

(Node) Exchangeability

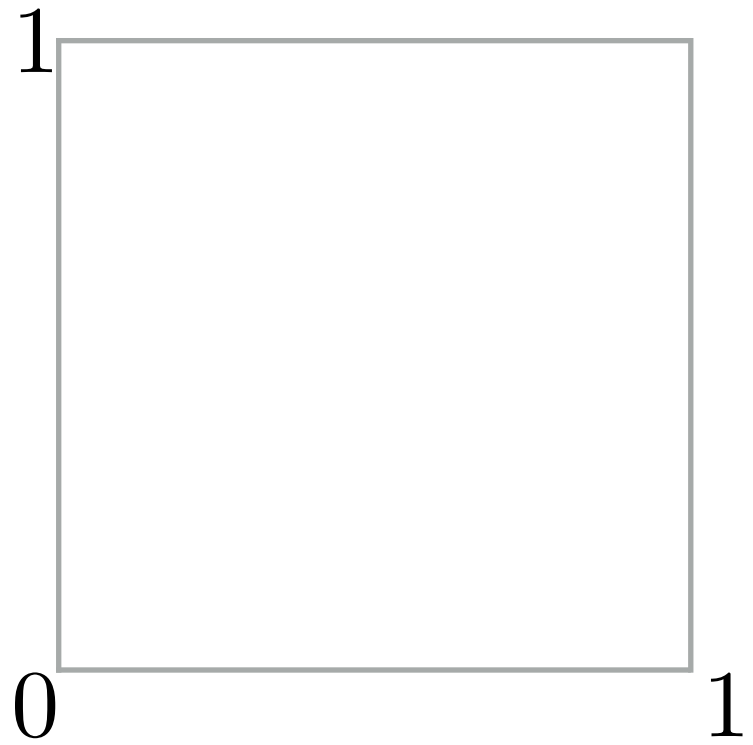


(Node) Exchangeability

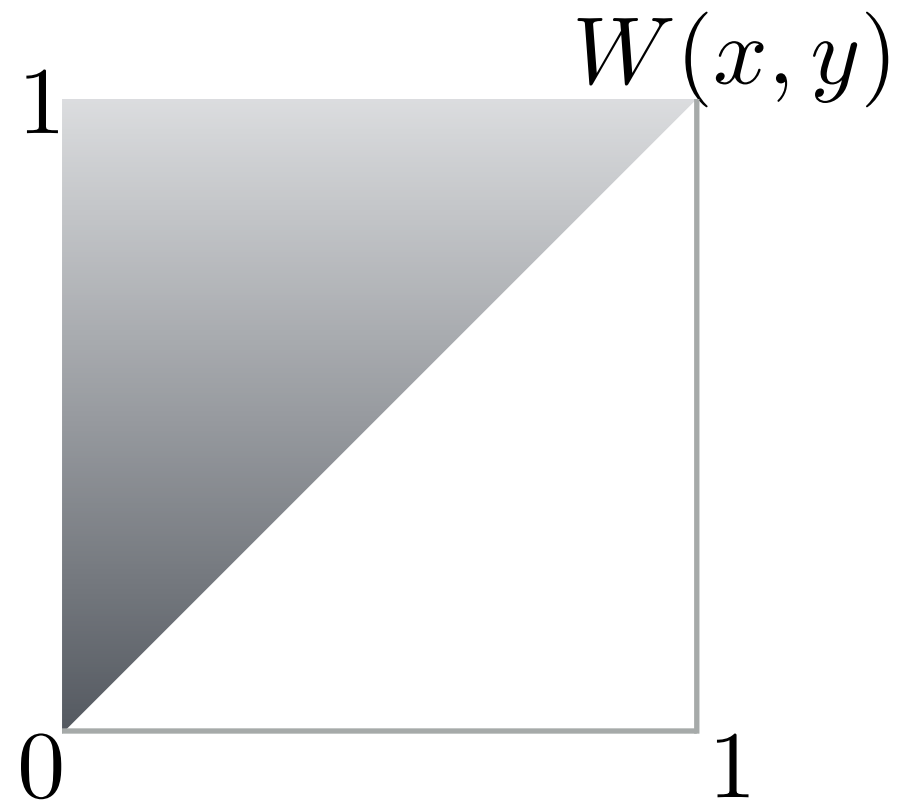


$$p(\text{graph with nodes 1, 2, 3, 4}) = p(\text{graph with nodes 1, 2, 3, 4})$$

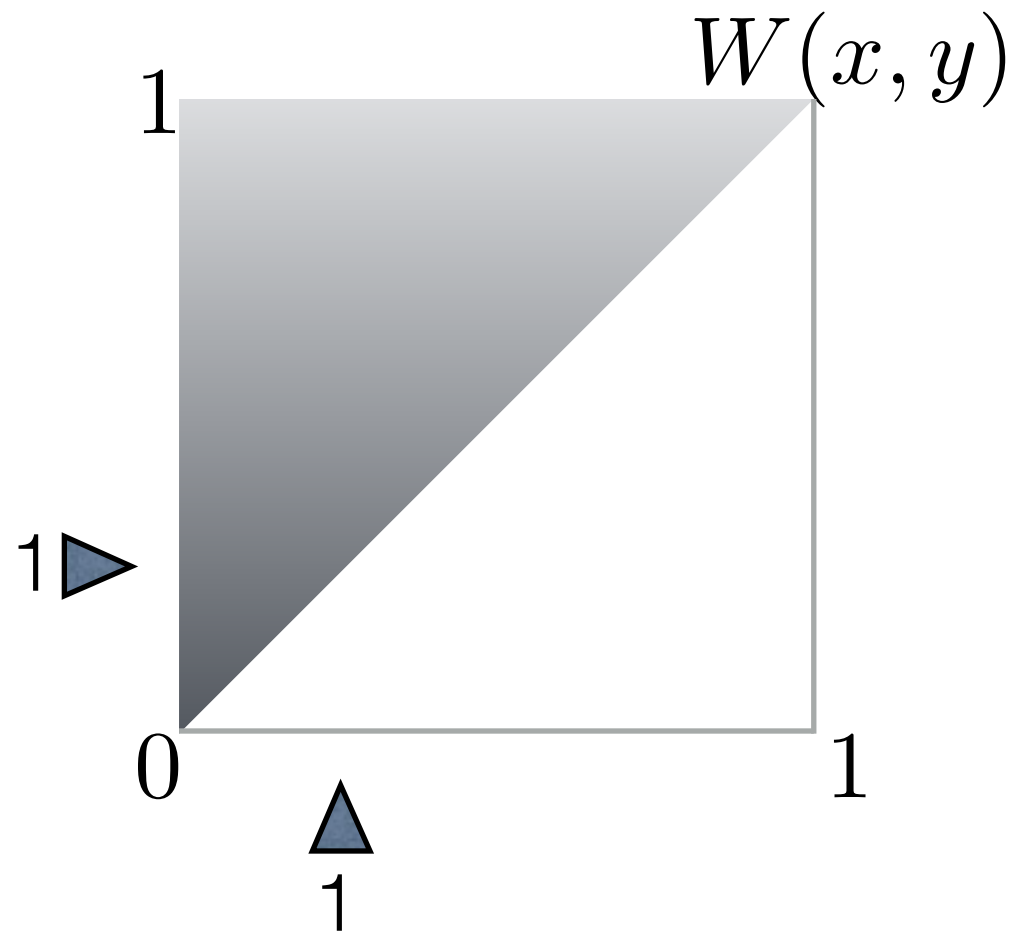
Aldous-Hoover



Aldous-Hoover

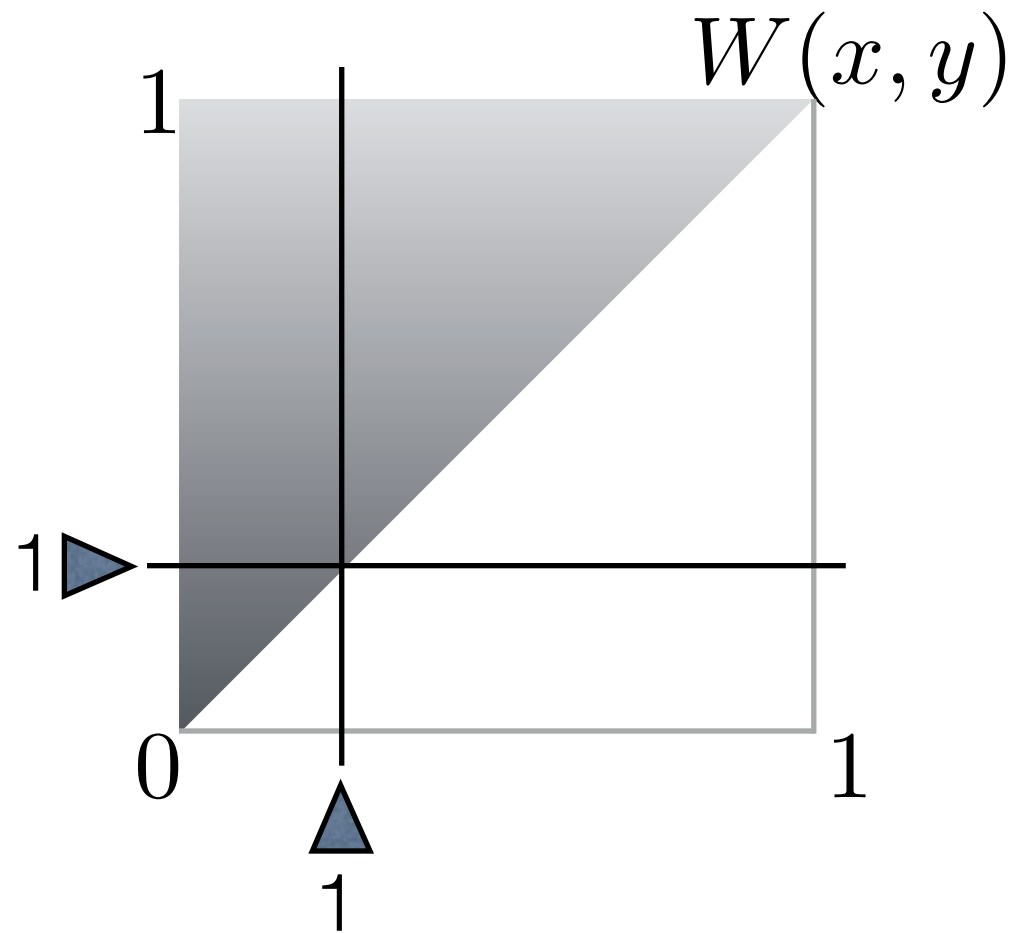


Aldous-Hoover



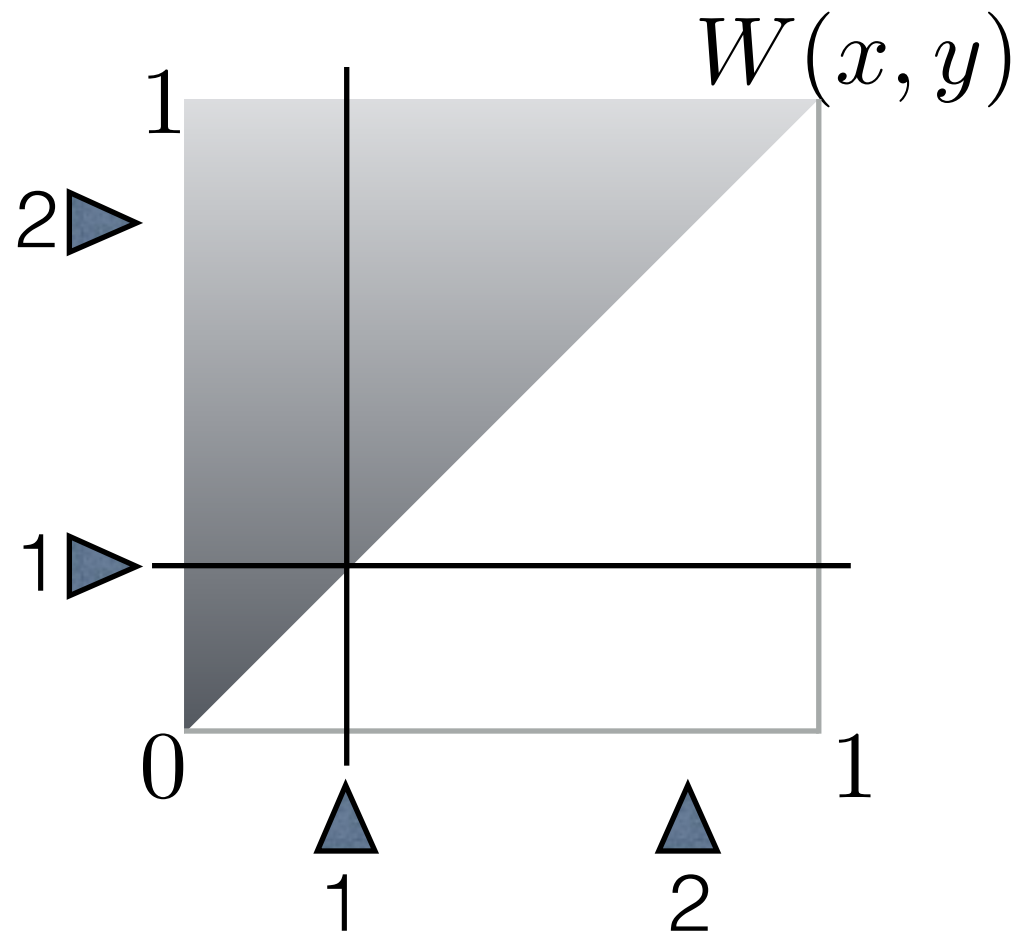
1

Aldous-Hoover



1

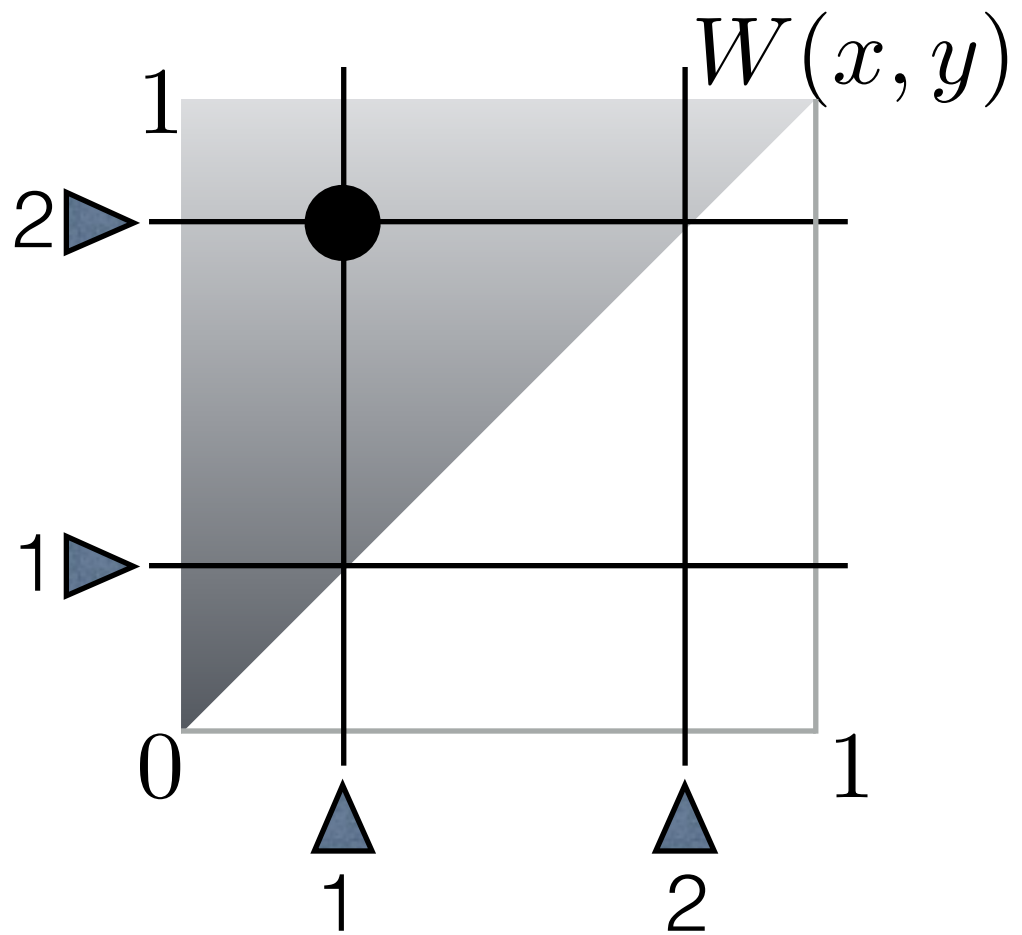
Aldous-Hoover



2

1

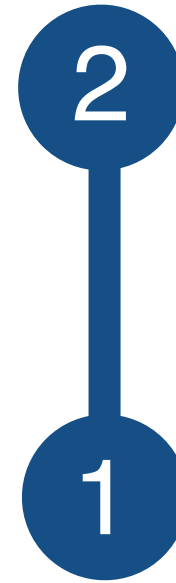
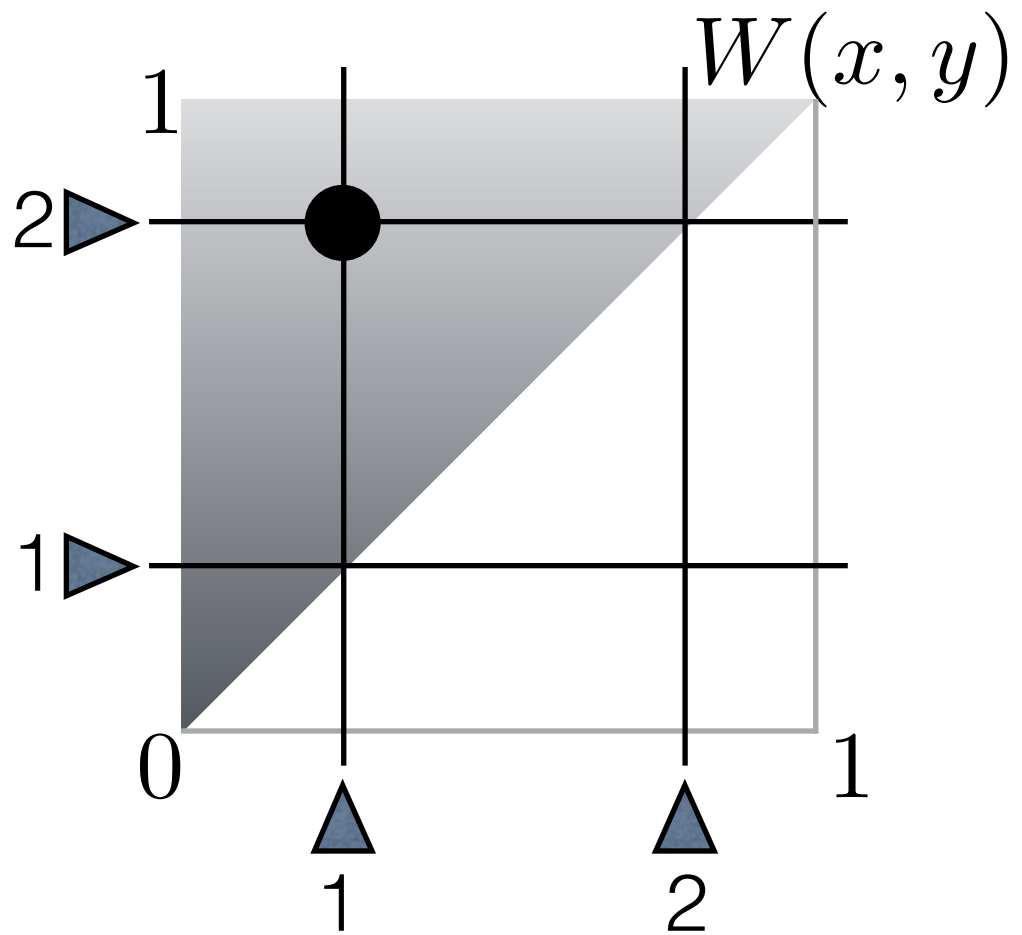
Aldous-Hoover



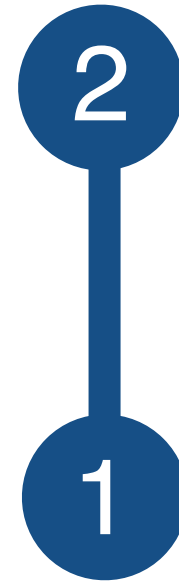
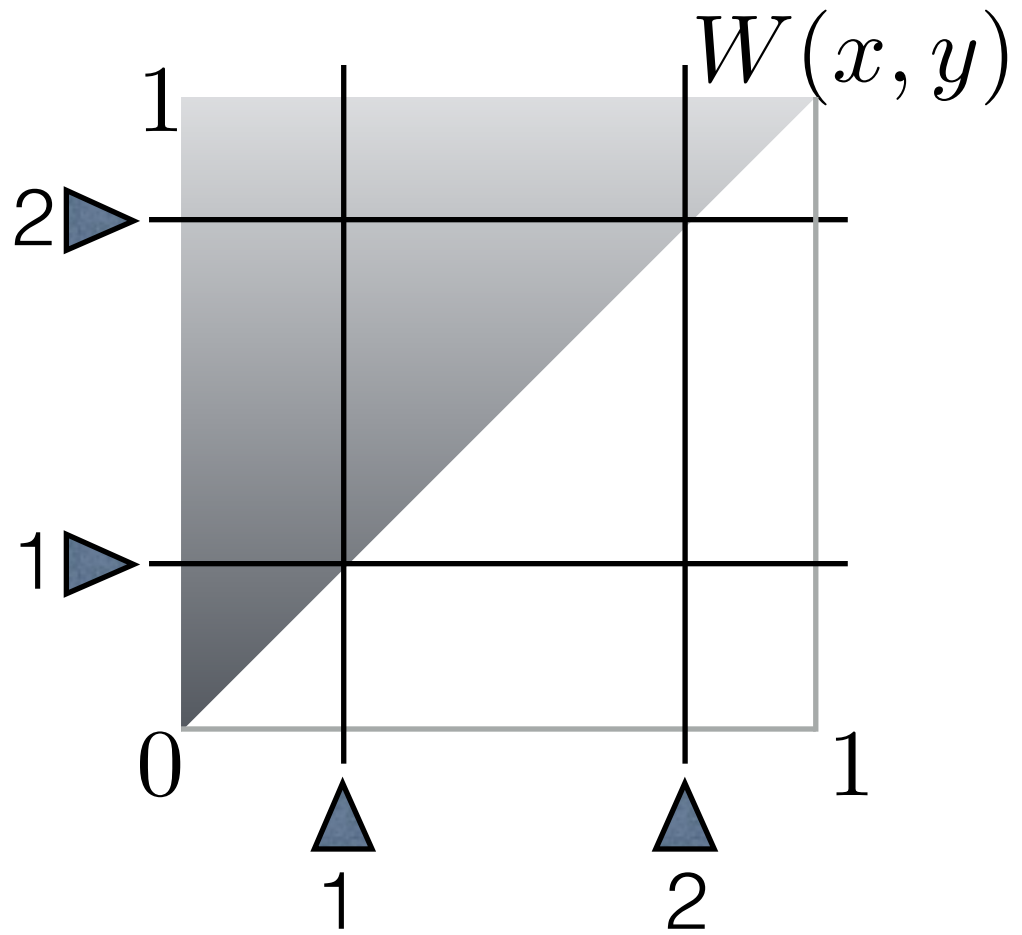
2

