

Random generation of combinatorial structures using Boltzmann samplers

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Plan

- 1 Recursive counting and recursive sampling
- 2 Generating functions and Boltzmann samplers
- 3 New constructions for Boltzmann samplers
- 4 Random sampling of plane partitions

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 - Multisets
 - Cycles
- ④ Random sampling of plane partitions

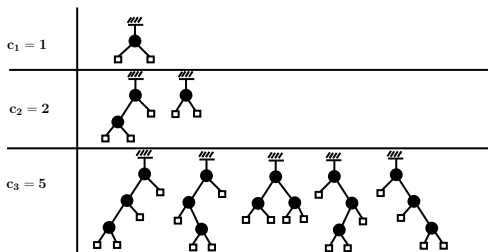
Combinatorial classes

A combinatorial class \mathcal{C} is a set of objects such that

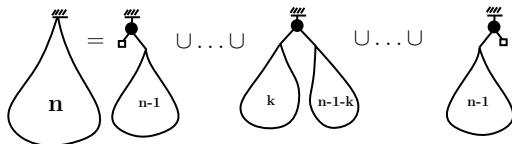
- Each object $\gamma \in \mathcal{C}$ has a **size** $|\gamma| \in \mathbb{N}$ (e.g. number of vertices in a graph)
- For $n \geq 0$, the number of objects of size n in \mathcal{C} is **finite**.
This number c_n is called the **n th coefficient** of \mathcal{C}

Example: binary trees

- Each inner node has a left son and a right son
- The size is the number of inner nodes



$$c_n = c_0 c_{n-1} + \dots + c_k c_{n-1-k} + \dots + c_{n-1} c_0$$

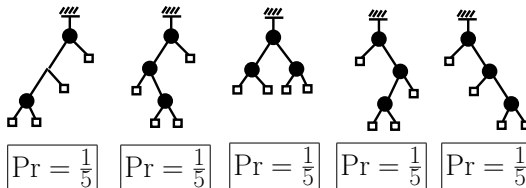


Random generation at a fixed size n

For a given size $n \geq 0$, we want a procedure that picks up an object of size n under the **uniform** distribution:

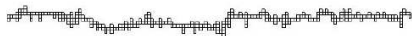
$$\Pr(\gamma) = \frac{1}{c_n} \text{ for each } \gamma \in \mathcal{C} \text{ of size } n$$

Binary trees: uniform distribution for $n = 3$

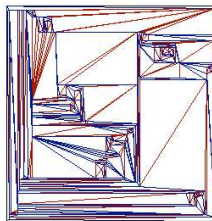
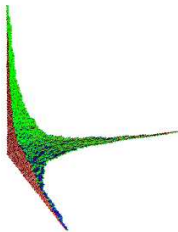
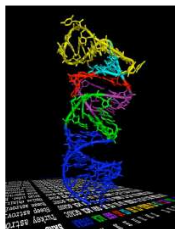


Motivations for random generation

- Observation of asymptotic phenonema



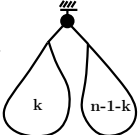
- Generation of structures for experimentation :
 - bio-informatics
 - software testing
 - ...



A general procedure: the recursive method

Idea: (Nijenhuis and Wilf'78, Flajolet et al'94) compute the correct **probability at the root** of the decomposition **from the coefficients** to have the **uniform** distribution.

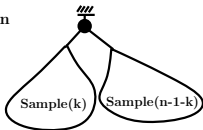
$$c_n = c_0 c_{n-1} + \dots + c_k c_{n-1-k} + \dots + c_{n-1} c_0$$

Proportion of  $= \frac{c_k c_{n-1-k}}{c_n}$

\Rightarrow Recursive algorithm:

Sample(n): 1) choose $k \in \{0, \dots, n-1\}$ under the distribution $\boxed{\Pr(k) = \frac{c_k c_{n-1-k}}{c_n}}$

2) return



Drawback: large auxiliary memory

To sample at size n , we **need** the coefficients c_1, \dots, c_n
 \Rightarrow this requires a **quadratic** number of bits

n	c_n	n	c_n	n	c_n
1	1	11	58786	21	24466267020
2	2	12	208012	22	91482563640
3	5	13	742900	23	343059613650
4	14	14	2674440	24	1289904147324
5	42	15	9694845	25	4861946401452
6	132	16	35357670	26	18367353072152
7	429	17	129644790	27	69533550916004
8	1430	18	477638700	28	263747951750360
9	4862	19	1767263190	29	1002242216651368
10	16796	20	6564120420	30	3814986502092304

