

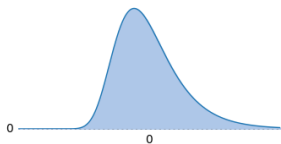
# Lost Relatives of the Gumbel Trick

Matej Balog

Nilesh Tripuraneni

Zoubin Ghahramani

Adrian Weller

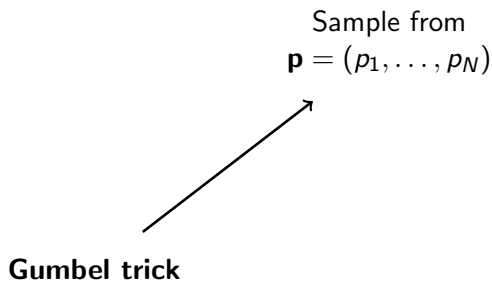


ICML 2017, Sydney, Australia

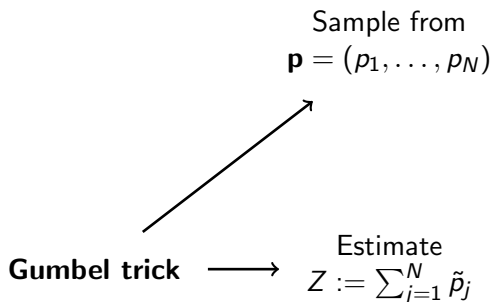
Slides: <http://matejbalog.eu/en/research/>

Code: <https://github.com/matejbalog/gumbel-relatives>

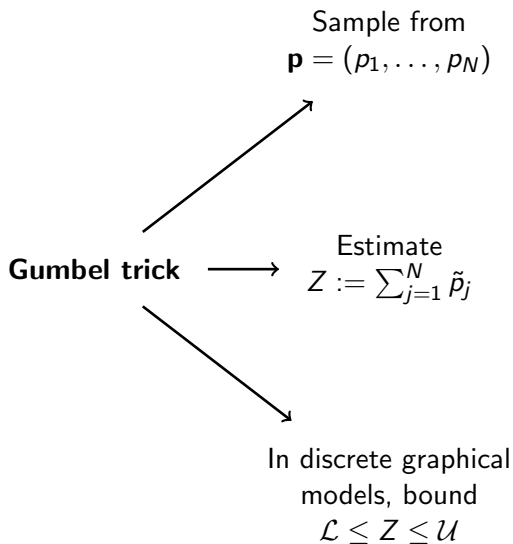
## Lost Relatives of the Gumbel Trick



## Lost Relatives of the Gumbel Trick



## Lost Relatives of the Gumbel Trick



# Lost Relatives of the Gumbel Trick



Competing  
exponential  
clocks

$$\xrightarrow{-\ln t - c}$$

**Gumbel trick**

Sample from  
 $\mathbf{p} = (p_1, \dots, p_N)$

Estimate  
 $Z := \sum_{j=1}^N \tilde{p}_j$

In discrete graphical  
models, bound  
 $\mathcal{L} \leq Z \leq \mathcal{U}$

# Lost Relatives of the Gumbel Trick



Competing  
exponential  
clocks



...

Fréchet tricks

**Gumbel trick**

Exponential trick

Weibull tricks

Sample from  
 $\mathbf{p} = (p_1, \dots, p_N)$

Estimate  
 $Z := \sum_{j=1}^N \tilde{p}_j$

In discrete graphical  
models, bound  
 $\mathcal{L} \leq Z \leq \mathcal{U}$

# Lost Relatives of the Gumbel Trick



Competing  
exponential  
clocks



...

Fréchet tricks

Gumbel trick

Exponential trick

Weibull tricks

Sample from  
 $\mathbf{p} = (p_1, \dots, p_N)$   
tricks equivalent

Estimate  
 $Z := \sum_{j=1}^N \tilde{p}_j$

In discrete graphical  
models, bound  
 $\mathcal{L} \leq Z \leq \mathcal{U}$

# Lost Relatives of the Gumbel Trick



Competing  
exponential  
clocks



Fréchet tricks



Gumbel trick



Exponential trick



Weibull tricks



...

Sample from  
 $\mathbf{p} = (p_1, \dots, p_N)$   
tricks equivalent

Estimate  
 $Z := \sum_{j=1}^N \tilde{p}_j$   
family of  
estimators  $\hat{Z}$

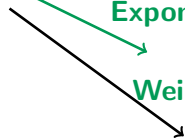
In discrete graphical  
models, bound  
 $\mathcal{L} \leq Z \leq \mathcal{U}$



# Lost Relatives of the Gumbel Trick



Competing  
exponential  
clocks



**Fréchet tricks**

**Gumbel trick**

**Exponential trick**

**Weibull tricks**

...