1

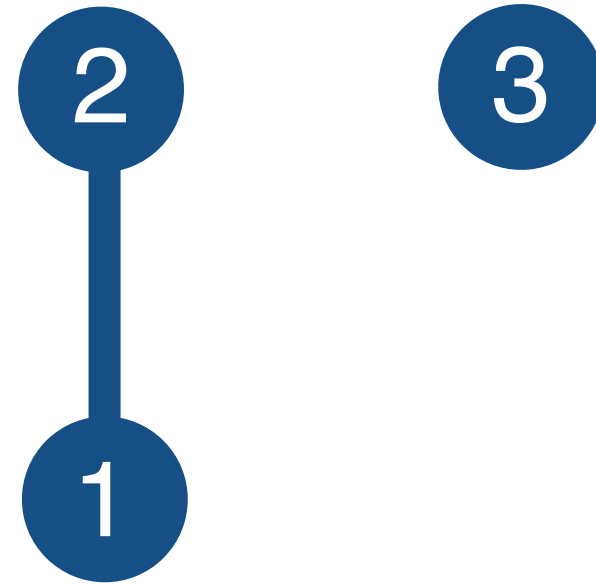
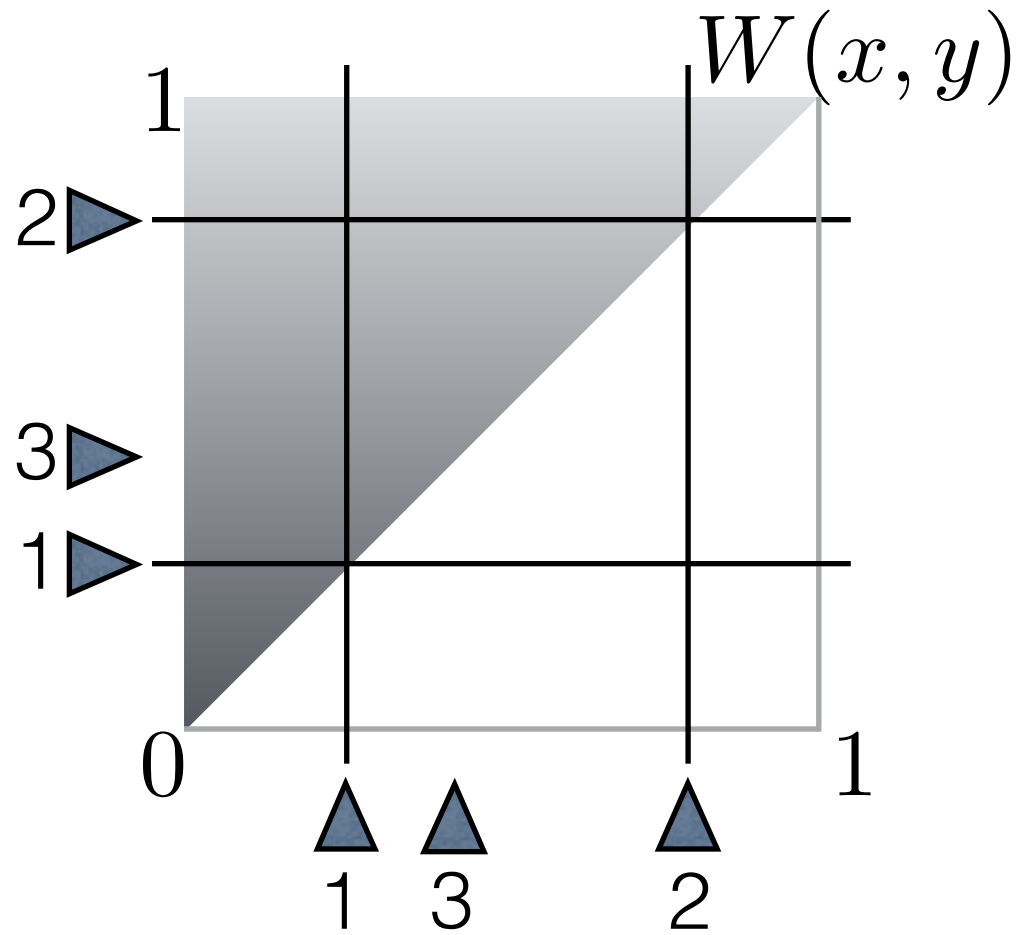
Aldous-Hoover



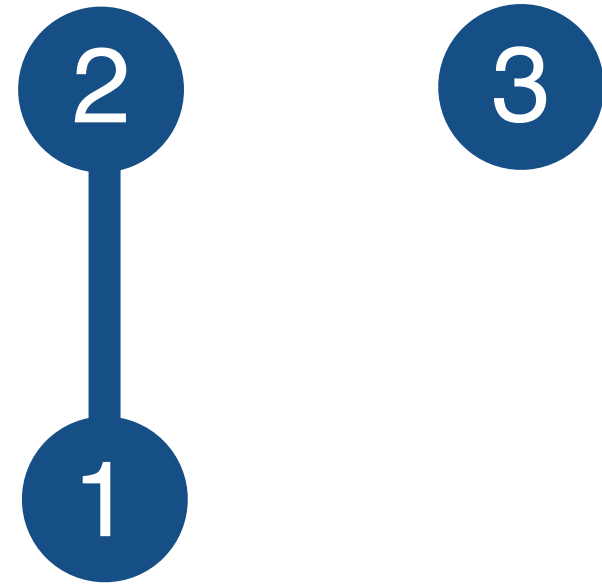
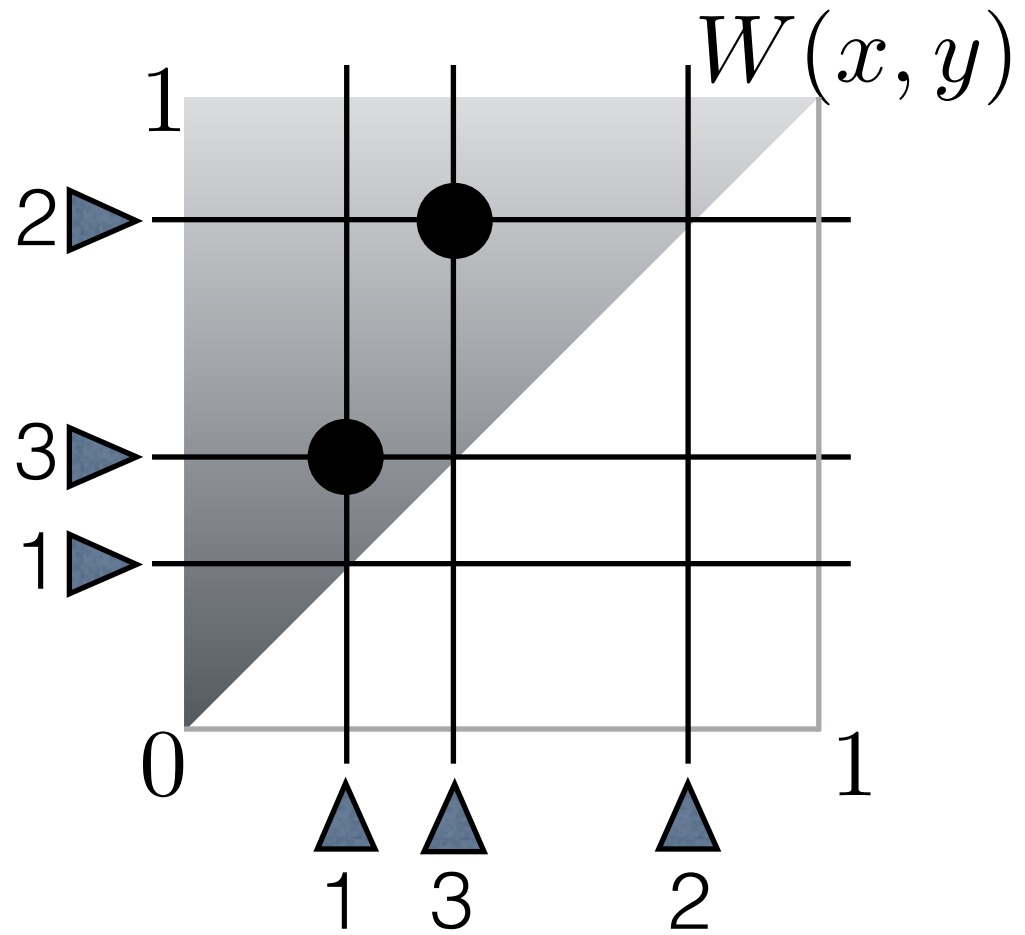
Aldous-Hoover



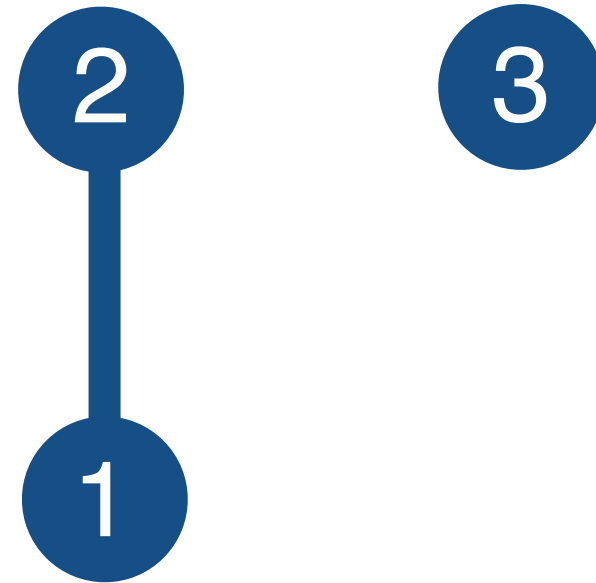
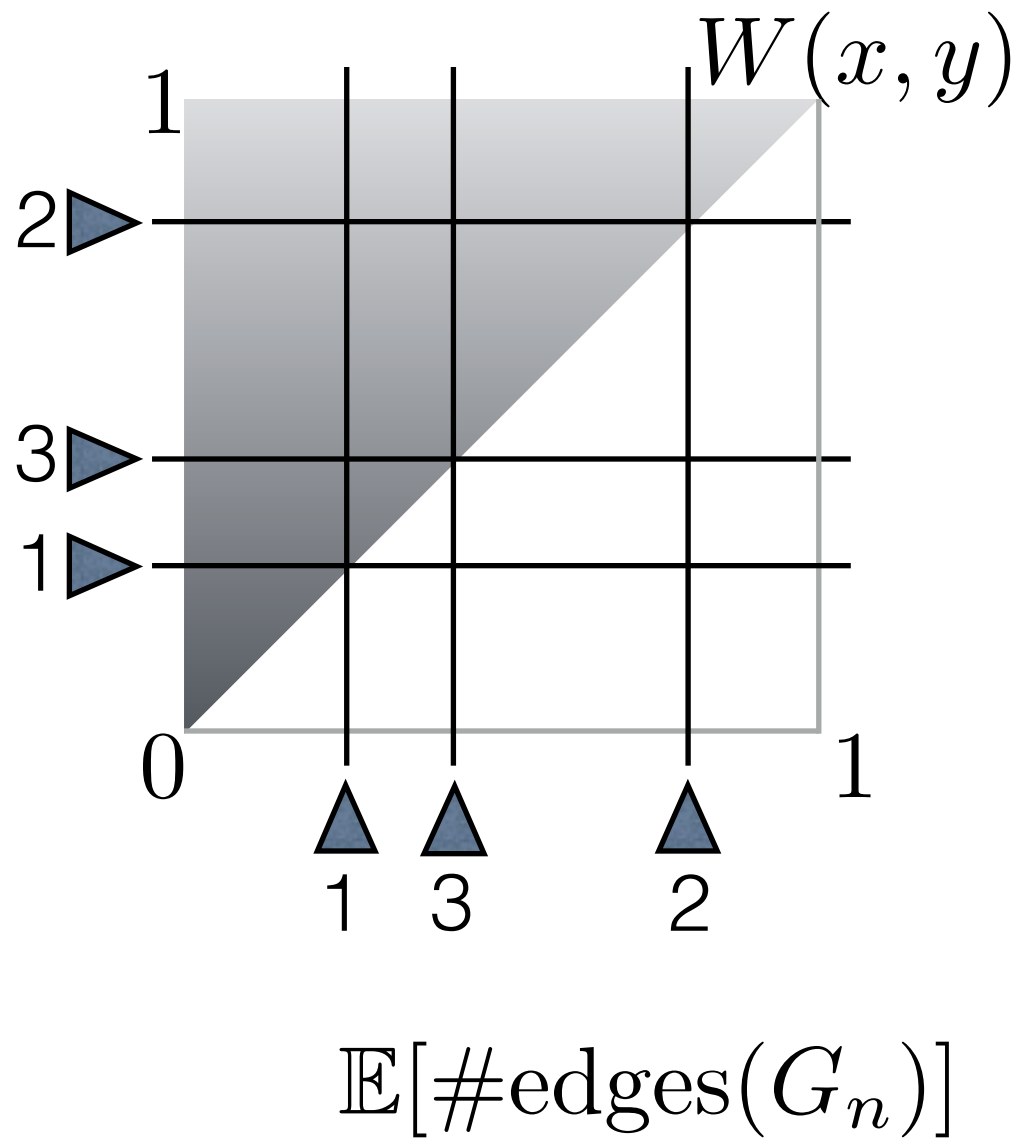
Aldous-Hoover



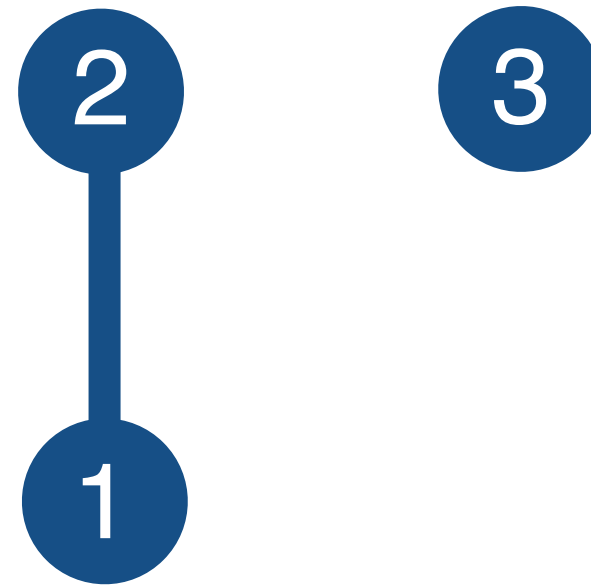
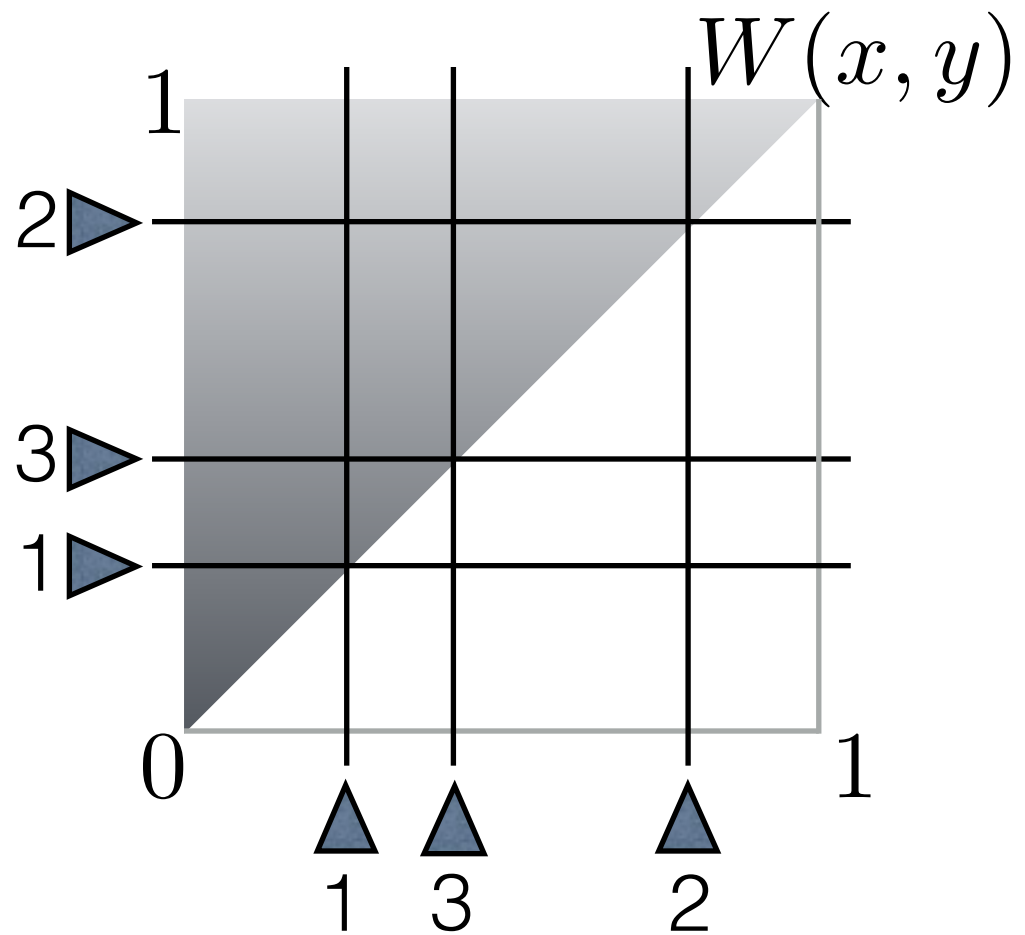
Aldous-Hoover



Aldous-Hoover

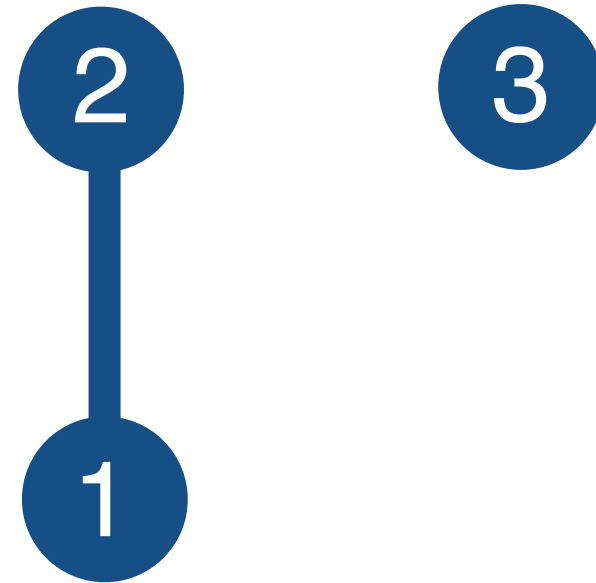
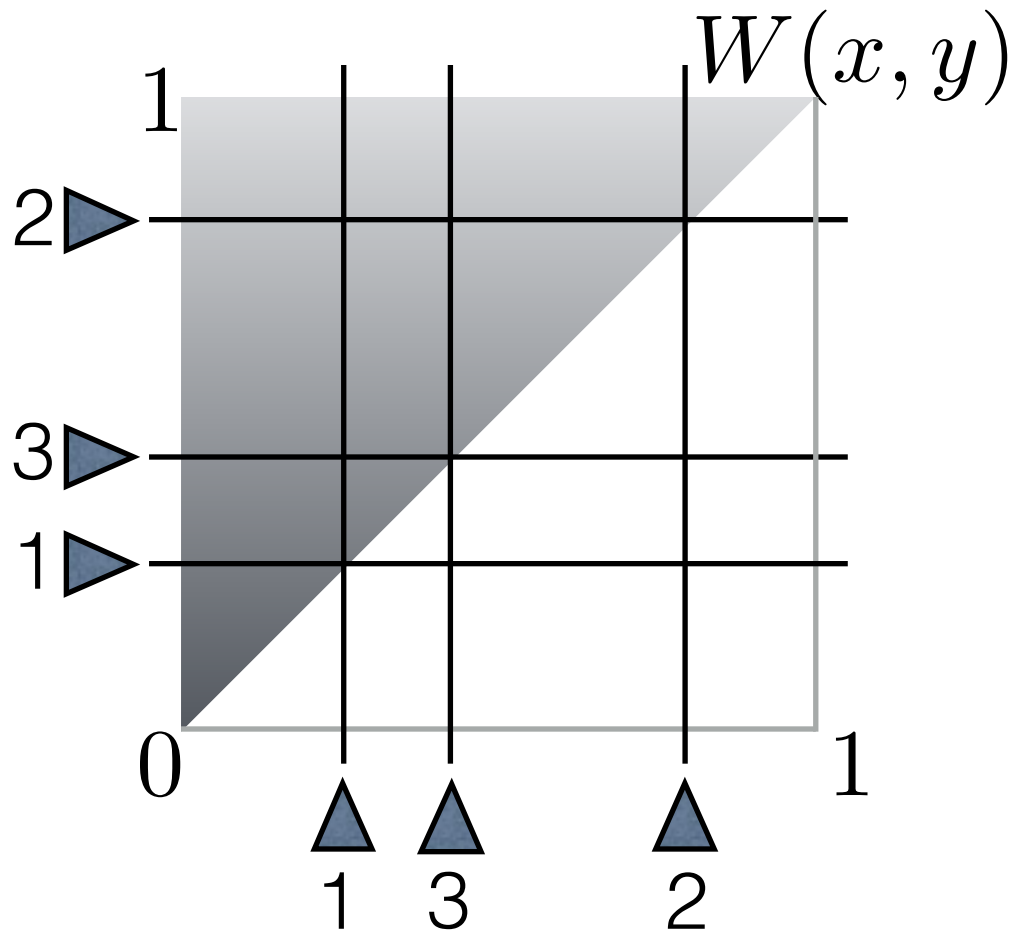


