

Automatic Reparameterisation in Probabilistic Programming

Maria I. Gorinova, Dave Moore, Matthew D. Hoffman

A probabilistic program: Schools

```
mu ~ normal(0, 5)
```

```
tau ~ halfCauchy(0, 5)
```

```
for(n in 1 .. 3)
```

```
    theta[n] ~ normal(mu, tau)
```

```
    y[n] ~ normal(theta, sigma[n])
```

```
observe y = [28, 8, -3]
```

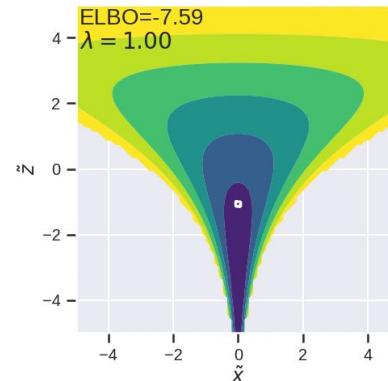
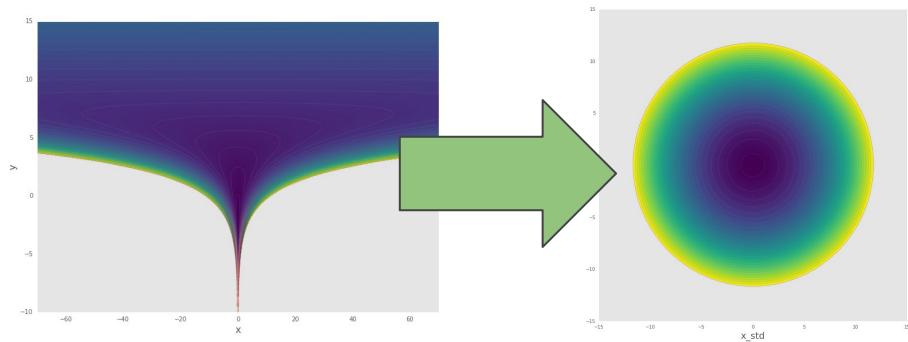
```
observe sigma = [15, 10, 16]
```



Inference

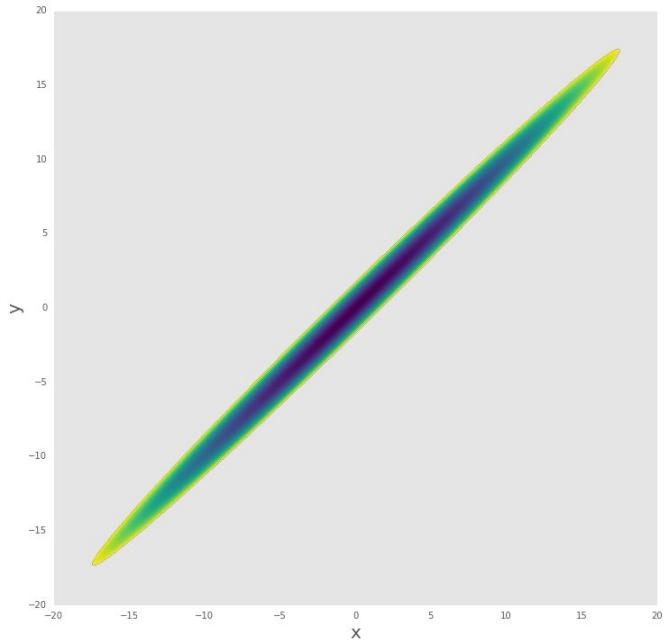
Automatic reparameterisation overview

1. What is reparameterisation and why is it difficult?
2. Reparameterisation in probabilistic programming
3. Variationally inferred parameterisation (VIP)