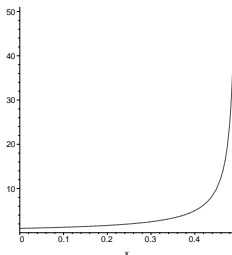
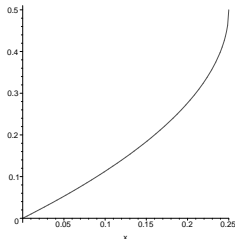
- ① Recursive counting and recursive sampling
- ② **Generating functions and Boltzmann samplers**
- ③ New constructions for Boltzmann samplers
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Generating functions

The **generating function** of a class \mathcal{C} is defined as:

$$\begin{aligned} C(x) &:= \sum_{\gamma \in \mathcal{C}} x^{|\gamma|} \\ &= \sum_{n \geq 0} c_n x^n \end{aligned}$$

There is a **critical value** $\rho > 0$ such that the sum defining the generating function **converges** for $x < \rho$ and not for $x > \rho$



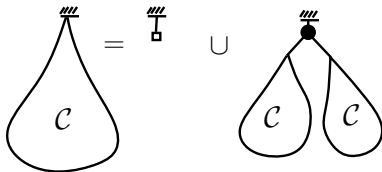
Generating functions: rules of calculations

- Disjoint union: $\boxed{C = \mathcal{A} \cup \mathcal{B} \Rightarrow C(x) = A(x) + B(x)}$

Proof: $\sum_{\gamma \in \mathcal{A} \cup \mathcal{B}} x^{|\gamma|} = \sum_{\gamma \in \mathcal{A}} x^{|\gamma|} + \sum_{\gamma \in \mathcal{B}} x^{|\gamma|}$

- Cartesian prod: $\boxed{C = \mathcal{A} \times \mathcal{B} \Rightarrow C(x) = A(x) \cdot B(x)}$

Proof: $\sum_{(\gamma_1, \gamma_2) \in \mathcal{A} \times \mathcal{B}} x^{|(\gamma_1, \gamma_2)|} = \sum_{\gamma_1, \gamma_2} x^{|\gamma_1| + |\gamma_2|} = \sum_{\gamma_1 \in \mathcal{A}} x^{|\gamma_1|} \sum_{\gamma_2 \in \mathcal{B}} x^{|\gamma_2|}$



$$\boxed{C(x) = 1 + C(x)x C(x)}$$

simpler than $c_n = c_0 c_{n-1} + \dots + c_k c_{n-1-k} + \dots + c_{n-1} c_0$.

Boltzmann samplers

- Introduced by Duchon, Flajolet, Louchard and Schaeffer (2002)
- Relax the constraint of fixed size (cf [recursive method](#)) for random generation.
- The distribution is spread over **all objects** of the class.
- An object is drawn with probability proportional to the **exponential** of its size (cf statistical physics)

Boltzmann samplers: definition

- Let \mathcal{C} be an **unlabelled** combinatorial class
(e.g. binary trees)

Ordinary generating function:

$$C(x) = \sum_{\gamma \in \mathcal{C}} x^{|\gamma|} = \sum_{n \geq 0} c_n x^n,$$

where $|\gamma|$ is the **size** of γ .

- Given $x > 0$ ($x \leq \rho_C$) a **fixed real value**,
a **Boltzmann sampler** $\Gamma_C(x)$ is a procedure that draws each
object γ of \mathcal{C} with probability:

$$\Pr(\gamma) = \frac{x^{|\gamma|}}{C(x)}$$

Analogy with statistical physics

Combinatorics \longleftrightarrow Stat. Phys.

