

Discrete Random Simulation

Flipping a coin or more

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MOSIG 1 Mathematics for Computer Science



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1 Introduction

2 UNIFORM : Uniform Random Variable

3 DISCRETE : Discrete Random Variable

1 Introduction**2** UNIFORM : Uniform Random Variable**3** DISCRETE : Discrete Random Variable

STORY OF DICE

Coins, dice wheels, ...

Physical mechanism :

Sequence of observations : $x_1, x_2, x_3, \dots, x_n, \dots$ in $\{1, 2, \dots, K\}$

Probabilistic model

The sequence of observations is modeled by a sequence of

- ▶ random variables,
- ▶ independent,
- ▶ identically distributed,
- ▶ with a uniform distribution on the set $\{1, 2, \dots, K\}$ denoted by $\{X_n\}_{n \in \mathbb{N}}$

Notations and properties

For all n and for all sequence in $\{x_1, \dots, x_n\}$ in $\{1, 2, \dots, K\}^n$

$$\begin{aligned}\mathbb{P}(X_1 = x_1, \dots, X_n = x_n) &= \mathbb{P}(X_1 = x_1) \cdots \mathbb{P}(X_n = x_n) \text{ independence;} \\ &= \mathbb{P}(X = x_1) \cdots \mathbb{P}(X = x_n) \text{ same distribution;} \\ &= \frac{1}{K} \cdots \frac{1}{K} = \frac{1}{K^n} \text{ uniform law.}\end{aligned}$$

DICE STORY (CONT.)

Coin \mapsto Dice-8

From throws of coins simulate a 8 faces dice :

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Dice-8()

Data: Function "Coin()" uniform generator in $\{0, 1\}$

Result: A sequence i.i.d. variables uniform on $\{1, \dots, 8\}$

$A_0 = \text{Coin}()$

$A_1 = \text{Coin}()$

$A_2 = \text{Coin}()$

$S = A_0 + 2 * A_1 + 4 * A_2 + 1$

return S

TALES OF DICE : PROOF OF THE ALGORITHMS

Specification :

a sequence of calls of **Dice-8()** function is modeled by a sequence of random variables independent and identically distributed (i.i.d.) with uniform probability law on $\{1, \dots, 8\}$.

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Hypothesis :

$C_0, C_1, \dots, C_n, \dots$ sequence of calls to **Coin()** i.i.d. sequence uniform on $\{0, 1\}$

TALES OF DICE : PROOF OF THE ALGORITHMS

Specification :

a sequence of calls of **Dice-80** function is modeled by a sequence of random variables independent and identically distributed (i.i.d.) with uniform probability law on $\{1, \dots, 8\}$.

Hypothesis :

$C_0, C_1, \dots, C_n, \dots$ sequence of calls to **Coin0** i.i.d. sequence uniform on $\{0, 1\}$

Preuve :

Denote by $S_0, S_1, \dots, S_n, \dots$ the sequence of random variables modeling the results obtained by the successive calls to **Dice-80**.

Let $n \in \mathbb{N}$ and $(x_0, x_1, \dots, x_n) \in \{1, \dots, 8\}^{n+1}$. We should show that

$$\mathbb{P}(S_0 = x_0, \dots, S_n = x_n) = \frac{1}{8^{n+1}} \quad \text{cqfd.}$$

TALES OF DICE : PROOF OF THE ALGORITHMS (2)

We have

$$\mathbb{P}(S_0 = x_0, \dots, S_n = x_n)$$

$$= \mathbb{P}(S_0 = x_0) \cdots \mathbb{P}(S_n = x_n)$$

car S_k depends only on $C_{3k}, C_{3k+1}, C_{3k+2}$ and C_i are independent;

les S_0, \dots, S_n, \dots are indépendent;

$$= \mathbb{P}(S_0 = x_0) \cdots \mathbb{P}(S_0 = x_n) \text{ because } (C_{3k}, C_{3k+1}, C_{3k+2}) \text{ have the same law}$$

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But for i dans $\{1, \dots, 8\}$, $i - 1$ has a unique binary decomposition $i - 1 =_2 a_2a_1a_0$.

$$\mathbb{P}(S_0 = i) = \mathbb{P}(C_0 = a_0, C_1 = a_1, C_2 = a_2)$$

= $\mathbb{P}(C_0 = a_0)\mathbb{P}(C_1 = a_1)\mathbb{P}(C_2 = a_2)$ calls to Coin() are independent;

$$= \frac{1}{2} \frac{1}{2} \frac{1}{2} = \frac{1}{8} \text{ have the same law on } \{0, 1\}.$$

then

$$\mathbb{P}(S_0 = x_0, \dots, S_n = x_n) = \frac{1}{8^{n+1}} \quad \text{cqfd.}$$

TALES OF DICE (3)

Coin \mapsto Dice- 2^k

From one coin design a random generator of a 2^k -sided dice.

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Dice(k)

Data: A function "Coin()" random generator on $\{0, 1\}$

Result: A sequence of iid numbers uniformly distributed on $\{1, \dots, 2^k\}$

$S=0$

for $i = 1$ **to** k

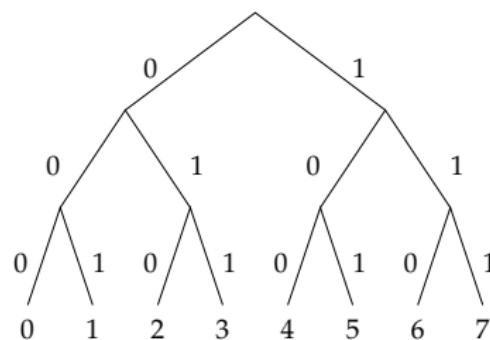
$\lfloor S=\text{Coin}() + 2.S$ // cf Hörner's Scheme

$S = S + 1$

return S

Preuve: Same proof as for **Dice-8**, based on the unicity of the binary decomposition of an integer in $\{0, \dots, 2^k - 1\}$ by a k bits vector.

BINARY REPRESENTATION :



$5 =_2 101$, $2 =_2 010$, $42 =_2 101010 \dots$

TALES OF DICE (4)

Coin \mapsto Dice-6

From a coin design a 6-sided dice.

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Coin \mapsto Dice-6

From a coin design a 6-sided dice.

