Algorithm Design: Nondeterministic and Randomized Algorithms

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- 2 Non-deterministic Algorithms, Generally
- Non-deterministic Algorithms for Decision Problems
- Randomized Algorithms
 - Random Variable
 - Example of Monte Carlo Algorithm: Primality Test
 - Las Vegas Algorithms
 - Example of Las Vegas Algorithm: k-median



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Problem solved by an algorithm

An algorithm A solves a problem P if:

- for any instance p of P, there is an initial configuration $\langle A, \sigma_p \rangle$ such that σ_p includes data structures describing p;
- the execution starting from the initial configuration $\langle A, \sigma_p \rangle$ ends into a final configuration $\langle \cdot, \sigma' \rangle$, write $\langle A, \sigma \rangle \Rightarrow^* \langle ., \sigma' \rangle$; and
- σ' includes data structures that describes P(p).

Formally:

P is specified by (pre, post)

A rsolves
$$P \equiv (\forall \sigma)$$
 with $\sigma \models pre(\exists \sigma')$ s.t. $\langle A, \sigma \rangle \Rightarrow^* \langle ., \sigma' \rangle$ and $\sigma' \models post$



The execution time for an instance: the deterministic case

Deterministic algorithm: for any reachable configuration $\langle A_i, \sigma_i \rangle$ there is at most a successor configuration, i.e., at most a $\langle A', \sigma' \rangle$ such that $\langle A_i, \sigma_i \rangle \Rightarrow \langle A', \sigma' \rangle$.

All algorithms we considered up to now are deterministic! Later we shall consider nondeterministic algorithms as well.

Let P be a problem and A a deterministic algorithm that solves P.

For each $p \in P$ there is an unique execution path E_p .

The time for computing P(p) is $time_d(A, p) = time_d(E_p)$ where $d \in \{log, unif, lin\}$.



The size of an instance

The dimension of a state σ is

$$size_d(\sigma) = \sum_{\mathbf{x} \mapsto \mathbf{v} \in \sigma} size_d(\mathbf{v})$$

The dimension of a configuration is

$$size_d(\langle A, \sigma \rangle) = size_d(\sigma)$$

where $d \in \{log, unif, lin\}$.

Let P be a problem, $p \in P$, and A a deterministic algorithm that solves P.

The size of p is the the size of its intial configuration:

$$size_d(p) = size_d(\langle A, \sigma_p \rangle) \ \ (= size(\sigma_p))$$

where $d \in \{log, unif, , lin\}$.



The worst case time complexity

Let P be a problem and A a determinstic algorithm that solves P and fix $d \in \{log, unif, lin\}$.

Group the instances p of P into equivalences classes: p and p' are in the same equivalence class iff size(p) = size(p').

A natural number n can be seen as the equivalence class of instances p of size n ($size_d(p) = n$).

The worst case time complexity:

$$T_{A,d}(n) = \max\{time_d(A, p) \mid p \in P, size_d(p) = n\}$$



Experiments with Alk interpreter1/3

```
isPrime1(x) {
  if (x < 2) return false;
  for (i= 2; i <= x/2; ++i)
    if (x % i == 0) return false;
  return true;
}</pre>
```

Experiments with Alk interpreter 2/3

```
A worst case:
print(isPrime1(2147483647));
$ time alki.sh -a isPrime.alk
^C
real 41m3.065s
user 40m45.849s
sys 0m15.643s
A more favorable case:
print(isPrime1(2147483647*457241)); //457241^2=209069332081
$ time alki.sh -a isPrime.alk
false
real 0m3.480s
user 0m5.921s
sys 0m0.236s
```

Experiments with Alk interpreter 3/3

A minor change could bring major improvements:

```
isPrime2(x) {
  if (x < 2) return false;
  for (i = 2; i*i \le x; ++i)
    if (x % i == 0) return false;
  return true;
print(isPrime2(2147483647));
$ time alki.sh -a isPrime.alk
true
real 0m1.659s
user 0m3.475s
sys 0m0.163s
```