Structure γ

State s

size n

Energy E

Generating function

Partition function

$$C(x) = \sum_{\gamma} x^{|\gamma|}$$

$$Z = \sum_s e^{-\beta E}$$

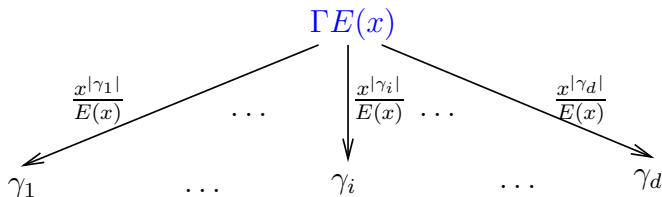
$$\text{Boltz: } \mathbb{P}(\gamma) = \frac{x^{|\gamma|}}{C(x)}$$

$$\text{Boltz: } \mathbb{P}(s) = \frac{e^{-\beta E}}{Z}$$

Finite sets

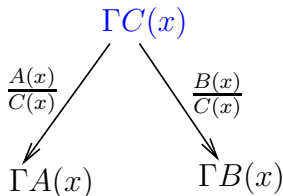
Let $\mathcal{E} = (\gamma_1, \dots, \gamma_d)$

$$E(x) = \sum_{i=1}^d x^{|\gamma_i|}$$



The basic construction rules: union

Union: Let $\mathcal{C} = \mathcal{A} \cup \mathcal{B}$. Assume we have Boltzmann samplers $\Gamma A(x)$ for \mathcal{A} and $\Gamma B(x)$ for \mathcal{B} . Define $\Gamma C(x)$ as:



Then $\Gamma C(x)$ is a Boltzmann sampler for $\mathcal{A} \cup \mathcal{B}$.

Proof: Let $\gamma \in \mathcal{A} \cup \mathcal{B}$

- If $\gamma \in \mathcal{A}$, then $\Pr(\gamma) = \frac{A(x)}{C(x)} \cdot \frac{x^{|\gamma|}}{A(x)} = \frac{x^{|\gamma|}}{C(x)}$.
- If $\gamma \in \mathcal{B}$, then $\Pr(\gamma) = \frac{B(x)}{C(x)} \cdot \frac{x^{|\gamma|}}{B(x)} = \frac{x^{|\gamma|}}{C(x)}$.

The basic construction rules: product

Product: Let $\mathcal{C} = \mathcal{A} \times \mathcal{B}$. Assume we have Boltzmann samplers $\Gamma A(x)$ for \mathcal{A} and $\Gamma B(x)$ for \mathcal{B} . Define $\Gamma C(x)$ as:

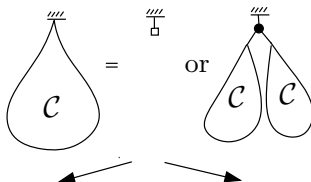
$$\begin{array}{ll} \Gamma C(x) & : \quad \gamma_1 \leftarrow \Gamma A(x) \\ & \quad \gamma_2 \leftarrow \Gamma B(x) \\ & \quad \text{return } (\gamma_1, \gamma_2) \end{array}$$

Then $\Gamma C(x)$ is a Boltzmann sampler for $\mathcal{A} \cup \mathcal{B}$:

Proof: an object $\gamma = (\gamma_1, \gamma_2)$ has probability:

$$\frac{x^{|\gamma_1|}}{A(x)} \frac{x^{|\gamma_2|}}{B(x)} = \frac{x^{|\gamma_1|+|\gamma_2|}}{A(x) \cdot B(x)} = \frac{x^{|\gamma|}}{C(x)}$$

Example: binary trees



Generating function

$$C(x) = 1 + xC(x)^2$$

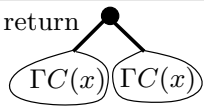
Boltzmann sampler

$$\Gamma C(x)$$

$\text{Pr} = \frac{1}{C(x)}$
 $\text{Pr} = \frac{xC(x)^2}{C(x)}$

return

return



A first Sampling dictionary

Theorem

A Boltzmann sampler can be designed for any class having a *recursive specification* with the constructions \cup and \times . The complexity is *linear* in the size of the output object.

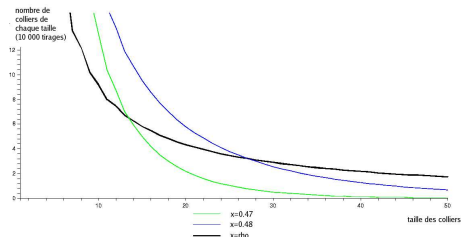
construction	generator
$\mathcal{C} = \emptyset$	$\Gamma C(x) := \text{return } \emptyset$
$\mathcal{C} = \{\bullet\}$	$\Gamma C(x) := \text{return } \{\bullet\}$
$\mathcal{C} = \mathcal{A} + \mathcal{B}$	$\Gamma C(x) := \left(\text{Bern } \frac{A(x)}{C(x)} \longrightarrow \Gamma A(x) \mid \Gamma B(x) \right)$
$\mathcal{C} = \mathcal{A} \times \mathcal{B}$	$\Gamma C(x) := (\Gamma A(x); \Gamma B(x))$

