Combinatorial sampling techniques Multivariate tuning Examples and applications

# Polynomial tuning of multiparametric combinatorial samplers

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Combinatorial sampling techniques Multivariate tuning Examples and applications

- 1 Combinatorial sampling techniques
- Multivariate tuning
- 3 Examples and applications

### Outline

- 1 Combinatorial sampling techniques
- 2 Multivariate tuning

3 Examples and applications

Examples and applications

The recursive method Boltzmann sampler Multiparametric sampling

### Warm-up example: binary trees



#### **Definition**

$$\mathcal{B} = \mathcal{Z}|(\mathcal{B})\mathcal{Z}(\mathcal{B})$$

$$\mathcal{B} = \{\mathcal{Z}, (\mathcal{Z})\mathcal{Z}(\mathcal{Z}), ((\mathcal{Z})\mathcal{Z}(\mathcal{Z}))\mathcal{Z}(\mathcal{Z}), \mathcal{Z}(\mathcal{Z})((\mathcal{Z})\mathcal{Z}(\mathcal{Z})), \ldots\}$$

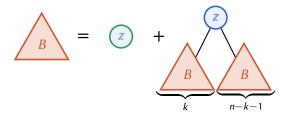
#### **Problem**

Generate uniformly at random binary trees with *n* nodes.



The recursive method Boltzmann sampler Multiparametric sampling

### Warm-up example: binary trees



#### Recursive method

$$T_n = \sum_{k=1}^n T_k T_{n-k-1}$$
,  $p_k = \frac{T_k T_{n-k-1}}{T_n}$ 

### The recursive method

■ For each n, k precompute

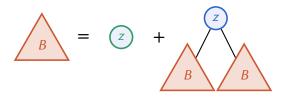
$$p_k^{(n)} = \frac{T_k T_{n-k-1}}{T_n}$$

- Function generate(n):
  - If n = 1 return  $\mathcal{Z}$
  - Generate *k* from probability distribution

$$k \sim (p_k^{(n)})_{k=1}^n$$

- Left subtree L := generate(k)
- Right subtree R := generate(n-k-1)
- Return resulting tree  $(L)\mathcal{Z}(R)$

### Warm-up example: binary trees



### Boltzmann sampling (a.k.a. Galton-Watson process)

- Function generate(p):
  - $\blacksquare$  X := Bernoulli(p)
  - If X = 0 return Z
  - If X = 1 return (generate(p)) $\mathcal{Z}$ (generate(p))



### Generating function for trees

#### Definition.

$$T(z) = T_0 + T_1 z + T_2 z^2 + \dots$$

$$T(z) = z + zT^{2}(z)$$
,  $T(z) = \frac{1 - \sqrt{1 - 4z^{2}}}{2z}$ 

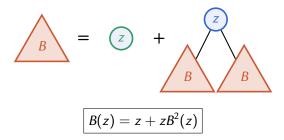
# Boltzmann sampling with generating functions

- Look at the equation  $T(z) = z + zT^2(z)$
- Function generate(z):
  - Generate Bernoulli random variable *X*

$$\begin{cases} \mathbb{P}(X=0) = \frac{z}{z + zT^2(z)} \\ \mathbb{P}(X=1) = \frac{zT^2(z)}{z + zT^2(z)} \end{cases}$$

- If X = 0 return  $\mathcal{Z}$
- If X = 1
  - $\blacksquare$  L := generate(z)
  - $\blacksquare$  R := generate(z)
  - Return  $(L)\mathcal{Z}(R)$

# Univariate Boltzmann sampler

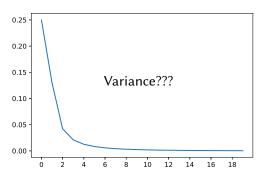


■ Boltzmann sampler  $\Gamma B(z)$ :

$$\Gamma B(z) := \begin{cases} \mathcal{Z} & \text{with probability } \frac{z}{z + zB^2(z)}, \\ (\Gamma B(z))\mathcal{Z}(\Gamma B(z)) & \text{with probability } \frac{zB^2(z)}{z + zB^2(z)}. \end{cases}$$

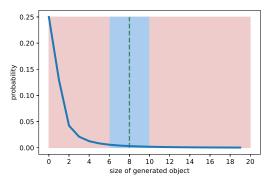
### What is the distribution of size?

- Expected size of an object =  $z \frac{B'(z)}{B(z)}$  increasing function. Take z = 0.499.
- $\mathbb{P}(\text{tree of size } n) = \frac{b_n z^n}{B(z)}$ , generation <u>inside the size</u> is uniform



### Approximate-size sampling

How long do we wait until an object from  $[n(1-\varepsilon), n(1+\varepsilon)]$ ?