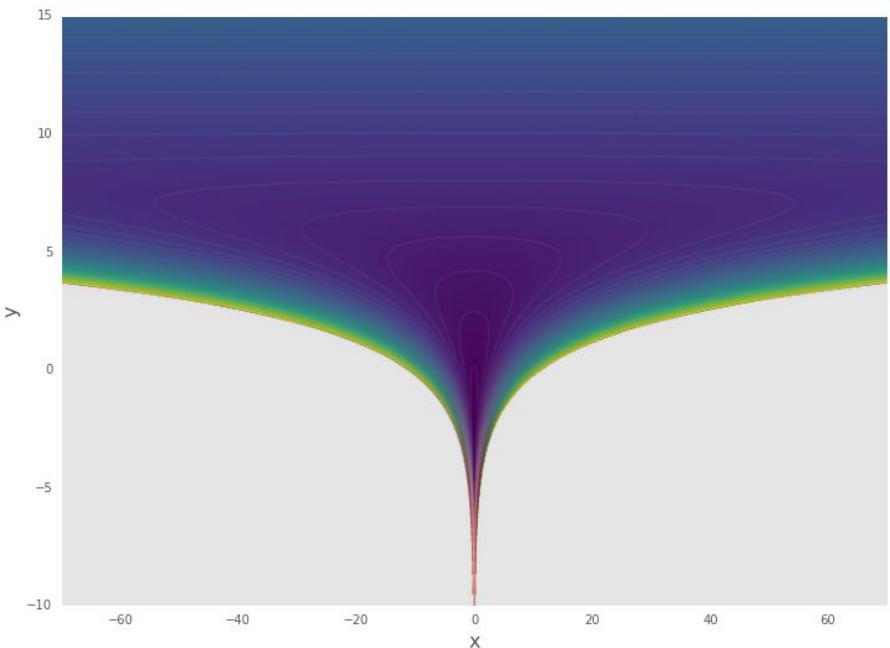


Problem: The posterior geometry affects quality of inference

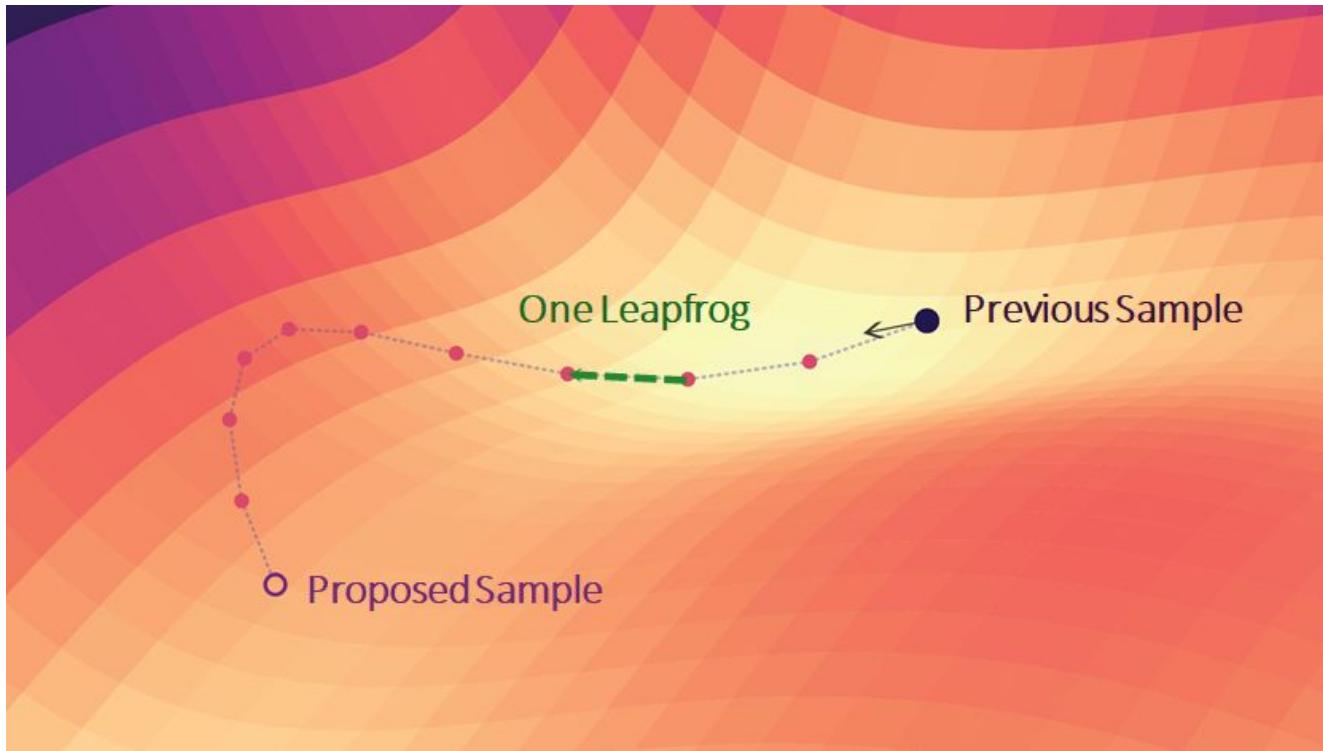
$$y \sim \mathcal{N}(0, 1)$$
$$x \sim \mathcal{N}(y, 0.1)$$



$$y \sim \mathcal{N}(0, 3)$$
$$x \sim \mathcal{N}(0, e^{y/2})$$

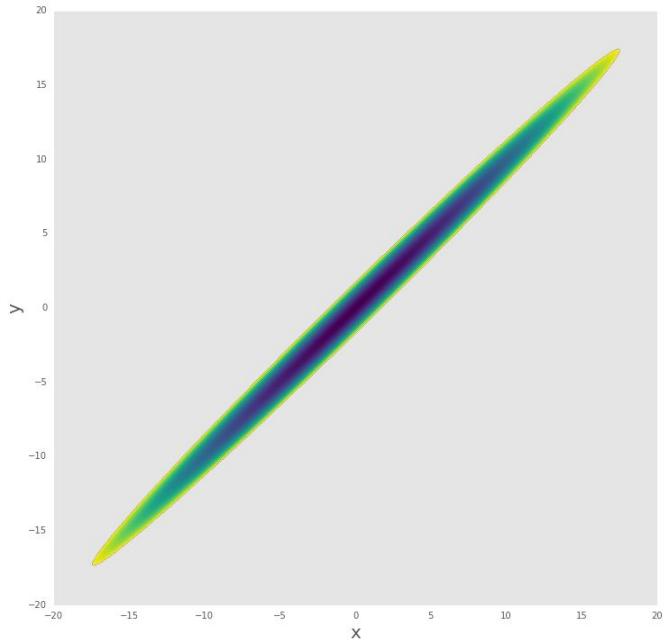


Hamiltonian Monte Carlo (HMC)

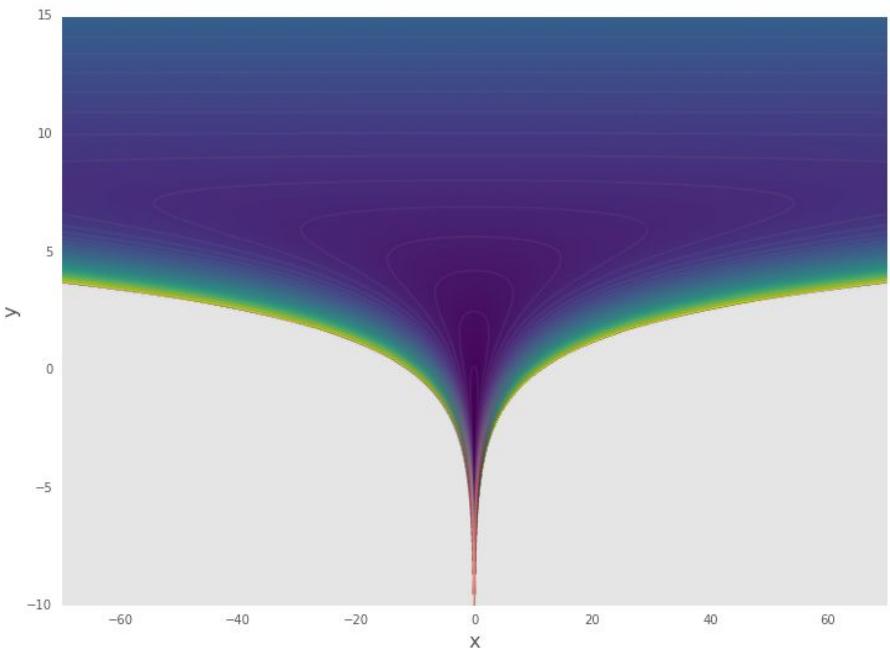


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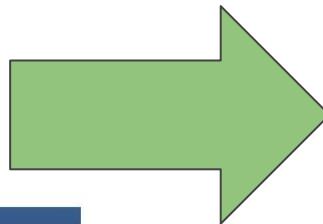