Aldous-Hoover



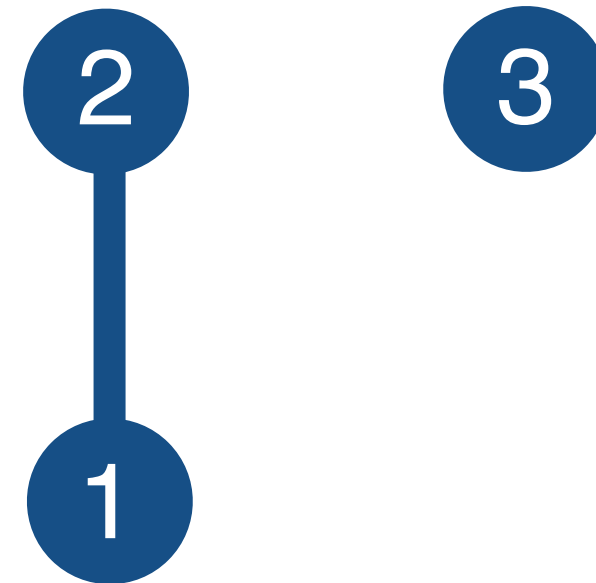
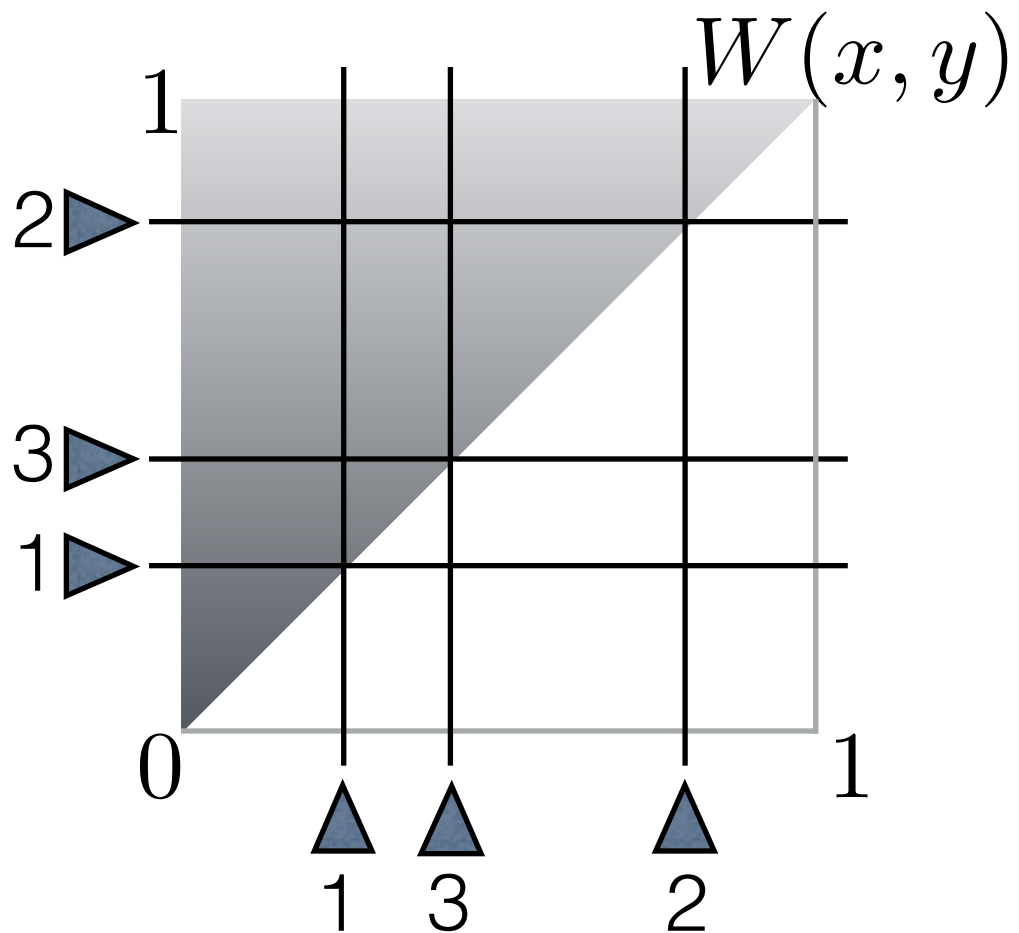
$$\mathbb{E}[\#\text{edges}(G_n)] = \binom{n}{2} \frac{1}{2} \int_0^1 \int_0^1 W(x, y) dx dy$$

Aldous-Hoover



$$\begin{aligned}\mathbb{E}[\#\text{edges}(G_n)] &= \binom{n}{2} \frac{1}{2} \int_0^1 \int_0^1 W(x, y) dx dy \\ &= cn^2 = c \cdot \#\text{vertices}(G_n)^2\end{aligned}$$

Aldous-Hoover



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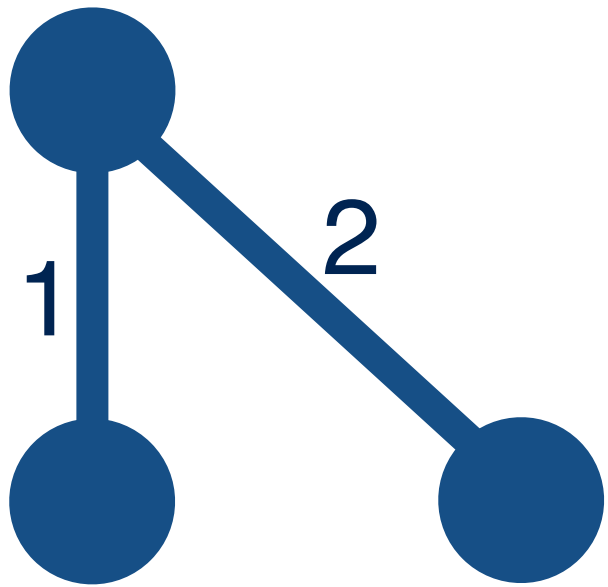
$$= cn^2 = c \cdot \#\text{vertices}(G_n)^2$$

(Might be empty)

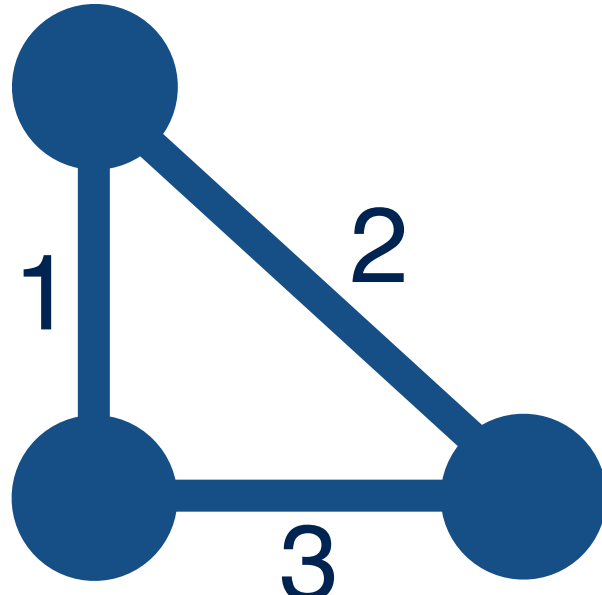
Sequence of graphs



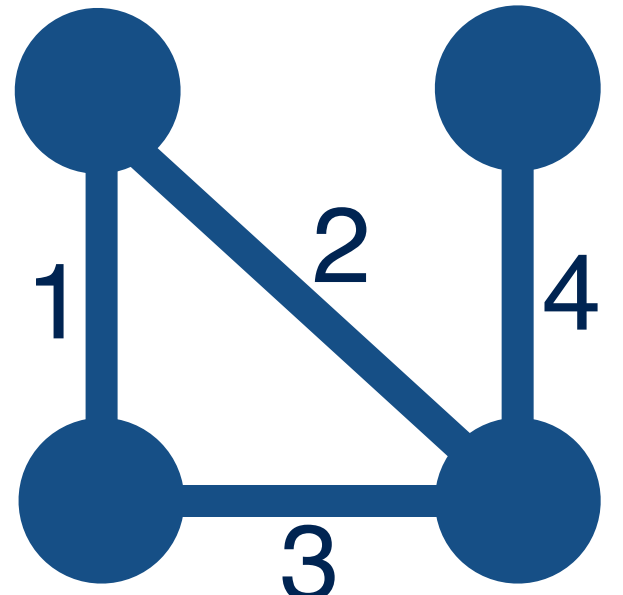
G_1



G_2



G_3

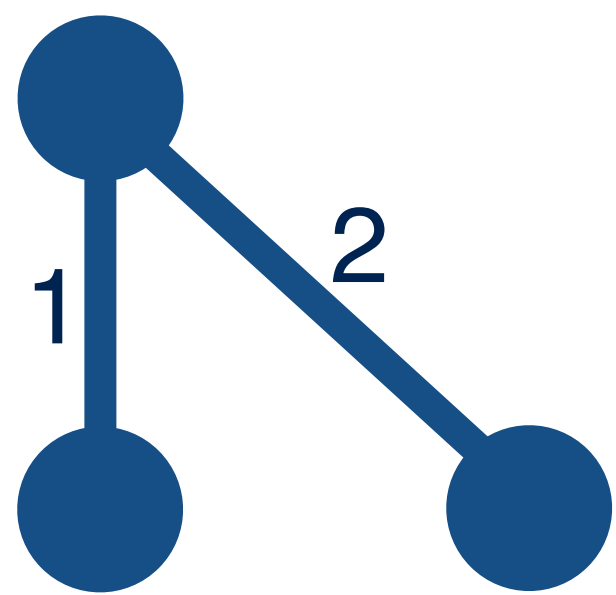


G_4

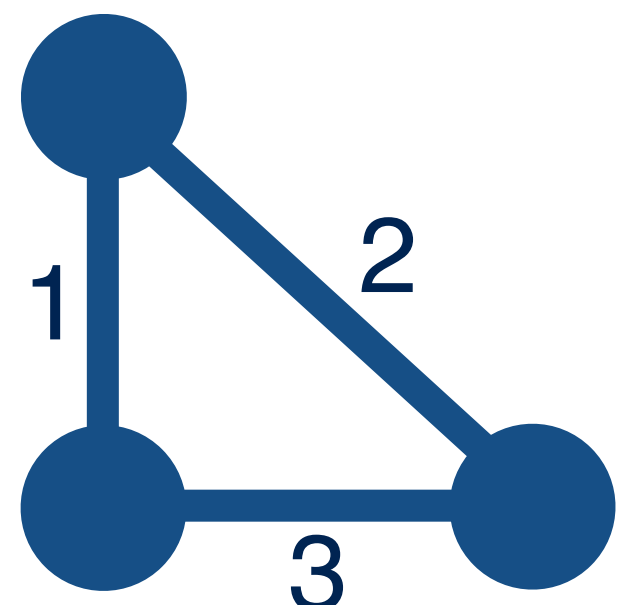
Sequence of graphs



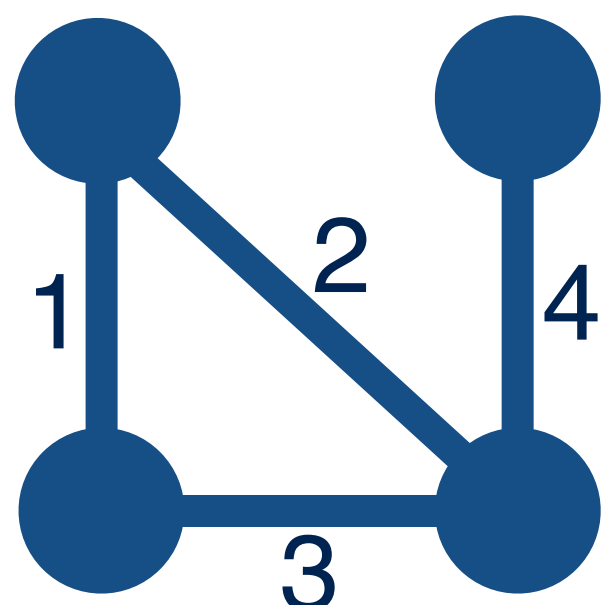
G_1



G_2



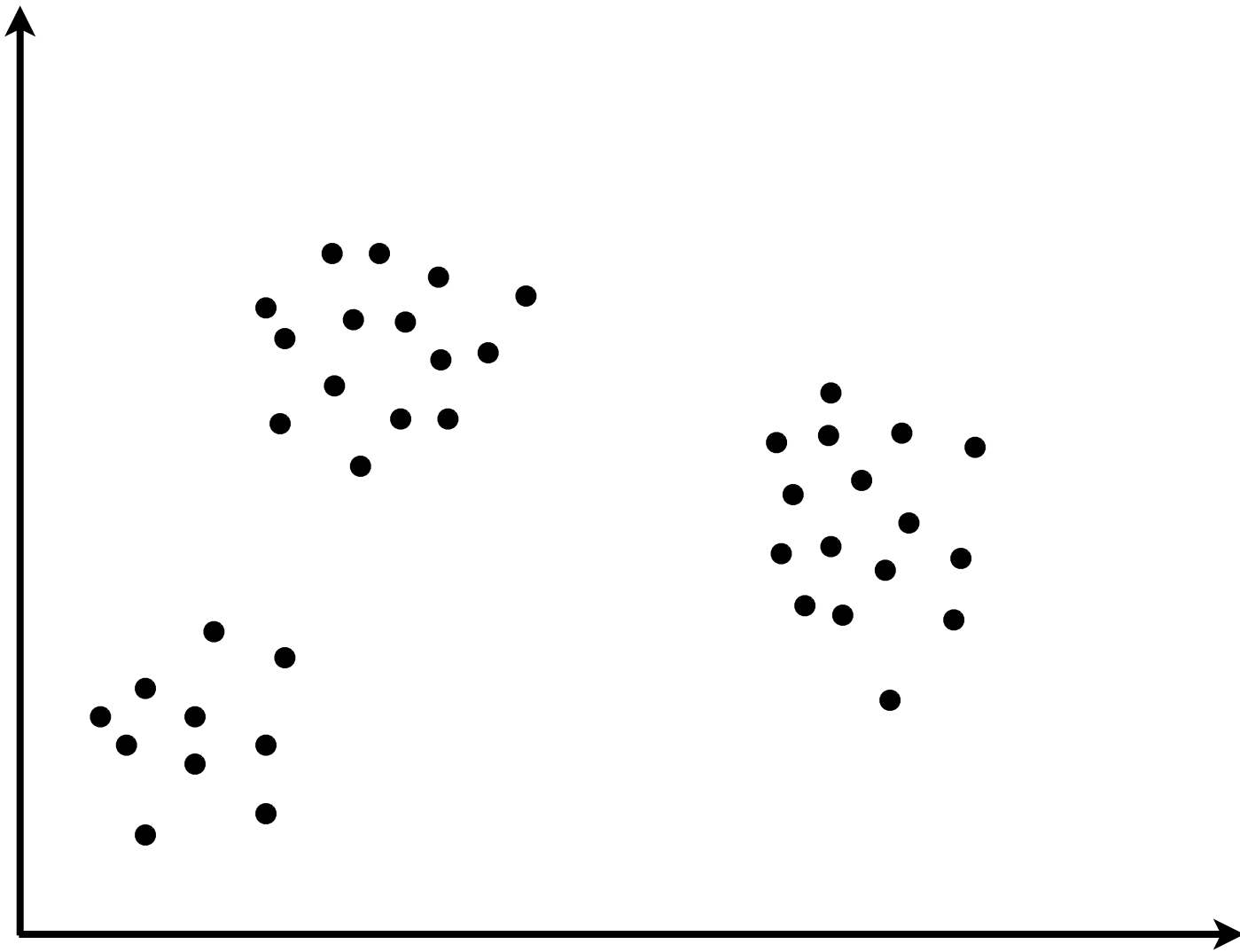
G_3



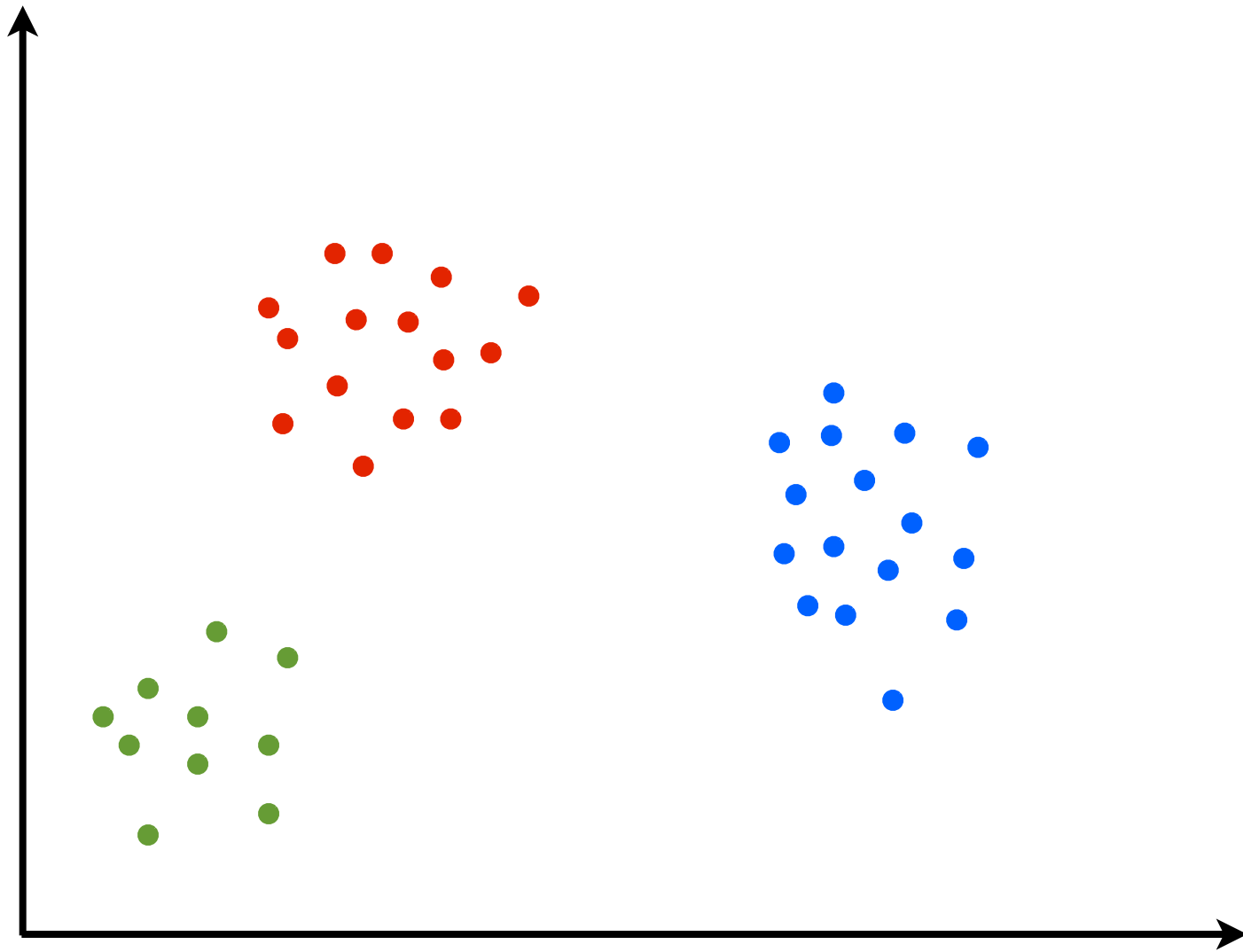
G_4

$$p(\text{Graph with edges } 1, 2, 3, 4 \text{ as in } G_4) = p(\text{Graph with edges } 2, 4, 3, 1 \text{ as in } G_4)$$

Clustering/partition

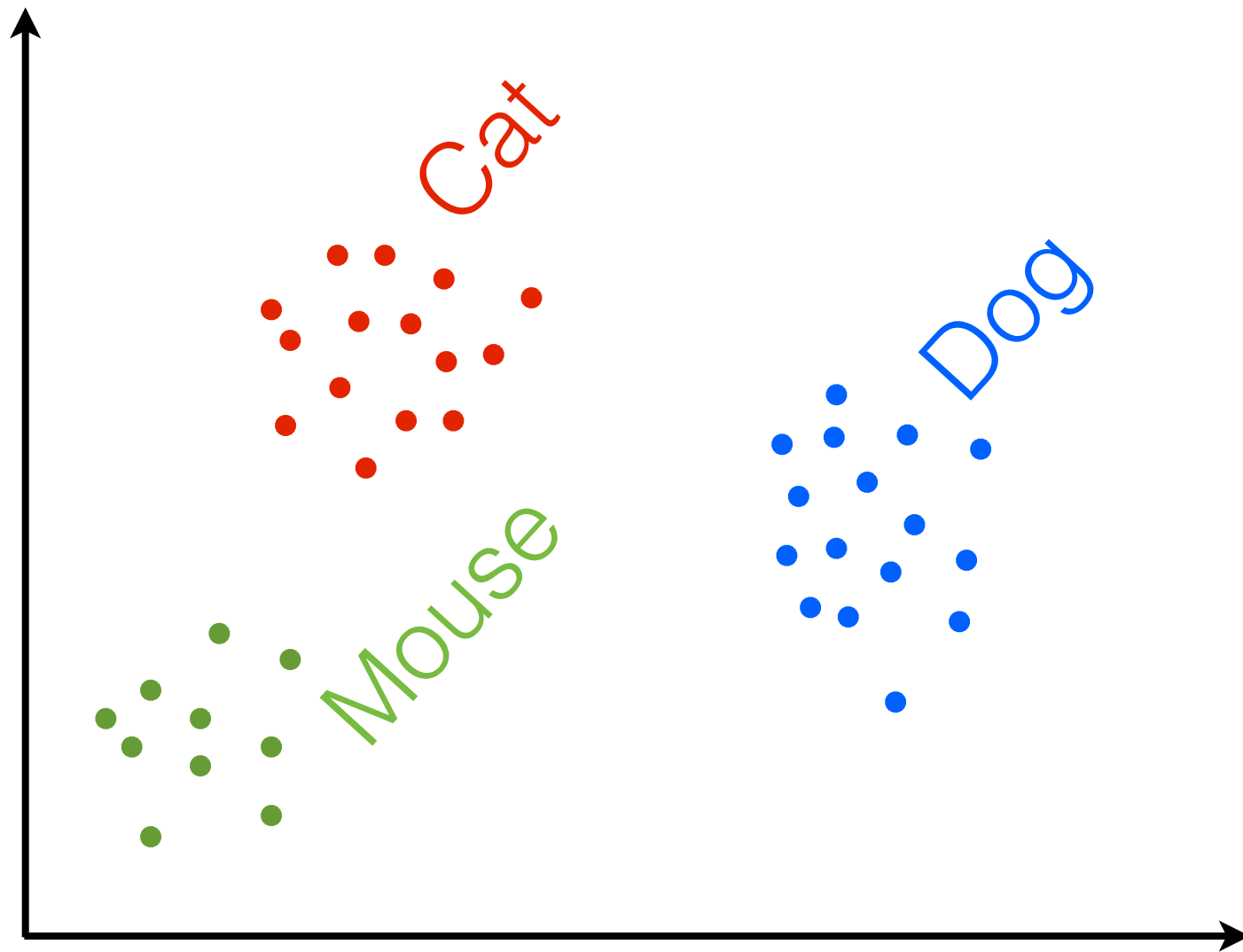


Clustering/partition



“Clusters”,
“classes”,
“blocks of a partition”

Clustering/partition



“Clusters”,
“classes”,
“blocks of a partition”

Clustering/partition

| | Cat | Dog | Mouse | Lizard | Sheep |
|-----------|-------|-------|-------|--------|-------|
| Picture 1 | Black | White | White | White | White |
| Picture 2 | Black | White | White | White | White |
| Picture 3 | White | Black | White | White | White |
| Picture 4 | White | White | Black | White | White |
| Picture 5 | White | Black | White | White | White |
| Picture 6 | White | White | White | Black | White |
| Picture 7 | Black | White | White | White | White |

Feature allocation

| | Cat | Dog | Mouse | Lizard | Sheep |
|-----------|-------|-------|-------|--------|-------|
| Picture 1 | Black | White | White | White | Black |
| Picture 2 | Black | White | White | Black | Black |
| Picture 3 | Black | Black | White | Black | Black |
| Picture 4 | White | White | Black | Black | Black |
| Picture 5 | White | Black | White | White | Black |
| Picture 6 | White | White | White | Black | Black |
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“Features”,
“topics”

Feature allocation

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| Picture 1 | Black | White | White | White | Black |
| Picture 2 | Black | White | White | Black | Black |
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| Picture 4 | White | White | Black | Black | Black |
| Picture 5 | White | Black | White | White | Black |
| Picture 6 | White | White | White | Black | Black |
| Picture 7 | White | White | White | White | White |

“Features”,
“topics”