Dice-6()

Data: A function **Dice-8()** random generator on $\{1, \dots, 8\}$

Result: A sequence of i.i.d. random numbers uniformly distributed on $\{1, \dots, 6\}$

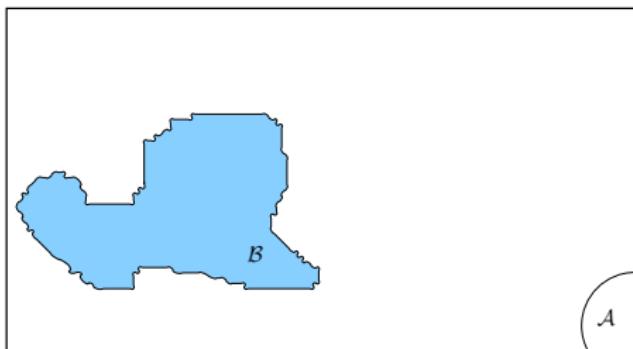
```
repeat
    | X =Dice-8()
until X ≤ 6
return X
```

Proof: later

GENERATION METHODS BASED ON REJECTION

Principle

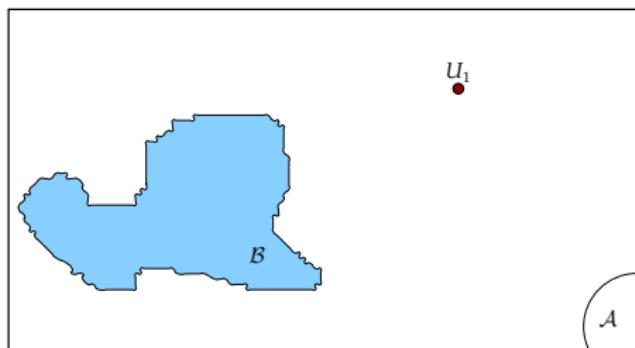
Generate uniformly on \mathcal{A} accept if the point is in \mathcal{B} .



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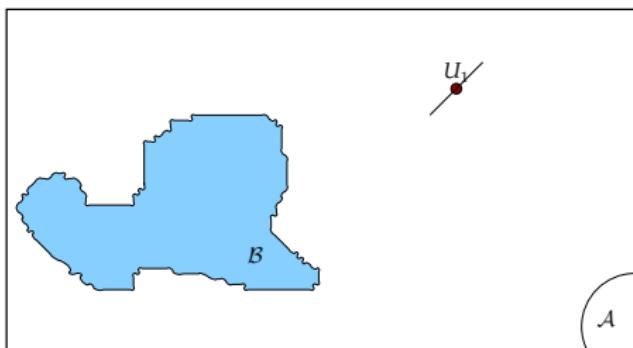
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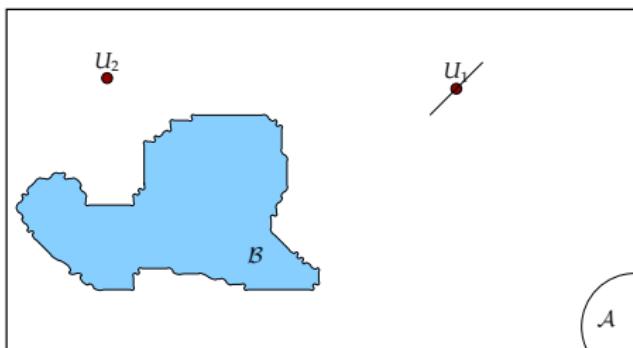
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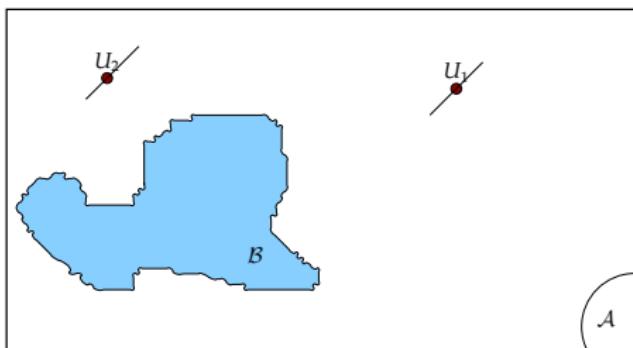
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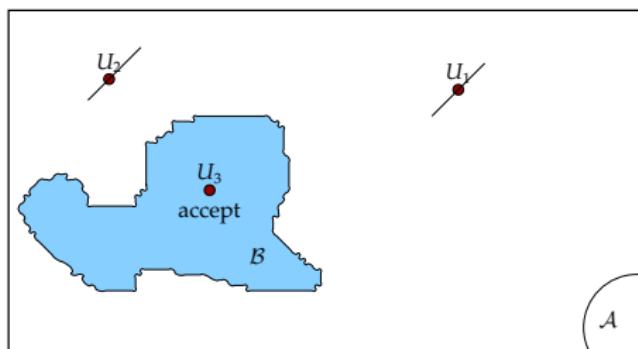
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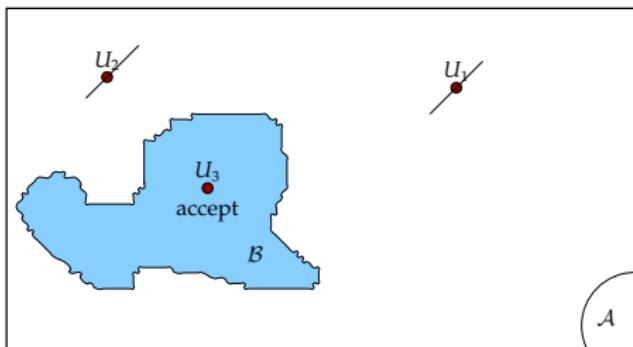
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GENERATION METHODS BASED ON REJECTION

Principle

Generate uniformly on \mathcal{A} accept if the point is in \mathcal{B} .



Algorithm

Generation-unif(\mathcal{B})

Data:

Uniform generator on \mathcal{A}

Result:

Uniform generator on \mathcal{B}

repeat

| $X = \text{Generator-unif}(\mathcal{A})$

until $X \in \mathcal{B}$

return X

GENERATION METHODS BASED ON REJECTION: PROOF

Génère-unif(\mathcal{B})

Data:

Uniform generator on \mathcal{A}

Result:

Uniform generator on \mathcal{B}

$N = 0$

repeat

| X = Generator-unif(\mathcal{A})
| $N = N + 1$

until $X \in \mathcal{B}$

return X, N

Proof

Calls to **Generation-unif(\mathcal{A})**: $X_1, X_2, \dots, X_n, \dots$

$$\begin{aligned} & \mathbb{P}(X \in \mathcal{C}, N = k) \\ = & \mathbb{P}(X_1 \notin \mathcal{B}, \dots, X_{k-1} \notin \mathcal{B}, X_k \in \mathcal{C}) \\ = & \mathbb{P}(X_1 \notin \mathcal{B}) \cdots \mathbb{P}(X_{k-1} \notin \mathcal{B}) \mathbb{P}(X_k \in \mathcal{C}) \\ = & \left(1 - \frac{|\mathcal{B}|}{|\mathcal{A}|}\right)^{k-1} \frac{|\mathcal{C}|}{|\mathcal{A}|} \end{aligned}$$

$$\begin{aligned} \mathbb{P}(X \in \mathcal{C}) &= \sum_{k=1}^{+\infty} \mathbb{P}(X \in \mathcal{C}, N = k) \\ &= \sum_{k=1}^{+\infty} \left(1 - \frac{|\mathcal{B}|}{|\mathcal{A}|}\right)^{k-1} \frac{|\mathcal{C}|}{|\mathcal{A}|} = \frac{|\mathcal{C}|}{|\mathcal{B}|} \end{aligned}$$