$$y \sim \mathcal{N}(0, 3)$$
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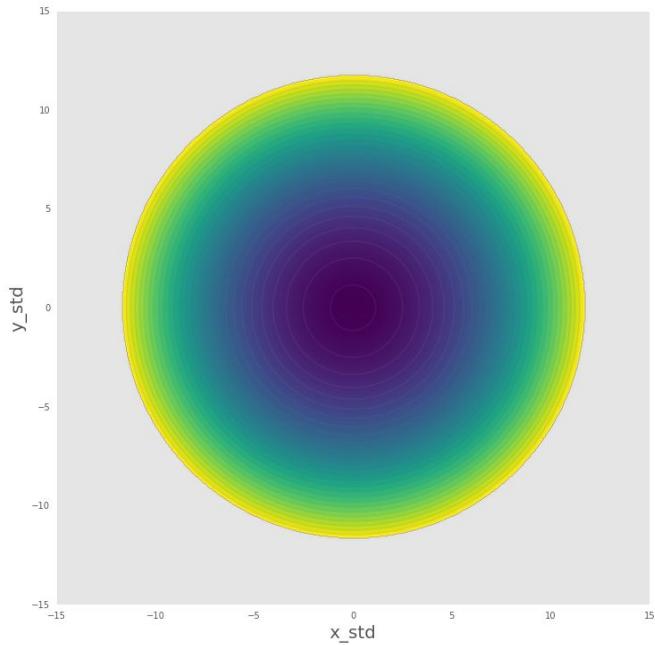
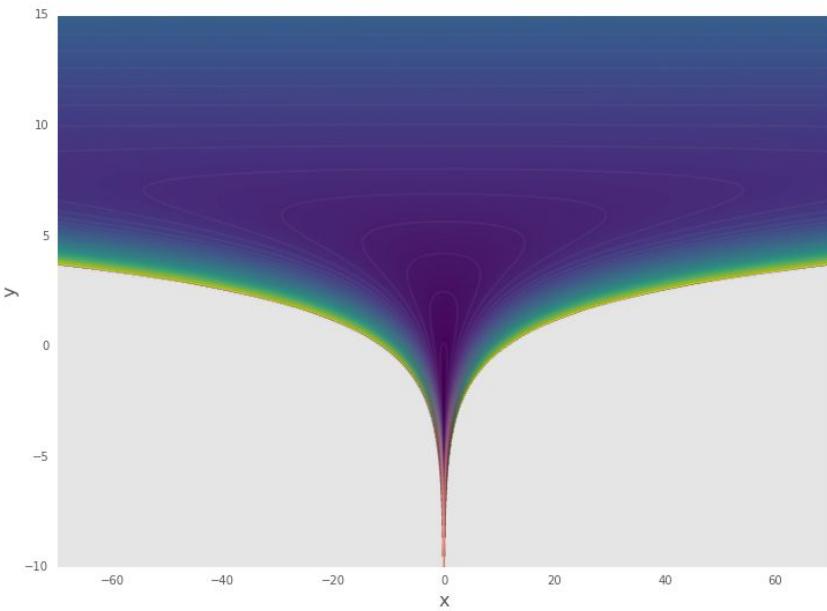
What is model reparameterisation?