- Exchangeable
- Finite # of features per data point

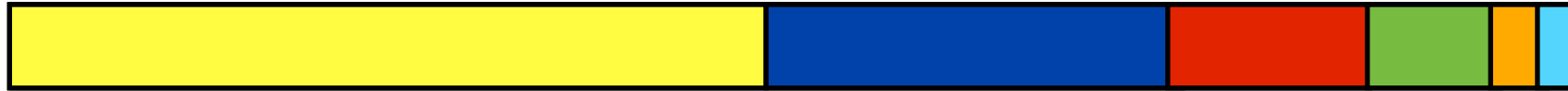
Paintboxes

Exchangeable partition: Kingman paintbox



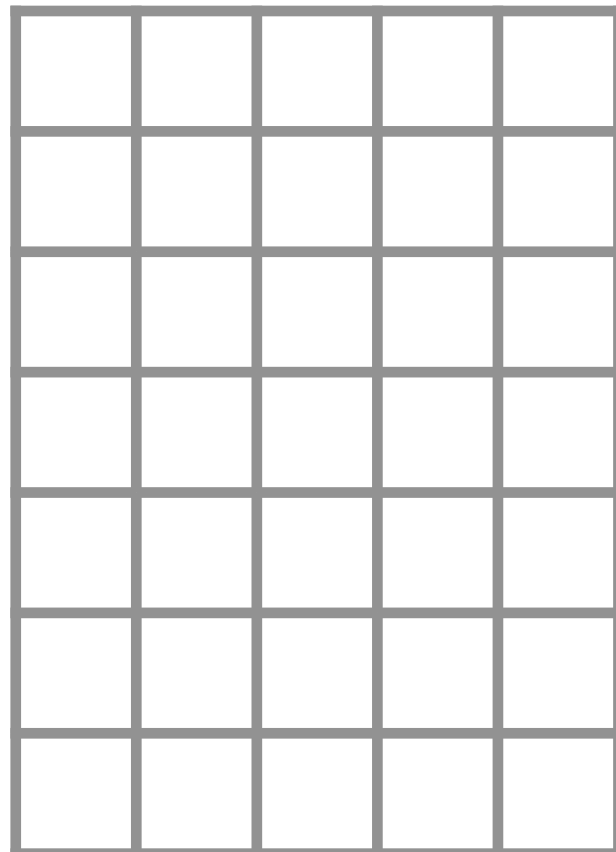
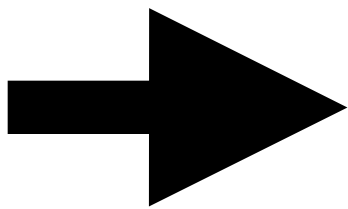
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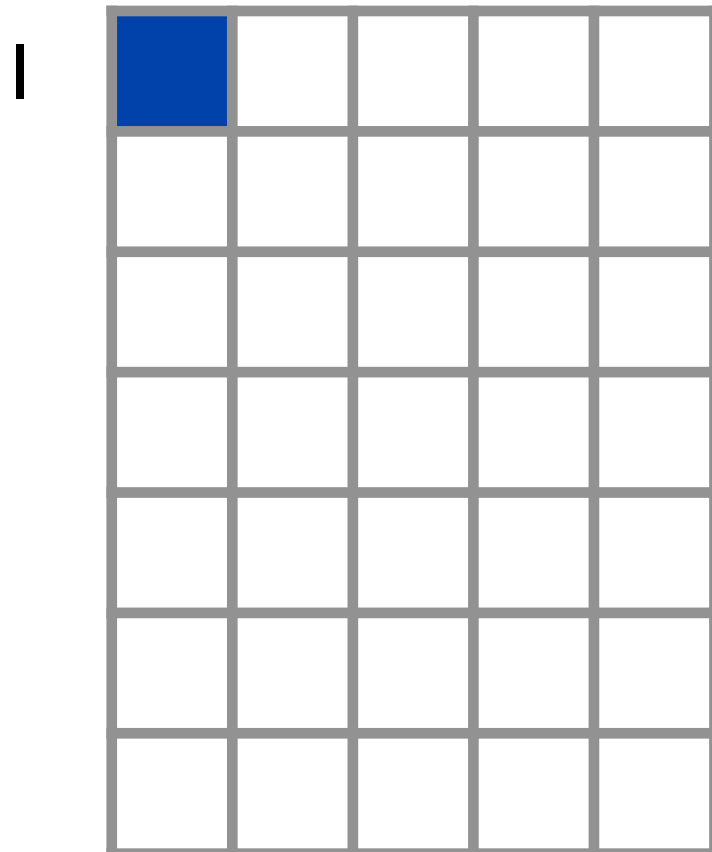
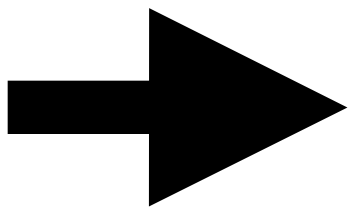
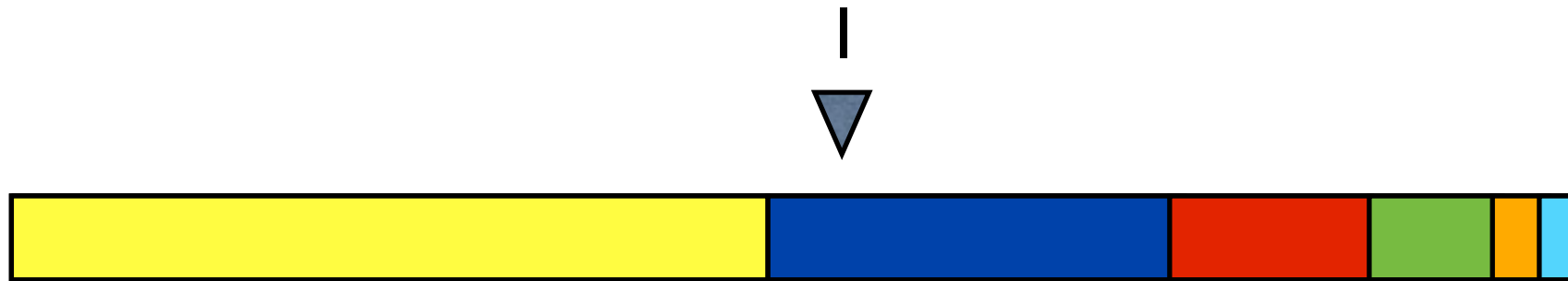
Paintboxes

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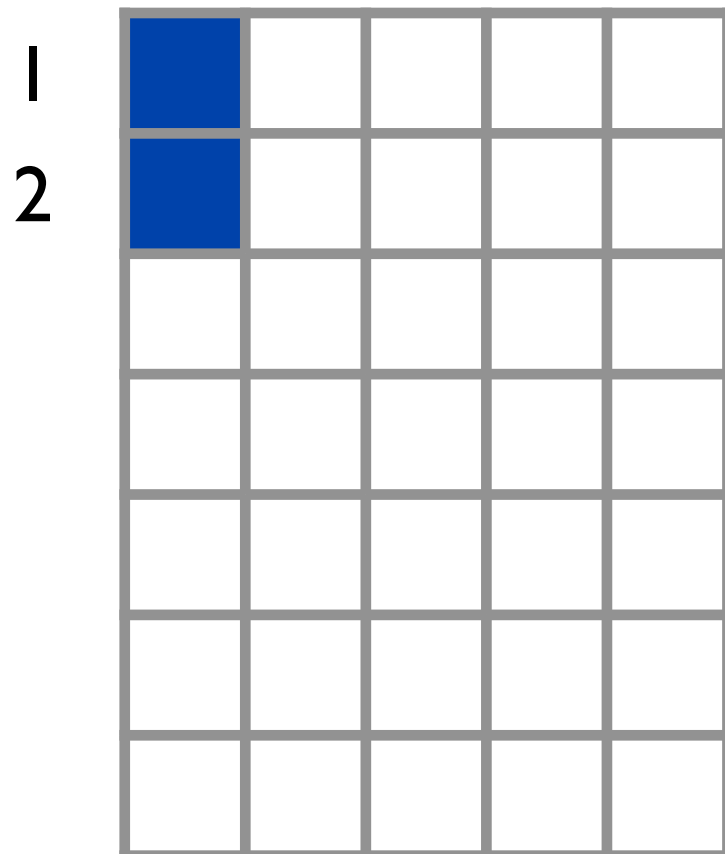
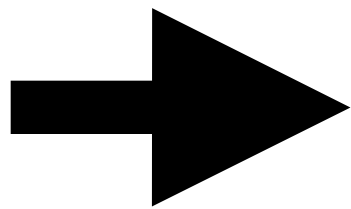
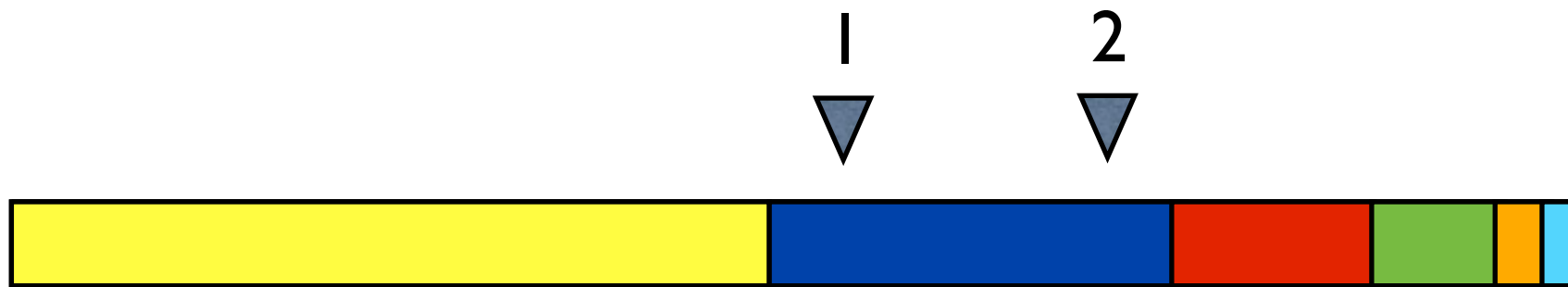
Paintboxes

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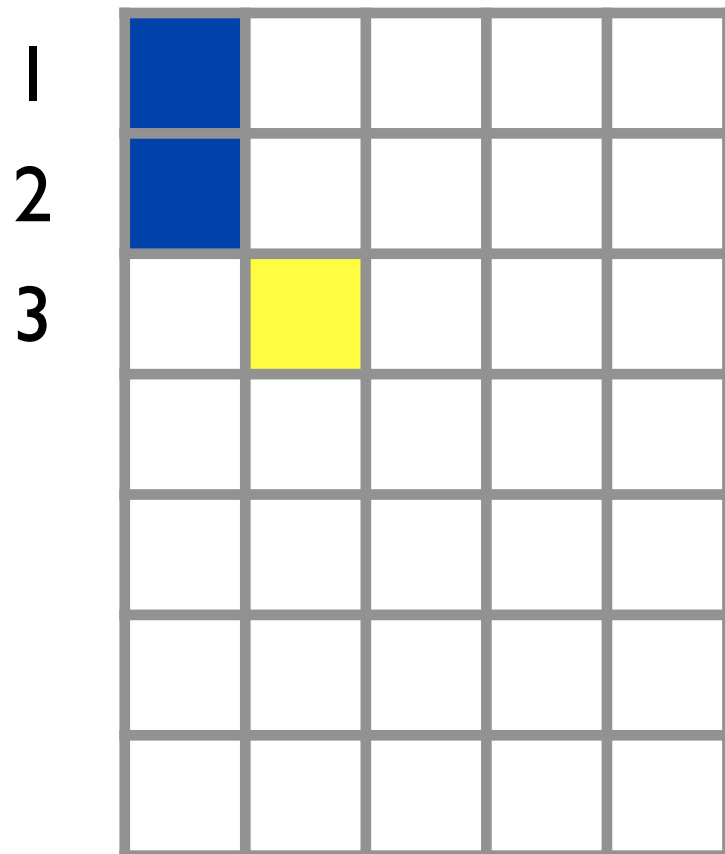
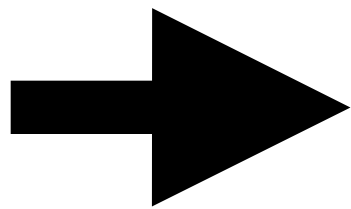
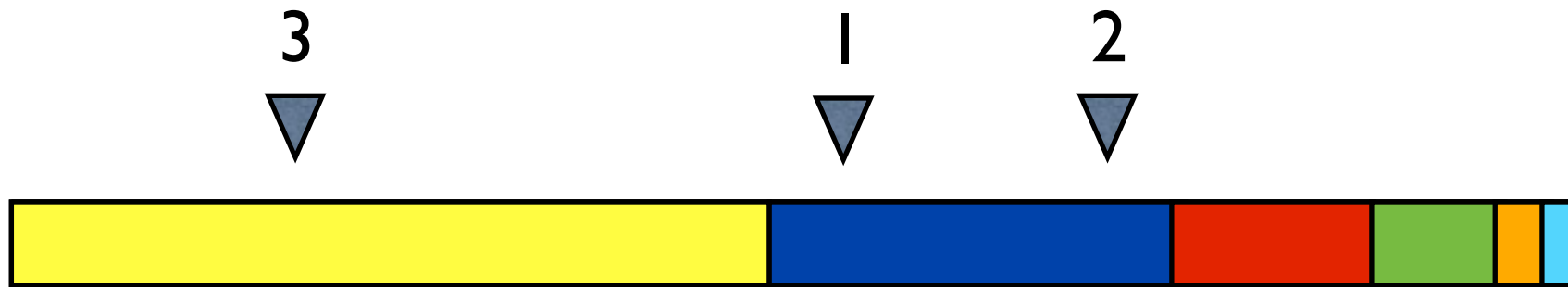
Paintboxes

Exchangeable partition: Kingman paintbox



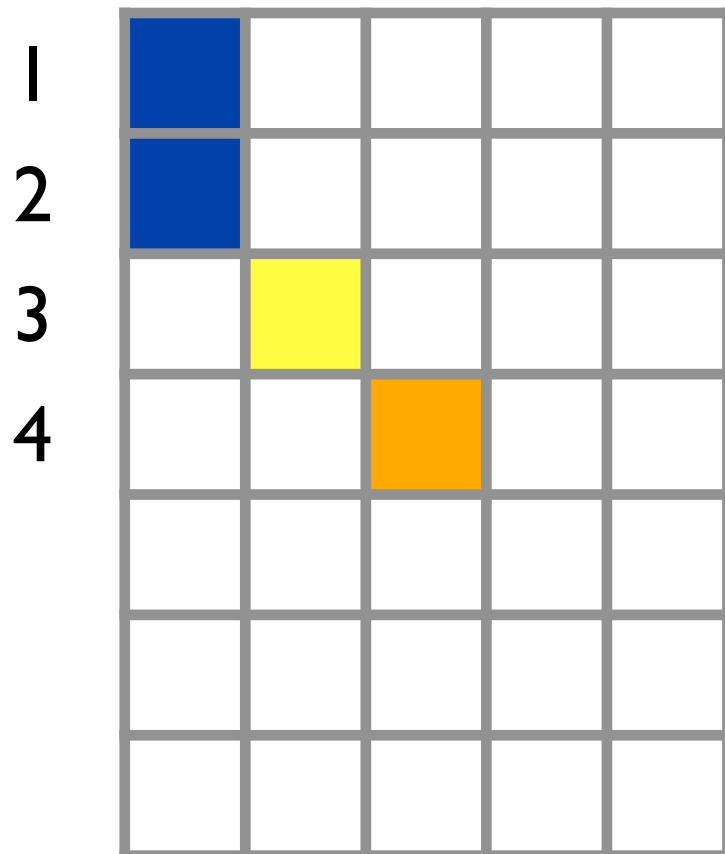
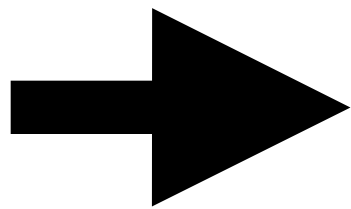
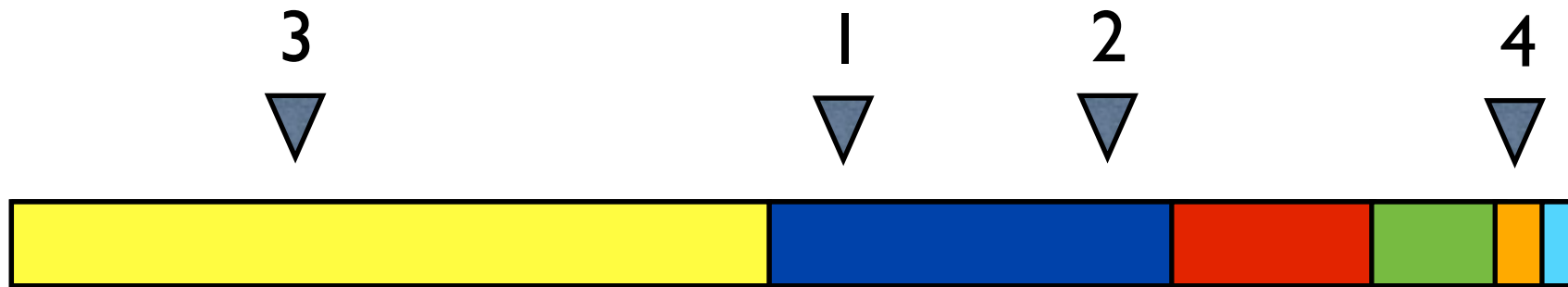
Paintboxes

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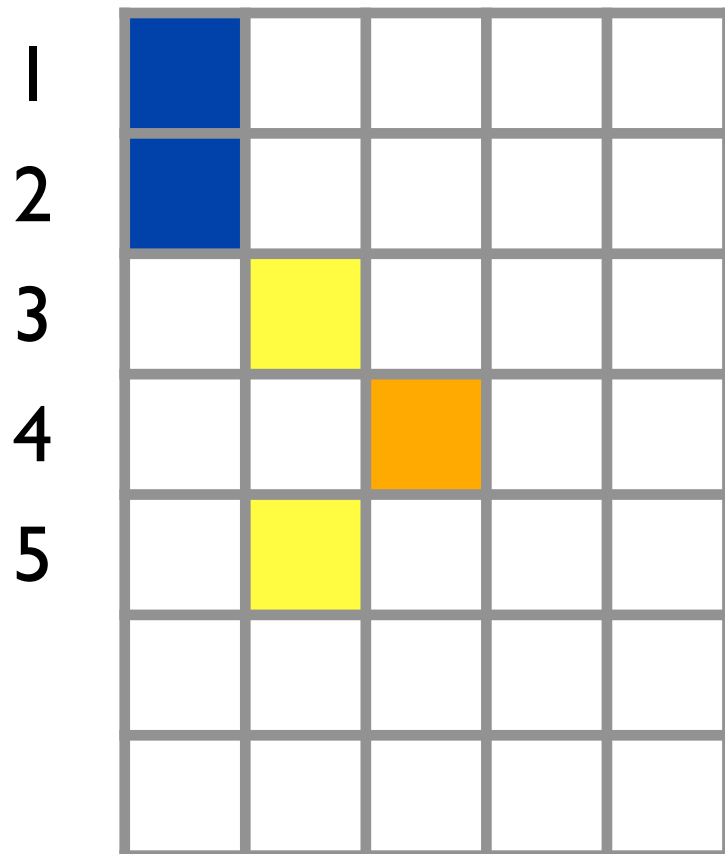
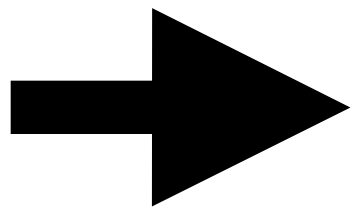
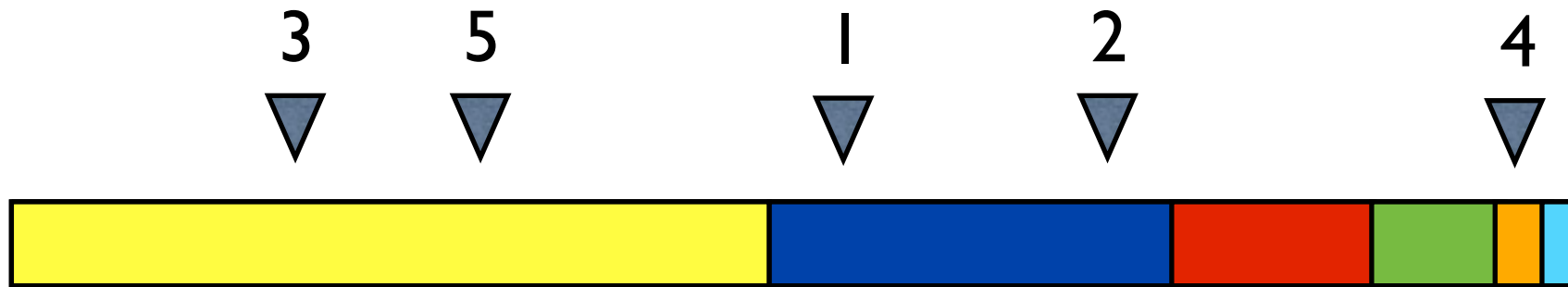
Paintboxes

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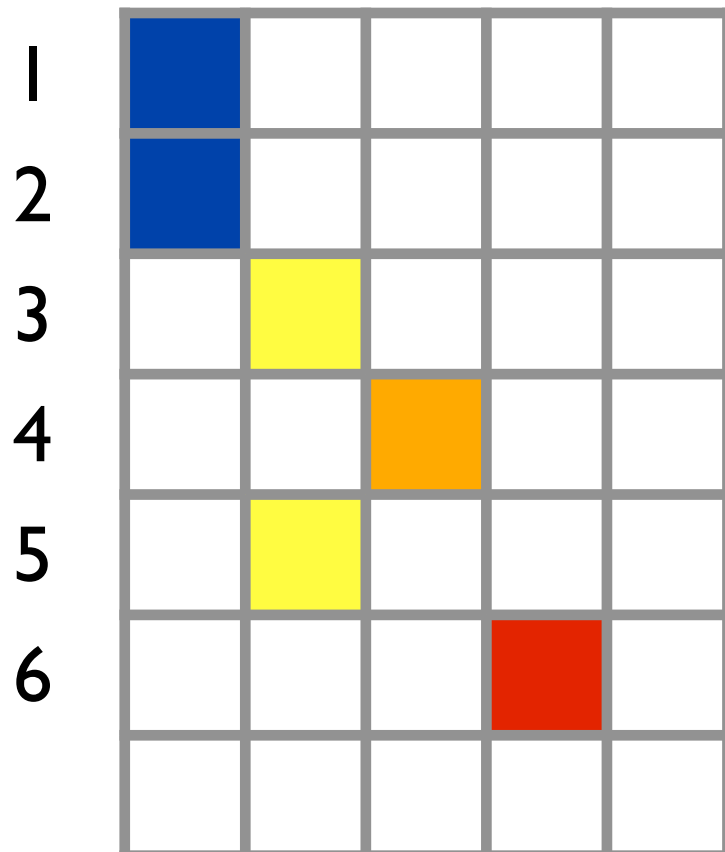
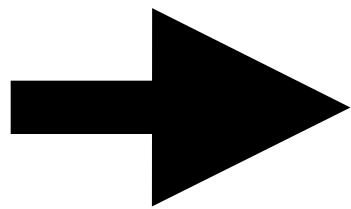
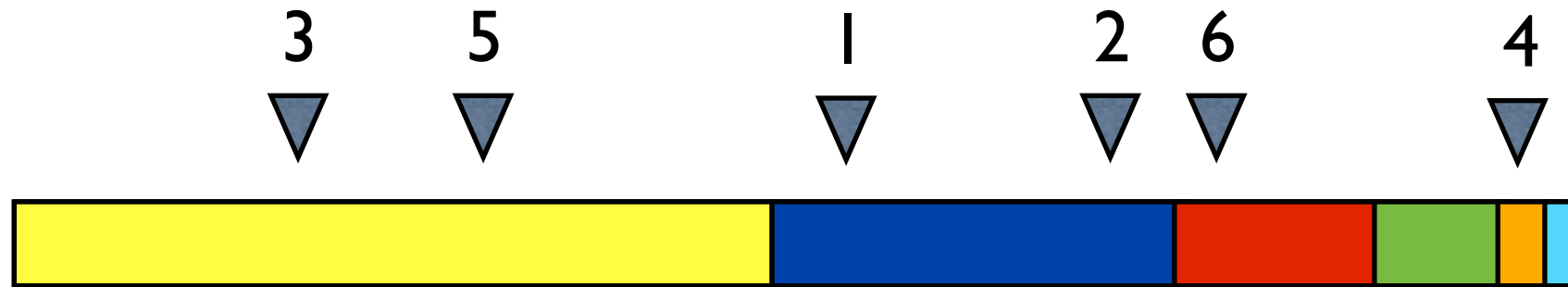
Paintboxes