Answer:  $O(C_{\varepsilon} \cdot n)$  for binary trees

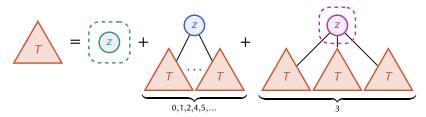
### Summary

- Recursive sampling:  $O(n^2)$
- Boltzmann exact size sampling:  $O(n^2)$
- Boltzmann approximate size sampling: O(n)

### Multiparametric sampling

#### **Problem**

Generate uniformly at random binary trees with n nodes, j leaves, and k nodes with 3 children.



$$T = zx + z\left(\frac{1}{1-T} - T^3\right) + zyT^3$$

#### **Problem**

Generate uniformly at random binary trees with n nodes, j leaves, and k nodes with 3 children.

#### Recursive method

Dynamic programming algorithm

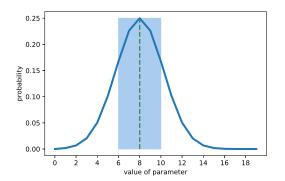
$$O(n^{\# \text{ parameters + 1}})$$

#### Boltzmann method\*

$$O\left(n^2 \cdot n^{\frac{\# \text{ parameters} - 1}{2}}\right)$$

### Gaussian distribution of parameters

Typically Gaussian with deviation  $\Theta(\sqrt{n})$  in algebraic systems.



The recursive method Boltzmann sampler Multiparametric sampling

### Relaxed problem formulation

Generate uniformly at random binary trees with approximately n nodes, j leaves, and k nodes with 3 children. «Approximately» means «in expectation».

### **Recursive method\*** (*n* is exact)

Dynamic programming algorithm

$$O\left(n^2\right)$$

### **Boltzmann method**\* (*n* is approximate)



### Pre-computation phase

For approximate-size random generation

$$T = zx + z\left(\frac{1}{1-T} - T^3\right) + zyT^3$$

Given the expectations, tune the arguments of generating function.

$$x, y, z = ?$$

- $O(\log n)^{\# \text{ parameters}} \leftarrow \text{exponential algorithm}$
- $Poly(\# parameters) \leftarrow current talk$

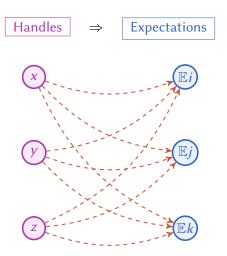
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# Idea of tuning



■ Tuning is an inverse problem. How to solve it?

### An example of ugly system

$$\begin{cases} A = 1 + xy^{2}B^{2} + \frac{zBC}{1 - yC} + ABD^{2}, \\ B = x + A^{3} + CD, \\ C = \frac{y}{1 - yz} + C^{3} + AD, \\ D = B + C^{4} \end{cases}$$

#### Problem

Find x, y, z such that

$$x\frac{A'_x}{A} = n$$
,  $y\frac{A'_y}{A} = j$ ,  $z\frac{A'_z}{A} = k$ .

# Optimisation approach

$$\log A(e^x, e^y, e^z) - (x, y, z)^\top (n, j, k) \to \min$$

Is equivalent to

$$\nabla_{x,y,z} \left[ \log A(e^x, e^y, e^z) - (x, y, z)^\top (n, j, k) \right] = 0$$

Is equivalent to

$$\begin{cases} x \frac{A'_x}{A} = n, \\ y \frac{A'_y}{A} = j, \\ z \frac{A'_z}{A} = k. \end{cases}$$

# Optimisation approach

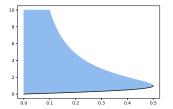
$$\begin{cases} \log A(e^{x}, e^{y}, e^{z}) - (x, y, z)^{\top}(n, j, k) \to \min, \\ A \ge 1 + xy^{2}B^{2} + \frac{zBC}{1 - yC} + ABD^{2}, \\ B \ge x + A^{3} + CD, \\ C \ge \frac{y}{1 - yz} + C^{3} + AD, \\ D \ge B + C^{4} \end{cases}$$

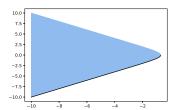
### Challenge

Optimisation problem is not convex!