$$y \sim \mathcal{N}(0, 3)$$
$$x \sim \mathcal{N}(0, e^{y/2})$$

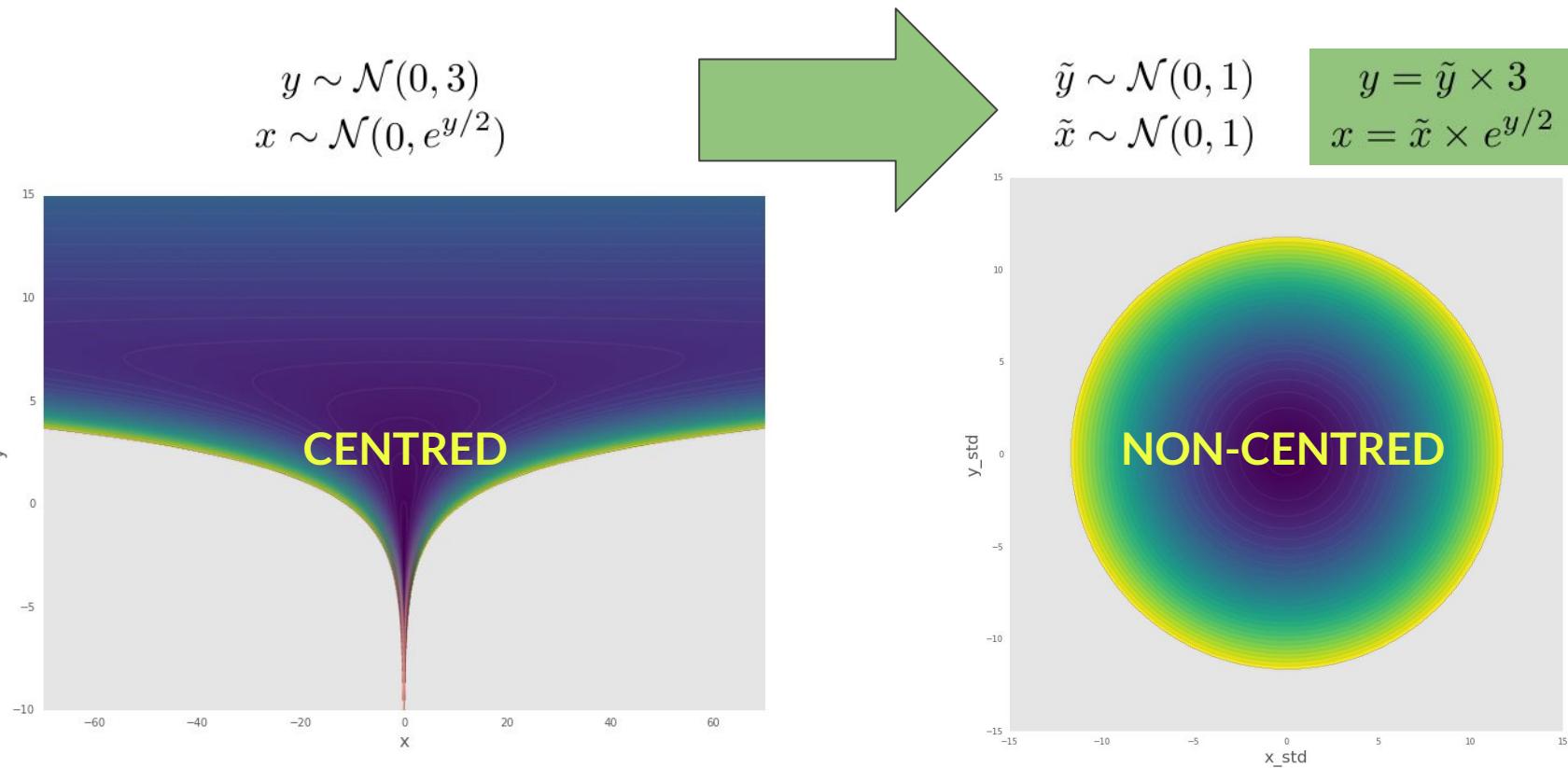


$$\tilde{y} \sim \mathcal{N}(0, 1)$$
$$\tilde{x} \sim \mathcal{N}(0, 1)$$

$$y = \tilde{y} \times 3$$
$$x = \tilde{x} \times e^{\tilde{y}/2}$$

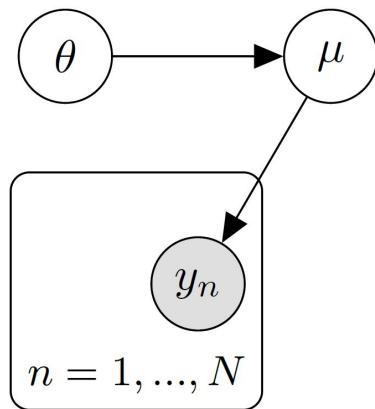


What is model reparameterisation?

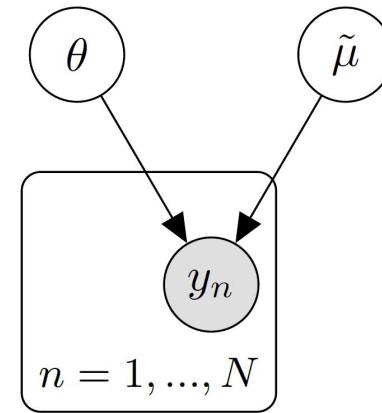


Understanding Reparameterisation Effects

Centred



Non-centred



$$\theta \sim \mathcal{N}(0, 1) \quad \mu \sim \mathcal{N}(\theta, \sigma_\mu)$$

$$y_n \sim \mathcal{N}(\mu, \sigma) \text{ for all } n \in 1 \dots N$$

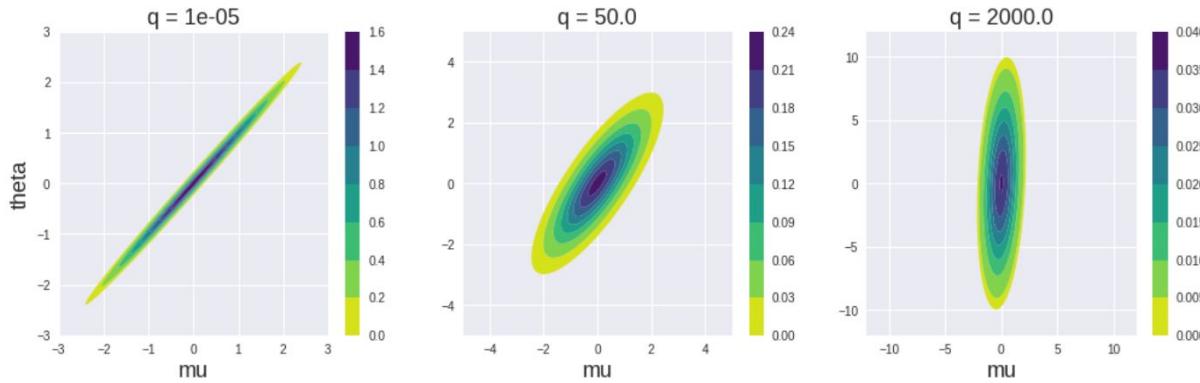
$$\theta \sim \mathcal{N}(0, 1) \quad \epsilon \sim \mathcal{N}(0, 1) \quad \mu = \theta + \sigma_\mu \epsilon$$

$$y_n \sim \mathcal{N}(\theta + \sigma_\mu \epsilon, \sigma) \text{ for all } n \in 1 \dots N$$