Choosing x to draw objects around a target-size

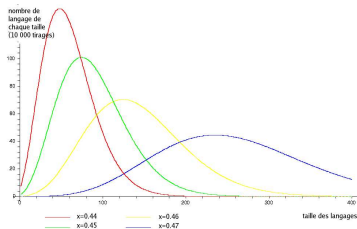
The probability of drawing an object of size n is:

$$\mathbb{P}_x(\text{Size} = n) = \sum_{|\gamma|=n} \frac{x^{|\gamma|}}{C(x)} = \frac{c_n x^n}{C(x)}$$

→ size distributions for different values of x .



Bicolored necklaces



Finite languages

Boltzmann samplers *vs* the recursive method

	Boltzmann	recursive method
size distribution	$Pr(size = n) = \frac{c_n x^n}{C(x)}$	fixed size n
auxiliary memory	$\mathcal{O}(\log(n))$	$\mathcal{O}(n^2)$
time per generation	$\mathcal{O}(n^2)$ Exact $\mathcal{O}(n)$ Approx	$\mathcal{O}(n \log(n))$ Exact

New constructions for Boltzmann samplers

(with Philippe Flajolet and Carine Pivoteau)

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A first construction: MSet₂

$\text{MSET}_2(\mathcal{A}) \cong$ **unordered pairs** of objects de \mathcal{A}

$$\begin{aligned}\mathcal{C} &= \text{MSET}_2(\mathcal{A}) \\ C(z) &= \frac{1}{2}A^2(z) + \frac{1}{2}A(z^2) \quad \left[2\text{MSET}_2(\mathcal{A}) = \mathcal{A}^2 + \Delta\mathcal{A}^2 \right]\end{aligned}$$

Algorithm: $\Gamma C(x)$

```
if  $\text{Bern}\left(\frac{1}{2} \frac{A^2(x)}{C(x)}\right) = 1$  then
  Return (  $\Gamma A(x), \Gamma A(x)$  )
else
   $a \leftarrow \Gamma A(x^2)$ ;
  Return (  $a, a$  );
end if
```

Proof that the algorithm is correct

Proof.

Let $\gamma = \langle \gamma_1, \gamma_2 \rangle$ be an unordered pair of objects of \mathcal{A} . The probability that γ is drawn by $\Gamma C(x)$ is:

❶ $\gamma_1 \neq \gamma_2$

$$\mathbb{P}_x(\gamma) = \frac{1}{2} \frac{A(x)^2}{C(x)} \frac{x^{|\gamma_1|}}{A(x)} \frac{x^{|\gamma_2|}}{A(x)} \times 2 = \frac{x^{|\gamma|}}{C(x)}$$

❷ $\gamma_1 = \gamma_2$

$$\mathbb{P}_x(\gamma) = \frac{1}{2} \frac{A(x)^2}{C(x)} \frac{x^{|\gamma_1|}}{A(x)} \frac{x^{|\gamma_1|}}{A(x)} + \frac{1}{2} \frac{A(x^2)}{C(x)} \frac{x^{2|\gamma_1|}}{A(x^2)} = \frac{x^{|\gamma|}}{C(x)}$$



Application

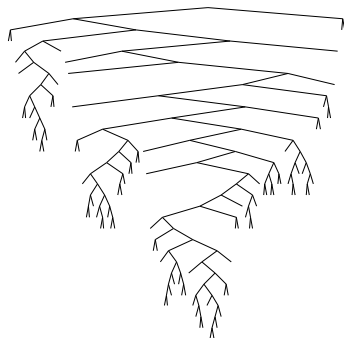
Unembedded binary trees
 (Otter trees)

$$\mathcal{B} = \mathcal{Z} + \text{MSET}_2(\mathcal{B})$$

$$B(z) = z + \frac{1}{2}B^2(z) + \frac{1}{2}B(z^2)$$

```

→ □
→ ■⟨ ΓB(x), ΓB(x) ⟩
→ ot ← ΓB(x2);
return ■⟨ ot, ot ⟩;
```



Application

Unembedded binary trees
 (Otter trees)