Sample from  
 $\mathbf{p} = (p_1, \dots, p_N)$   
tricks equivalent

Estimate  
 $Z := \sum_{j=1}^N \tilde{p}_j$   
family of  
estimators  $\hat{Z}$

In discrete graphical  
models, bound  
 $\mathcal{L} \leq Z \leq \mathcal{U}$   
family of bounds  
 $\mathcal{L}(\alpha), \mathcal{U}(\alpha)$

# Competing Exponential Clocks

$N$  independent clocks started simultaneously:



$\sim \text{Exp}(\lambda_1)$



$\sim \text{Exp}(\lambda_2)$

...



$\sim \text{Exp}(\lambda_N)$

# Competing Exponential Clocks

$N$  independent clocks started simultaneously:



$\sim \text{Exp}(\lambda_1)$



$\sim \text{Exp}(\lambda_2)$

...



$\sim \text{Exp}(\lambda_N)$

- 1 Probability  $q_i$  that clock  $i$  is the first to ring:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j}$$

# Competing Exponential Clocks

$N$  independent clocks started simultaneously:



$\sim \text{Exp}(\lambda_1)$



$\sim \text{Exp}(\lambda_2)$

...



$\sim \text{Exp}(\lambda_N)$

- 1 Probability  $q_i$  that clock  $i$  is the first to ring:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j}$$

- 2 First time  $T$  when a clock rings:

$$T \sim \text{Exp}(\lambda_1 + \cdots + \lambda_N)$$
$$\mathbb{E}[T] = \frac{1}{\lambda_1 + \cdots + \lambda_N}$$

# Competing Exponential Clocks

Unnormalized probability mass function  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_N)$ :



$\sim \text{Exp}(\lambda_1)$



$\sim \text{Exp}(\lambda_2)$

...



$\sim \text{Exp}(\lambda_N)$

- 1 Probability  $q_i$  that clock  $i$  is the first to ring:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j}$$

- 2 First time  $T$  when a clock rings:

$$T \sim \text{Exp}(\lambda_1 + \dots + \lambda_N)$$
$$\mathbb{E}[T] = \frac{1}{\lambda_1 + \dots + \lambda_N}$$

# Competing Exponential Clocks

Unnormalized probability mass function  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_N)$ :



$\sim \text{Exp}(\tilde{p}_1)$



$\sim \text{Exp}(\tilde{p}_2)$

...



$\sim \text{Exp}(\tilde{p}_N)$

- 1 Probability  $q_i$  that clock  $i$  is the first to ring:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j} = \frac{\tilde{p}_i}{\sum_{j=1}^N \tilde{p}_j} = \frac{\tilde{p}_i}{Z} = p_i$$

- 2 First time  $T$  when a clock rings:

$$T \sim \text{Exp}(\lambda_1 + \dots + \lambda_N) = \text{Exp}(Z)$$
$$\mathbb{E}[T] = \frac{1}{\lambda_1 + \dots + \lambda_N} = \frac{1}{Z}$$

# Competing Exponential Clocks

Unnormalized probability mass function  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_N) = (e^{\theta_1}, \dots, e^{\theta_N})$ :

$$\begin{array}{ccc} \begin{array}{c} \text{?} \\ \sim \theta_1 + \text{Gumbel}(0) \end{array} & \begin{array}{c} \text{?} \\ \sim \theta_2 + \text{Gumbel}(0) \end{array} & \dots \quad \begin{array}{c} \text{?} \\ \sim \theta_N + \text{Gumbel}(0) \end{array} \end{array}$$

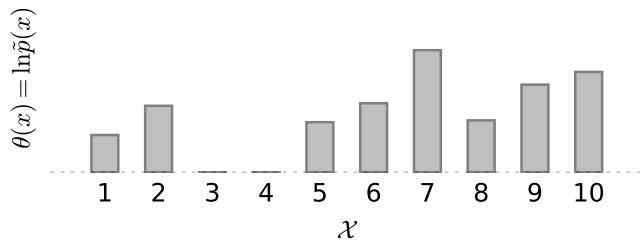
- 1 Probability  $q_i$  of  $\tilde{\theta}_i$  being the maximal perturbed potential:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j} = \frac{\tilde{p}_i}{\sum_{j=1}^N \tilde{p}_j} = \frac{\tilde{p}_i}{Z} = p_i$$

- 2 Maximal perturbed potential:

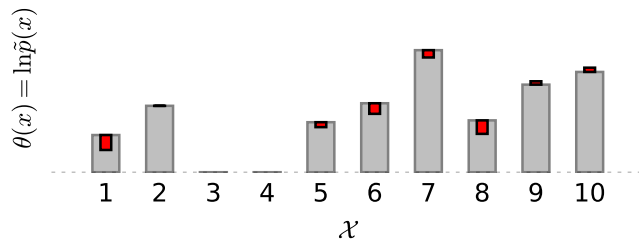
$$\begin{aligned} -\ln T - c &\sim \ln Z + \text{Gumbel}(0) \\ \mathbb{E}[-\ln T - c] &= \ln Z \end{aligned}$$

