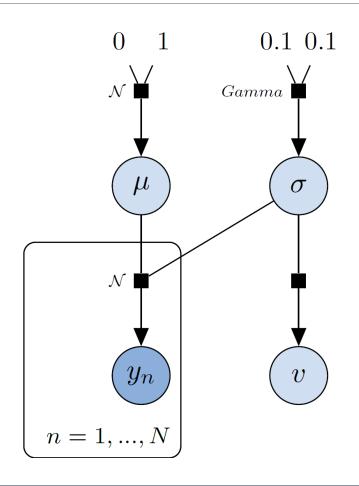
Optimising Probabilistic Programs using Information Flow Analysis

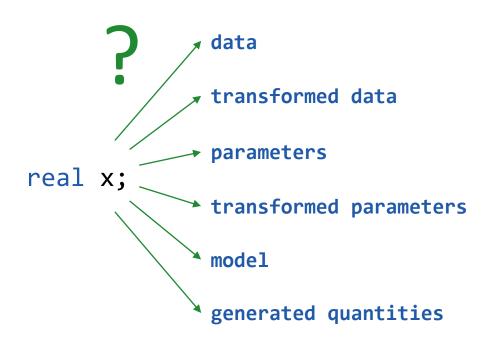
Maria I. Gorinova, Andrew D. Gordon, Charles Sutton

What is Stan?

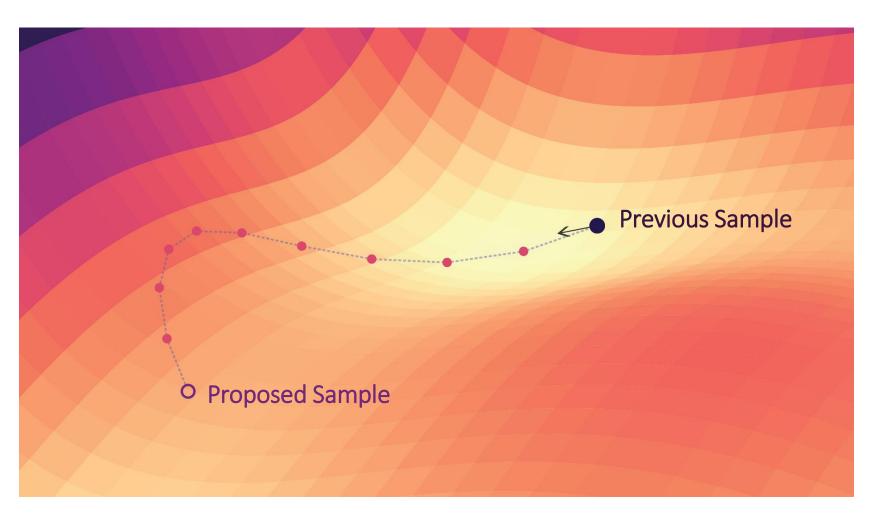
```
data {
   int N;
   real y[N];
parameters {
   real mu;
   real sigma;
model {
   sigma \sim gamma(0.1, 0.1);
   mu \sim normal(0, 1);
   y ~ normal(mu, sigma);
generated quantities {
   real variance;
   variance = sigma * sigma;
```



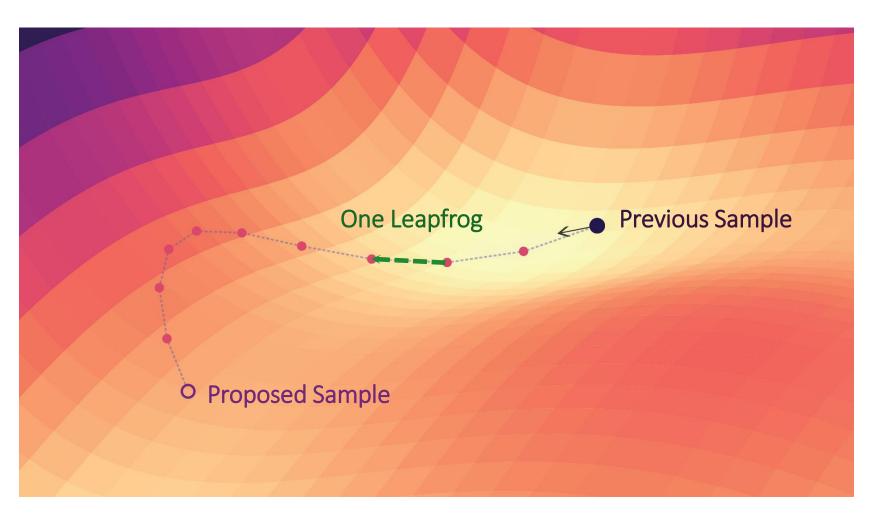
Why blocks matter?