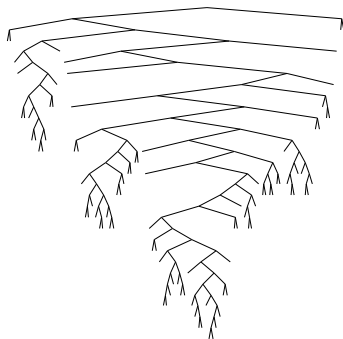
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→ □

→ ■ $\langle \Gamma B(x), \Gamma B(x) \rangle$

→ ot $\leftarrow \Gamma B(x^2);$
return ■ $\langle \text{ot}, \text{ot} \rangle;$



Application

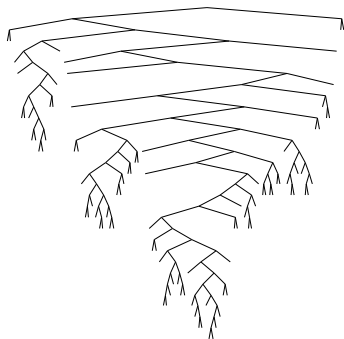
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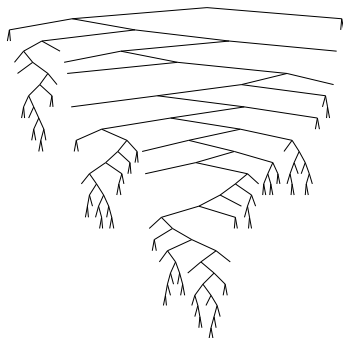
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General MSet

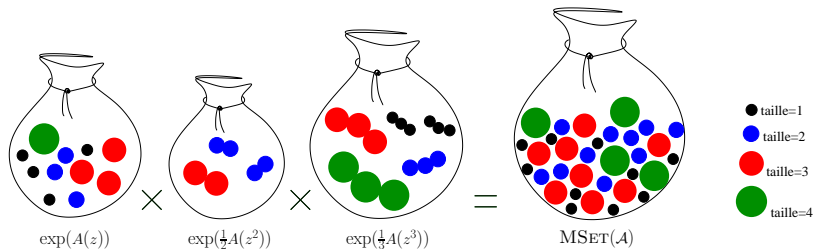
Let $\mathcal{M} := \text{MSET}(\mathcal{A})$ be the class of all multisets of objects of \mathcal{A} .

$$M(z) = \exp \left(\sum_{k=1}^{\infty} \frac{1}{k} A(z^k) \right) = \prod_{k=1}^{\infty} \exp \left(\frac{1}{k} A(z^k) \right)$$

General MSet

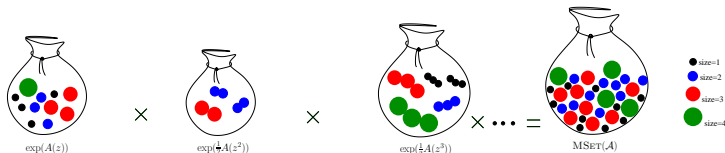
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Algorithm for general MSet

$$M(z) = \exp \left(\sum_{k=1}^{\infty} \frac{1}{k} A(z^k) \right) = \prod_{k=1}^{\infty} \exp \left(\frac{1}{k} A(z^k) \right)$$



repeat $\text{Pois}(A(x))$ times
 $\gamma \leftarrow \Gamma A(x)$
 add γ

repeat $\text{Pois}(\frac{A(x^2)}{2})$ times
 $\gamma \leftarrow \Gamma A(x^2)$
 add 2 copies of γ

repeat $\text{Pois}(\frac{A(x^3)}{3})$ times
 $\gamma \leftarrow \Gamma A(x^3)$
 add 3 copies of γ

Algorithm for general MSet (2)

Algorithm $\Gamma MSet[\mathcal{A}](x)$

```
 $k \leftarrow \text{MaxIndex}(x);$   
for  $i$  from 1 to  $k - 1$  do {  
   $p \leftarrow \text{Pois}(\frac{1}{i}A(x^i));$   
  repeat  $p$  {  
     $\gamma \leftarrow \Gamma A(x^i);$   
    Add  $i$  copies of  $\gamma$  to the MSET  
  }  
}  
 $p \leftarrow \text{Pois}_{\geq 1}(\frac{1}{k}A(x^k));$   
repeat  $p$  {  
   $\gamma \leftarrow \Gamma A(x^k);$   
  Add  $k$  copies of  $\gamma$  to the MSET  
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    Add  $k$  copies of  $\gamma$  to the MSET  
}
```

Result

Theorem

If we have a Boltzmann sampler $\Gamma A(x)$ for \mathcal{A} , then $\Gamma MSet[\mathcal{A}](x)$ is a Boltzmann sampler for $MSET(\mathcal{A})$.