## Classical Gumbel trick

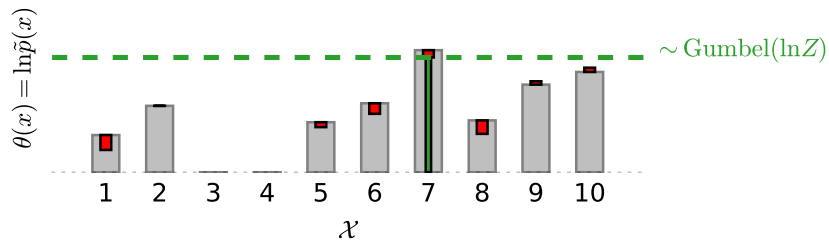




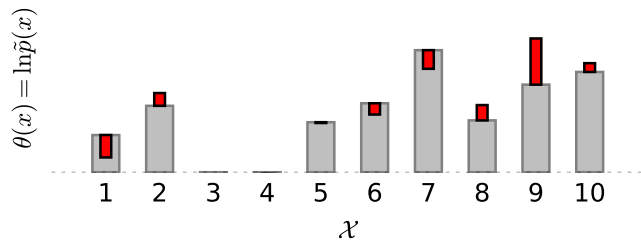
## Classical Gumbel trick



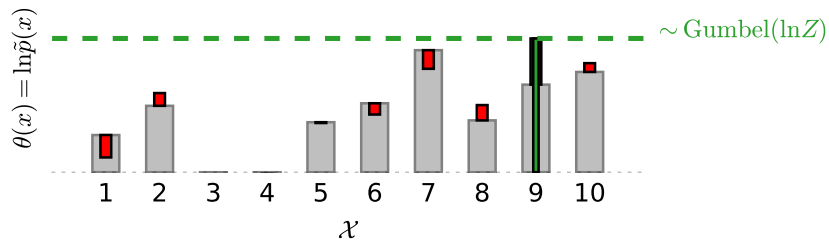
## Classical Gumbel trick



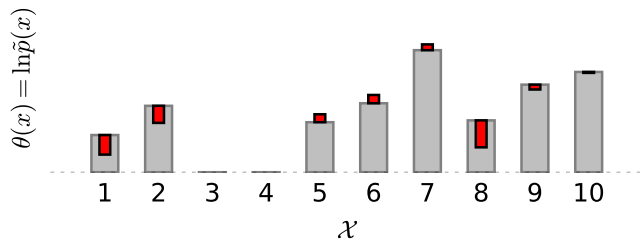
## Classical Gumbel trick



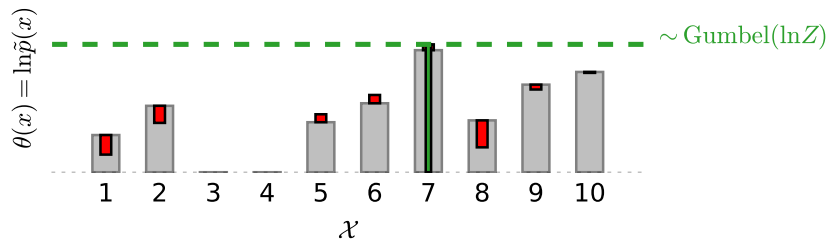
# Classical Gumbel trick



## Classical Gumbel trick



# Classical Gumbel trick



## Generalizing the Gumbel trick

Recall:

Competing exponential clocks  $\xrightarrow{-\ln x - c}$  Gumbel trick

$\text{Exp}(Z)$  random var.  $\xrightarrow{-\ln x - c}$   $\ln Z + \text{Gumbel}(0)$  random var.

Estimator of  $\frac{1}{Z}$   $\xrightarrow{-\ln x - c}$  Estimator of  $\ln Z$

## Generalizing the Gumbel trick

Recall:

Competing exponential clocks  $\xrightarrow{-\ln x - c}$  Gumbel trick

$\text{Exp}(Z)$  random var.  $\xrightarrow{-\ln x - c}$   $\ln Z + \text{Gumbel}(0)$  random var.