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Motivație

- abstraction of the state space is useful in analysis
- non-deterministic algorithms bring an additional abstraction level,
 which combines state abstraction with procedural abstraction
- ignores details how some data structures are created
- useful in complexity analysis
- preliminary notion for randomized algorithms

Non-deterministic Algorithms, Intuitively

- for some configurations there are more than one way to continue the execution
- consequently, for the same input the algorithm may have many executions with different results
- angelic version: the algorithm "guesses" the execution that leads to the correct result
- execution time: the time of the execution that leads to the correct result

Extending the Language

```
choose x in S;
- returns an element from S, arbitrarily chosen
- execution time (uniform): O(1)
choose x in S s.t. B;
- returns an element from S that satisfies B

    equivalent to

choose x in S:
if (\neg B(x)) ends with failure;
- execution time: T(B)
```

Demo with the new statements

```
choose x1 in { 1 .. 5 };
$ alki.sh -a choose.alk
    x1 |-> 2
```

Note that the executed algorithm is nondeterministic. \$ alki.sh -a choose.alk

Note that the executed algorithm is nondeterministic.

Demo with the new statements

```
d(x)
  return x % 2 == 1:
choose x1 in \{1...5\} s.t. odd(x1);
choose x2 in { 1 .. 5 } s.t. odd(x2);
$ alki.sh -a choosest.alk
    x1 | -> 3
    x2 |-> 1
Note that the executed algorithm is nondeterministic.
$ alki.sh -a choosest.alk
    x1 \mid -> 5
    x2 \mid -> 5
```

Note that the executed algorithm is nondeterministic.

Demo with the new statements

```
odd(x) {
  return x % 2 == 1;
}

L = emptyList;
for (i = 0; i < 8; i = i+2)
  L.pushBack(i);
choose x in L s.t. odd(x);

$ alki.sh -a failure.alk

Error at line 8: Choose can't find any suitable value.</pre>
```

Problem Solved by an Non-deterministic Algorithm

 a non-deterministic algorithm A has many executions for the same input

so, what means that A solves a problem P?

we say that A solves P if ∀x ∈ P
 ∃ an execution that
 is terminating and
 whose final configuration includes P(x)

Example: N Queens Problem

Input: a chessboard $n \times n$.

```
Output: place n chess queens so that no two queens attack each other.
attacked(i, j, b) {
  attack = false:
  for (k = 0; k < i; ++k)
     if ((b[k] == j) \mid | ((b[k]-j) == (k-i)) \mid | ((b[k]-j) == (i-k)))
       attack = true;
  return(attack);
}
nqueens (n) {
   for (i = 0; i < n; ++i) {
     choose j in { 0 .. n-1 } s.t. ! (attacked(i, j, b));
     b[i] = j;
    }
```

Execution time: $O(n^2)$ Details on the blackboard

Example: N Queens Problem, demo

```
b = [-1 | i from [0..n-1]];

$ alki.sh -a nqueens.alk

Error at line 19: Choose can't find any suitable value. i.e. failure

$ alki.sh -a nqueens.alk
b |-> [2, 0, 3, 1]
i |-> 3
n |-> 4
```

Note that the executed algorithm is nondeterministic.

n = 4:

Example: Subset Sum Problem (SSP)

```
/*
Input: A set S of integers, M a positive integer.
Output: A subset of S' \subseteq S s.t. \sum_{x \in S'} x = M, if any.
*/
PM = 0:
/* choose a maximal size for the subset */
choose k in {1 .. S.size()};
/* try to choose at most k-1 elements */
for(i = 0; i < k-1; ++i) {
  choose x in S s.t. PM + x <= M;
  S = S \setminus singletonSet(x);
  PM = PM + x:
/* try to choose the k-th element, if needed */
if (PM != M)
  choose x in S s.t. PM + x == M:
TExecution time: O(n), where n = S.size() (we assumed
T(S \setminus singletonSet(x)) = O(1).
```

Details on blackboard.