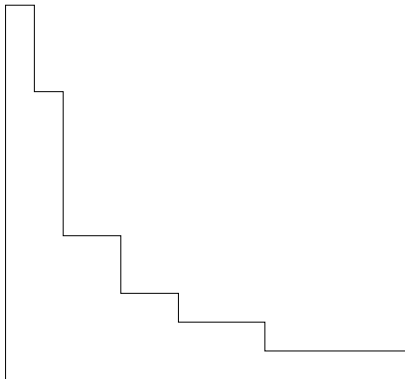
Generation of a partition (multiset of integers)

$$k = 3;$$

$$p_1 = 5;$$

$$p_2 = 3;$$

$$p_3 = 1;$$



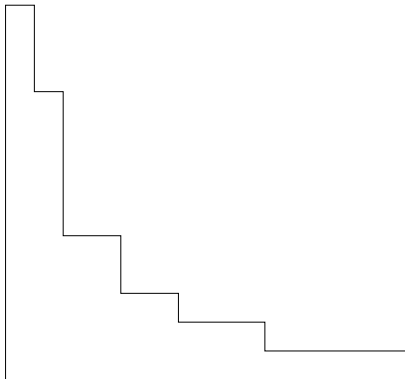
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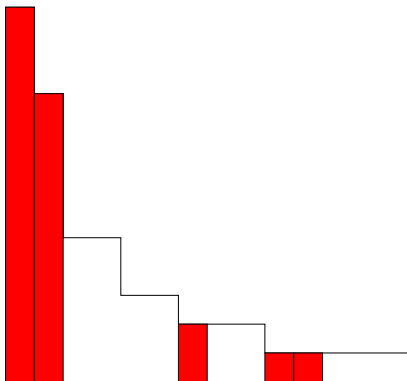
$$k = 3;$$

$$p_1 = 5;$$

$$p_2 = 3;$$

$$p_3 = 1;$$

$$\rightarrow 13, 10, 2, 1, 1$$



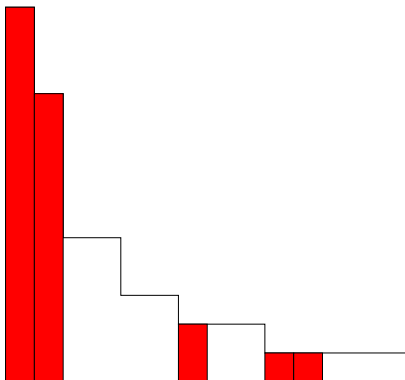
Generation of a partition (multiset of integers)

$$k = 3;$$

$$p_1 = 5;$$

$$p_2 = 3;$$

$$p_3 = 1;$$



Generation of a partition (multiset of integers)

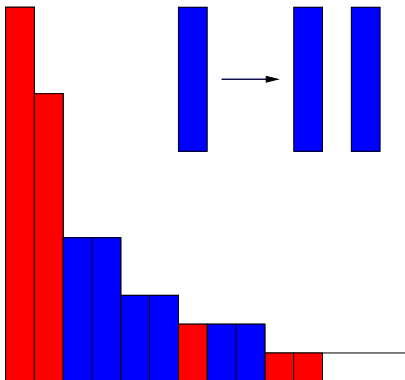
$k = 3;$

$p_1 = 5;$

$p_2 = 3;$

$p_3 = 1;$

$\rightarrow 5, 3, 2$



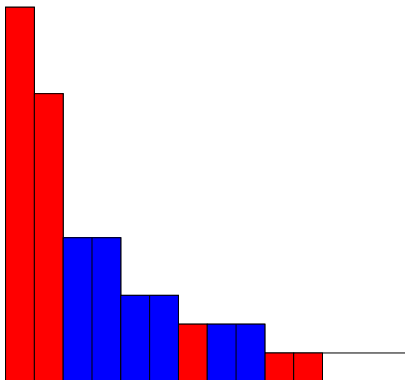
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$$k = 3;$$

$$p_1 = 5;$$

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Generation of a partition (multiset of integers)