Estimator of  $\frac{1}{Z}$   $\xrightarrow{-\ln x - c}$  Estimator of  $\ln Z$

Unbiased estimator of  $\ln Z$ :

$$\widehat{\ln Z} = \frac{1}{M} \sum_{m=1}^M G_m \quad \text{where} \quad G_1, \dots, G_M \stackrel{\text{i.i.d.}}{\sim} \text{Gumbel}(\ln Z)$$



## Generalizing the Gumbel trick

Recall:

Competing exponential clocks  $\xrightarrow{-\ln x - c}$  Gumbel trick

Exp( $Z$ ) random var.  $\xrightarrow{-\ln x - c}$   $\ln Z + \text{Gumbel}(0)$  random var.

Estimator of  $\frac{1}{Z}$   $\xrightarrow{-\ln x - c}$  Estimator of  $\ln Z$

Unbiased estimator of  $\ln Z$ :

$$\widehat{\ln Z} = \frac{1}{M} \sum_{m=1}^M G_m \quad \text{where} \quad G_1, \dots, G_M \stackrel{\text{i.i.d.}}{\sim} \text{Gumbel}(\ln Z)$$

Biased estimator of  $Z$ :  $\hat{Z} = \exp \widehat{\ln Z}$ .

## Generalizing the Gumbel trick

Recall:

Competing exponential clocks  $\xrightarrow{-\ln x - c}$  Gumbel trick

Exp( $Z$ ) random var.  $\xrightarrow{-\ln x - c}$   $\ln Z + \text{Gumbel}(0)$  random var.

Estimator of  $\frac{1}{Z}$   $\xrightarrow{-\ln x - c}$  Estimator of  $\ln Z$

Unbiased estimator of  $\ln Z$ :

$$\widehat{\ln Z} = \frac{1}{M} \sum_{m=1}^M G_m \quad \text{where} \quad G_1, \dots, G_M \stackrel{\text{i.i.d.}}{\sim} \text{Gumbel}(\ln Z)$$

Biased estimator of  $Z$ :  $\hat{Z} = \exp \widehat{\ln Z}$ .

*How about applying different functions to the clocks?*

## Example: Weibull tricks

Unnormalized probability mass function  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_N)$ :



$\sim \text{Exp}(\tilde{p}_1)$



$\sim \text{Exp}(\tilde{p}_2)$

...



$\sim \text{Exp}(\tilde{p}_N)$

- 1 Probability  $q_i$  that clock  $i$  is the first to ring:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j} = \frac{\tilde{p}_i}{\sum_{j=1}^N \tilde{p}_j} = \frac{\tilde{p}_i}{Z} = p_i$$

- 2 First time  $T$  when a clock rings:

$$T \sim \text{Exp}(\lambda_1 + \dots + \lambda_N) = \text{Exp}(Z)$$
$$\mathbb{E}[T] = \frac{1}{\lambda_1 + \dots + \lambda_N} = \frac{1}{Z}$$

## Example: Weibull tricks

Unnormalized probability mass function  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_N)$ :

$$\left( \text{🕒} \right)^\alpha \sim \frac{1}{\tilde{p}_1^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right) \quad \left( \text{🕒} \right)^\alpha \sim \frac{1}{\tilde{p}_2^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right) \quad \dots \quad \left( \text{🕒} \right)^\alpha \sim \frac{1}{\tilde{p}_N^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right)$$

- 1 Probability  $q_i$  that clock  $i$  is the first to ring:

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j} = \frac{\tilde{p}_i}{\sum_{j=1}^N \tilde{p}_j} = \frac{\tilde{p}_i}{Z} = p_i$$

- 2 First time  $T$  when a clock rings:

$$T \sim \text{Exp}(\lambda_1 + \dots + \lambda_N) = \text{Exp}(Z)$$
$$\mathbb{E}[T] = \frac{1}{\lambda_1 + \dots + \lambda_N} = \frac{1}{Z}$$

## Example: Weibull tricks

Unnormalized probability mass function  $\tilde{\mathbf{p}} = (\tilde{p}_1, \dots, \tilde{p}_N)$ :

$$\begin{aligned} & \left( \text{🕒} \right)^\alpha \sim \frac{1}{\tilde{p}_1^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right) \quad \sim \frac{1}{\tilde{p}_2^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right) \quad \dots \quad \sim \frac{1}{\tilde{p}_N^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right) \end{aligned}$$

- ① Probability  $q_i$  of the minimum being at configuration  $i$ :

$$q_i = \frac{\lambda_i}{\sum_{j=1}^N \lambda_j} = \frac{\tilde{p}_i}{\sum_{j=1}^N \tilde{p}_j} = \frac{\tilde{p}_i}{Z} = p_i$$

- ② Transformed first ringing time:

$$\begin{aligned} T^\alpha & \sim \frac{1}{Z^\alpha} \text{Weibull}\left(1, \frac{1}{\alpha}\right) \\ \mathbb{E}[T^\alpha] & = Z^{-\alpha} \Gamma(1 + \alpha) \end{aligned}$$