Inference in Stan: Hamiltonian Monte Carlo



Inference in Stan: Hamiltonian Monte Carlo



SlicStan vs. Stan

```
real mu ~ normal(0, 1);

real alpha = 0.1;
real beta = 0.1;
real tau ~ gamma(alpha, beta);
real sigma = pow(tau, -0.5);

data int N;
data real[N] y ~ normal(mu, sigma);

real variance = sigma * sigma;
```

```
data {
     int N;
     real y[N];
transformed data {
     real alpha = 0.1;
     real beta = 0.1;
parameters {
     real mu;
     real tau;
transformed parameters {
     real sigma;
     sigma = pow(tau, -0.5);
model {
     tau ~ gamma(alpha, beta);
     mu \sim normal(0, 1);
     y ~ normal(mu, sigma);
generated quantities {
     real variance;
     variance = sigma * sigma;
}
```

Information Flow

Transfer of information between two variables

$$y = x + 5$$
if $x > 5$ then $y = 1$ else $y = 0$

Information Flow

PUBLIC < SECRET

```
p: PUBLIC, s: SECRET

s = p

p = s

if s > 5 then p = 1 else p = 0
```

Information Flow in Stan

```
data {
   int N;
  real y[N];
                                                             DATA
   real mu mu;
   real sigma mu;
transformed data {
   real alpha = 0.1;
   real beta = 0.1;
parameters {
   real mu y;
   real tau y;
transformed parameters {
   real sigma y;
   sigma_y = pow(tau_y, -0.5);
model {
  tau y ~ gamma(alpha, beta);
  mu y ~ normal(mu mu, sigma mu);
   y ~ normal(mu y, sigma y);
generated quantities {
                                                     GENQUANT
   real variance y;
   variance_y = sigma_y * sigma_y;
```

Key idea

 Find all possible roles a variable can have during inference, w.r.t. the information flow:

DATA
$$\leq$$
 MODEL \leq GENQUANT

- data real x → level(x) = DATA
- real x, ≠ → level(x) ≥ MODEL
- $x = foo(y) \rightarrow level(x) \ge level(y)$
- $x \sim foo(y) \rightarrow level(x) \leq MODEL$ and $level(y) \leq MODEL$

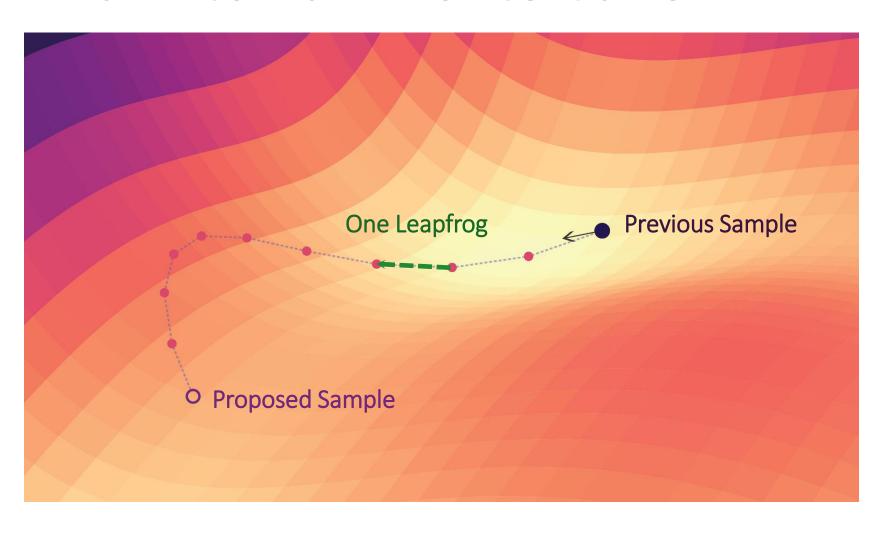
Key idea

• Find all **possible roles** a variable can have during inference, w.r.t. the **information flow**:

```
DATA \leq MODEL \leq GENQUANT
```

- data real x → level(x) = DATA
- real x, ≠ → level(x) ≥ MODEL
- $x = foo(y) \rightarrow level(x) \ge level(y)$
- $x \sim foo(y) \rightarrow level(x) \leq MODEL$ and $level(y) \leq MODEL$
- Not unique... Which one do we choose?

Hamiltonian Monte Carlo



Performance ordering

Block	Execution	Level
data		DATA
transformed data	once	DATA
parameters	once per leapfrog	MODEL
transformed parameters	once per leapfrog	MODEL
model	once per leapfrog	MODEL
generated quantities	once per sample	GENQUANT

DATA < GENQUANT < MODEL

Key insight

• Find all **possible roles** a variable can have during inference, w.r.t. the **information flow**:

DATA
$$\leq$$
 MODEL \leq GENQUANT

 Choose the most optimal role, w.r.t. the performance ordering:

```
DATA < GENQUANT < MODEL
```

```
real alpha = 0.1;
real beta = 0.1;
real tau_y ~ gamma(alpha, beta);

data real mu_mu;
data real sigma_mu;
real mu_y ~ normal(mu_mu, sigma_mu);

real sigma_y = pow(tau_y, -0.5);
data int N;
data real[N] y;
y ~ normal(mu_y, sigma_y);

real variance_y = pow(sigma_y, 2);
```

```
DATA real alpha = 0.1;
DATA real beta = 0.1;
MODEL real tau_y ~ gamma(alpha, beta);

data DATA real mu_mu;
data DATA real sigma_mu;
MODEL real mu_y ~ normal(mu_mu, sigma_mu);

MODEL real sigma_y = pow(tau_y, -0.5);
data DATA int N;
data DATA real[N] y;
y ~ normal(mu_y, sigma_y);

GENQUANT real variance_y = pow(sigma_y, 2);
```

```
DATA real alpha = 0.1;
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data DATA real mu_mu;
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MODEL real mu_y ~ normal(mu_mu, sigma_mu);

MODEL real sigma_y = pow(tau_y, -0.5);
data DATA int N;
data DATA real[N] y;
y ~ normal(mu_y, sigma_y);

GENQUANT real variance_y = pow(sigma_y, 2);
```

Stan

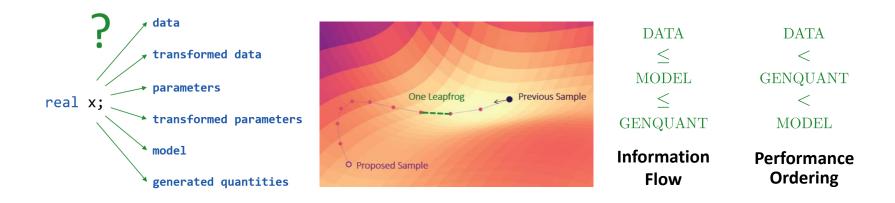
```
data {
   int N;
   real y[N];
   real mu mu;
   real sigma mu;
transformed data {
   real alpha = 0.1;
   real beta = 0.1;
parameters {
   real mu y;
   real tau_y;
transformed parameters {
   real sigma_y;
   sigma y = pow(tau y, -0.5);
model {
  tau_y ~ gamma(alpha, beta);
   mu y ~ normal(mu_mu, sigma_mu);
  y ~ normal(mu_y, sigma_y);
generated quantities {
   real variance_y;
   variance_y = sigma_y * sigma_y;
```

```
real nc_normal(real m, real s) {
   real raw ~ normal(0, 1);
   return s * raw + m;
}
real y = nc_normal(0, 3);
real x = nc_normal(0, exp(y/2));
```

```
Stan (efficient)
parameters {
   real y raw;
   real x raw;
transformed parameters {
   real y;
   real x;
   y = 3.0 * y_raw;
   x = \exp(y/2) * x_raw;
model {
   y_raw \sim normal(0, 1);
   x_{\text{raw}} \sim \text{normal}(0, 1);
```

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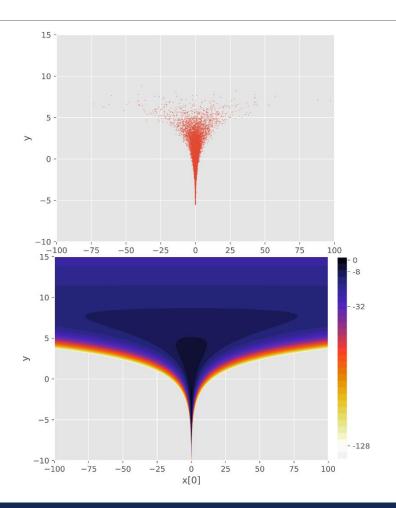
Email: m.gorinova@ed.ac.uk

SlicStan PPS page: https://tiny.cc/slicstan

Technical paper available soon: ask me for details!

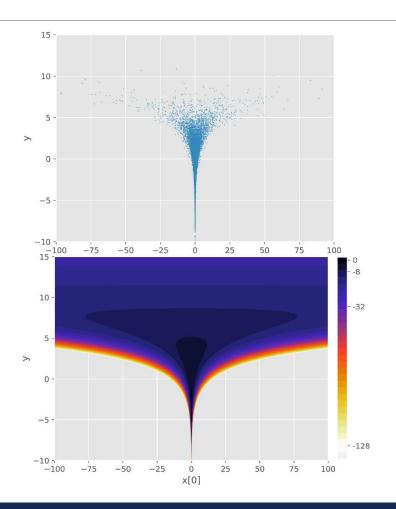






Stan (direct implementation)

```
parameters {
    real y;
    real x;
}
model {
    y ~ normal(0, 3.0);
    x ~ normal(0, exp(y/2));
}
```



```
Stan (efficient)
parameters {
   real y_raw;
   real x_raw;
transformed parameters {
   real y;
   real x;
   y = 3.0 * y_raw;
   x = \exp(y/2) * x_raw;
model {
   y_raw \sim normal(0, 1);
   x_raw \sim normal(0, 1);
```

```
real nc_normal(real m, real s) {
   real raw ~ normal(0, 1);
   return s * raw + m;
}
real y = nc_normal(0, 3);
real x = nc_normal(0, exp(y/2));
```

```
Stan (efficient)
parameters {
   real y raw;
   real x raw;
transformed parameters {
   real y;
   real x;
   y = 3.0 * y_raw;
   x = \exp(y/2) * x_raw;
model {
   y_raw \sim normal(0, 1);
   x_{\text{raw}} \sim \text{normal}(0, 1);
```