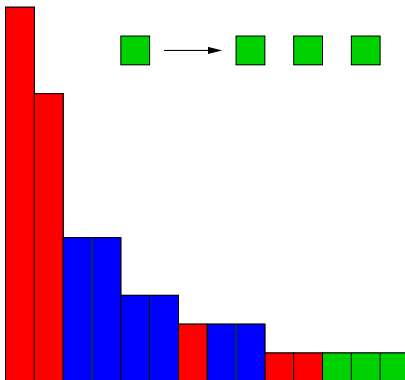
$k = 3;$

$p_1 = 5;$

$p_2 = 3;$

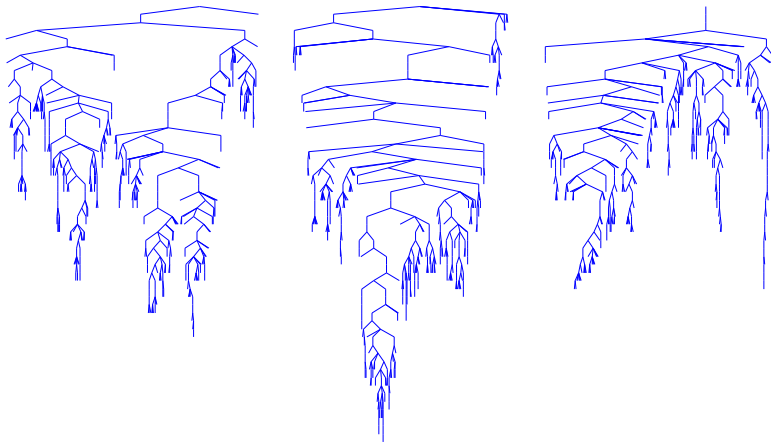
$p_3 = 1;$

$\rightarrow 1$



General unembedded trees

$$\mathcal{T} = \mathcal{Z} \times \text{MSET}(\mathcal{T})$$

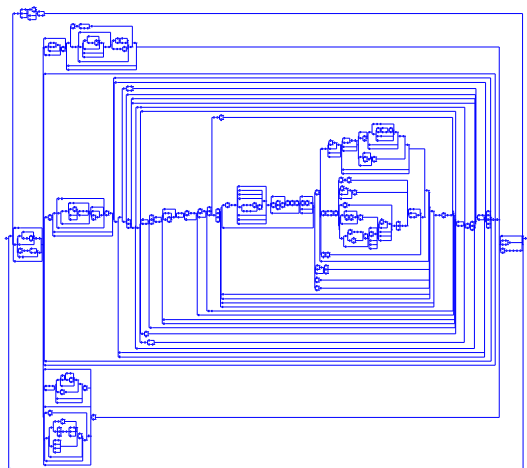
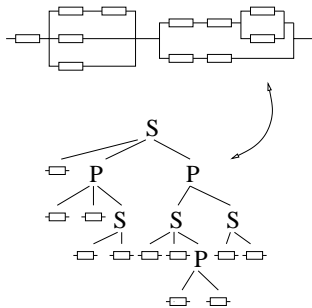


Series-parallel circuits

$$\mathcal{C} = \mathcal{P} + \mathcal{S} + \mathcal{Z}$$

$$\mathcal{S} = \text{SEQ}_{\geq 2}(\mathcal{P} + \mathcal{Z})$$

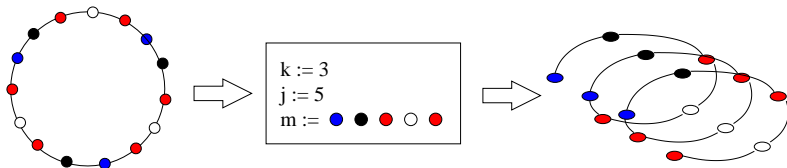
$$\mathcal{P} = \text{MSET}_{\geq 2}(\mathcal{S} + \mathcal{Z})$$



- 1 Recursive counting and recursive sampling
- 2 Generating functions and Boltzmann samplers
- 3 New constructions for Boltzmann samplers**
 - Multisets
 - **Cycles**
- 4 Random sampling of plane partitions

Generating function for cycles

$$\mathcal{C} = \text{Cyc}(\mathcal{A}) \Rightarrow C(z) = \sum_{k \geq 1} \frac{\varphi(k)}{k} \log \frac{1}{1 - A(z^k)}$$