Consequently the law is **uniform** on \mathcal{B}

GENERATION METHODS BASED ON REJECTION

Génère-unif(\mathcal{B})

Data:

Uniform generator on \mathcal{A}

Result:

Uniform generator on \mathcal{B}

$N = 0$

repeat

$X = \text{Generator-unif}(\mathcal{A})$

$N = N + 1$

until $X \in \mathcal{B}$

return X, N

Complexity

N Number of iterations

$$\begin{aligned}\mathbb{P}(N = k) &= \mathbb{P}(X \in \mathcal{B}, N = k) \\ &= \left(1 - \frac{|\mathcal{B}|}{|\mathcal{A}|}\right)^{k-1} \frac{|\mathcal{B}|}{|\mathcal{A}|}\end{aligned}$$

Geometric probability distribution with parameter

$$p_a = \frac{|\mathcal{B}|}{|\mathcal{A}|}.$$

Expected number of iterations

$$\begin{aligned}\mathbb{E} N &= \sum_{k=1}^{+\infty} k(1 - p_a)^{k-1} p_a \\ &= \frac{1}{(1 - (1 - p_a))^2} p_a = \frac{1}{p_a}.\end{aligned}$$

$$\text{Var } N = \frac{1 - p_a}{p_a^2}$$

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3 DISCRETE : Discrete Random Variable

GENERATING RANDOM OBJECTS

Denote by X the generated object $\in \{1, \dots, n\}$

Distribution (proportion of observations, input of the load injector)

$$p_k = \mathbb{P}(X = k).$$

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Remarks :

$$0 \leq p_i \leq 1; \quad \sum_k p_k = 1.$$

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$$p_k = \mathbb{P}(X = k).$$

Remarks :

$$0 \leq p_i \leq 1; \quad \sum_k p_k = 1.$$

For integer valued random variables $X \in \mathbb{N}$:

$$\mathbb{E}X = \sum_k k \cdot \mathbb{P}(X = k) = \sum_k kp_k. \text{Expectation}$$

Variance and standard deviation

$$\mathbb{V}arX = \sum_k (k - \mathbb{E}X)^2 \mathbb{P}(X = k) = \mathbb{E}(X - \mathbb{E}X)^2 = \mathbb{E}X^2 - (\mathbb{E}X)^2.$$

$$\sigma(X) = \sqrt{\mathbb{V}arX}.$$

THE RANDOM FUNCTION

Random bit generator (see previous lecture)

double drand48(void) (48 bits encoded in 8 bytes)

(manpage)

The rand48() family of functions generates pseudo-random numbers using a linear congruential algorithm working on integers 48 bits in size. The particular formula employed is $r(n+1) = (a * r(n) + c) \bmod m$ where the default values are for the multiplicand $a = 0xfdeece66d = 25214903917$ and the addend $c = 0xb = 11$. The modulo is always fixed at $m = 2^{48}$. $r(0)$ is called the seed of the random number generator.

The sequence of returned values from a sequence of calls to the random function is modeled by a sequence of real independent random variables uniformly distributed on the real interval $[0, 1]$

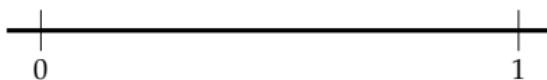
Probabilistic Model

$\{U_n\}_{n \in \mathbb{N}}$ sequence of i.i.d real random variables

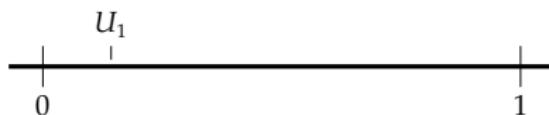
For all $n \in \mathbb{N}$, for all the intervals $[a_i, b_i)$ with $0 \leq i \leq n$ and $0 \leq a_i < b_i \leq 1$,

$$\mathbb{P}(U_0 \in [a_0, b_0), \dots, U_n \in [a_n, b_n)) = (b_0 - a_0) \times \dots \times (b_n - a_n).$$

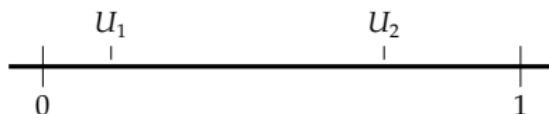
THE RANDOM FUNCTION



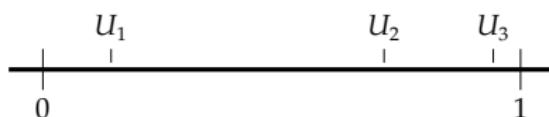
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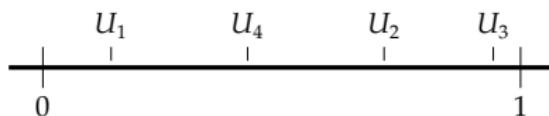
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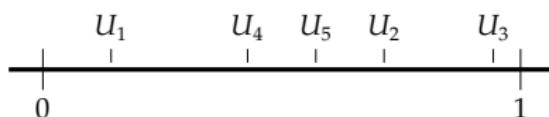
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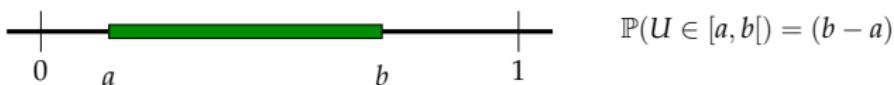
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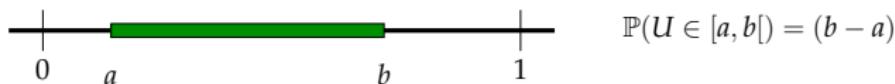
THE RANDOM FUNCTION



THE RANDOM FUNCTION



THE RANDOM FUNCTION



Problem

All the difficulty is to find a function (an algorithm) that maps the $[0, 1[$ in a set with a right probability.