## Generalizing the Gumbel trick

Competing exponential clocks  $\xrightarrow{x^\alpha}$  Weibull trick

Exp( $Z$ ) random variable  $\xrightarrow{x^\alpha}$  Weibull( $Z^{-\alpha}, \frac{1}{\alpha}$ ) rand. variable

Estimator of  $\frac{1}{Z}$   $\xrightarrow{x^\alpha}$  Estimator of  $Z^{-\alpha}\Gamma(1 + \alpha)$

## Generalizing the Gumbel trick

Competing exponential clocks  $\xrightarrow{x^\alpha}$  Weibull trick

Exp( $Z$ ) random variable  $\xrightarrow{x^\alpha}$  Weibull( $Z^{-\alpha}, \frac{1}{\alpha}$ ) rand. variable

Estimator of  $\frac{1}{Z}$   $\xrightarrow{x^\alpha}$  Estimator of  $Z^{-\alpha}\Gamma(1 + \alpha)$

Unbiased estimator of  $Z^{-\alpha}$ :

$$\widehat{Z^{-\alpha}} = \frac{1}{\Gamma(1 + \alpha)} \frac{1}{M} \sum_{m=1}^M W_m \quad \text{where} \quad \{W_m\}_{m=1}^M \stackrel{\text{i.i.d.}}{\sim} \text{Weibull}(Z^{-\alpha}, \frac{1}{\alpha})$$

## Generalizing the Gumbel trick

Competing exponential clocks  $\xrightarrow{x^\alpha}$  Weibull trick

Exp( $Z$ ) random variable  $\xrightarrow{x^\alpha}$  Weibull( $Z^{-\alpha}, \frac{1}{\alpha}$ ) rand. variable

Estimator of  $\frac{1}{Z}$   $\xrightarrow{x^\alpha}$  Estimator of  $Z^{-\alpha}\Gamma(1 + \alpha)$

Unbiased estimator of  $Z^{-\alpha}$ :

$$\begin{aligned}\widehat{Z^{-\alpha}} &= \frac{1}{\Gamma(1 + \alpha)} \frac{1}{M} \sum_{m=1}^M W_m \quad \text{where} \quad \{W_m\}_{m=1}^M \stackrel{\text{i.i.d.}}{\sim} \text{Weibull}(Z^{-\alpha}, \frac{1}{\alpha}) \\ &= \frac{1}{\Gamma(1 + \alpha)} \frac{1}{M} \sum_{m=1}^M e^{-\alpha(G_m+c)} \quad \text{where} \quad \{G_m\}_{m=1}^M \stackrel{\text{i.i.d.}}{\sim} \text{Gumbel}(\ln Z)\end{aligned}$$



## Generalizing the Gumbel trick

Competing exponential clocks  $\xrightarrow{x^\alpha}$  Weibull trick

Exp( $Z$ ) random variable  $\xrightarrow{x^\alpha}$  Weibull( $Z^{-\alpha}, \frac{1}{\alpha}$ ) rand. variable

Estimator of  $\frac{1}{Z}$   $\xrightarrow{x^\alpha}$  Estimator of  $Z^{-\alpha}\Gamma(1 + \alpha)$

Unbiased estimator of  $Z^{-\alpha}$ :

$$\begin{aligned}\widehat{Z^{-\alpha}} &= \frac{1}{\Gamma(1 + \alpha)} \frac{1}{M} \sum_{m=1}^M W_m \quad \text{where} \quad \{W_m\}_{m=1}^M \stackrel{\text{i.i.d.}}{\sim} \text{Weibull}(Z^{-\alpha}, \frac{1}{\alpha}) \\ &= \frac{1}{\Gamma(1 + \alpha)} \frac{1}{M} \sum_{m=1}^M e^{-\alpha(G_m + c)} \quad \text{where} \quad \{G_m\}_{m=1}^M \stackrel{\text{i.i.d.}}{\sim} \text{Gumbel}(\ln Z)\end{aligned}$$

Biased estimator of  $Z$ :  $\hat{Z} = \left(\widehat{Z^{-\alpha}}\right)^{-1/\alpha}$ .