Understanding Reparameterisation Effects

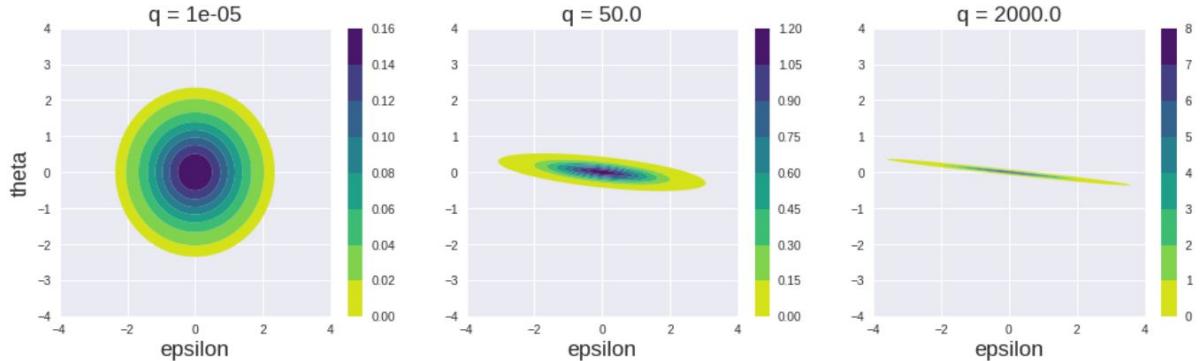
$$q = N/\sigma$$

Centred



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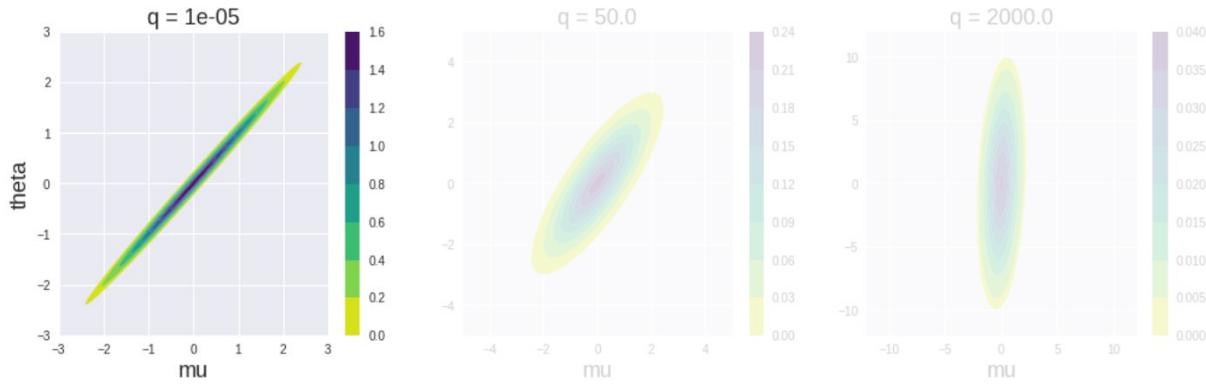
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Understanding Reparameterisation Effects

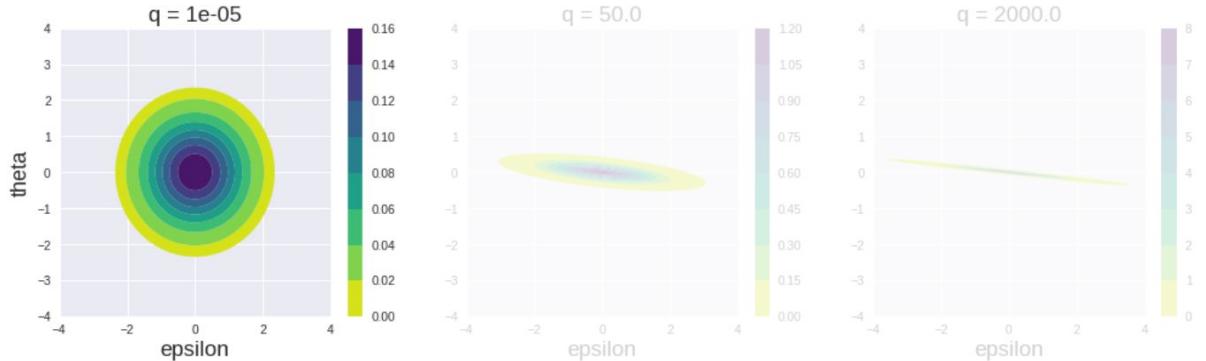
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Centred



source

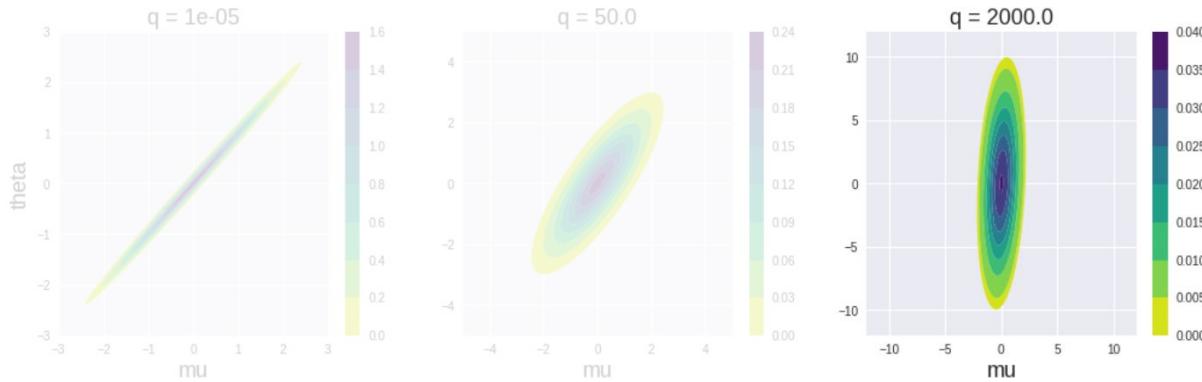
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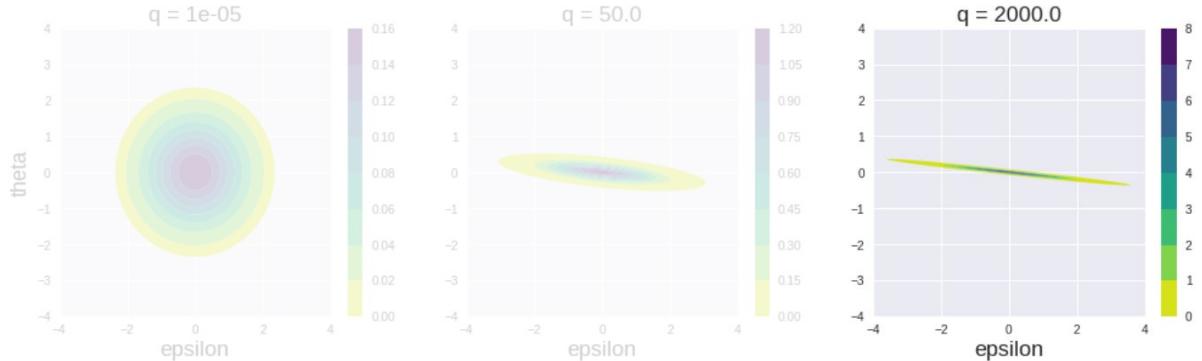
Understanding Reparameterisation Effects

$$q = N/\sigma$$

Centred



Non-centred



Stan diagnostics example

Goal: Free modellers of the need to choose model parameterisation

Reparameterisation in probabilistic programming

Centred

```
def model(N, sigma, sigma_mu):  
  
    theta = Normal(0., 3.)  
  
    mu = Normal(theta, sigma_mu)  
  
    y = Normal(mu, sigma)  
    return y
```

Non-centred

```
def model_ncp(N, sigma, sigma_mu):  
  
    theta_std = Normal(0., 1.)  
    theta = 3. * theta_std  
  
    mu_std = Normal(0., 1.)  
    mu = theta + mu_std * sigma_mu  
  
    y = Normal(mu, sigma)  
    return y
```

Algebraic effect handlers

```
handler h {  
    read(_) -> "I <3 PPLs"  
}
```

```
x = read(file1)  
y = read(file2)  
print(concatenate(x, y))  
  
with h handle:  
    x = read(file1)  
    y = read(file2)  
    print(concatenate(x, y))  
  
> "Contents of file1Contents of file2"  
  
> "I <3 PPLsI <3 PPLs"
```


