## If an algorithm samples exact knockoff for any distribution with only access to evaluating the distribution's unnormalized density $\Phi$ , then almost surely,

number of evaluations of the density  $\geq 2^{\left|\{j:X_j\neq \tilde{X}_j\}\right|}-1$ 

Theorem 2 (Bates, Candès, Janson and Wang, 2019, informal version)

```
•Make | \{j: X_j 
eq 	ilde{X}_j\} | small, but we will give up power
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#### Settle for approximate knockoffs?

#### Focus on important class of distributions

#### parametric family (e.g., Gaussian, discrete Markov chains)



```
Recall: need density at all points of the
form (Z_1,Z_2,\ldots,Z_p), Z_j equal to X_j or X_j
```



#### reduced degree of freedom of the densities at these points

#### graphical structure

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# graphical structure

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reduced degree of freedom of the densities at these points

## Graphical model and junction tree

 $X_i$  independent of  $X_j$  given the remaining variables if no edge connects i and j