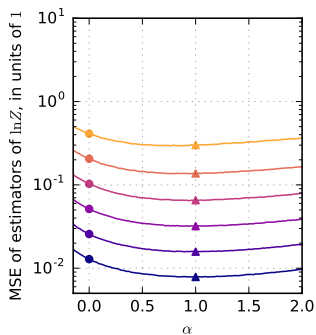
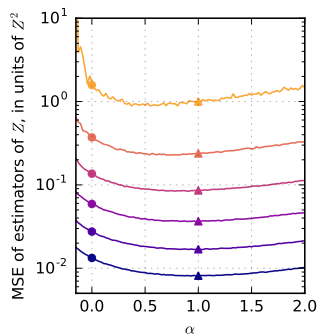
## Generalizing the Gumbel trick

Trick	$g(x)$	Mean $f(Z)$
Gumbel	$-\ln x - c$	$\ln Z$
Exponential	$x$	$\frac{1}{Z}$
Weibull $\alpha$	$x^\alpha, \alpha > 0$	$Z^{-\alpha}\Gamma(1 + \alpha)$
Fréchet $\alpha$	$x^\alpha, \alpha \in (-1, 0)$	$Z^{-\alpha}\Gamma(1 + \alpha)$
Pareto	$e^x$	$\frac{Z}{Z-1}$ for $Z > 1$
Tail $t$	$\mathbb{1}_{\{x>t\}}$	$e^{-tZ}$

## Generalizing the Gumbel trick

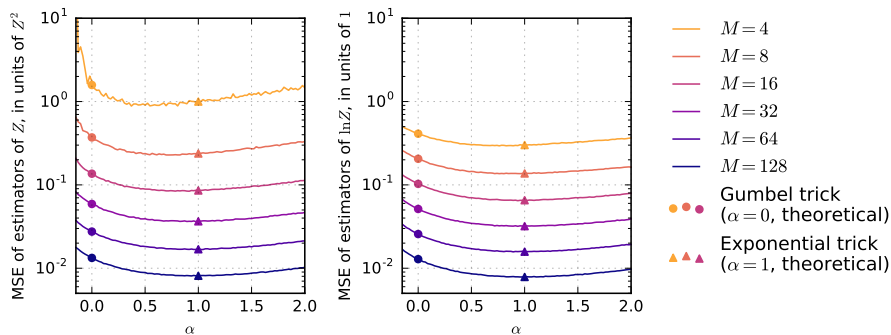
Trick	$g(x)$	Mean $f(Z)$	Asymptotic var. of $\hat{Z}$
Gumbel	$-\ln x - c$	$\ln Z$	$\frac{\pi^2}{6} Z^2$
Exponential	$x$	$\frac{1}{Z}$	$Z^2$
Weibull $\alpha$	$x^\alpha, \alpha > 0$	$Z^{-\alpha} \Gamma(1 + \alpha)$	$\frac{1}{\alpha^2} \left( \frac{\Gamma(1+2\alpha)}{\Gamma(1+\alpha)^2} - 1 \right) Z^2$
Fréchet $\alpha$	$x^\alpha, \alpha \in (-1, 0)$	$Z^{-\alpha} \Gamma(1 + \alpha)$	$\frac{1}{\alpha^2} \left( \frac{\Gamma(1+2\alpha)}{\Gamma(1+\alpha)^2} - 1 \right) Z^2$
Pareto	$e^x$	$\frac{Z}{Z-1}$ for $Z > 1$	$\frac{Z^2}{(Z-2)^2}$
Tail $t$	$\mathbb{1}_{\{x>t\}}$	$e^{-tZ}$	$\frac{(1-e^{-tZ})^2}{t^2}$

# Comparing tricks



- $M=4$
- $M=8$
- $M=16$
- $M=32$
- $M=64$
- $M=128$
- Gumbel trick  
( $\alpha=0$ , theoretical)
- Exponential trick  
( $\alpha=1$ , theoretical)

# Comparing tricks



## Takeaway:

Save up to 40% samples by using the Exponential trick instead of the Gumbel trick. Applications:

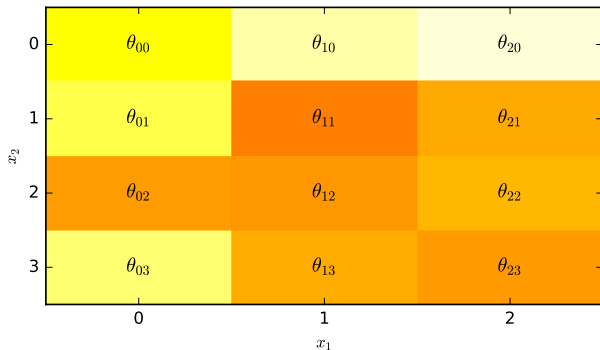
- *Large-scale discrete sampling* of [Chen and Ghahramani, 2016]
- *A\* sampling* of [Maddison et al., 2014]

# Low-rank perturbations

Discrete graphical model with  $n$  variables:  $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_n$ .