# Log-Exp transform for binary trees

$$\begin{cases} z \to \mathsf{max}, \\ T \ge z + z T^2 \end{cases} \quad \Rightarrow \quad \begin{cases} \zeta \to \mathsf{max}, \\ b \ge \log(e^\zeta + e^\zeta e^{2b}) \end{cases}$$





#### Lemma

Log-exp transform will make an optimisation problem convex.

$$\begin{cases} A \ge 1 + xy^{2}B^{2} + \frac{zBC}{1 - yC} + ABD^{2}, \\ B \ge x + A^{3} + CD, \\ C \ge \frac{y}{1 - yz} + C^{3} + AD, \\ D \ge B + C^{4} \end{cases}$$

$$\begin{cases} A \ge 1 + xy^2B^2 + \frac{zBC}{1 - yC} + ABD^2, \\ B \ge x + A^3 + CD, \\ C \ge \frac{y}{1 - yz} + C^3 + AD, \\ D \ge B + C^4 \end{cases}$$

$$\begin{cases} e^{\alpha} \ge 1 + xy^2 B^2 + \frac{zBC}{1 - yC} + e^{\alpha} BD^2, \\ B \ge x + e^{3\alpha} + CD, \\ C \ge \frac{y}{1 - yz} + C^3 + e^{\alpha} D, \\ D \ge B + C^4 \end{cases}$$

$$\begin{cases} e^{\alpha} \geq 1 + xy^2 B^2 + \frac{zBC}{1 - yC} + e^{\alpha}BD^2, \\ B \geq x + e^{3\alpha} + CD, \\ C \geq \frac{y}{1 - yz} + C^3 + e^{\alpha}D, \\ D \geq B + C^4 \end{cases}$$

$$\begin{cases} e^{\alpha} \ge 1 + xy^2 e^{2\beta} + \frac{ze^{\beta}C}{1 - yC} + e^{\alpha}e^{\beta}D^2, \\ e^{\beta} \ge x + e^{3\alpha} + CD, \\ C \ge \frac{y}{1 - yz} + C^3 + e^{\alpha}D, \\ D \ge e^{\beta} + C^4 \end{cases}$$

$$\begin{cases} e^{\alpha} \geq 1 + xy^{2}e^{2\beta} + \frac{ze^{\beta}C}{1 - yC} + e^{\alpha}e^{\beta}D^{2}, \\ e^{\beta} \geq x + e^{3\alpha} + CD, \\ C \geq \frac{y}{1 - yz} + C^{3} + e^{\alpha}D, \\ D \geq e^{\beta} + C^{4} \end{cases}$$

$$\begin{cases} e^{\alpha} \geq 1 + xy^{2}e^{2\beta} + \frac{ze^{\beta}e^{\gamma}}{1 - ye^{\gamma}} + e^{\alpha}e^{\beta}D^{2}, \\ e^{\beta} \geq x + e^{3\alpha} + e^{\gamma}D, \\ e^{\gamma} \geq \frac{y}{1 - yz} + e^{3\gamma} + e^{\alpha}D, \\ D \geq e^{\beta} + e^{4\gamma} \end{cases}$$

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$$\begin{cases} e^{\alpha} \geq 1 + xy^{2}e^{2\beta} + \frac{\mathbf{z}e^{\beta}e^{\gamma}}{1 - ye^{\gamma}} + e^{\alpha}e^{\beta}e^{2\delta}, \\ e^{\beta} \geq x + e^{3\alpha} + e^{\gamma}e^{\delta}, \\ e^{\gamma} \geq \frac{y}{1 - y\mathbf{z}} + e^{3\gamma} + e^{\alpha}e^{\delta}, \\ e^{\delta} \geq e^{\beta} + e^{4\gamma} \end{cases}$$

$$\left\{egin{aligned} &e^{lpha} \geq 1 + rac{e^{\xi}e^{2\eta}}{1-e^{\eta}e^{\gamma}} + rac{e^{lpha}e^{\gamma}}{1-e^{\eta}e^{\gamma}} + e^{lpha}e^{eta}e^{2\delta}, \ &e^{eta} \geq rac{e^{\xi}}{1-e^{\eta}e^{\zeta}} + e^{3\gamma} + e^{lpha}e^{\delta}, \ &e^{\gamma} \geq rac{e^{\eta}}{1-e^{\eta}e^{\zeta}} + e^{3\gamma} + e^{lpha}e^{\delta}, \ &e^{\delta} \geq e^{eta} + e^{4\gamma} \end{aligned}
ight.$$

$$egin{cases} e^{lpha} \geq 1 + e^{\xi}e^{2\eta}e^{2eta} + rac{e^{\zeta}e^{eta}e^{\gamma}}{1 - e^{\eta}e^{\gamma}} + e^{lpha}e^{eta}e^{2\delta}, \ e^{eta} \geq e^{\xi} + e^{3lpha} + e^{\gamma}e^{\delta}, \ e^{\gamma} \geq rac{e^{\eta}}{1 - e^{\eta}e^{\zeta}} + e^{3\gamma} + e^{lpha}e^{\delta}, \ e^{\delta} \geq e^{eta} + e^{4\gamma} \end{cases}$$