Example: Subset Sum Problem (SSP), demo

```
ssd.in
S |-> {1, 3, 4, 7, 9} M |-> 14
Execution:
$ alki.sh -a ssd.alk -i ssd.in
Error at line 18: Choose can't find any suitable value. failure
$ alki.sh ssd.alk -i ssd.in
S \rightarrow 3, 7 success
x |-> 1
i |-> 3
k |-> 4
M \mid -> 14
PM |-> 14
```

Note that the executed algorithm is nondeterministic.

Reduction to Deterministic Algorithms

Let \sim be an equivalence between states. For instance, $\sigma \sim \sigma'$ iff σ and σ' encode the same instance p of a problem P or both encode the answer P(p).

Definition

We say that an algorithm A is equivalent to an algorithm B (w.r.t. \sim) iff:

- **1** $\langle A, \sigma_1 \rangle \Rightarrow^* \langle \cdot, \sigma_1' \rangle$ and $\sigma_1 \sim \sigma_2$ implies the existence of σ_2' s.t. $\langle B, \sigma_2 \rangle \Rightarrow^* \langle \cdot, \sigma_2' \rangle$ și $\sigma_1' \sim \sigma_2'$, and
- 2 reciprocally, $\langle B, \sigma_2 \rangle \Rightarrow^* \langle \cdot, \sigma_2' \rangle$ si $\sigma_1 \sim \sigma_2$ the existence of σ_1' s.t. $\langle A, \sigma_1 \rangle \Rightarrow^* \langle \cdot, \sigma_1' \rangle$ și $\sigma_1' \sim \sigma_2'$.

Theorem

For any non-deterministic algorithm A there is an equivalent deterministic algorithm B, which has the worst case execution time $T_B(n) = O(2^{T_A(n)})$.

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The Approach

- there a two main steps:
 - first "guesses" a certain structure S
 - \bullet then checks if S satisfies the property requested by the question
 - if yes the the execution finishes with success, otherwise it finishes with failure;
- Extending the language:

```
success; - signals the successful termination of an execution
failure; - signals the termination of a failing execution
```

Example

SAT

Instance: A set of n propositional variables and a propositional formula F in conjunctive normal form.

Question: Is F satisfiable?

```
// guess
```

```
for (i = 0; i < n; ++i) {
  choose z in {false, true};
  x[i] = z;
}
// check
if (f(x)) success;
else faulure;</pre>
```

Example of SAT instance

Demo

```
$ alki.sh -a sat.alk
failure
x |-> [false, false, false, true]
i |-> 4
z |-> true
n |-> 4
Note that the executed algorithm is nondeterministic.
$ alki.sh -a sat.alk
failure
x |-> [true, true, true, false]
i I-> 4
z \mid -> false
n |-> 4
Note that the executed algorithm is nondeterministic.
```

Demo

```
$ alki.sh -a sat.alk
failure
x |-> [false, true, true, false]
i |-> 4
z |-> false
n |-> 4
Note that the executed algorithm is nondeterministic.
$ alki.sh -a sat.alk
success
x |-> [true, true, true, true]
i |-> 4
z |-> true
n |-> 4
```

Note that the executed algorithm is nondeterministic.

Example: Subset sum Problem (SSP3)

```
/*
Instance: A set S of intyegers, M a positive integer.
Question: Is there a subset S' \subseteq S s.t. \sum_{x \in S'} x = M?
*/
PM = 0:
choose k in 1 .. S.size();
for(i = 0; i < k; ++i) {
  choose x in S;
  S = S \setminus singletonSet(x);
  PM = PM + x:
if (PM == M) print("success");
else print("failure");
```

Demo (SSD3)

```
$ alki.sh -a ssd3.alk -i ssd.in
failure
S \mid -> 1, 3, 7
x |-> 4
i |-> 2
k |-> 2
M \mid -> 14
PM |-> 13
Note that the executed algorithm is nondeterministic.
$ alki.sh -a ssd3.alk -i ssd.in
success
S |-> 1, 9
x |-> 7
i |-> 3
k I-> 3
M \mid -> 14
PM |-> 14
Note that the executed algorithm is nondeterministic.
```

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Definition

Definition

A random variable is a function X defined over a set of possible outcomes Ω of a random phenomenon.