UNIFORM DISCRETE RANDOM VARIABLES

Example : flip a coin

Coin ()

```
u=Random () if u <  $\frac{1}{2}$ 
  Return 0 // or returns Head
else
  Return 1 // or returns Tail
```

Bernoulli scheme

Roll a n-sided dice

Dice (n)

Data: n : Number of possible outcomes
Result: a single outcome in $\{1, \dots, n\}$
 $u=Random ()$
 Return $\lceil n * u \rceil$
 // smallest integer greater
 than $u \times n$

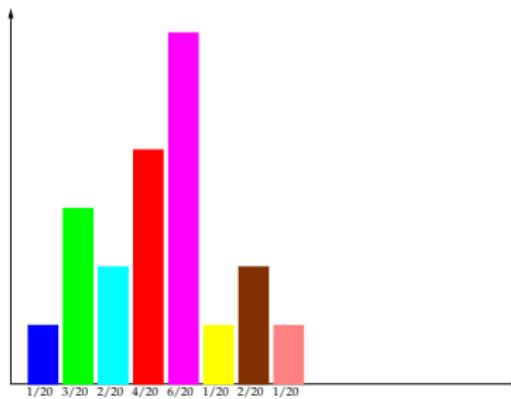
The problem

Given a discrete distribution

$$p = (p_1, p_2, \dots, p_n), \quad 0 \leq p_i \leq 1 \quad \sum_{i=1}^n p_i = 1;$$

Design an algorithm that generates pseudo random numbers according probability p .
Prove such an algorithm and evaluate its (average) **complexity**

PROBABILITIES ON A FINITE SET



TABULATION METHOD

Pre-computation

$$p_k = \frac{m_k}{m} \text{ where } \sum_k m_k = m.$$

Create a table T with size m .

Fill T such that m_k cells contains k .

Computation cost : m steps

Memory cost : m

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Table construction

Build_Table (p)

Data: p a rational distribution $p_i = \frac{m_i}{m}$

Result: Tabulation of distribution p

l=1

```
for i = 1, i <= n, i ++
    for j = 1, j <= m_i, j ++
        T[l]=i
        l++
```

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Generation

Generate uniformly on the set

$\{1, \dots, m\}$

Returns the value in the table

Computation cost : $\mathcal{O}(1)$ step

Memory cost : $\mathcal{O}(m)$

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Generation algorithm

Generation (T)

Data: T Tabulation of distribution p

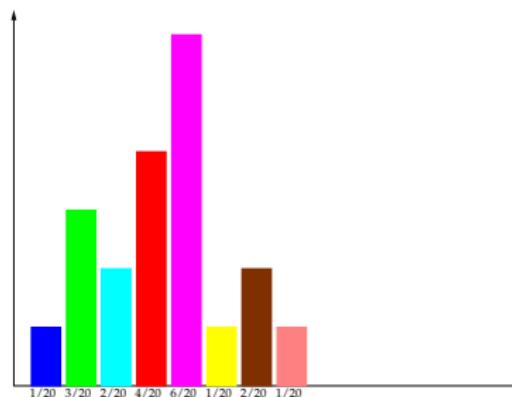
Result: A random number following distribution p

$u=\text{Random}()$

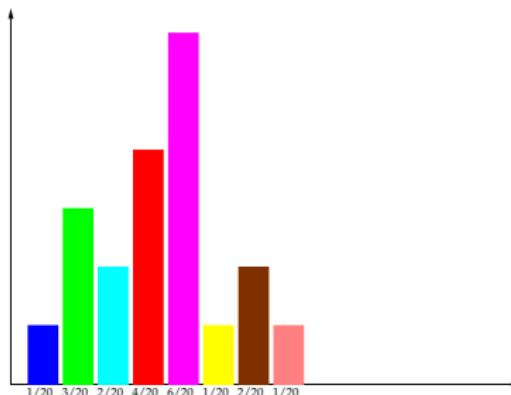
$l = \lceil m * u \rceil$

Return $T[l]$

PROBABILITIES ON A FINITE SET



PROBABILITIES ON A FINITE SET

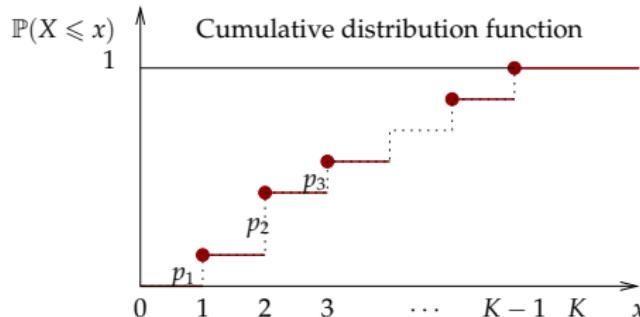


Histogram : Flat representation



$$\text{Cost(average number of comparisons)} : \hat{C}(P) = \sum_{k=1}^K k.p_k = 4.35$$

INVERSE OF PROBABILITY DISTRIBUTION FUNCTION



Generation

Divide $[0, 1]$ in intervals with length p_k

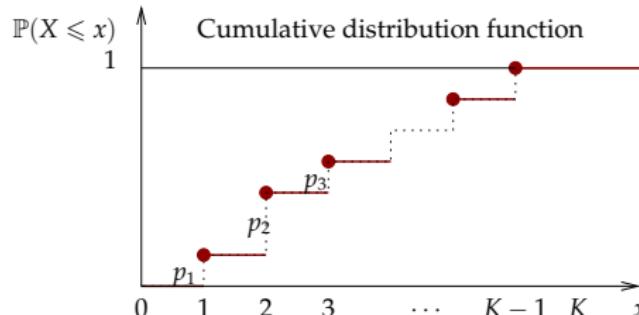
Find the interval in which *Random* falls

Returns the index of the interval

Computation cost : $\mathcal{O}(\mathbb{E}X)$ steps

Memory cost : $\mathcal{O}(1)$

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Inverse function algorithm

Generation (p)

Data: A distribution p

Result: A random number following distribution p

$u = \text{Random}()$

$S = 0$

$k = 0$

while $u > s$

$k = k + 1$

$s = s + p_k$

Return k

SEARCHING OPTIMIZATION

Optimization methods

- ▶ pre-compute the pdf in a table
- ▶ rank objects by decreasing probability



- ▶ use a dichotomy algorithm
- ▶ use a tree searching algorithm (optimality = Huffmann coding tree)

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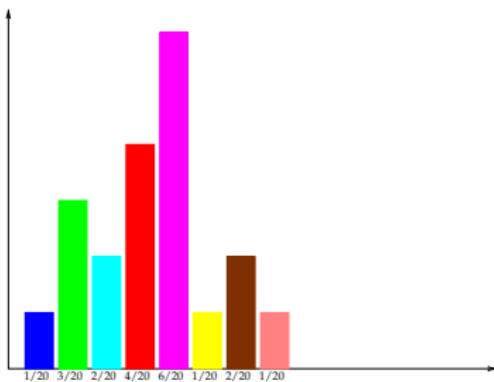