## Example of transformation of an ugly system

Optimisation problem with respect to variables  $(\alpha, \beta, \gamma, \delta, \xi, \eta, \zeta)$ :

$$\begin{cases} \alpha - \mathbb{E}i \cdot \xi - \mathbb{E}j \cdot \eta - \mathbb{E}k \cdot \zeta \to \min, \\ \alpha \ge \log\left(1 + e^{\xi + 2\eta + 2\beta} + \frac{e^{\zeta + \beta + \gamma}}{1 - e^{\eta + \gamma}} + e^{\alpha + \beta + 2\delta}\right), \\ \beta \ge \log\left(e^{\xi} + e^{3\alpha} + e^{\gamma + \delta}\right), \\ \gamma \ge \log\left(\frac{e^{\eta}}{1 - e^{\eta + \zeta}} + e^{3\gamma} + e^{\alpha + \delta}\right), \\ \delta \ge \log\left(e^{\beta} + e^{4\gamma}\right). \end{cases}$$

#### Bonus

We obtain the values of generating functions at target points

$$A(x, y, z), B(x, y, z), C(x, y, z), D(x, y, z)$$



# Optimisation complexity

#### **Theorem**

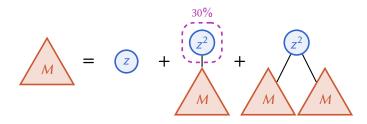
For multiparametric combinatorial systems with description length L, the tuning problem can be solved with precision  $\varepsilon$  in time

$$O\left(L^{3.5}\log\frac{1}{\varepsilon}\right)$$
.

Typically,  $\varepsilon^{-1} \sim \#_{\rm of}$  nodes. Moreover, in practice, using sparse system implementations this can be often reduced to

$$O\left(L^{2.5}\log\frac{1}{\varepsilon}\right)$$
 .

## Implementation. Boltzmann Brain



$$M(z) = z + uz^2 M(z) + z^2 M^2(z)$$

```
-- Motzkin trees

MotzkinTree = Leaf

| Unary MotzkinTree (2) [0.3]

| Binary MotzkinTree MotzkinTree (2).
```

### Generating Haskell module

### >cat motzkin.in

```
-- Motzkin trees

MotzkinTree = Leaf

| Unary MotzkinTree (2) [0.3]

| Binary MotzkinTree MotzkinTree (2).
```

>bb motzkin.in > Motzkin.hs
>vim Motzkin.hs

### Contents of Motzkin.hs

```
module Sampler
          (MotzkinTree(...), genRandomMotzkinTree, sampleMotzkinTree) where
  import Control.Monad (guard)
  import Control.Monad.Trans (lift)
10 import Control, Monad, Trans, Maybe (MaybeT(..), runMaybeT)
11 import Control.Monad.Random (RandomGen(..), Rand, getRandomR)
 data MotzkinTree = Leaf
                      Unary MotzkinTree
                     Binary MotzkinTree MotzkinTree
  randomP :: RandomGen g => MaybeT (Rand g) Double
  randomP = lift (getRandomR (0, 1))
  genRandomMotzkinTree ::
                          RandomGen g => Int -> MaybeT (Rand g) (MotzkinTree, Int)
  genRandomMotzkinTree ub
    = do quard (ub > 0)
         if p < 0.37837770210556015 then return (Leaf, 1) else
           if p < 0.6216213625599037 then
             do (x0, w0) <- genRandomMotzkinTree (ub - 2)
                 return (Unary x0, 2 + w0)
             else
             do (x0, w0) <- genRandomMotzkinTree (ub - 2)
                 (x1, w1) <- genRandomMotzkinTree (ub - 2 - w0)
                 return (Binary x0 x1, 2 + w1 + w0)
34 sampleMotzkinTree ::
                       RandomGen g => Int -> Int -> Rand g MotzkinTree
  sampleMotzkinTree lb ub
    = do sample <- runMaybeT (genRandomMotzkinTree ub)</pre>
         case sample of
             Nothing -> sampleMotzkinTree lb ub
              Just (x, s) -> if lb <= s && s <= ub then return x else
                               sampleMotzkinTree lb ub
```