Example (only discrete variables)

- 1. D2 (two dice):
 - random phenomenon: rolling two dice
 - D2 returns the pair representing the numbers on the two dice
- 2. SD2 (the sum of two dice):
 - random phenomenon: rolling two dice
 - SD2 returns the sum of numbers on the two dice
- 3. CB ("chocolate bar"):
 - ullet random phenomenon: randomly choose a number i in the set $\{1,2,\ldots,n\}$, n>1
 - *CB* returns $\max(\frac{i}{n}, \frac{n-i}{n}), i = 1, \dots, n-1$



Probability Distribution

$$X:\Omega\to V$$

$$X(\Omega) = x_0, x_1, x_2, \dots$$

$$p_i = \text{Prob}(X = x_i) \ (= \text{Prob}(\omega \in \Omega \mid X(\omega) = x_i))$$

SD2:

$$SD2(\Omega) = \{2, 3, 4, \dots, 12\}$$

$$\begin{split} &SD2(\Omega) = \{2,3,4,\dots,12\} \\ &\operatorname{Prob}(SD2 = 2) = \frac{1}{36}, \, \operatorname{Prob}(SD2 = 3) = \frac{2}{36}, \, \operatorname{Prob}(SD2 = 4) = \frac{3}{36}, \, \dots \end{split}$$



Extending the Language: "Function" random()

```
random(n) - returns an integer x \in \{0, 1, ..., n-1\} uniformly chosen
(i.e. with the probability \frac{1}{-})
Execution time: O(1)
test-random.alk:
n = random(5):
print(n);
Running test-random.alk
$alki.sh -a test-random.alk
4
n |-> 4
```

The probability for this execution is: 0.2000000000



Experiment with random()

```
Executing the algorithm
```

```
a = [0, 0, 0, 0];
for (i = 0; i < 10000; ++i) {
    j = random(4);
    a[j] = a[j] + 1;
}
we get the following final state:
$ alki.sh -a random.alk
a |-> [2508, 2537, 2486, 2469]
i |-> 10000
j |-> 0
```

The probability for this execution is: 0E-10

The probabilities experimentally computed (e.g. $\frac{2508}{10000}$) are close to the theoretical ones; in fact are approximations of them.

Random Variables as Algorithms

```
D2()
  d[0] = random(6) + 1;
  d[1] = random(6) + 1;
  return d;
SD2()
  d1 = random(6) + 1;
  d2 = random(6) + 1;
  return d1 + d2;
}
CB(n)
  i = random(n-1) + 1;
  s1 = float(i) / float(n);
  s2 = float(n - i) / float(n);
  if (s1 > s2 ) return s1;
  return s2;
```

Random Variable: the Expected Value

Consider only discrete random variable X, whose values are real numbers x_1, x_2, \ldots

$$p_i = Pr(X = x_i)$$
 - probability as X to have the value x_i

Expected Value of X:
$$E(X) = \sum_i x_i \cdot p_i$$

Properties:

$$E(X + Y) = E(X) + E(Y)$$

 $E(X \cdot Y) = E(X) \cdot E(Y)$
(X si Y independente)



Expected value of CB

- 0 n odd:
 - possible values for *CB* are $\left\{\frac{k}{n} \mid k=n-1,n-2,\ldots,\frac{n+1}{2}\right\}$, each of them with the probability $\frac{2}{n-1}$

$$E(CB) = \sum_{k=\frac{n+1}{2}}^{n-1} \frac{k}{n} \frac{2}{n-1} = \frac{3n-1}{4n} < \frac{3}{4}$$

- 2 n even:

$$E(CB) = \sum_{k=\frac{n}{2}+1}^{n-1} \frac{k}{n} \frac{2}{n-1} + \frac{1}{2(n-1)} = \frac{3n-4}{4n-4} < \frac{3}{4}$$

Obs. $\frac{3n-4}{4n-4} = \frac{3(n-1)-1}{4(n-1)}$, which implies that the expected values for n and n-1 are the same if n is even.