Algorithm

$\Gamma_{Cyc}[\mathcal{A}](x)$

$k \leftarrow \text{ReplicationOrder}(x);$ # how many copies of s
 $j \leftarrow \text{Loga}(A(x^k));$ length of s
 $s \leftarrow \underbrace{\Gamma A(x^k), \dots, \Gamma A(x^k)}_{j \text{ times}};$ sequence
 Return $(\underbrace{m, \dots, m}_{k \text{ times}});$

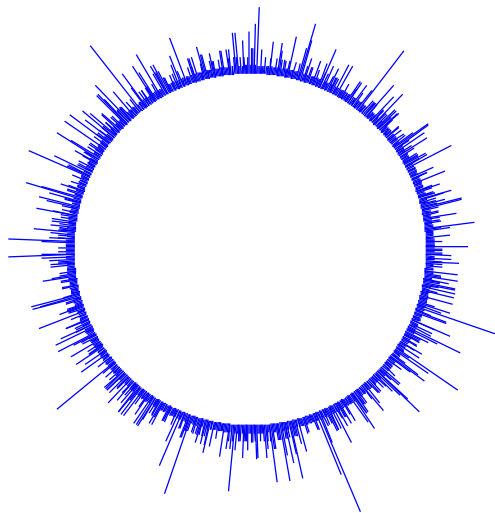
Definition: X follows a Loga law of parameter λ if:

$$\mathbb{P}(X = j) = \frac{1}{\log(1 - \lambda)^{-1}} \frac{\lambda^j}{j}$$

Cycles of integers

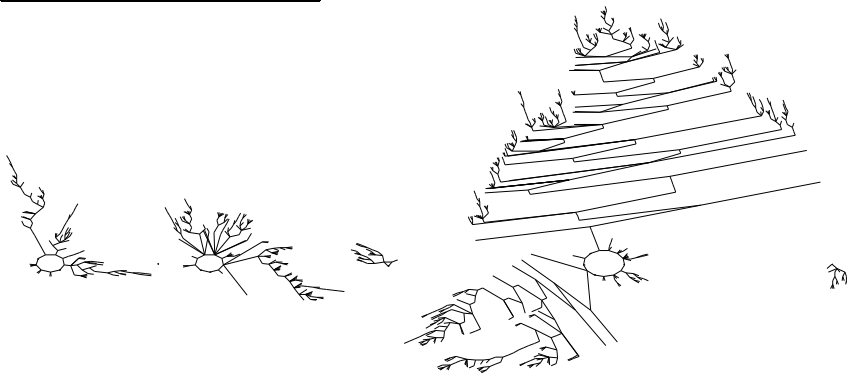
$$\mathcal{C} = \text{CYC}(\mathcal{Z} \times \text{SEQ}(\mathcal{Z}))$$

$$C(z) = \sum_{k=1}^{\infty} \frac{\varphi(k)}{k} \log \frac{1}{1 - \frac{z^k}{1-z^k}}$$



Functional graphs

$$\begin{aligned}\mathcal{M} &= \text{MSET}(\mathcal{C}) \\ \mathcal{C} &= \text{CYC}(\mathcal{G}) \\ \mathcal{G} &= \mathbb{Z} \times \text{MSET}(\mathcal{G})\end{aligned}$$



Result

Theorem

- If a combinatorial class \mathcal{C} has a recursive specification with the constructions

$$\{\cup, \times, \text{SEQ}, \text{MSET}, \text{CYC}\}$$

then a **Boltzmann sampler** can be designed for \mathcal{C} .

- This list of constructions can be completed by constructions with *cardinality restrictions* (e.g. MSET_2)

This applies for several classes:

- partitions, compositions, necklaces,...
- trees,
- regular languages,
- functional graphs,...

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- trees,
- regular languages,
- functional graphs,...

Complexity

Theorem

By choosing a suitable value for the parameter x , one has the following complexities for *approximate* size and *fixed* size:

<i>Integer partitions of size n</i>	$O(\sqrt{n} \log n)$	$O(n)$
<i>Unembedded trees of size n</i>	$O(n)$	$O(n^2)$
<i>Necklaces, circular compositions of size n</i>	$O(n)$	$O(n)$
<i>Mobiles of size n</i>	$O(n)$	$O(n^2)$
<i>Functional graphs of size n</i>	$O(n)$	$O(n\sqrt{n})$

Random sampling of plane partitions

(with Olivier Bodini and Carine Pivoteau)