- ▶ use a dichotomy algorithm
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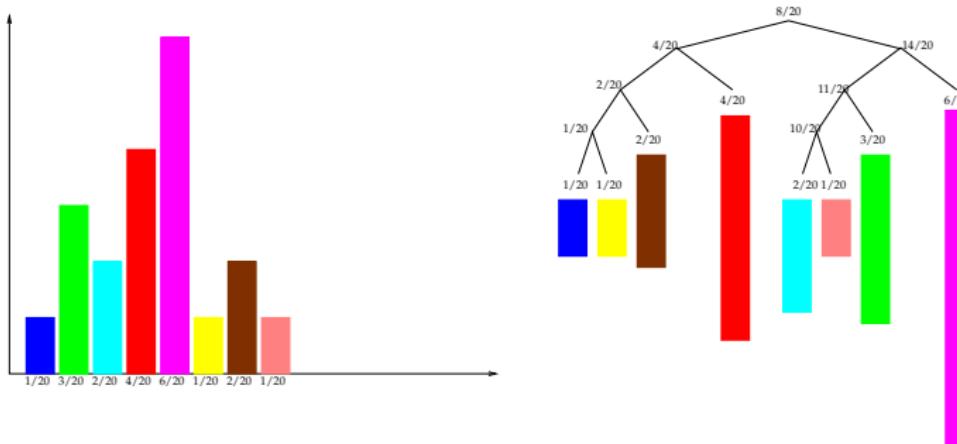
Comments

- Depends on the usage of the generator (repeated use or not)
- pre-computation usually $\mathcal{O}(K)$ could be huge
-

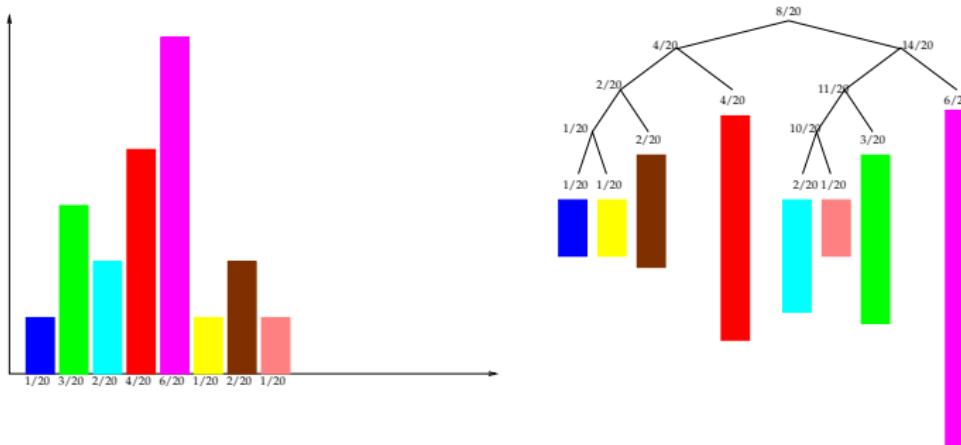
OPTIMALITY



OPTIMALITY



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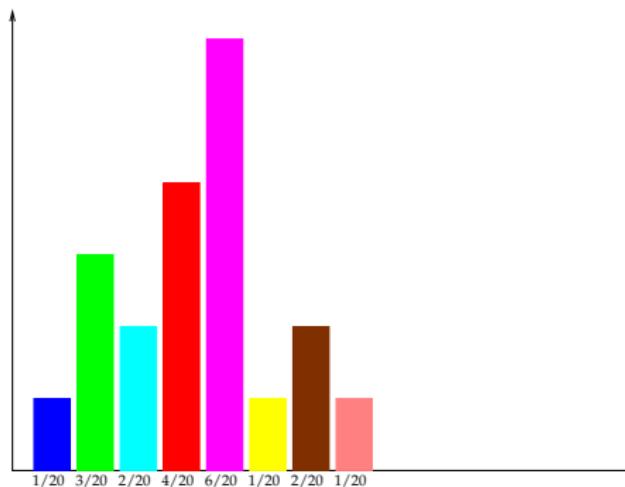


Number of comparisons

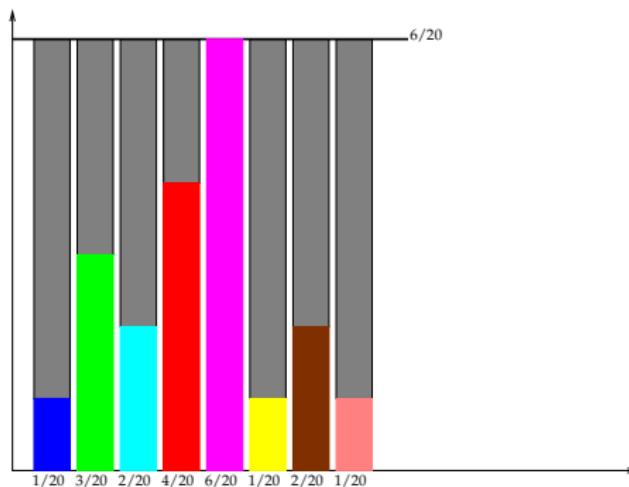
Binary Search Tree Structure

$$\mathbb{E}N = \sum_{k=1}^K p_k.l_k = 3,75, \text{ Entropie} = \sum_{k=1}^K p_k(-\log_2 p_k) = 3.70$$

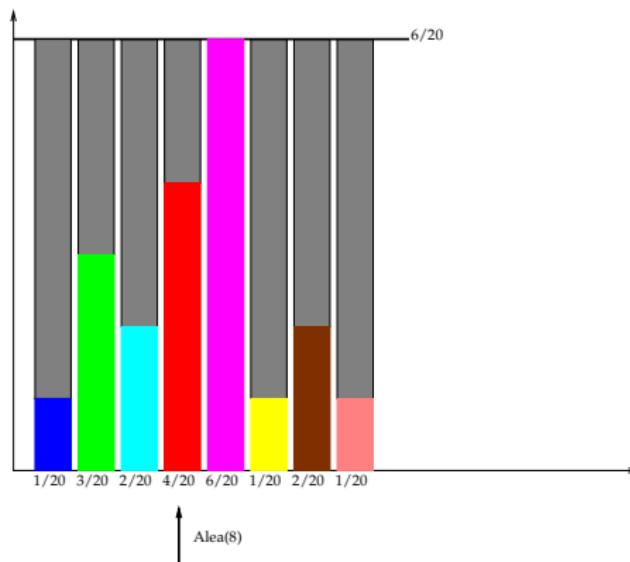
REJECTION BASED METHODS



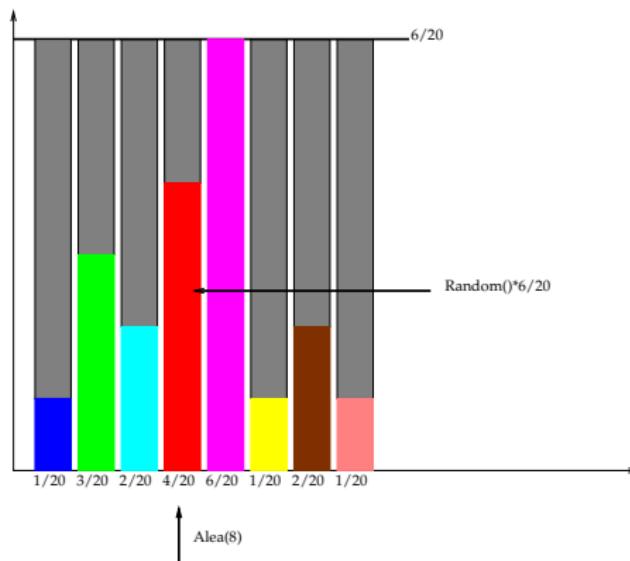
REJECTION BASED METHODS



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REJECTION BASED METHODS

Generation_Reject(p)