Example

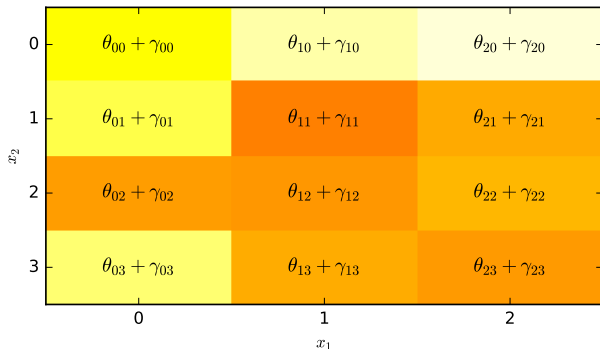
$n = 2$



# Low-rank perturbations

Discrete graphical model with  $n$  variables:  $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_n$ .

Example  
 $n = 2$



# Low-rank perturbations

Discrete graphical model with  $n$  variables:  $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_n$ .

Example  
 $n = 2$



	$+ \gamma_1(0)$	$+ \gamma_1(1)$	$+ \gamma_1(2)$	
0	$\theta_{00} + \gamma_1(0) + \gamma_2(0)$	$\theta_{10} + \gamma_1(1) + \gamma_2(0)$	$\theta_{20} + \gamma_1(2) + \gamma_2(0)$	$+ \gamma_2(0)$
1	$\theta_{01} + \gamma_1(0) + \gamma_2(1)$	$\theta_{11} + \gamma_1(1) + \gamma_2(1)$	$\theta_{21} + \gamma_1(2) + \gamma_2(1)$	$+ \gamma_2(1)$
2	$\theta_{02} + \gamma_1(0) + \gamma_2(2)$	$\theta_{12} + \gamma_1(1) + \gamma_2(2)$	$\theta_{22} + \gamma_1(2) + \gamma_2(2)$	$+ \gamma_2(2)$
3	$\theta_{03} + \gamma_1(0) + \gamma_2(3)$	$\theta_{13} + \gamma_1(1) + \gamma_2(3)$	$\theta_{23} + \gamma_1(2) + \gamma_2(3)$	$+ \gamma_2(3)$
	0	1	2	

$x_1$



# Low-rank perturbations

Discrete graphical model with  $n$  variables:  $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_n$ .

Example  
 $n = 2$



	$+ \gamma_1(0)$	$+ \gamma_1(1)$	$+ \gamma_1(2)$	
0	$\theta_{00} + \gamma_1(0) + \gamma_2(0)$	$\theta_{10} + \gamma_1(1) + \gamma_2(0)$	$\theta_{20} + \gamma_1(2) + \gamma_2(0)$	$+ \gamma_2(0)$
1	$\theta_{01} + \gamma_1(0) + \gamma_2(1)$	$\theta_{11} + \gamma_1(1) + \gamma_2(1)$	$\theta_{21} + \gamma_1(2) + \gamma_2(1)$	$+ \gamma_2(1)$
2	$\theta_{02} + \gamma_1(0) + \gamma_2(2)$	$\theta_{12} + \gamma_1(1) + \gamma_2(2)$	$\theta_{22} + \gamma_1(2) + \gamma_2(2)$	$+ \gamma_2(2)$
3	$\theta_{03} + \gamma_1(0) + \gamma_2(3)$	$\theta_{13} + \gamma_1(1) + \gamma_2(3)$	$\theta_{23} + \gamma_1(2) + \gamma_2(3)$	$+ \gamma_2(3)$
	0	1	2	

$x_2$  (vertical axis label)  
 $x_1$  (horizontal axis label)

$$U := \max_{\mathbf{x} \in \mathcal{X}} \left\{ \theta(\mathbf{x}) + \sum_{i=1}^n \gamma_i(x_i) \right\}$$

# Low-rank perturbations

Discrete graphical model with  $n$  variables:  $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_n$ .

Example

$n = 2$



	$+ \gamma_1(0)$	$+ \gamma_1(1)$	$+ \gamma_1(2)$	
0	$\theta_{00} + \gamma_1(0) + \gamma_2(0)$	$\theta_{10} + \gamma_1(1) + \gamma_2(0)$	$\theta_{20} + \gamma_1(2) + \gamma_2(0)$	$+ \gamma_2(0)$
1	$\theta_{01} + \gamma_1(0) + \gamma_2(1)$	$\theta_{11} + \gamma_1(1) + \gamma_2(1)$	$\theta_{21} + \gamma_1(2) + \gamma_2(1)$	$+ \gamma_2(1)$
2	$\theta_{02} + \gamma_1(0) + \gamma_2(2)$	$\theta_{12} + \gamma_1(1) + \gamma_2(2)$	$\theta_{22} + \gamma_1(2) + \gamma_2(2)$	$+ \gamma_2(2)$
3	$\theta_{03} + \gamma_1(0) + \gamma_2(3)$	$\theta_{13} + \gamma_1(1) + \gamma_2(3)$	$\theta_{23} + \gamma_1(2) + \gamma_2(3)$	$+ \gamma_2(3)$
	0	1	2	

$x_2$  (vertical axis label)  
 $x_1$  (horizontal axis label)

$$\ln Z \leq \mathbb{E}[U]$$

# Low-rank perturbations

Discrete graphical model with  $n$  variables:  $\mathcal{X} = \mathcal{X}_1 \times \dots \times \mathcal{X}_n$ .