### Sampling a combinatorial structure

>ghci Motzkin.hs
\*Sample> sampleMotzkinTree 50 100

```
Binary Leaf (Binary (Binary (Unary
(Unary (Unary (Binary (Unary Leaf) (Binary
(Unary Leaf) Leaf))))) (Unary (Unary (Binary
(Binary (Unary (Binary (Unary Leaf) Leaf))
(Unary (Binary (Unary (Unary (Unary
Leaf))) (Unary Leaf)) (Unary Leaf))))
Leaf)))) (Unary (Unary (Binary (Binary
(Unary (Binary Leaf (Unary (Binary Leaf
(Unary (Binary Leaf Leaf))))) Leaf) (Binary
(Binary Leaf Leaf) (Unary Leaf))))) (Unary
Leaf))
```

## Code is available on github

- https://github.com/maciej-bendkowski/boltzmann-brain
- https://github.com/maciej-bendkowski/ multiparametric-combinatorial-samplers

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Random tilings Tree-like structures Bose-Einstein condensate

### Random tilings

#### **Problem**

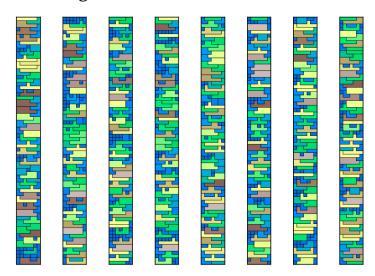
Tile a stripe  $7 \times n$  with 126 different types of tiles such that the area covered by each tile is (approximately) uniform.



### Tile construction principle

Attach a subset of unit squares to the base layer which is a single connected block.

## Generated tilings



# Lambda terms with given de Bruijn index distribution

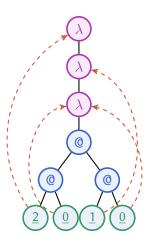
$$L = zL + zL^{2} + u_{1}z + u_{2}z^{2} + \dots + u_{8}z^{8} + \frac{z^{9}}{1 - z}$$

$$= + + \text{SEQ}_{\geq 1}(z)$$

Table 3. Empirical frequencies (with respect to the term size) of index distribution.

Index	<u>0</u>	1	2	<u>3</u>	<u>4</u>	<u>5</u>	<u>6</u>	<u>7</u>	<u>8</u>
Tuned frequency	8.00%	8.00%	8.00%	8.00%	8.00%	8.00%	8.00%	8.00%	8.00%
Observed frequency	7.50%	7.77%	8.00%	8.23%	8.04%	7.61%	8.53%	7.43%	9.08%
Default frequency	21.91%	12.51%	5.68%	2.31%	0.74%	0.17%	0.20%	0.07%	

# Closed lambda terms for property testing



- Number of abstractions
- Number of variables
- De Bruijn index distribution
- Number of redexes
- Number of head abstractions
- Number of closed subterms

### **Application**

Generate closed lambda terms (programs) with skewed distribution to find bugs in optimizing compilers.

## Integer partitions

### Example:

$$16 = 1 + 1 + 3 + 4 + 7$$

$$\mathcal{P} = \mathsf{MSET}(\mathsf{MSET}_{\geq 1}(\mathcal{Z}))$$

### Generalisation from statistical physics (Bose-Einstein)

In d-dimensional anisotropic harmonic trap the number of states for particle with energy  $\lambda$  is  $\binom{d+\lambda-1}{\lambda}$ . Each state is represented as a multiset of  $\lambda$  elements having d different colours.

$$\mathcal{P} = \mathsf{MSET}(\mathsf{MSET}_{\geq 1}(d\mathcal{Z}))$$

# d-dimensional quantum harmonic oscillator

Weighted partition	Random particle assembly			
Sum of numbers	Total energy			
Number of colours	Dimension (d)			
Row of Young table	Particle			
Number of rows	Number of particles			
Number of squares in the row	Energy of a particle $(\lambda)$			
$\frac{d+\lambda-1}{\lambda}$	Number of particle states			

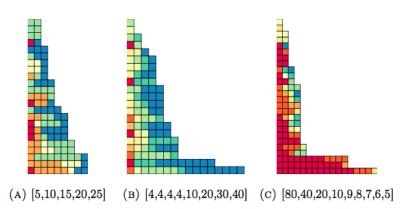
#### **Problem**

Generate random assemblies with given numbers of colours

$$(n_1, n_2, \ldots, n_d)$$

# Weighted integer partitions

(5,8,9 colours)



Random tilings Tree-like structures Bose-Einstein condensate

### That's all!

Thank you for your attention!