Reparameterisation in probabilistic programming

Effect Handler: A function that may change how and if a RV is constructed

```
def ncp(rv_constr, **args):
    if is_location_scale(rv_constr):
        std = rv_constr(0., 1.)
    return args["scale"] * std + args["loc"]

with handler(ncp):
    theta = Normal(0., 3.)
    mu = Normal(theta, 1.)
```

Reparameterisation in probabilistic programming

Effect Handler: A function that may change how and if a RV is constructed

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    if is_location_scale(rv_constr):
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```
with handler(ncp):
    theta = Normal(0., 3.)
    mu = Normal(theta, 1.)
```



```
theta_std = Normal(0., 1.)
theta = 3. * theta_std
mu_std = Normal(0., 1.)
mu = mu_std + theta
```

Reparameterisation in probabilistic programming

Centred



Non-centred

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Variationally Inferred Parameterisation (VIP)

$$\tilde{z} \sim \mathcal{N}(\lambda\mu, \sigma^\lambda)$$

$$z = \mu + \sigma^{1-\lambda}(\tilde{z} - \lambda\mu)$$

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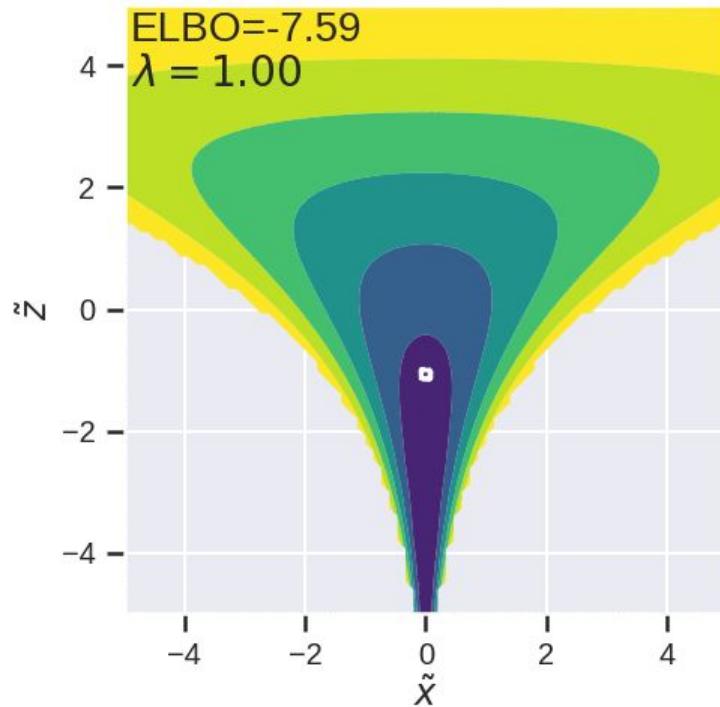
$$\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{\lambda}) = \mathbb{E}_{q(\tilde{\mathbf{z}}; \boldsymbol{\theta})} (\log