Example

$n = 2$



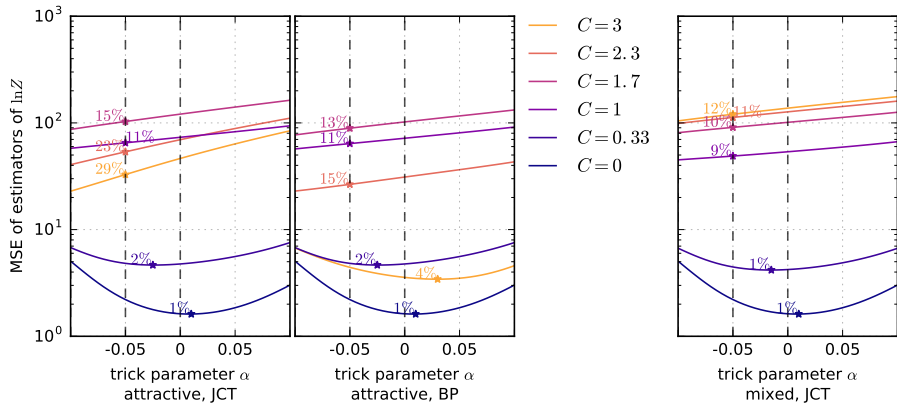
	$+ \gamma_1(0)$	$+ \gamma_1(1)$	$+ \gamma_1(2)$	
0	$\theta_{00} + \gamma_1(0) + \gamma_2(0)$	$\theta_{10} + \gamma_1(1) + \gamma_2(0)$	$\theta_{20} + \gamma_1(2) + \gamma_2(0)$	$+ \gamma_2(0)$
1	$\theta_{01} + \gamma_1(0) + \gamma_2(1)$	$\theta_{11} + \gamma_1(1) + \gamma_2(1)$	$\theta_{21} + \gamma_1(2) + \gamma_2(1)$	$+ \gamma_2(1)$
2	$\theta_{02} + \gamma_1(0) + \gamma_2(2)$	$\theta_{12} + \gamma_1(1) + \gamma_2(2)$	$\theta_{22} + \gamma_1(2) + \gamma_2(2)$	$+ \gamma_2(2)$
3	$\theta_{03} + \gamma_1(0) + \gamma_2(3)$	$\theta_{13} + \gamma_1(1) + \gamma_2(3)$	$\theta_{23} + \gamma_1(2) + \gamma_2(3)$	$+ \gamma_2(3)$
	0	1	2	

$x_1$

Gumbel trick:  $\ln Z \leq \mathbb{E}[U]$

Fréchet and Weibull tricks:  $\ln Z \leq C(\alpha, n) - \frac{1}{\alpha} \ln \mathbb{E}_\gamma \left[ e^{-\alpha U} \right]$

# Low-rank perturbations



## Also in the paper

Low-rank perturbations with the Fréchet, Weibull and Exponential tricks:

- 1 **Clamping** never hurts  $\ln Z$  estimation using any of the Fréchet or Weibull upper bounds  $\mathcal{U}(\alpha)$ .
- 2 **Sequential samplers** for the Gibbs distribution  $p$ .
- 3 **Lower bounds**  $\ln Z \geq \mathcal{L}(\alpha)$ , where

$$\mathcal{L}(\alpha) := c + \frac{\ln \Gamma(1 + \alpha)}{\alpha} - \frac{1}{n\alpha} \ln \mathbb{E}[\exp(-n\alpha L)].$$

- 4 **Advantages** of the Gumbel trick: theory such as

$$\underbrace{(\mathcal{U}(0) - \ln Z)}_{\text{error in } \ln Z \text{ bound}} + \underbrace{\text{KL}(x^* \parallel p)}_{\text{sampling error}} = \underbrace{\mathbb{E}_{\gamma_i} [\gamma_i(x_i^*)]}_{\text{error in entropy estimation}} - H(x^*).$$

# Thank you



**Matej Balog**

University of Cambridge & MPI-IS Tübingen



**Nilesh Tripuraneni**

UC Berkeley



**Zoubin Ghahramani**

University of Cambridge & Uber AI Labs



**Adrian Weller**

University of Cambridge & Alan Turing Institute

Poster: Tuesday (today) 18:30–22:00 at Gallery #117

Slides: <http://matejbalog.eu/en/research/>

Code: <https://github.com/matejbalog/gumbel-relatives>