Data: A distribution p

Result: A random number following distribution p

$N = 0$

repeat

$u = \text{Random}()$
 $k = \lceil n * u \rceil$
 $v = \text{Random}() * p_{\max}$
 $N++$

until $v \leq p_k$

Return k, N

Proof

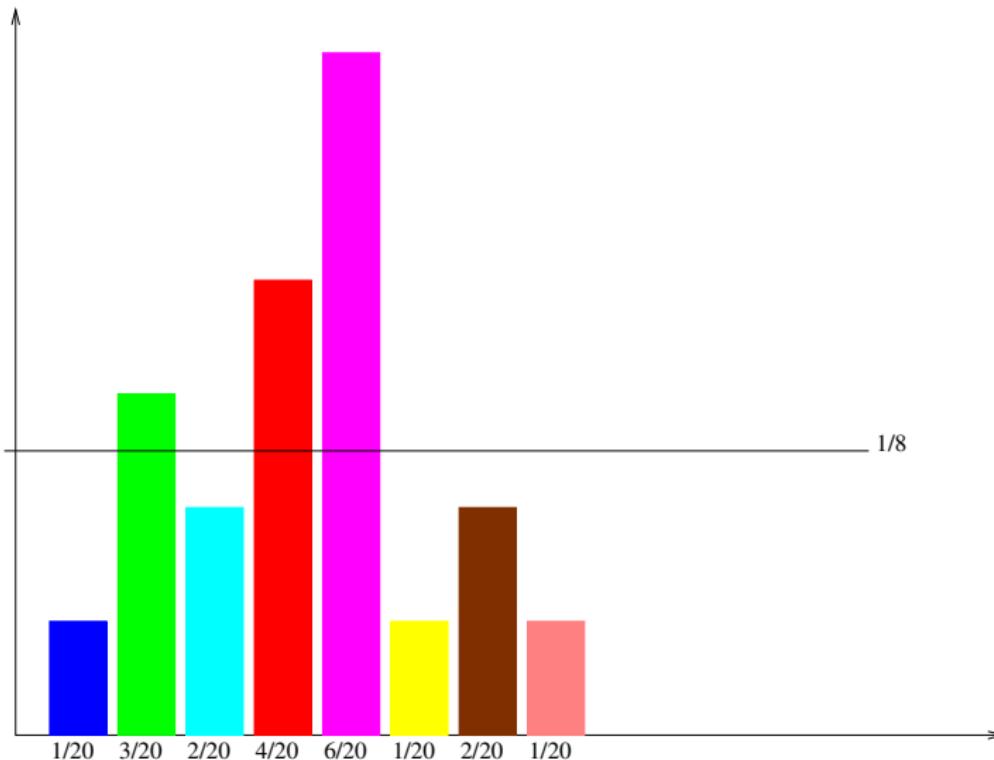
Same proof as for the uniform case

Complexity

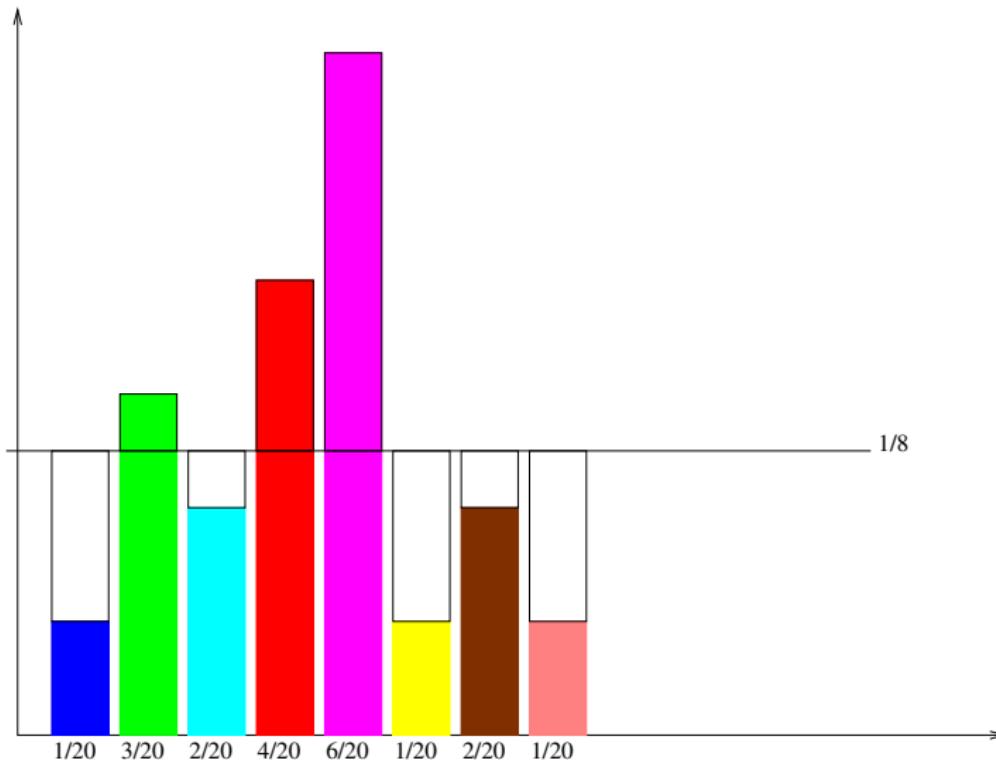
Average number of iterations :