Exchangeable partition: Kingman paintbox



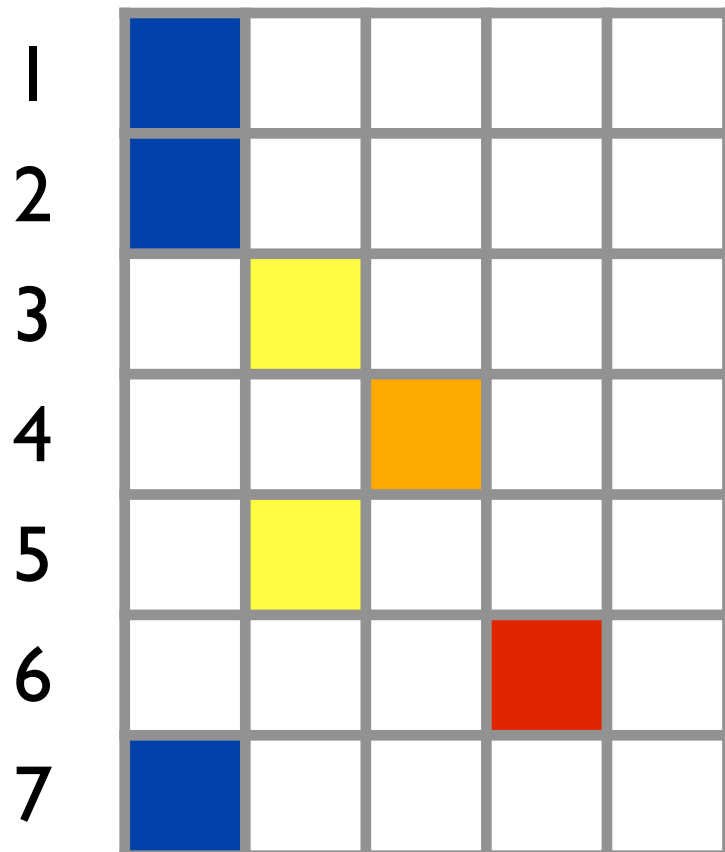
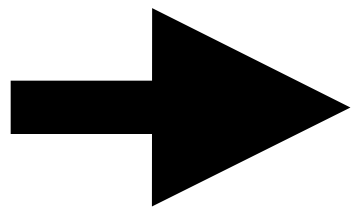
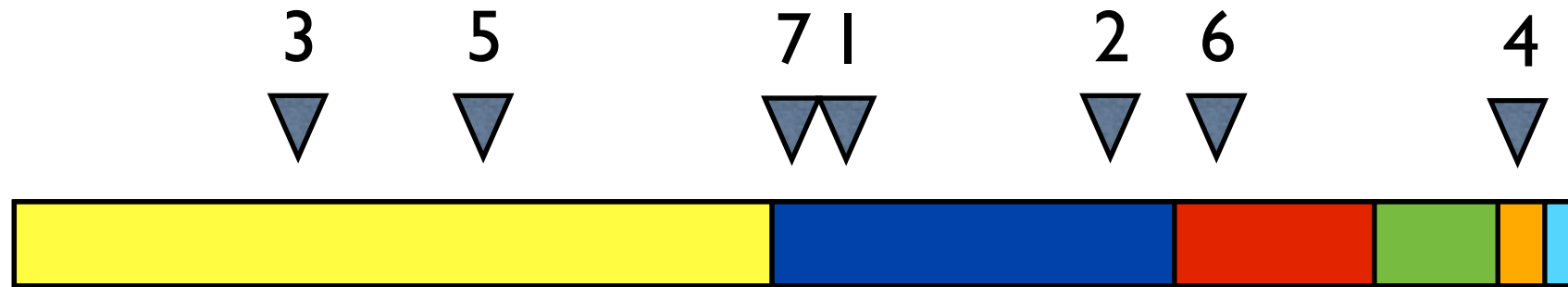
Paintboxes

Exchangeable partition: Kingman paintbox



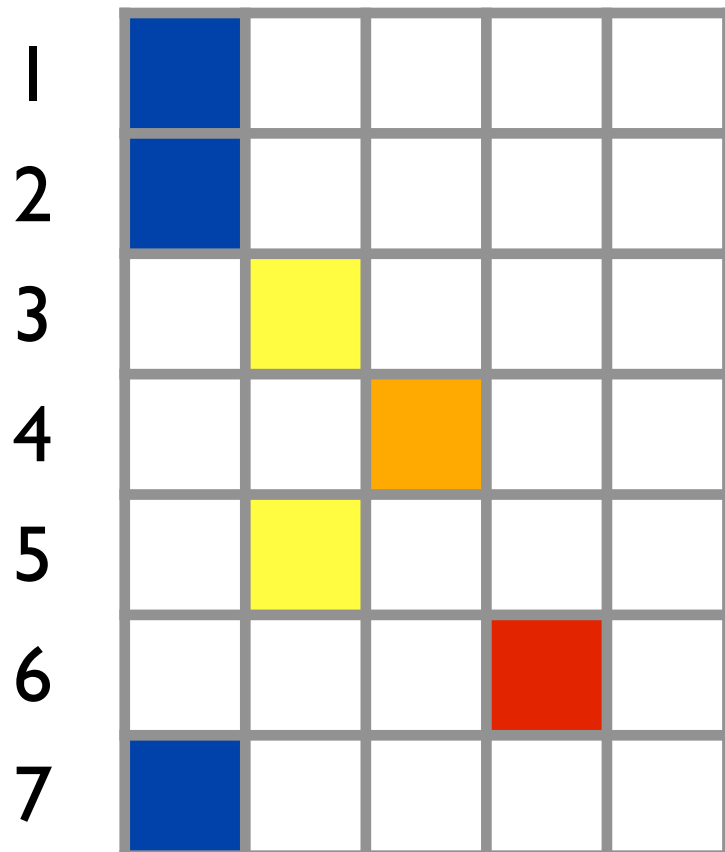
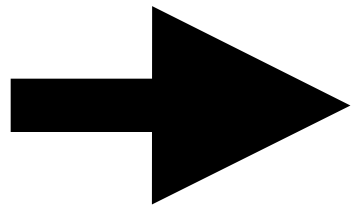
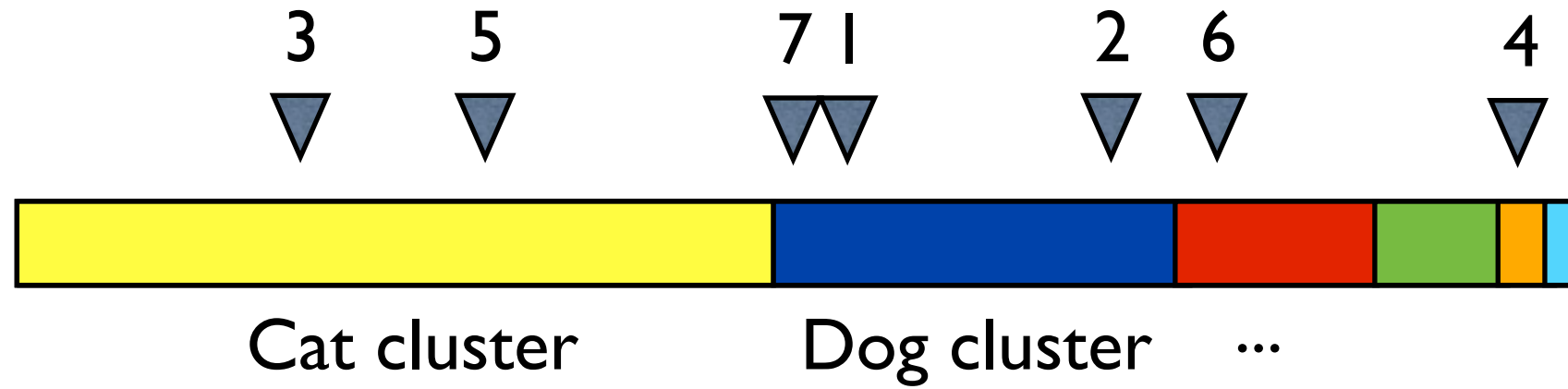
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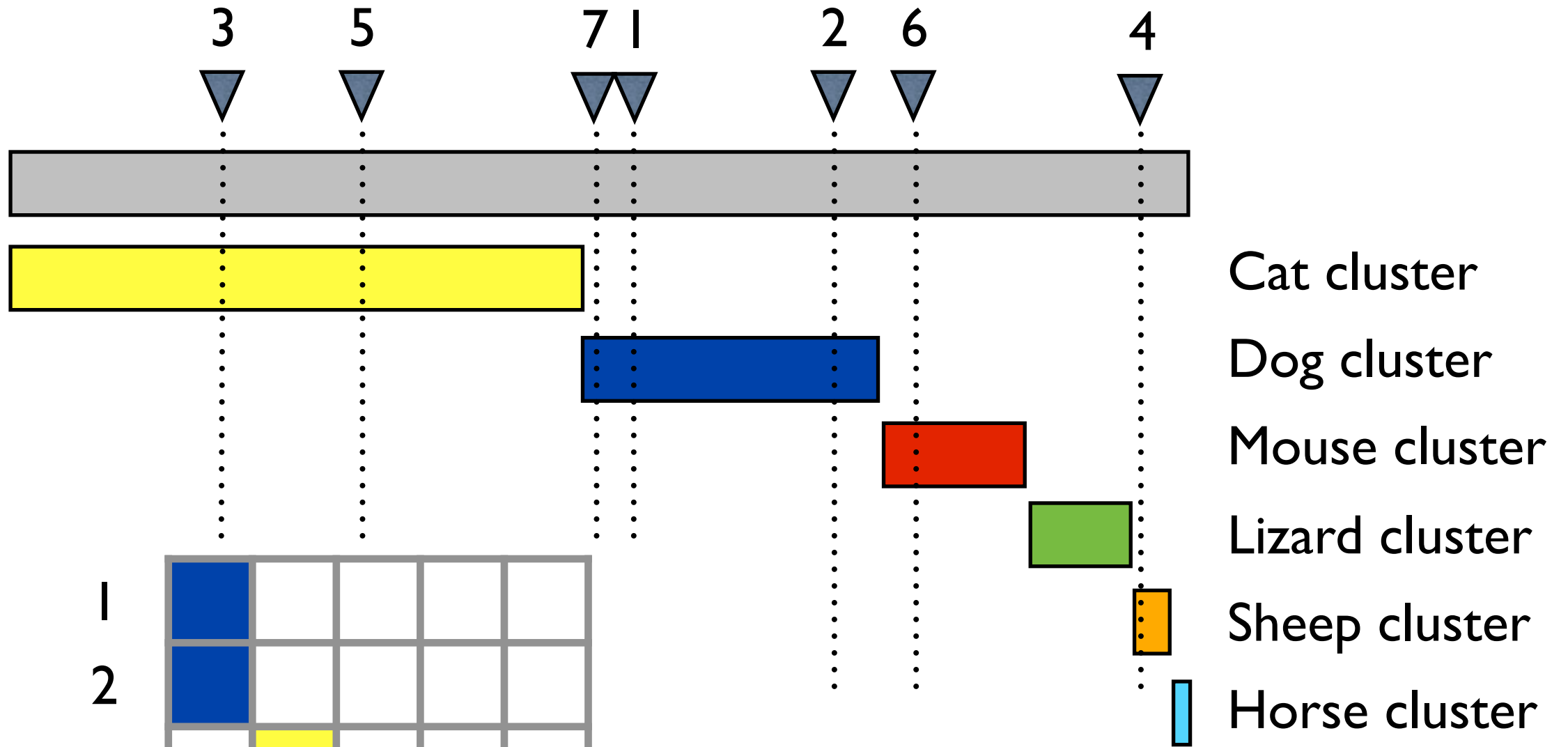
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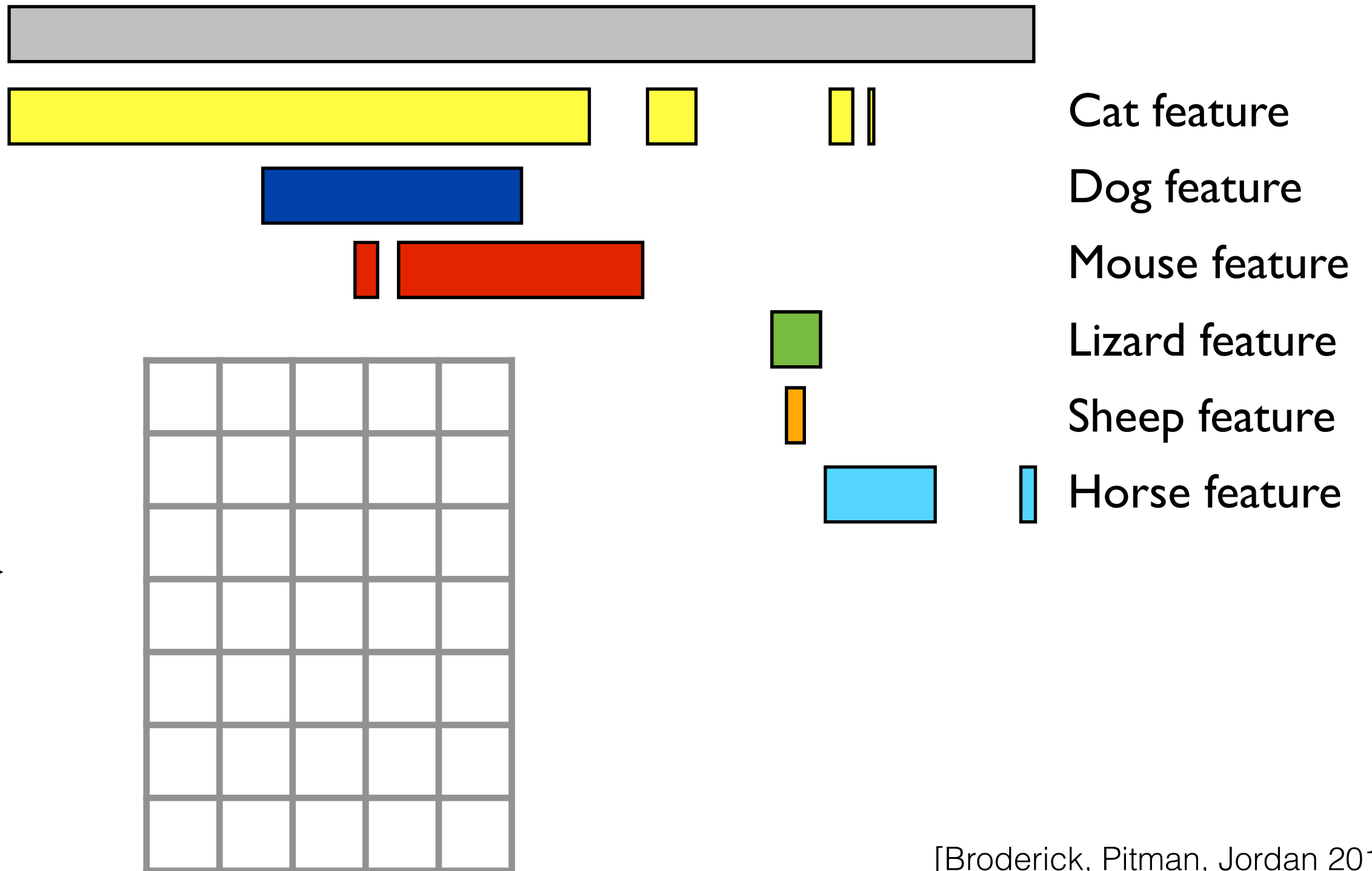


Paintboxes

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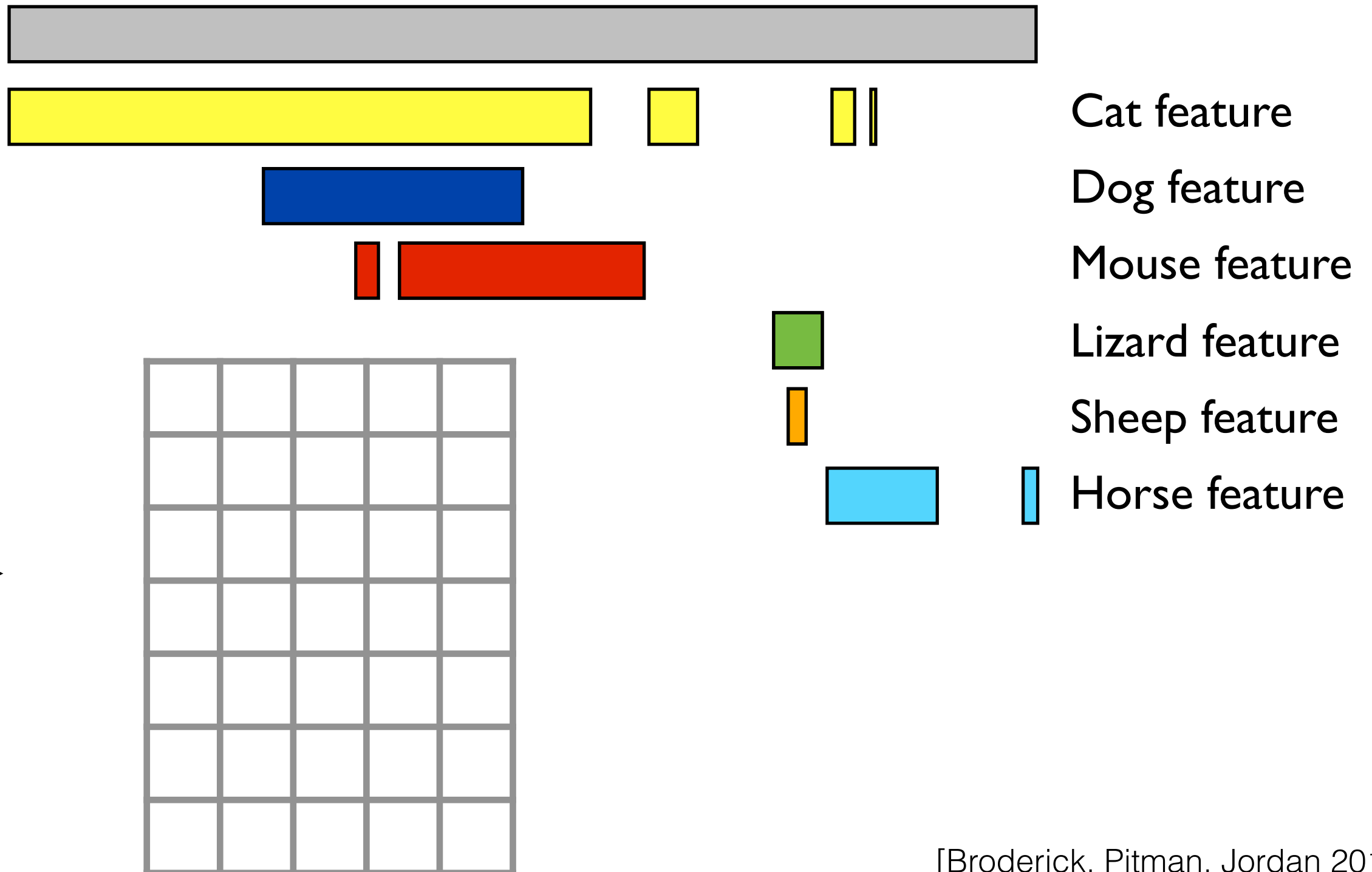


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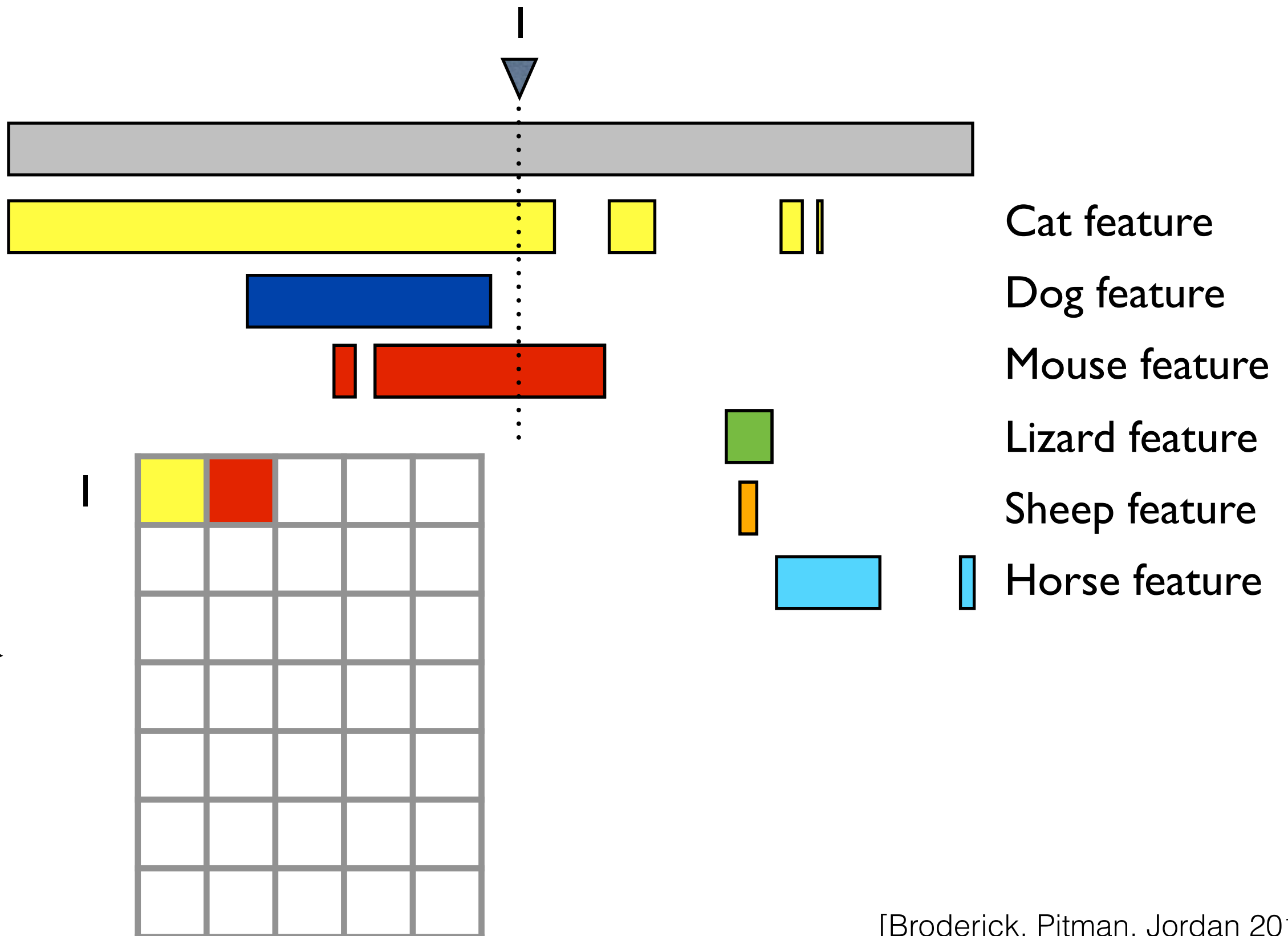
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Exchangeable **feature allocation: feature paintbox**