p(\mathbf{x}, \tilde{\mathbf{z}}; \boldsymbol{\lambda}) - \log q(\tilde{\mathbf{z}}; \boldsymbol{\theta}))$$

Example: Neal's funnel VIP

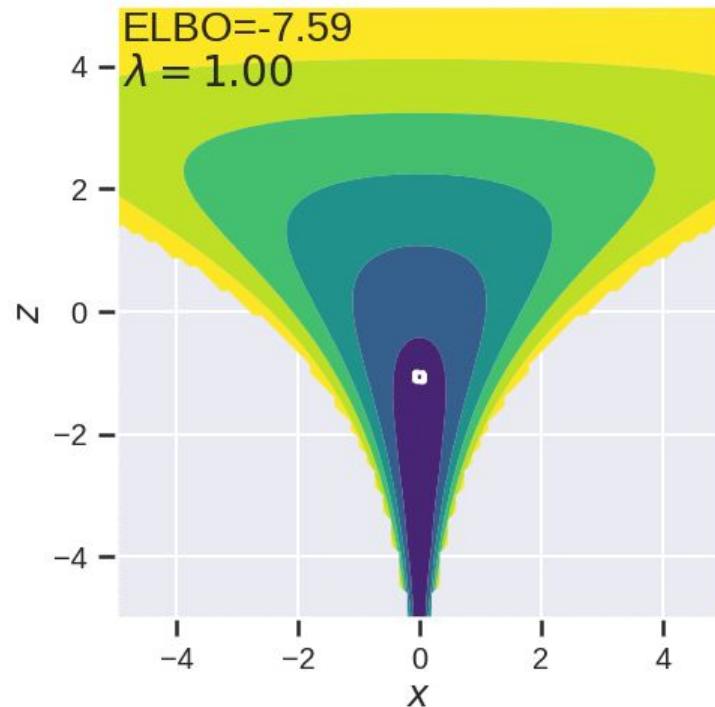
$$z \sim \mathcal{N}(0, 3)$$

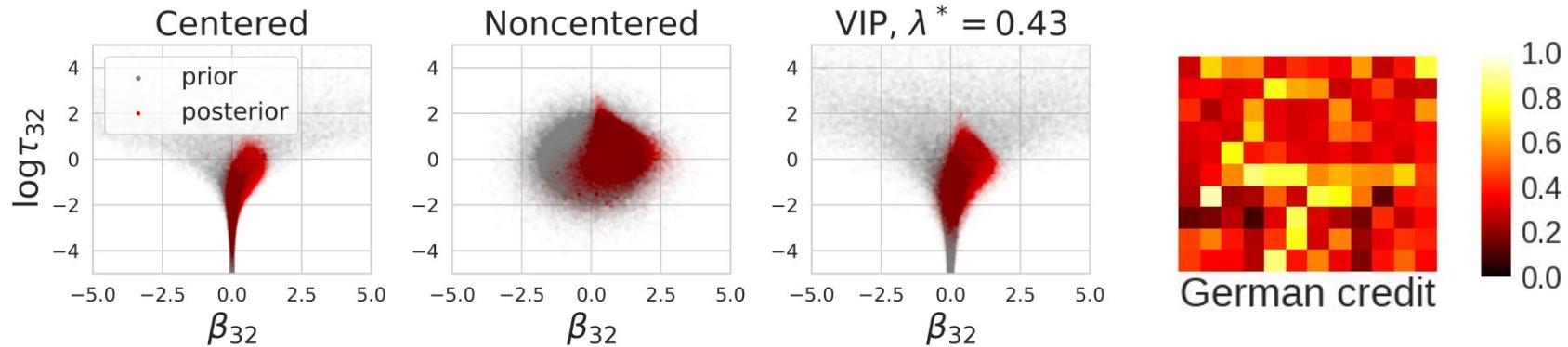
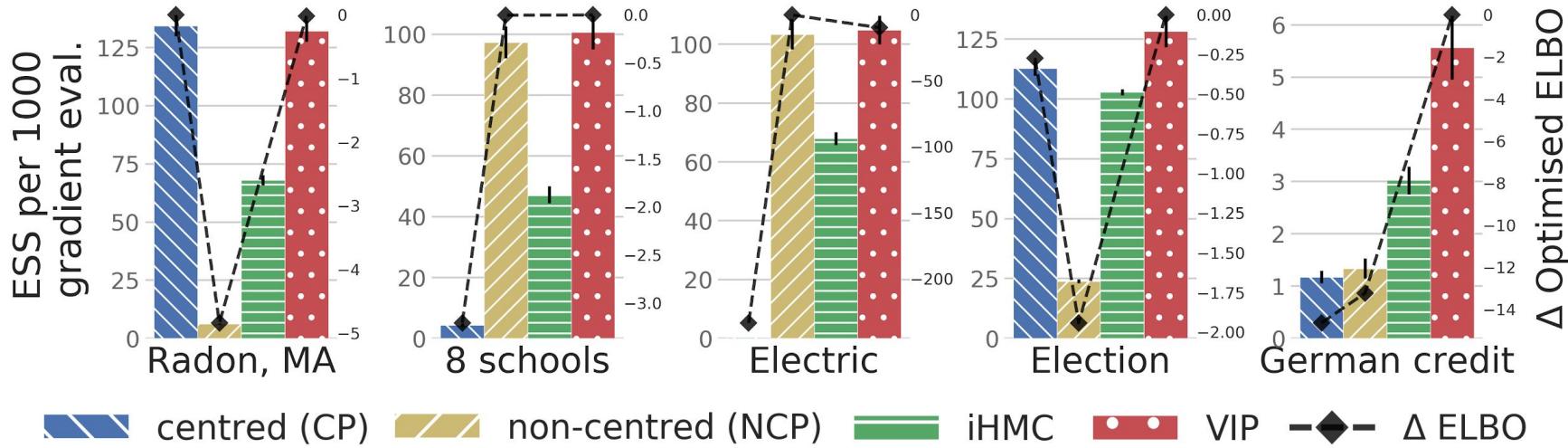
$$x \sim \mathcal{N}(0, e^{z/2})$$

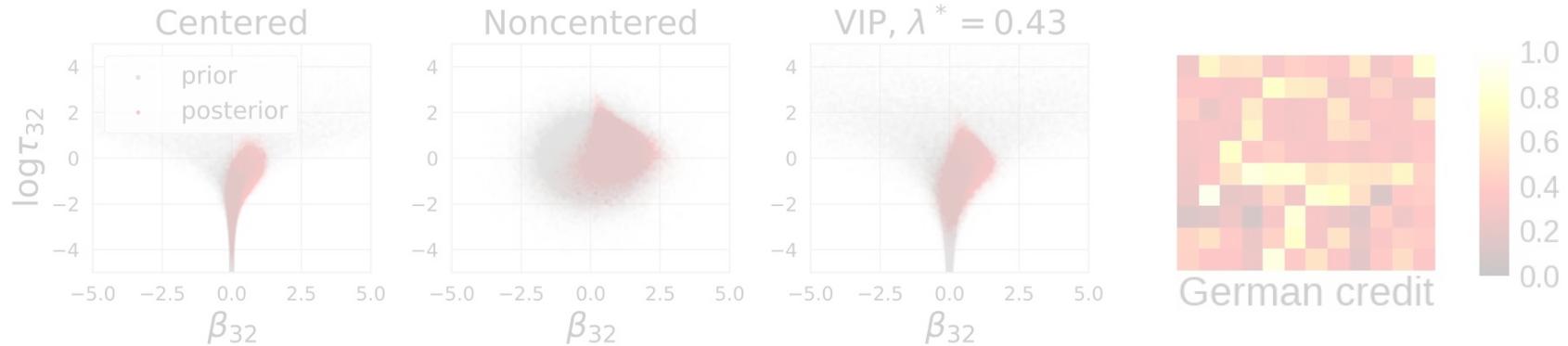
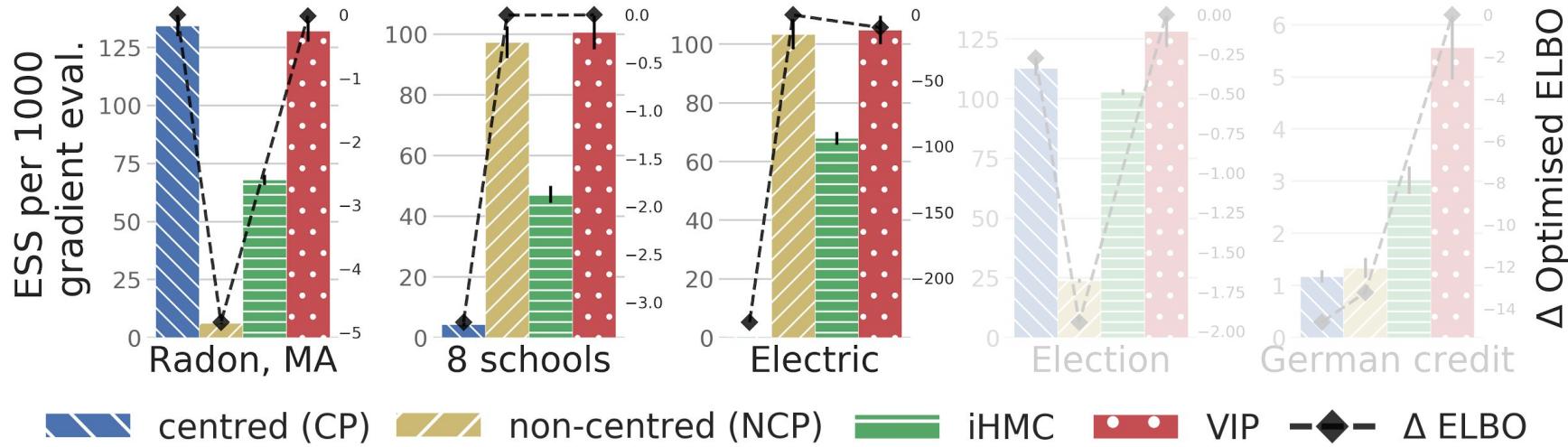
Reparameterized coordinates:

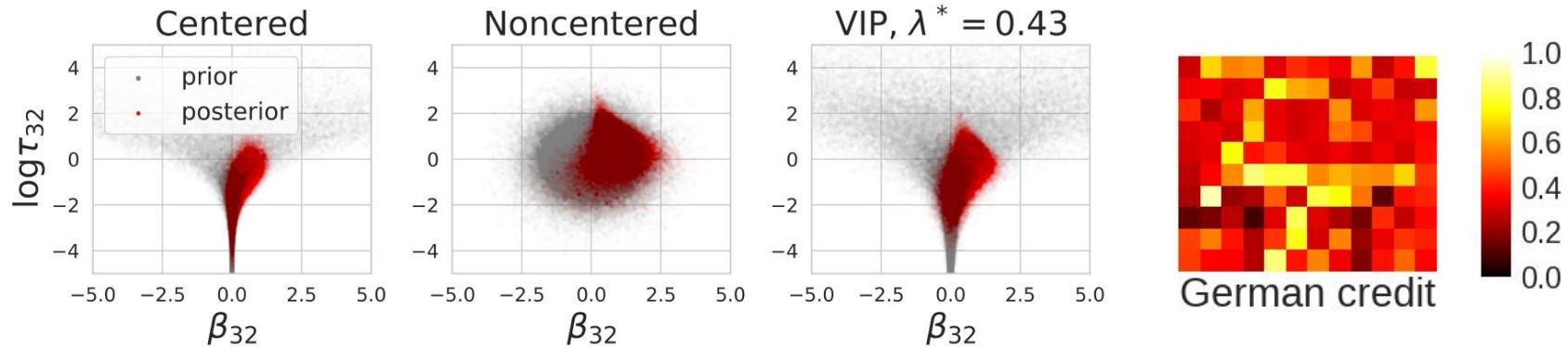
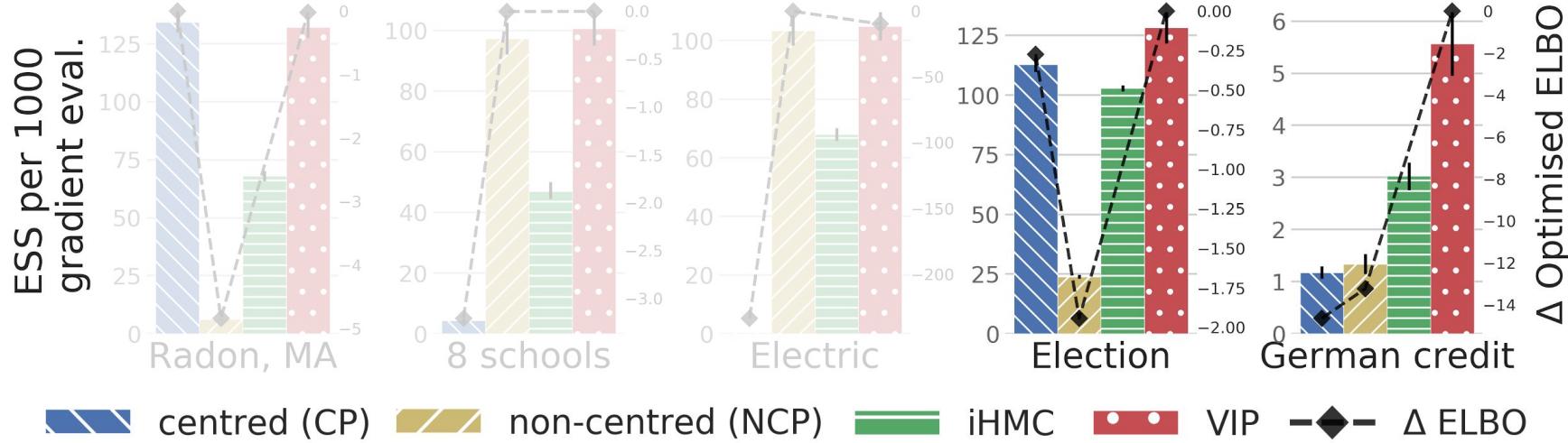


Original coordinates:



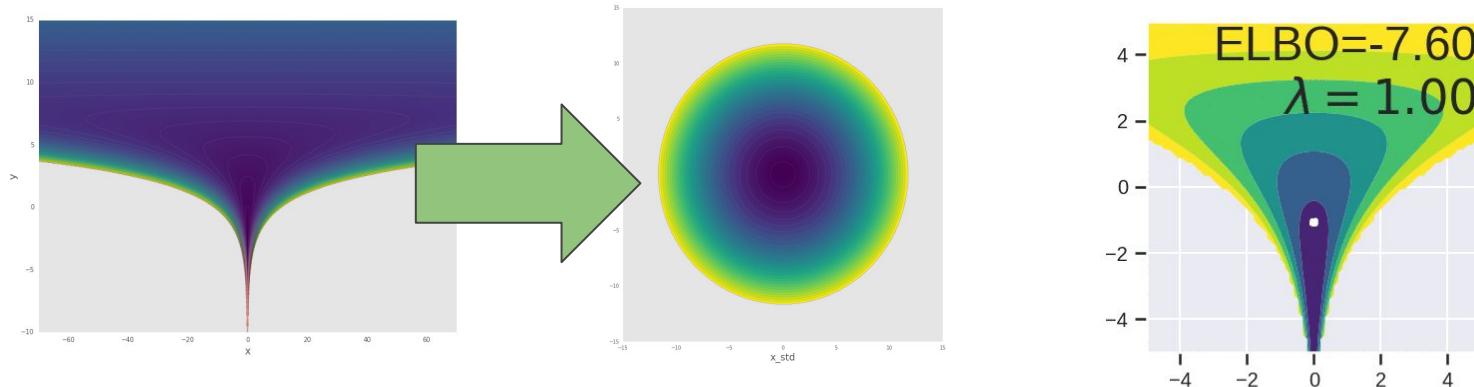






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Thank you!