Conclusion: $E(CB) < \frac{3}{4}$



Approximating the Expected Value by SuccessiveExecutions

```
sum = 0.0;
for (j = 0; j < 100; ++j)
  sum = sum + CB(31);

m = sum / float(31);</pre>
```

Values obtained using three runs: 0.7341935483870967741943, 0.7416129032258064516137, 0.7606451612903225806456.

Randomized Algorithms: Definition

There are two approaches:

- Monte Carlo Algorithms
 - may produce incorrect results with some small probability, but whose execution time is deterministic
 - if runned multiple times with independent random choices each time , the failure probability can be made arbitrarily small, at the cost of the running time .
- 2 Las Vegas Algorithms
 - never produce incorrect results, but whose execution time may vary from one run to another
 - random choices made within the algorithm are used to establish an expected running time for the algorithm that is, essentially, independent of the input



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Motivation 1/2

Naive algorithm for primality testing:

```
isPrime2(x) {
  if (x < 2) return false;
  for (i = 2; i*i <= x; ++i)
    if (x % i == 0) return false;
  return true;
}</pre>
```

Motivation 2/2

```
A first execution:
print(isPrime2(2147483647));
$ time alki.sh -a isPrime.alk
true
real 0m1.465s
user 0m3.385s
sys 0m0.155s
A second execution:
print(isPrime2(2305843009213693951));
$ time alki.sh -a isPrime.alk
^C
real 50m14.407s
user 49m18.198s
sys 0m20.615s
```

Nondeterministic and Randomized Algorithms

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Composite numbers: problem domain 1/3

Legendre Symbol:

$$(a/p) = \begin{cases} 0 & \text{if } a \equiv 0 \pmod{p}, \\ 1 & \text{if } a \not\equiv 0 \pmod{p} \text{ and there is } x \text{ s.t.} a \equiv x^2 \pmod{p}, \\ -1 & \text{if } a \not\equiv 0 \pmod{p} \text{ and there is NO such an } x. \end{cases}$$

where p is prime;

Jacobi Symbol:

$$(a|n) = (a/p_1)^{\alpha_1}(a/p_2)^{\alpha_2} \cdots (a/p_k)^{\alpha_k},$$

where *n* is a positive integer and $p_1^{\alpha_1}p_2^{\alpha_2}\cdots p_k^{\alpha_k}$ its prime factorization.



Composite numbers: problem domain 2/3

- If n > 3 and prime, the (a|n) = (a/n), therefore often is used the same notation $\frac{a}{n}$.
- 2 If $a \equiv b \pmod{n}$ then (a|n) = (b|n).
- **1** (ab|n) = (a|n)(b|n), so $(a^2|n) = 1$ or 0
- **3** (a|mn) = (a|m)(a|n), so $(a|n^2) = 1$ or 0



Composite numbers: problem domain 3/3

- If m and n are coprime, then $(m|n)(n|m) = (-1)^{\frac{m-1}{2} \cdot \frac{n-1}{2}} =$ $\begin{cases} 1 & \text{dacă } n \equiv 1 \pmod{4} \text{ or } m \equiv 1 \pmod{4}, \\ -1 & \text{dacă } n \equiv m \equiv 3 \pmod{4} \end{cases}$
- **6** $(-1|n) = (-1)^{\frac{n-1}{2}} = \begin{cases} 1 & \text{dacă } n \equiv 1 \pmod{4}, \\ -1 & \text{dacă } n \equiv 3 \pmod{4}, \end{cases}$
- (2|n) = $(-1)^{\frac{n^2-1}{8}}$ = $\begin{cases} 1 & \text{dacă } n \equiv 1,7 \pmod{8}, \\ -1 & \text{dacă } n \equiv 3,5 \pmod{8}. \end{cases}$



Other Properties (inferred)

$$(a \cdot 2|n) = (a|n) \cdot (2|n) = \begin{cases} -(a|n) & \text{if } n \equiv 3,5 \pmod{8} \\ (n|a) & \text{otherwise} \end{cases}$$

$$(a|n) = \begin{cases} -(n|a) & \text{if } a \neq 0 \neq n \text{ si } n \equiv a \equiv 3 \pmod{4} \\ (n|a) & \text{otherwise} \end{cases}$$