$$p_a = \frac{1}{n \cdot p_{\max}} \text{ et } \mathbb{E}N = np_{\max}$$

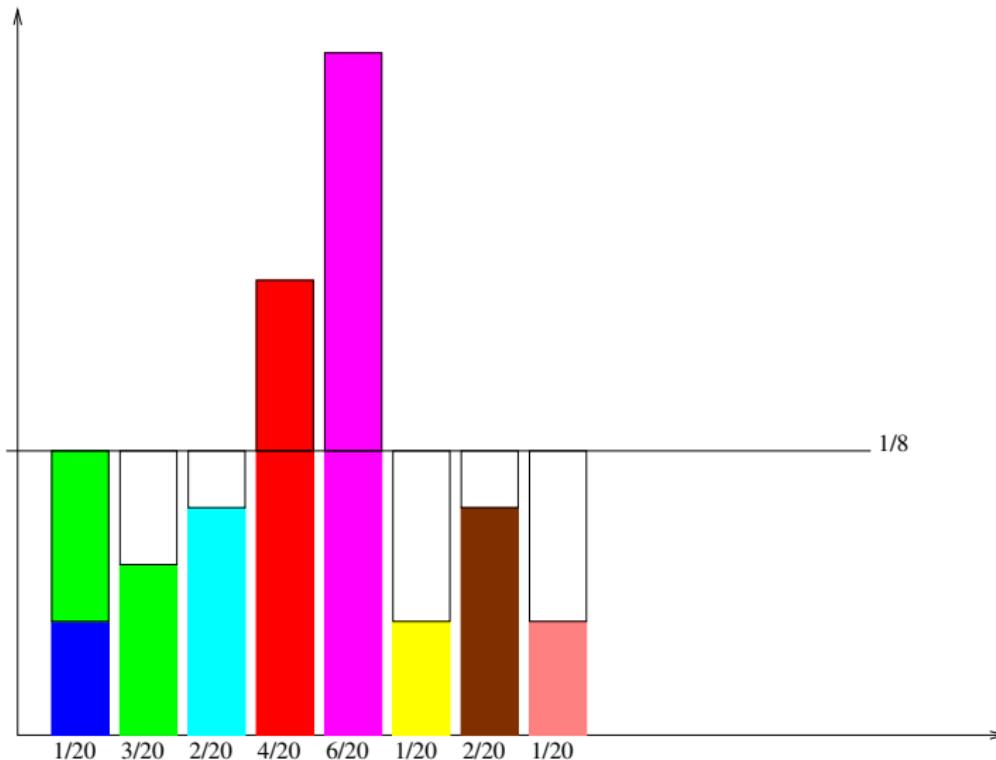
ALIASING METHOD



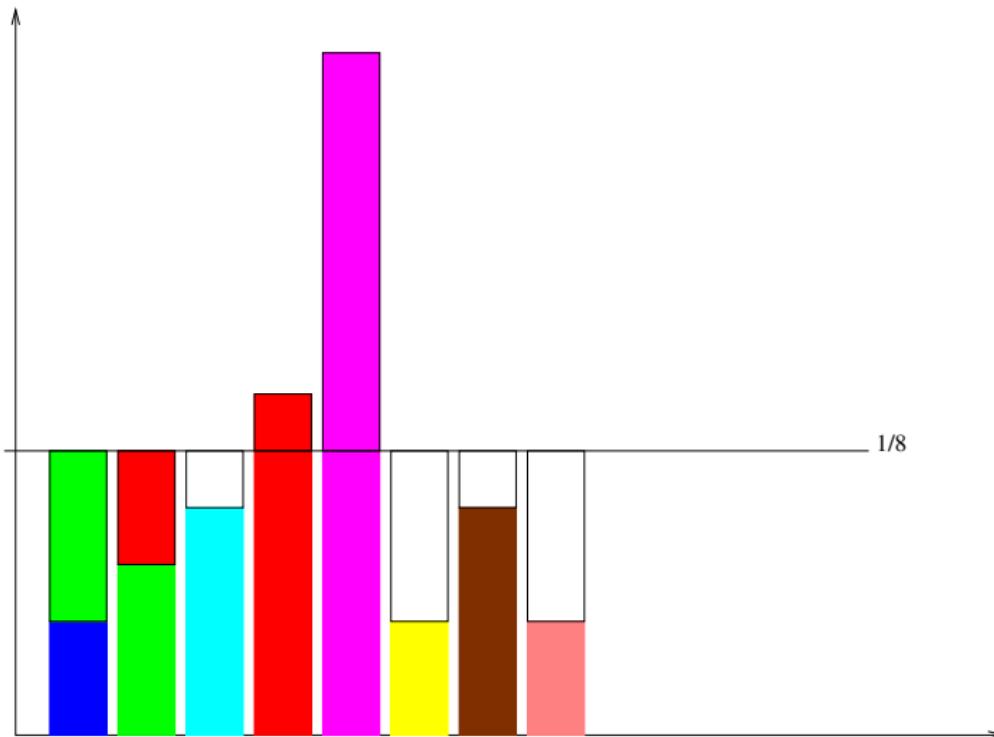
ALIASING METHOD



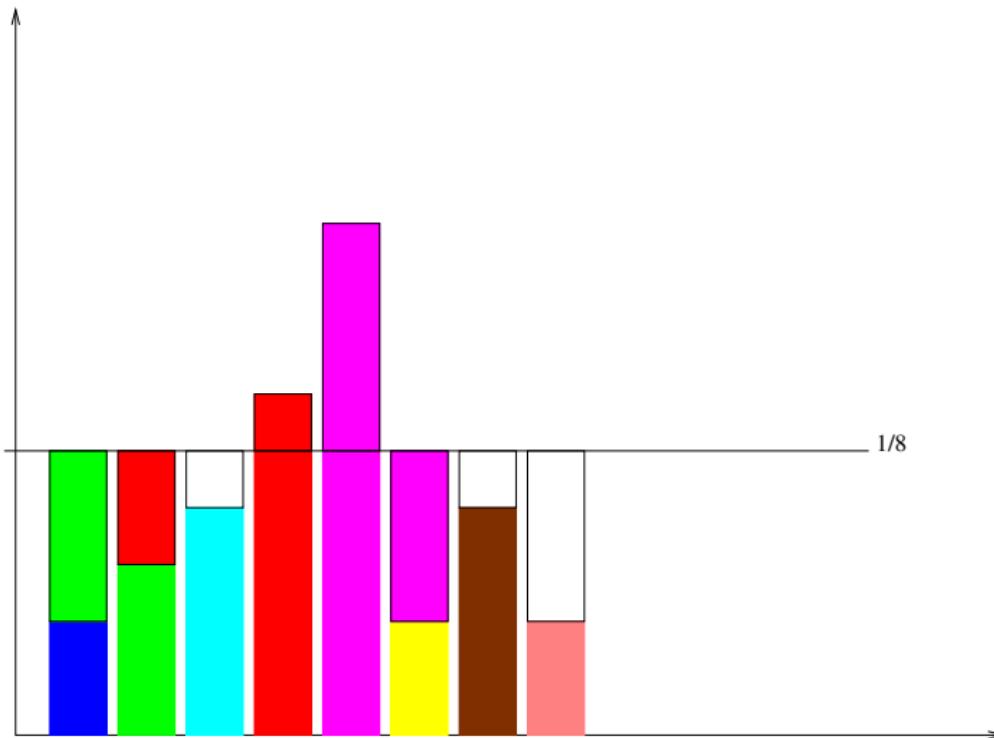
ALIASING METHOD



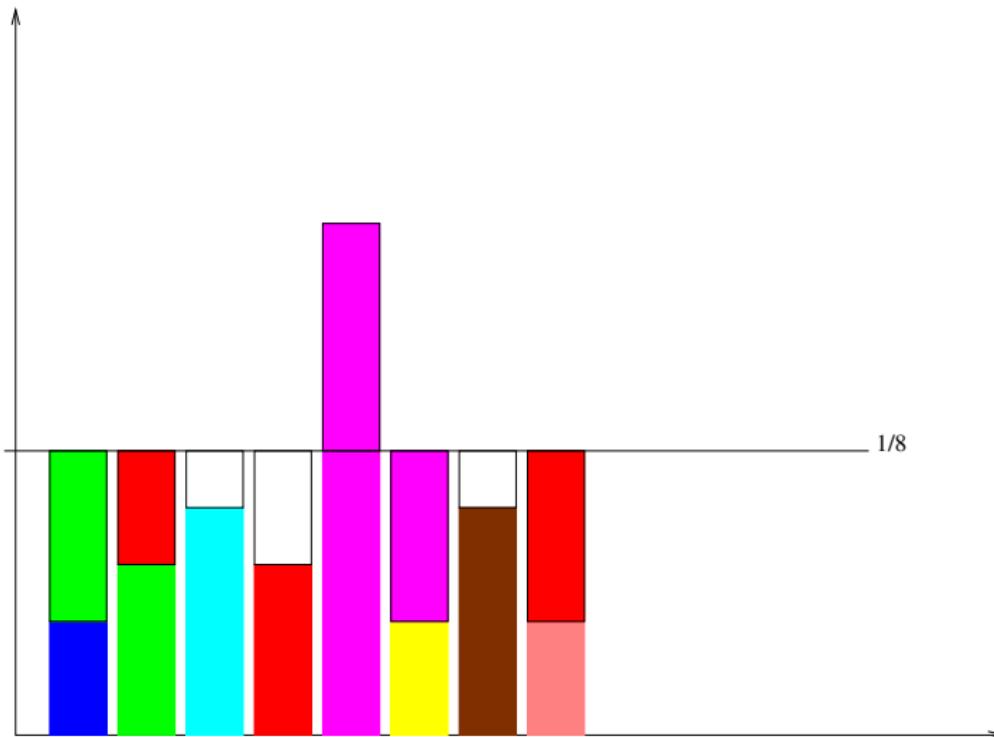
ALIASING METHOD



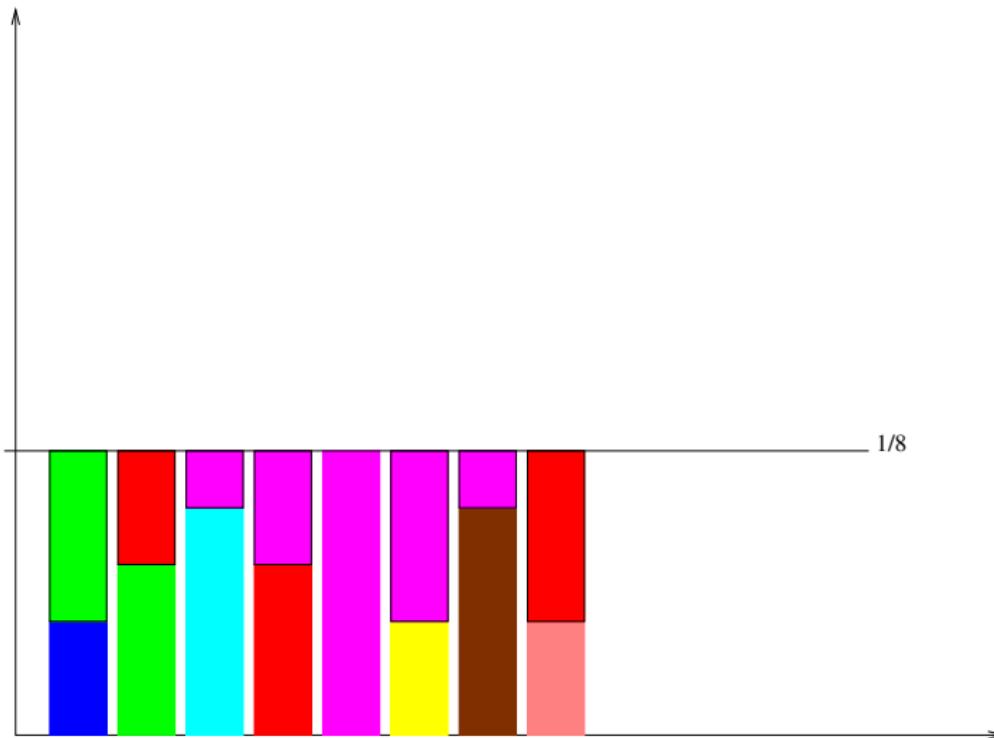
ALIASING METHOD



ALIASING METHOD



ALIASING METHOD



ALIASING METHOD : ALIAS TABLE

Table_Alias(p)

Data: A distribution p

Result: A vector of thresholds $s_1, \dots, s_n]$
and a vector of aliases a_1, \dots, a_n

$L = \emptyset$ $U = \emptyset$

for $k = 1$ **to** n

switch p_k **do**

case $p_k < \frac{1}{n}$ $L = L \cup \{k\}$

case $p_k > \frac{1}{n}$ $U = U \cup \{k\}$

while $L \neq \emptyset$

$i = Extract(L)$ $k = Extract(U)$

$s_i = p_i$ $a_i = k$

$p_k = p_k - (\frac{1}{n} - p_i)$

switch p_k **do**

case $< \frac{1}{n}$ $L = L \cup \{k\}$

case $> \frac{1}{n}$ $U = U \cup \{k\}$

ALIASING METHOD : GENERATION

Generation_Alias(s, a)

Data: A vector of thresholds $s_1, \dots, s_n]$

and a vector of aliases a_1, \dots, a_n according adistribution p

Result: A random number following distribution p

```
u =Random ()  
k = ⌈ n * u ⌉  
if Random(0  $\frac{1}{n}$  <  $s_k$   
    ↳ Return k  
else  
    ↳ Return  $a_k$ 
```

Complexity

Computation time :

- $\mathcal{O}(n)$ computation of thresholds and aliases
- $\mathcal{O}(1)$ generation

Memory :

- thresholds $\mathcal{O}(n)$ (same cost as p)
- alias $\mathcal{O}(n)$ (aliases)