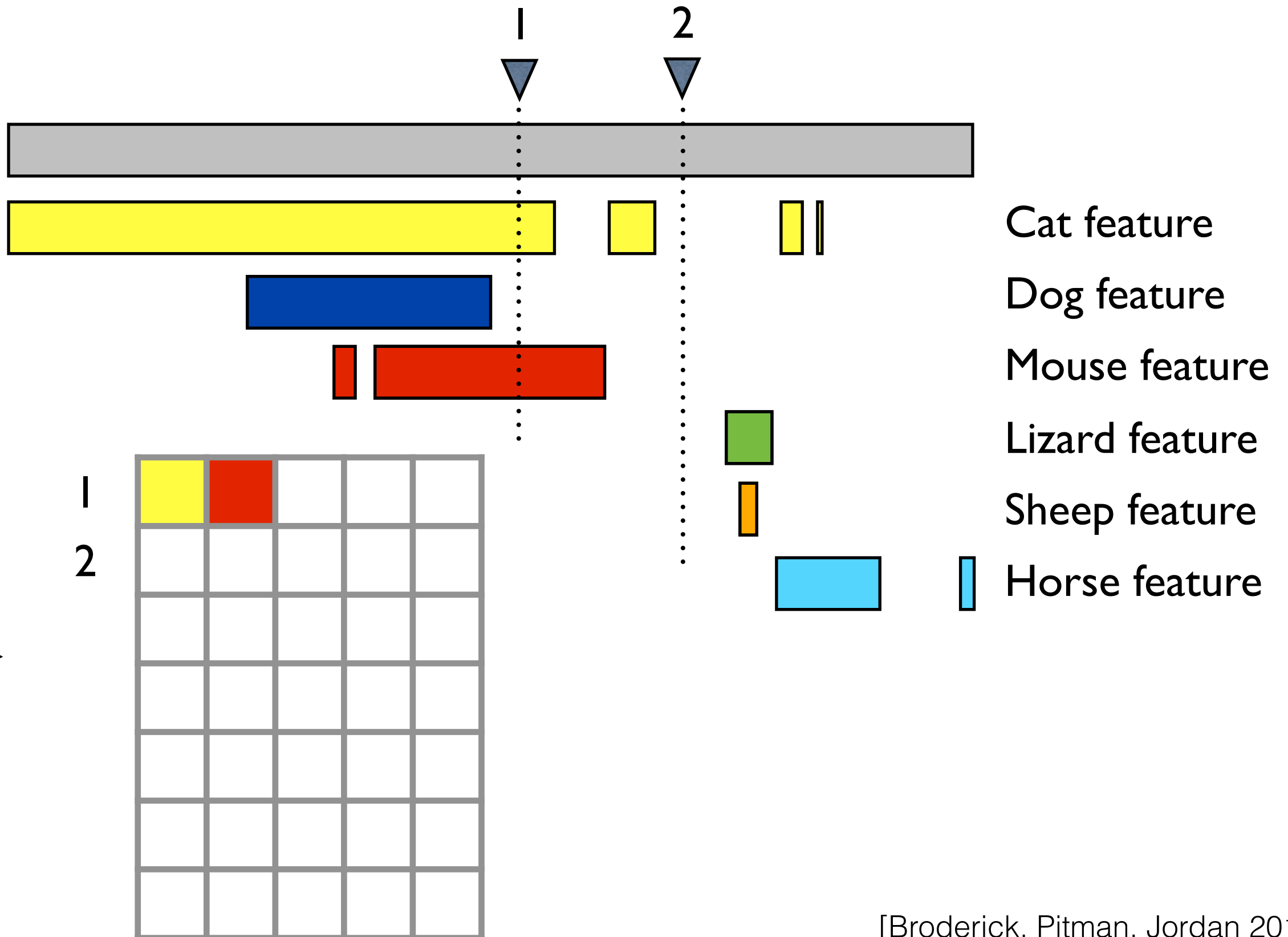
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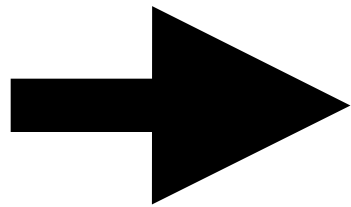
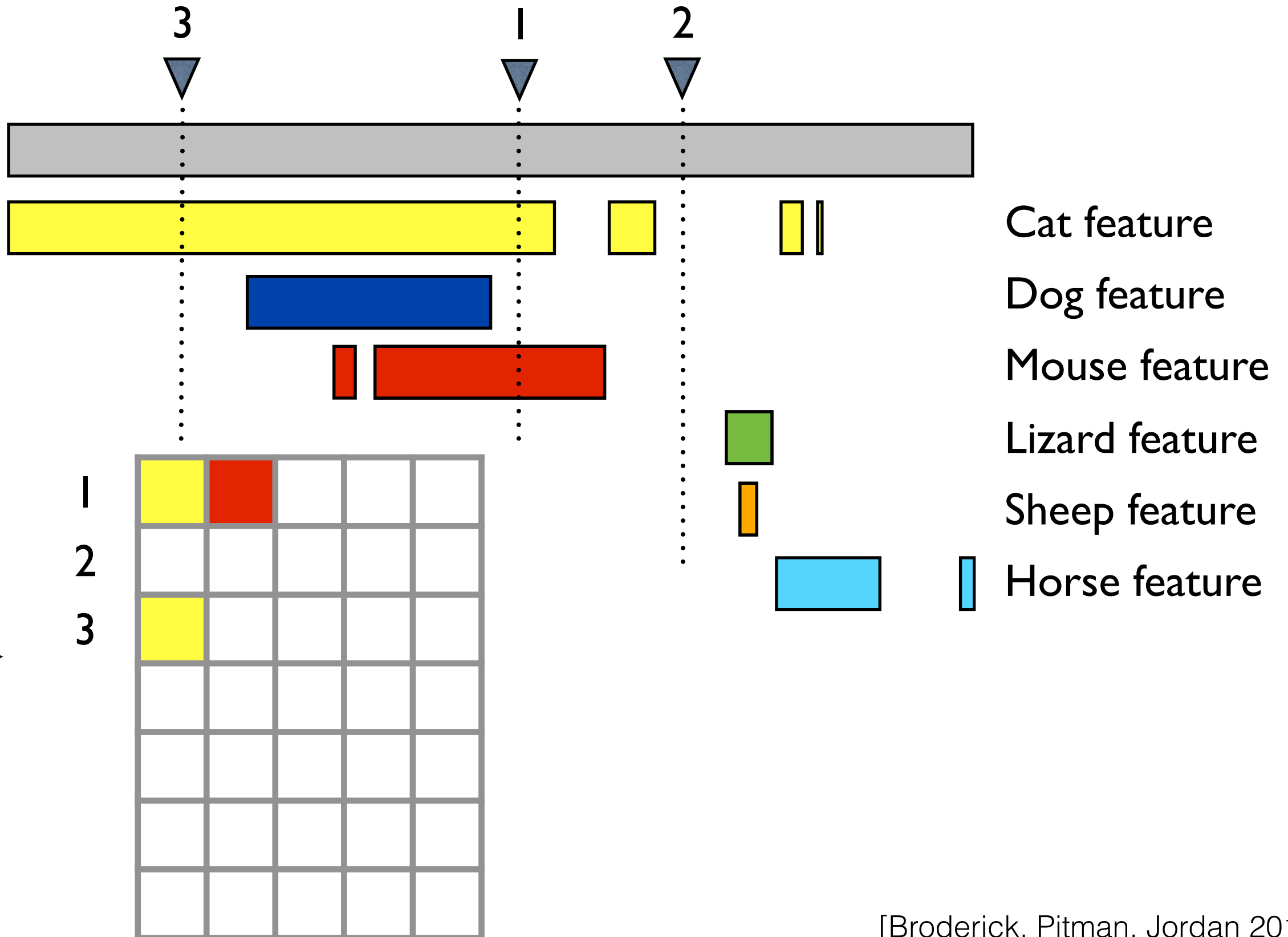
Paintboxes

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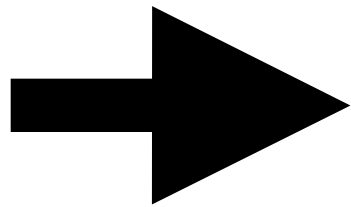
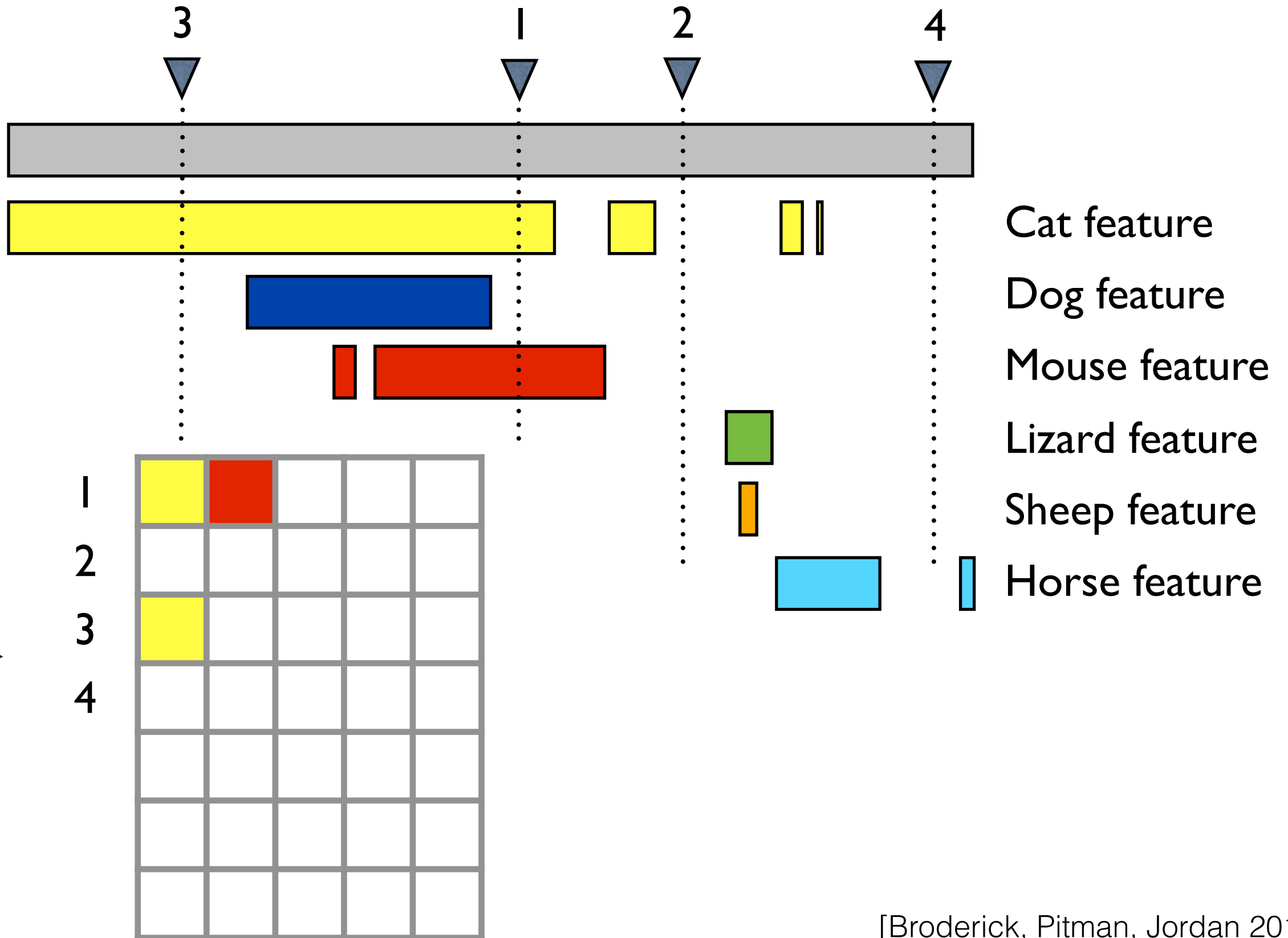
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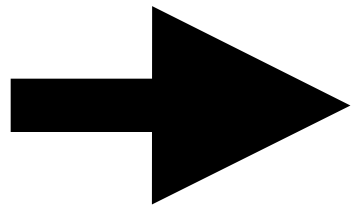
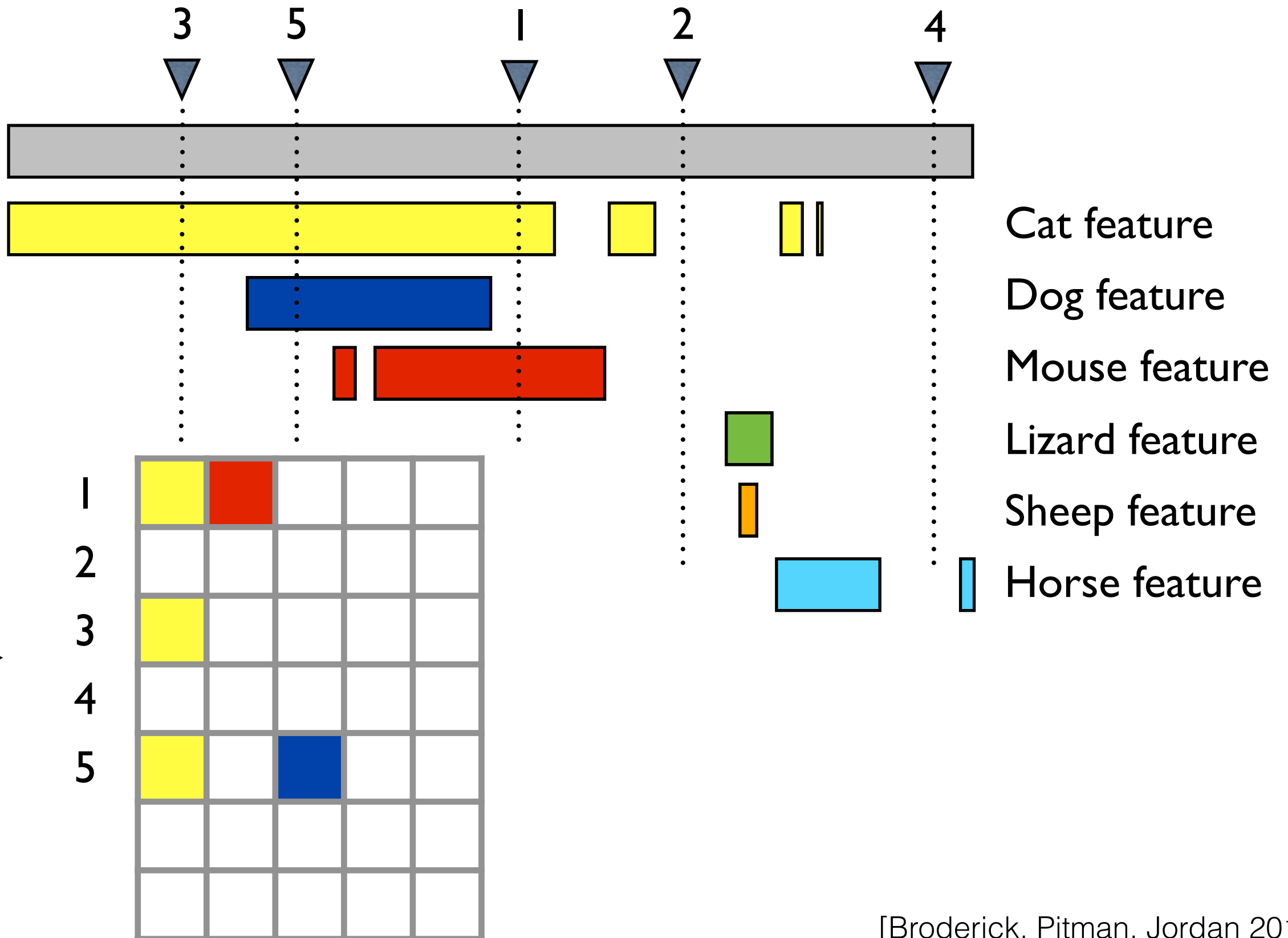
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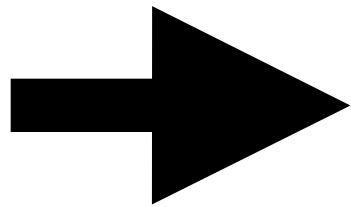
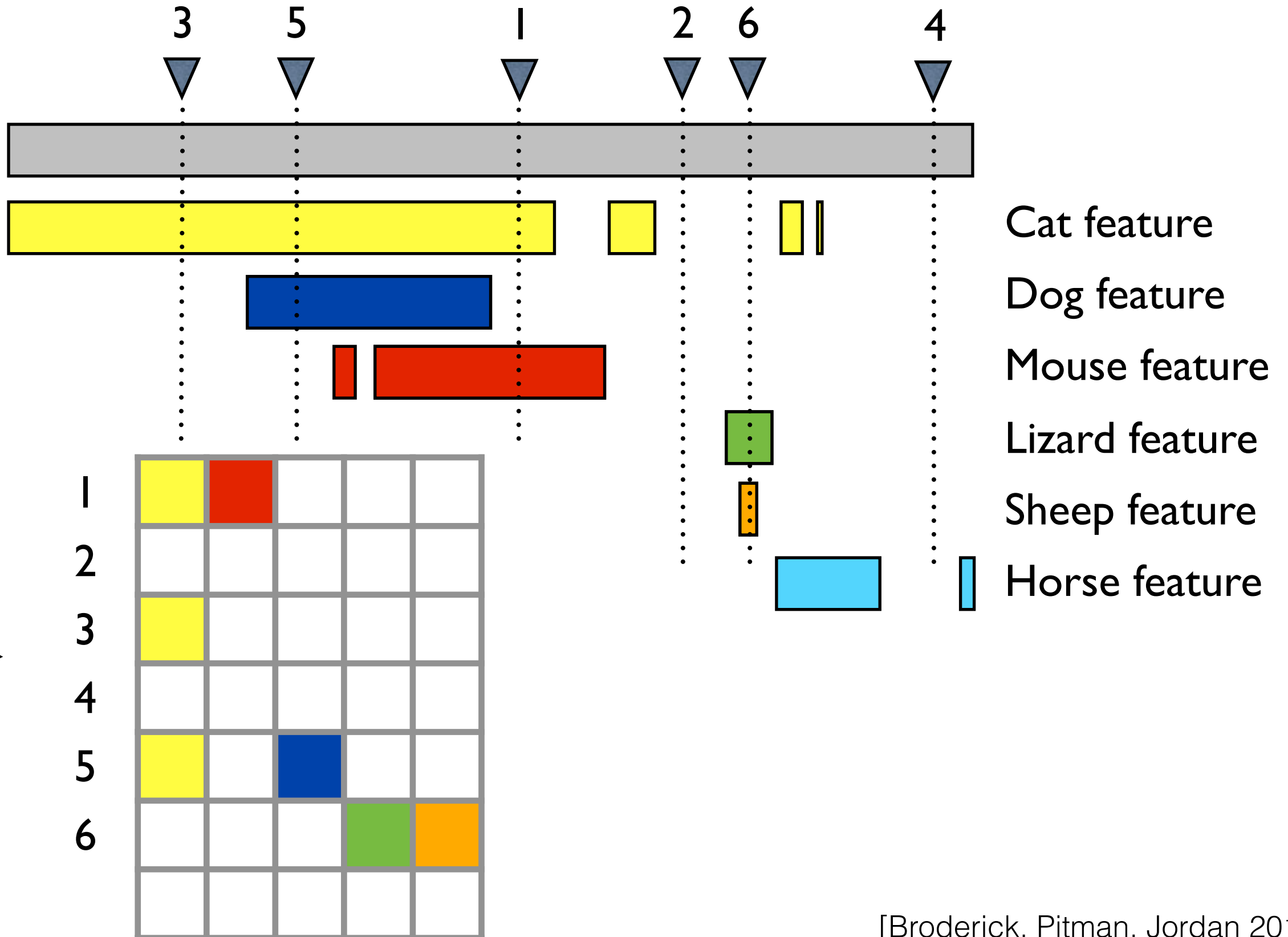
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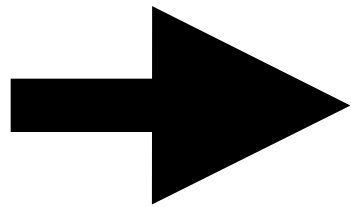
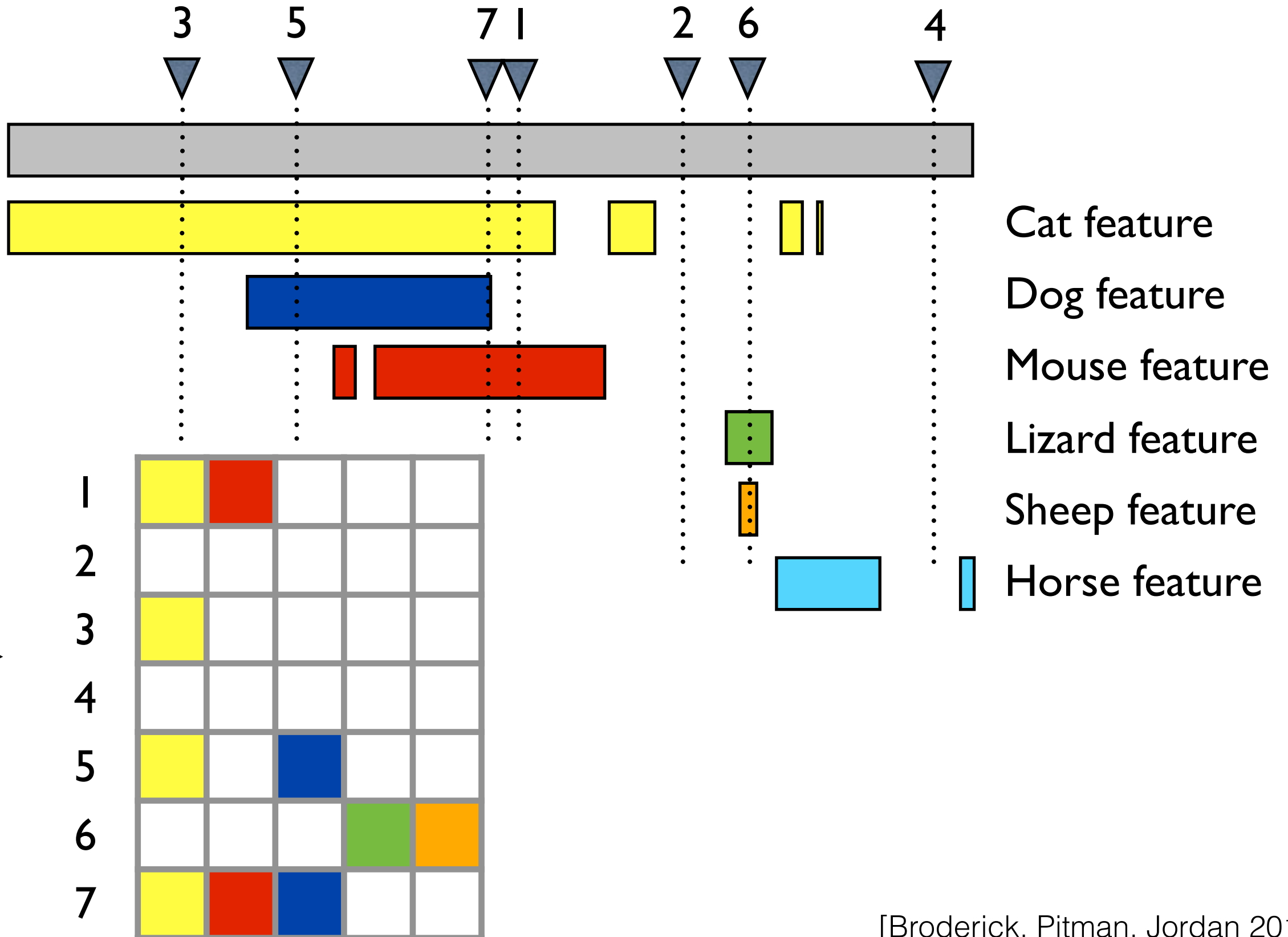
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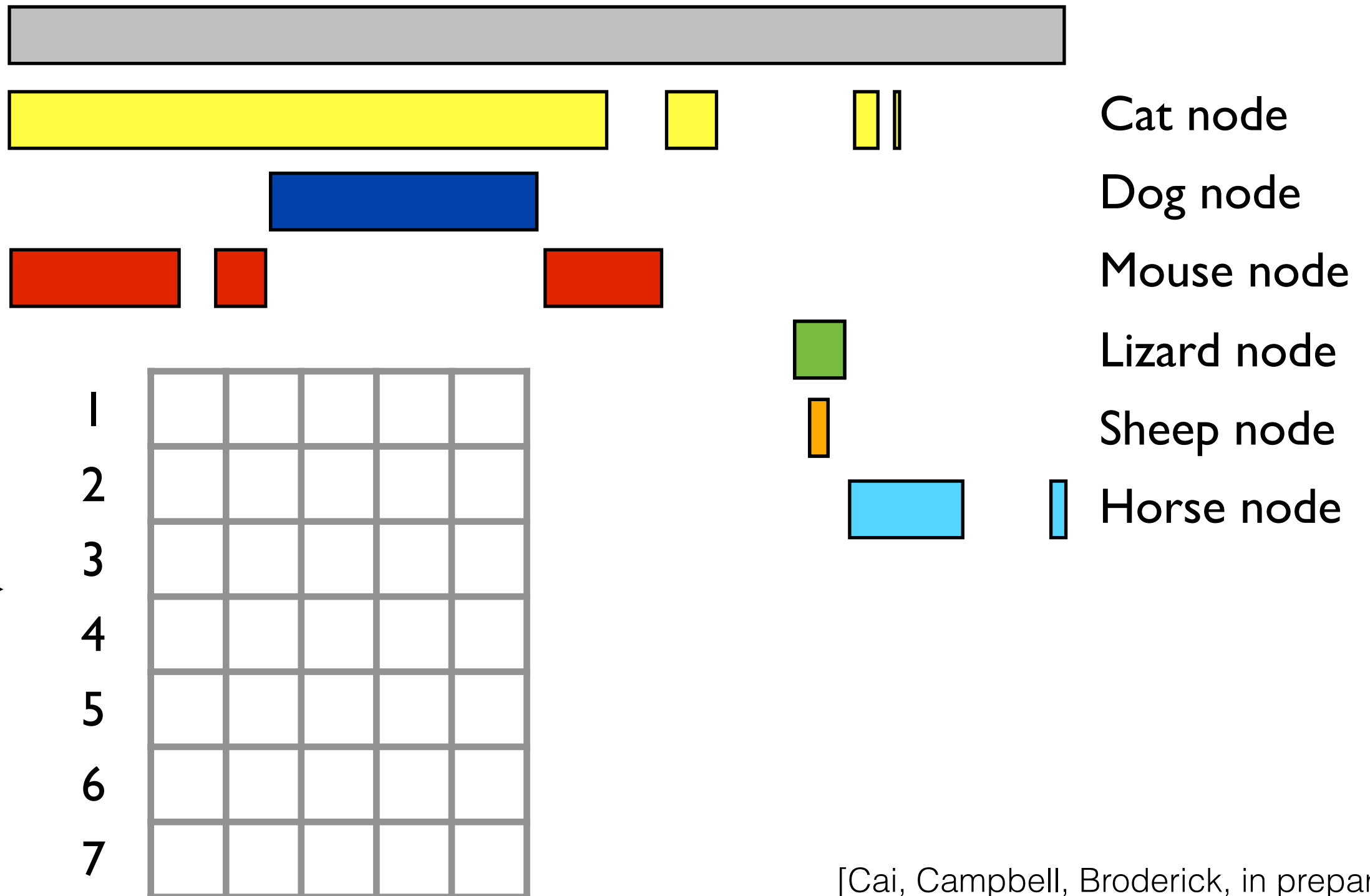
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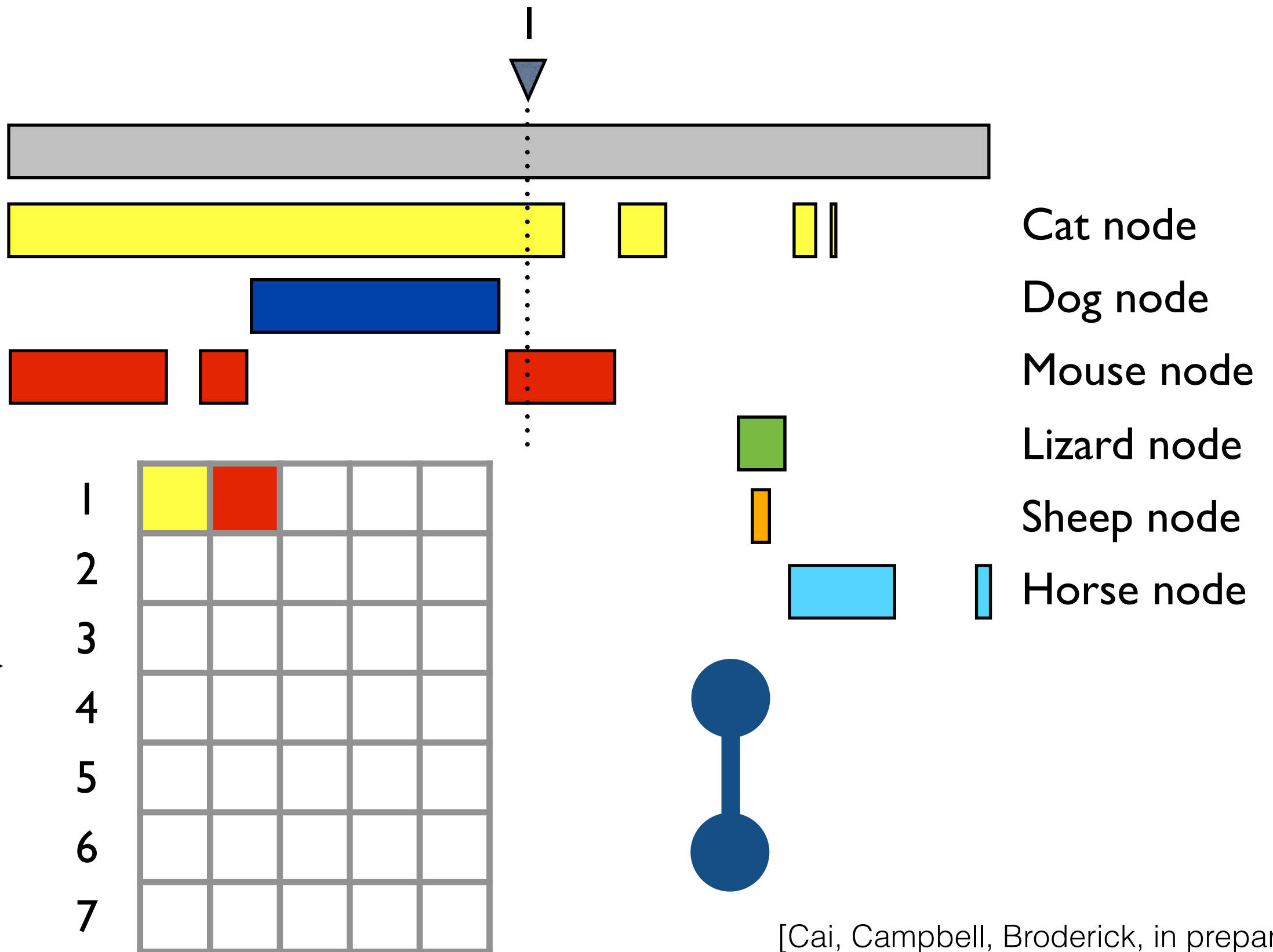
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Edge-exchangeable graph