From the problem domain to the algorithm

```
jacobi(a, n)
  j = 1;
  while (a != 0) {
    while (a \% 2 == 0) \{ // a \text{ is even} \}
      a = a / 2;
      if (n \% 8 == 3 || n \% 8 == 5) j = 0-j;
    }
    swap(a, n);
    if (a \% 4 == 3 \&\& n \% 4 == 3) j = 0-j;
    a = a \% n;
  if (n == 1) return j;
  else return 0;
```

Solovay-Strassen Algorithm: descriptive

Input: a odd positive integer *n*, *Output*: "composite" if *n* is composite, "maybe prime" otherwise

- randomly choose a in [2, n-1]
- **3** if x == 0 or $a^{(n-1)/2} \not\equiv x \pmod{n}$ then returns "composite"
- otherwise returns "maybe prime"

Solovay-Strassen Algorithm in Alk

```
isComp(n)
  a = random(n-3) + 2;
  if (gcd(a, n) != 1) return "composite";
  x = jacobi(a, n);
  if (x < 0) x = x + n;
  if (x != power(a, (n-1)/2, n)) return "composite";
  return "maybe prime";
}
```

Solovay-Strassen Algorithm: demo

```
m1[0] = 2147483647*457241:
m1[1] = isComp(m1[0]);
m2[0] = 2147483647;
m2[1] = isComp(m2[0]);
Rezultat:
$ time alki.sh -a compos.alk
m1 |-> [981917570237927, composite]
m2 \mid -> [2147483647, may be prime]
The probability for this execution is: 0E-10
real 0m0.570s
user 0m1.085s
sys 0m0.101s
```

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Solovay-Strassen Algorithm as a Prime Test with a Certain Probability

```
Input: a positive odd integer n,
a positive integer k representing the accuracy
Output: "composite" if n is composite, "probably prime" otherwise
isProbPrime(n, k) {
  while (k > 0 && isComp(n) != "composite")
    --k;
  if (k == 0) return "probably prime";
  return "composite";
}
```

Failure probability is 2^{-k} .

(A proof can be found in Richard M. Karp. An introduction to randomized algorithms. Discrete Applied Mathematics 34 (1991) 165-201.)

Solovay-Strassen Algorithm as a Prime Test: demo

```
m4[0] = 2305843009213693951;
m4[1] = isProbPrime(m4[0], 100);
Result:
$ time alki.sh -a compos.alk
m4 |-> [2305843009213693951, probably prime]
real 0m1.192s
user 0m3.043s
sys 0m0.161s
The test with the naive algorithm:
print(isPrime2(2305843009213693951));
$ time alki.sh -a isPrime.alk
^C
real 50m14.407s
user 49m18.198s
sys 0m20.615s
```

m3[0] = 170141183460469231731687303715884105727;

Solovay-Strassen Algorithm as a Prime Test: demo

```
m3[1] = isProbPrime(m3[0], 100);
Result:
$ time alki.sh -a compos.alk
m3 |-> [170141183460469231731687303715884105727, probably prime]
real 0m1.851s
user 0m4.856s
sys 0m0.262s
```

The test with the naive algorithm: an optimistic estimation for terminating is the end of the semester . . .

Nondeterministic and Randomized Algorithms

An Efficient Algorithm for the Power Function Modulo

From the problem domain:

```
a^{n} \pmod{p} = \begin{cases} 1 & \text{dacă } n = 0, \\ a \pmod{p} & \text{dacă } n = 1, \\ \left(a^{\frac{n}{2}} \pmod{p}\right) * \left(a^{\frac{n}{2}} \pmod{p}\right) \pmod{p} & \text{dacă } n \% 2 == 0, \\ \left(a * a^{n-1}\right) \pmod{p} & \text{dacă } n \% 2 == 1, \end{cases}
```

to the algorithm:

```
power(a, n, p) {
    x = 1;
    while (n > 0)
    if (n % 2 == 0) {
        a = (a * a) % p;
        n = n / 2;
    }
    else {
        x = (a * x) % p;
        n = n - 1;
    }
    return x;
}
```

Exercises

- 1. Find the execution time for power(a, n, p).
- 2. Find the execution time for isComp(n).
- 3. Find the execution time for isProbPrime(n, k).

