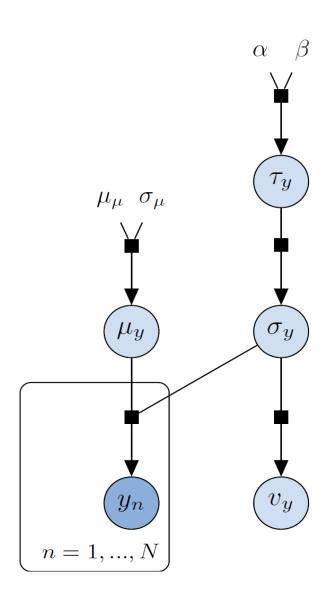
A Blockless Stan-like Language

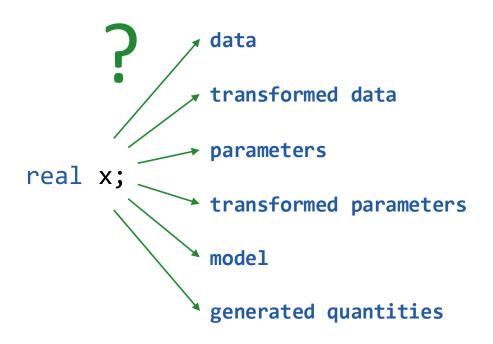
Maria I. Gorinova, Andrew D. Gordon, Charles Sutton



```
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;
```

# What is the problem?

- Lack of compositionality
- Inflexible user-defined functions
- Non-trivial to optimise



### SlicStan vs. Stan

```
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 ~ normal(mu_y, sigma_y);

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

```
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;
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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;
```

### Neal's Funnel

#### SlicStan

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

#### Stan

```
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);
```

### 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

X p = s

if s 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 < MODEL < 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 < MODEL < GENQUANT
```

- data real x → level(x) = DATA
  real x, ≠ → level(x) ≥ MODEL
  x = foo(y) → level(x) ≥ level(y)
  x ~ foo(y) → level(x) ≤ MODEL and level(y) ≤ MODEL
- Not unique... Which one do we choose?

# Performance ordering

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

DATA  $\leq$  GENQUANT  $\leq$  MODEL

# Key insight

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

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

DATA 
$$\leq$$
 GENQUANT  $\leq$  MODEL

### Translation to Stan

- 1. Elaboration: calls to user-defined functions are statically unrolled.
- 2. Transformation: the SlicStan code is shredded into different Stan program blocks.

```
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);
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DATA real alpha = 0.1;
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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;
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transformed data {
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```

### What comes next?

- User-defined functions vectorization.
- Deducing type constraints automatically.
- Formalising the semantics of Stan.

# SlicStan: Improving Probabilistic Programming using Information Flow Analysis

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SlicStan PPS page: <a href="https://tiny.cc/slicstan">https://tiny.cc/slicstan</a>