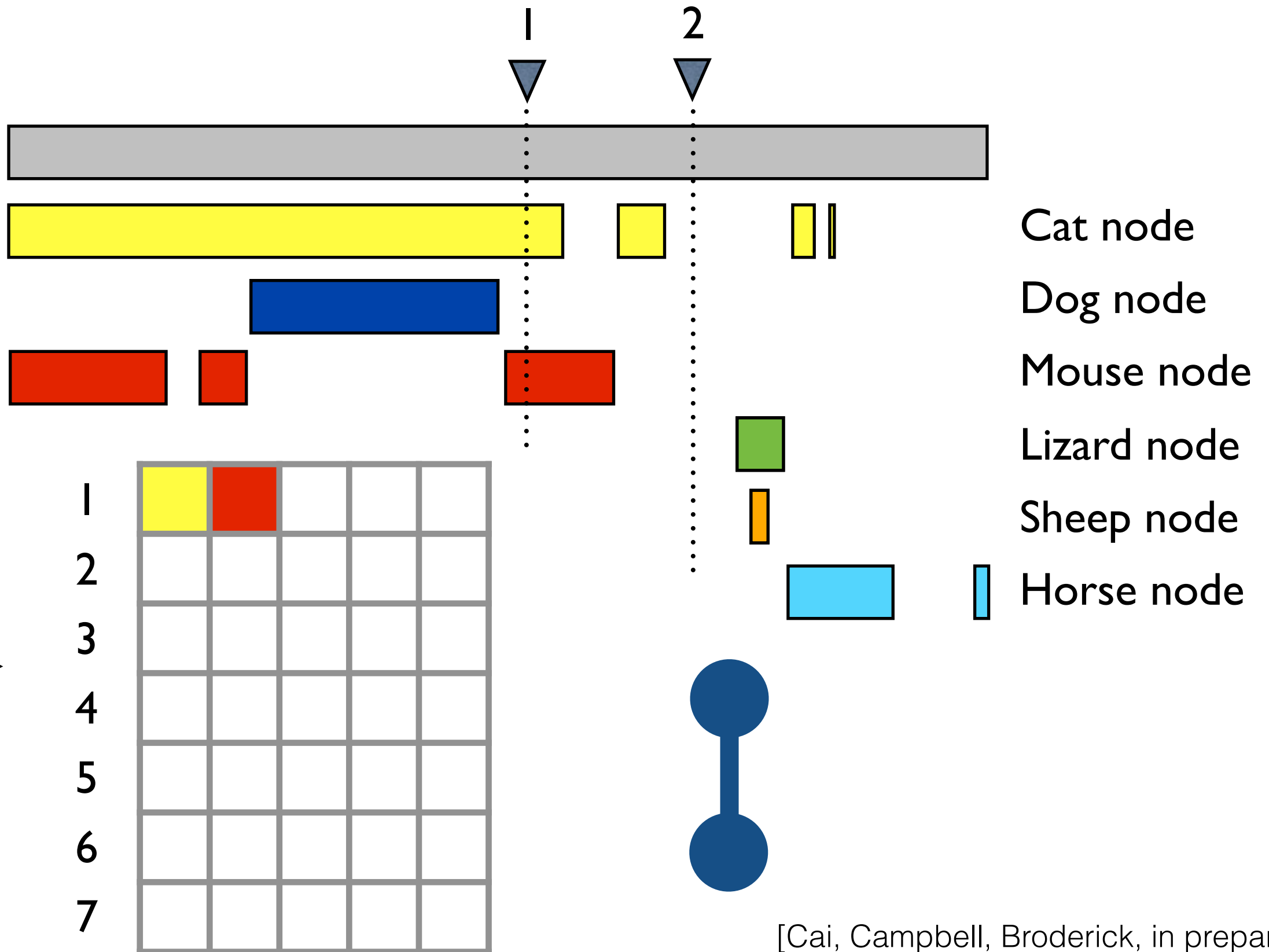
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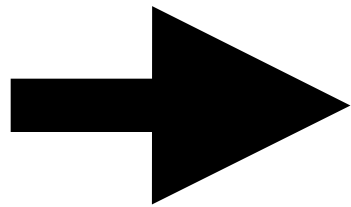
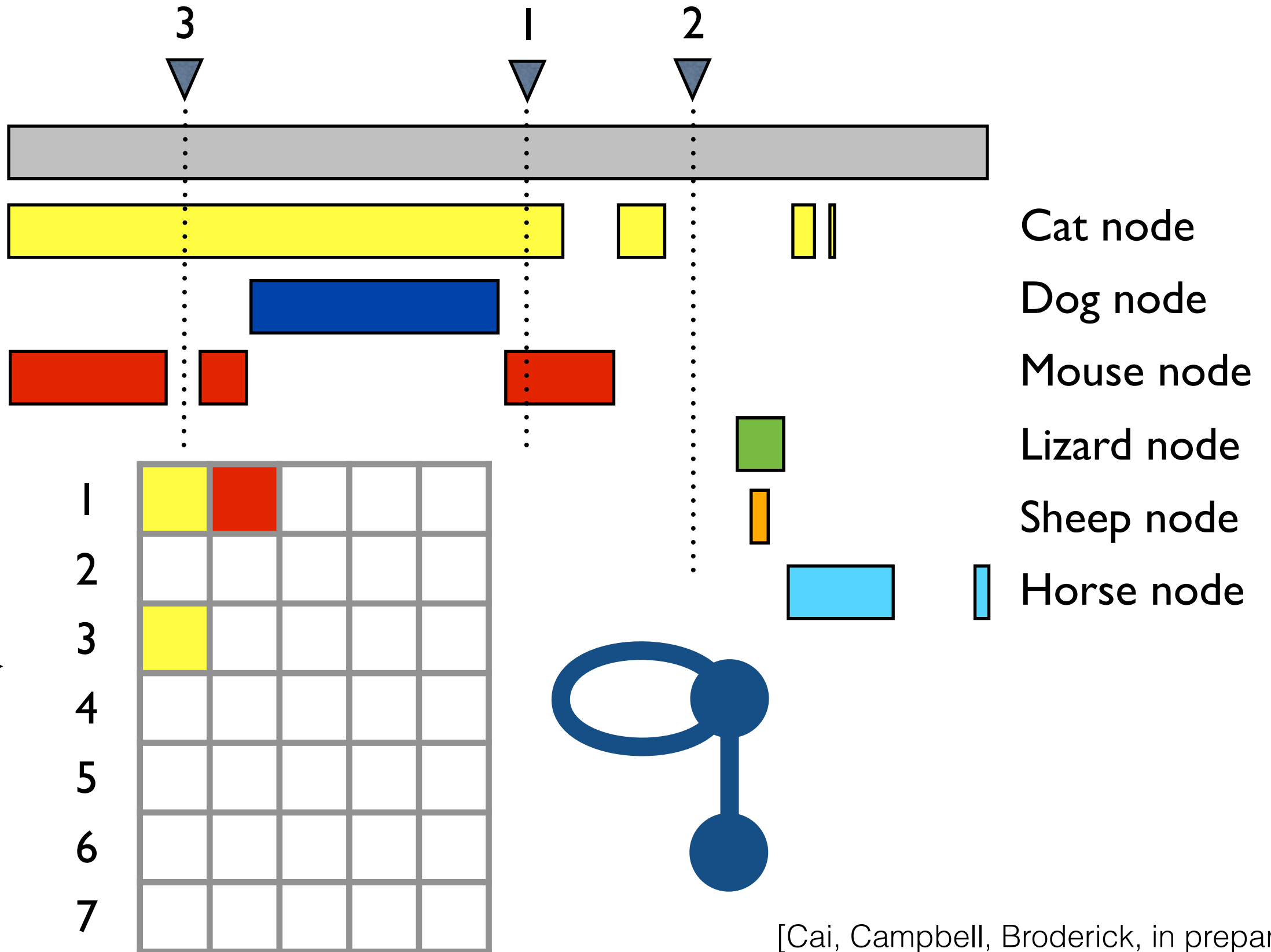
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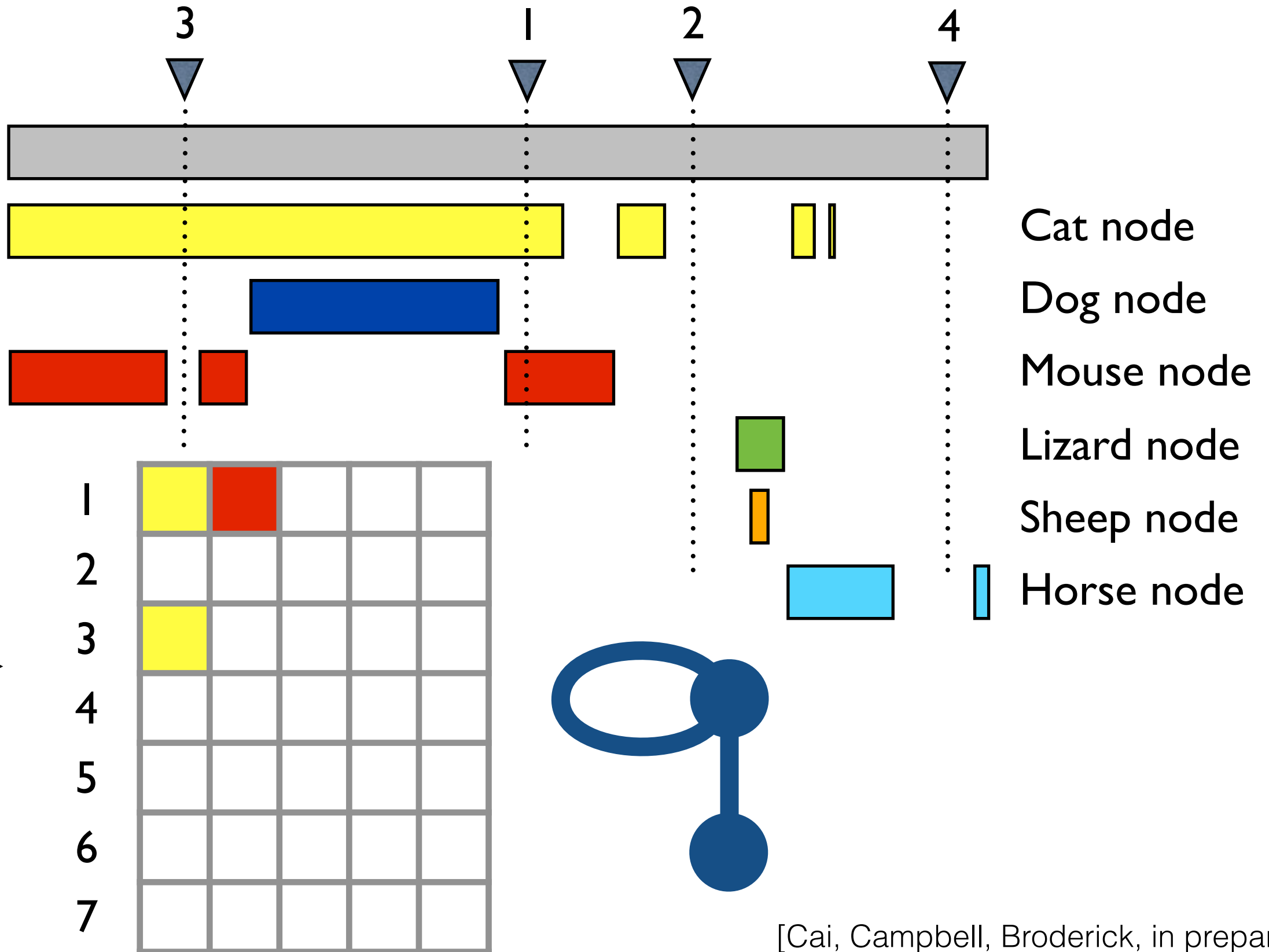
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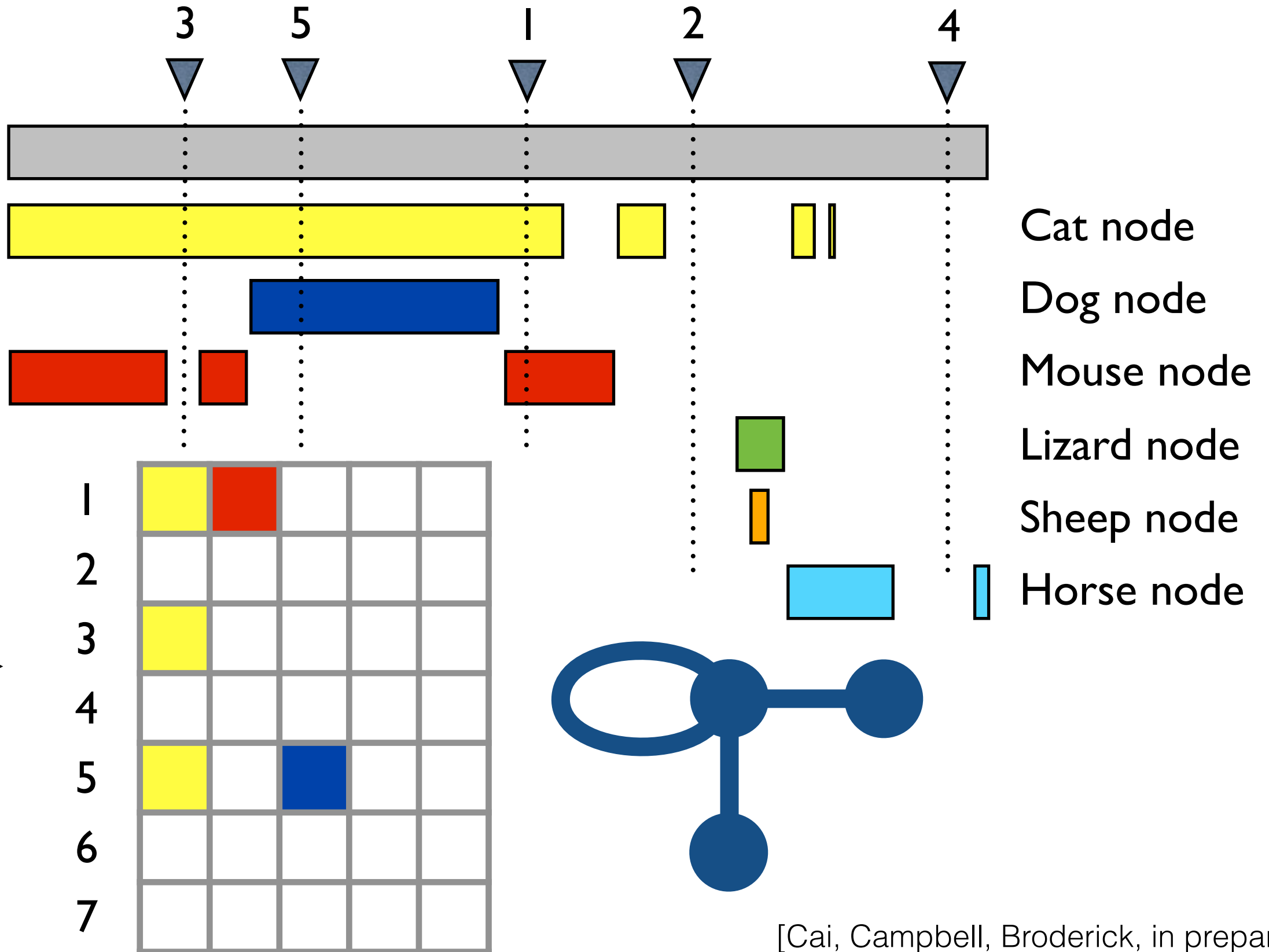
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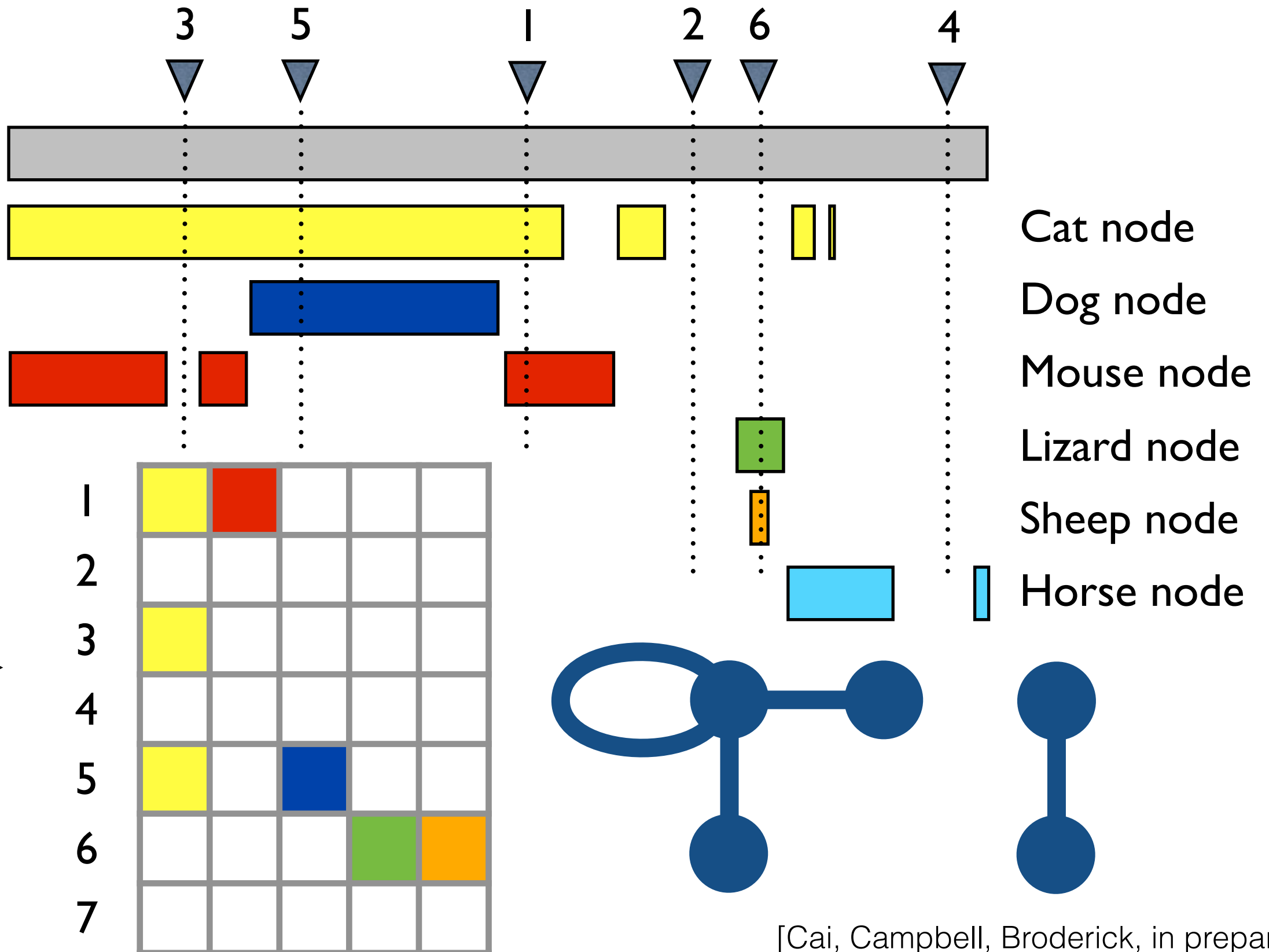
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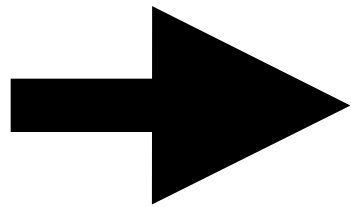
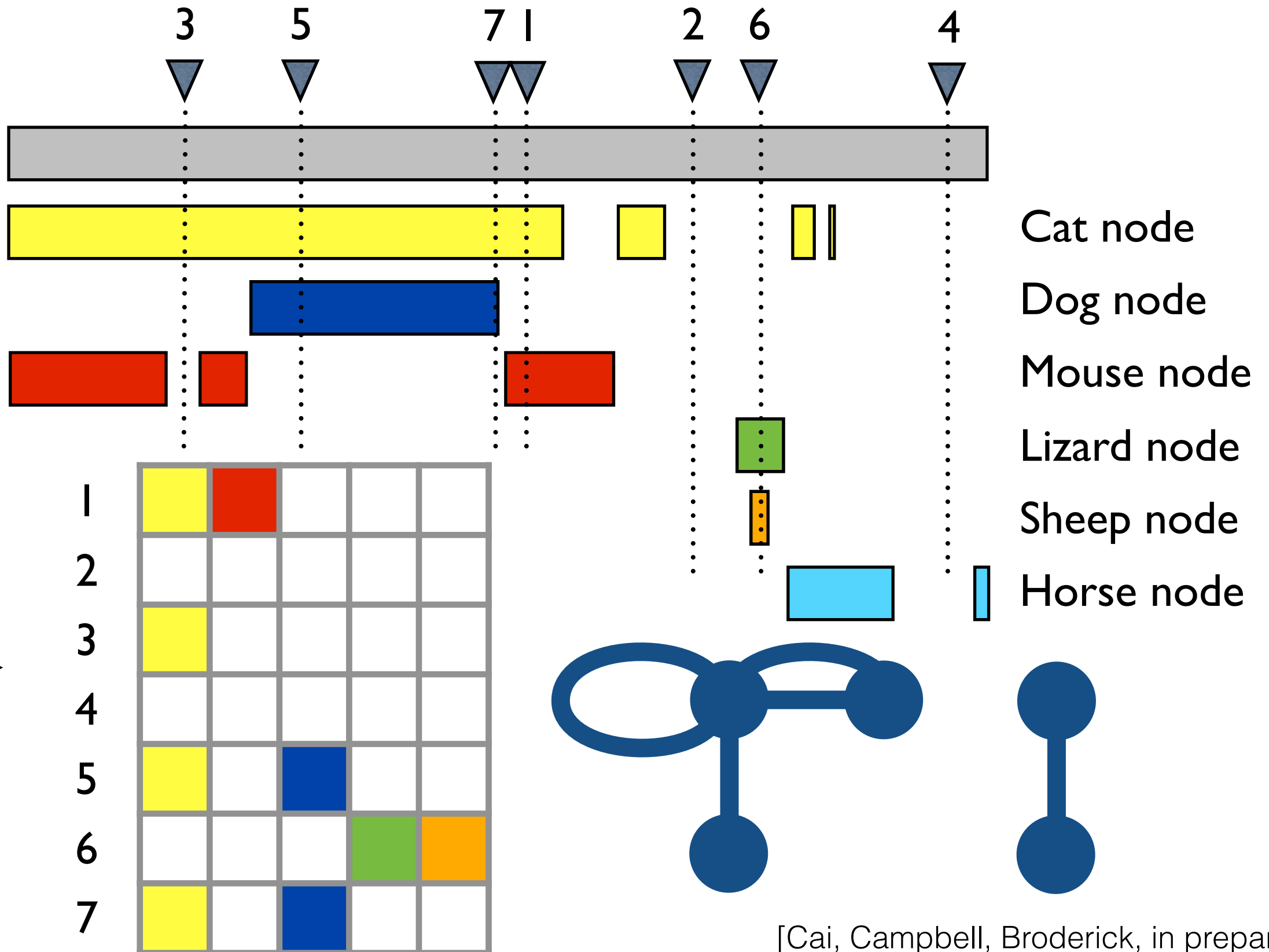
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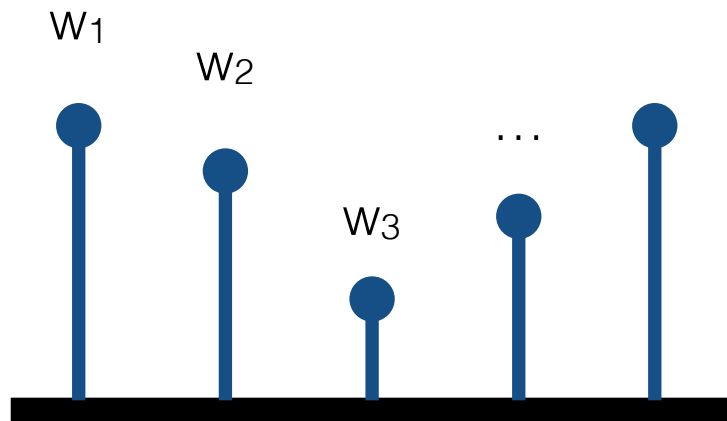
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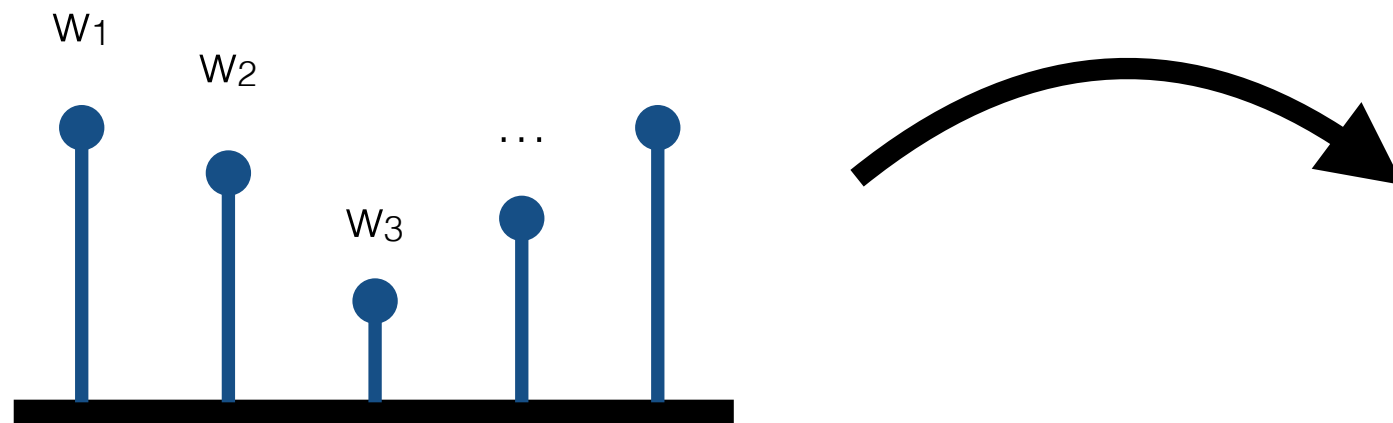
Allows sparse graphs

1. Draw discrete random measure $\sum_{j=1}^{\infty} w_j \delta_{\theta_j}$



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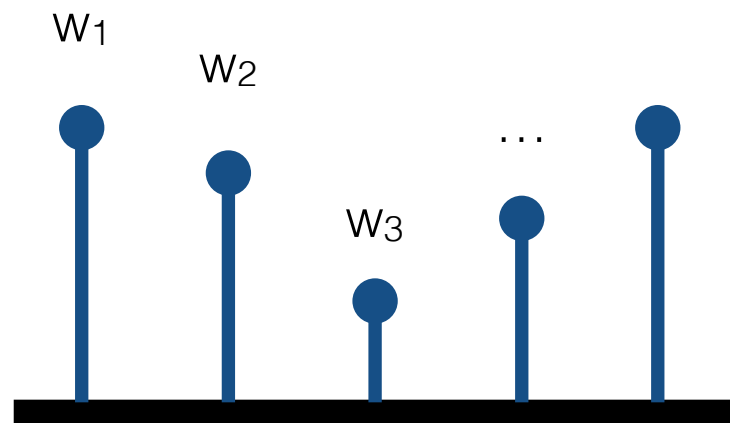
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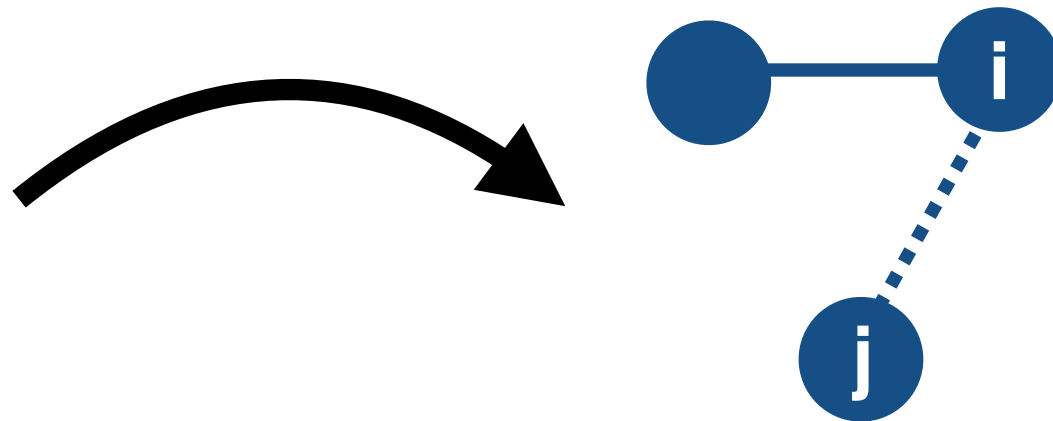
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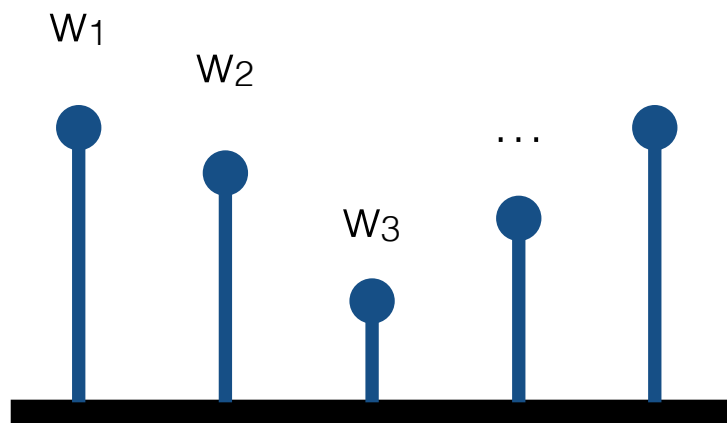
2. New edge $\{i, j\}$
w.p. prop. to $w_i w_j$



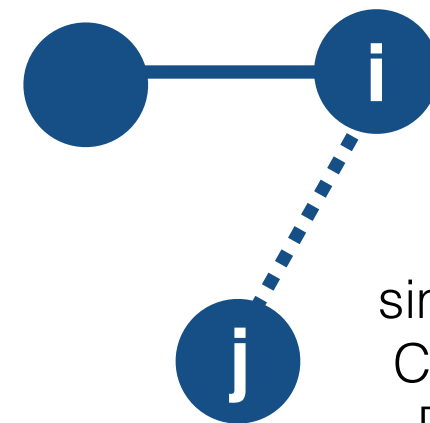
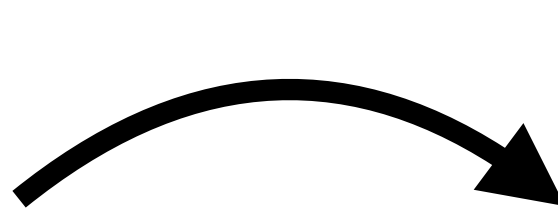
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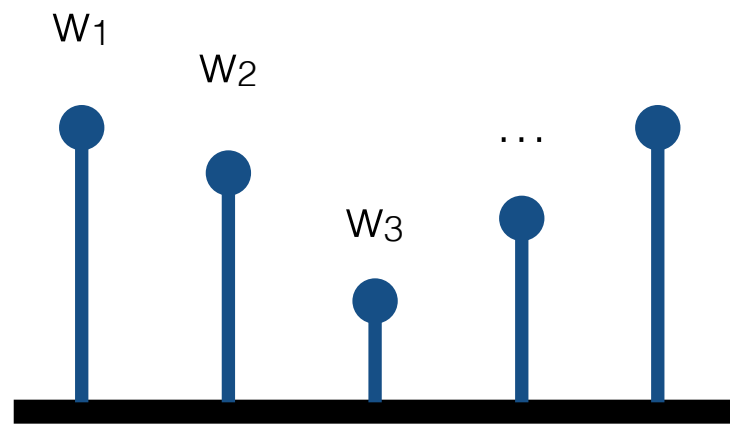


similar model using a CRM considered by [Caron, Fox 2015]

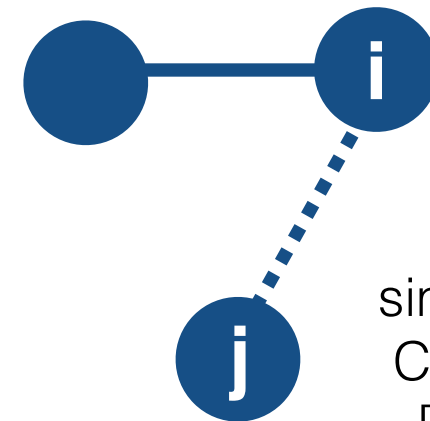
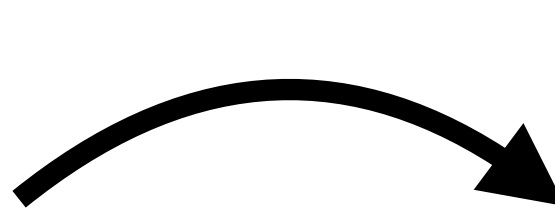
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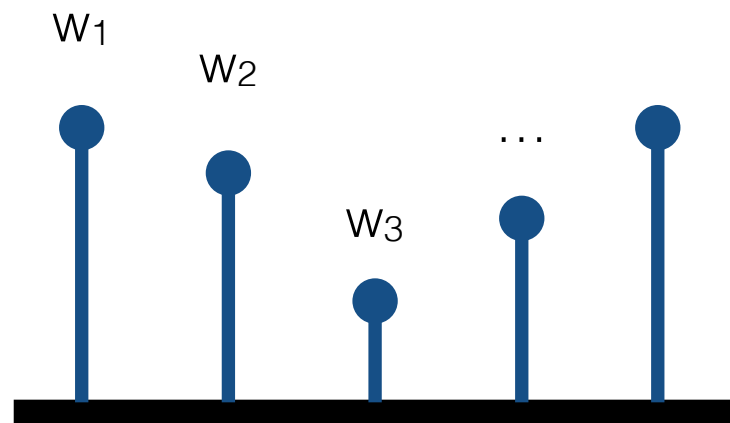
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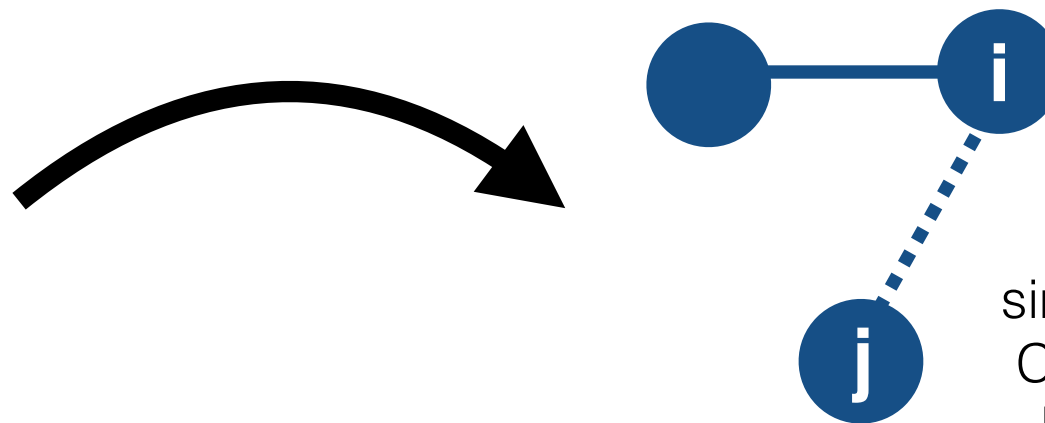
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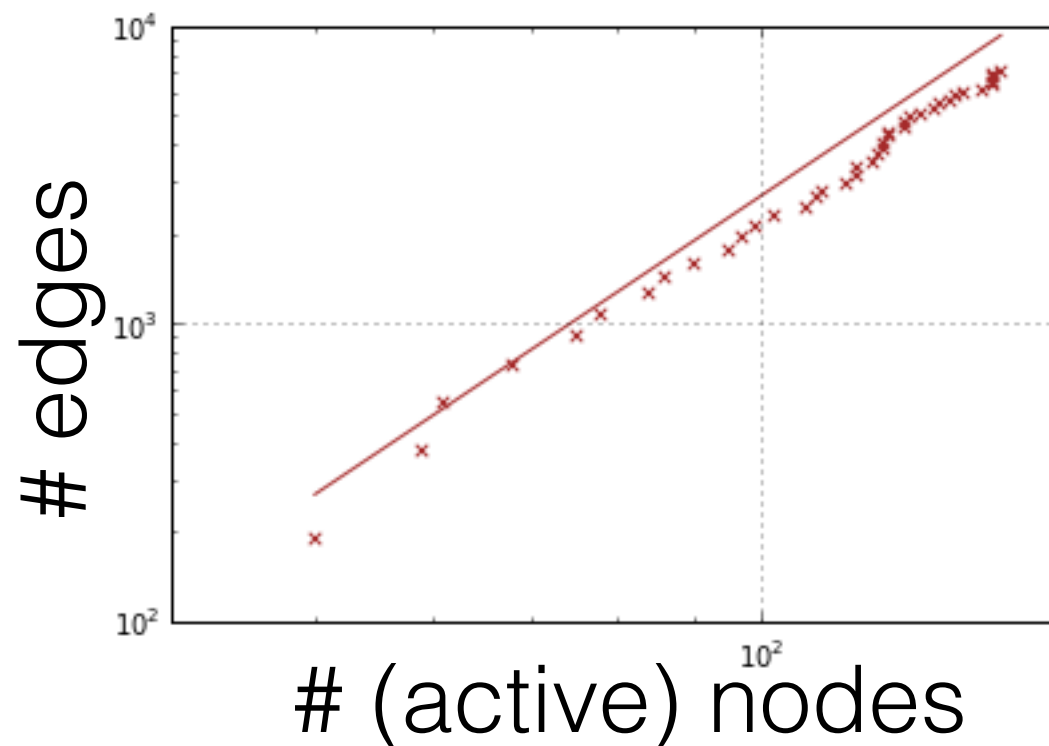


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- Truncation approximations

References

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Broderick, T, and Cai, D. Edge-exchangeable graphs and sparsity. *NIPS 2015 Workshop on Networks in the Social and Information Sciences*. 2015.

Cai D, Broderick T. Completely random measures for modeling power laws in sparse graphs. *NIPS 2015 Workshop on Networks in the Social and Information Sciences*. 2015.

Campbell T*, Huggins JH*, How J, and Broderick T. Truncated random measures. Under review. Preprint on arXiv:1603.00861