Plan

- Recap
- Non-deterministic Algorithms, Generally
- Non-deterministic Algorithms for Decision Problems
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 - Random Variable
 - Example of Monte Carlo Algorithm: Primality Test
 - Las Vegas Algorithms
 - Example of Las Vegas Algorithm: k-median



The Expected time for the Randomized Algorithms 1/2

- never produce incorrect results, but whose execution time may vary from one run to another
- random choices made within the algorithm are used to establish an expected running time for the algorithm that is, essentially, independent of the input

Notations:

 $prob_{A,x}(C)=$ the probability that the algorithm A to execute C for the input x

 $time_{A,x}(C)$ = the time that A to execute C for the input x (a bit different from the deterministic case)



The Expected time for the Randomized Algorithms 2/2

```
the expected time of A for the input x is exp-time(A,x)=E[time_{A,x}]=\sum_{C}prob_{A,x}(C)\cdot time_{A,x}(C). time_{A,x} is a random variable. the expected time of A for the worst case is
```

```
exp-time(A, n) = max\{exp-time(A, x) \mid size(x) = n\}
If A is understood from the context, we write only exp-time(n) (exp-time(x)) instead of exp-time(A, n) (resp. exp-time(A, x)).
```



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k-median: the problem

Definition

Let S be a list with n elements from a totally ordered set. The k-median is the k-th element from the sorted list S.

Assume that S is represented by an array.

Consider the next problem:

Input an array $(a[i] \mid 0 \le i < n)$ and a number $k \in \{0, 1, ..., n-1\}$, Output k-median

k-median: description of the algorihtm

Select a pivote x in a[0..n-1].

Partition the array a around x: the elements of the array are permuted such that a[j] = x and

$$(\forall i)(i < j \implies a[i] \le x) \land (i > j \implies a[i] \ge x)$$

which is equivalent to:

$$(\forall i)(i < j \implies a[i] \le a[j]) \land (i > j \implies a[i] \ge a[j])$$

- **1** $j = k \implies$ the problem is solved
- 2 $j < k \implies \text{search } k \text{ in a}[j+1..n-1]$
- \emptyset $j > k \implies \text{search } k \text{ in a } [0..j-1]$



Partitioning Lomuto

```
partition(out a, p, q)
 pivot = a[q];
  i = p - 1;
  for (j = p; j < q; ++j)
    if (a[j] < pivot) {</pre>
        i = i + 1:
        swap(a, i , j);
    }
  swap(a, i+1, q);
  return i + 1;
swap(out a, i, j) {
  if (i != j) {
    temp = a[i];
    a[i] = a[j];
    a[j] = temp;
```

Nondeterministic and Randomized Algorithms

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Analysis of the Lomuto Partitioning

Correctness:

The for invariant:

$$i < j \land (\forall \ell) (p \le \ell \le i \implies a[\ell] \le pivot) \land (i < \ell < j \implies a[i] > pivot)$$

After for:

the invariant and j = q, which implies a[i + 1] > pivot

After the last swap:

$$a[i+1] = pivot$$
 și

$$(\forall \ell)(p \leq \ell \leq i \implies a[\ell] \leq pivot) \land (i < \ell < q \implies a[i] > pivot).$$

The number of comparisons: q - p

Randomized Partioning

The pivot is randomly chosen from a[p..q]:

```
randPartition(out a, p, q) {
  if (p < q) {
    i = p + random(q - p);
    swap(a, i, q);
    return partition(a, p, q);
  }
}</pre>
```

k-median: Las Vegas Algorithm

```
randSelectRec(out a, p, q, k)
{
  j = randPartition(a, p, q);
  if (j == k) return a[j];
  if (j < k) return randSelectRec(a, j+1, q, k);</pre>
  return randSelectRec(a, p, j-1, k);
}
randSelect(out a, k)
  return randSelectRec(a, 0, a.size()-1, k);
}
```

randSelect: analysis 1/3

exp-time(n, k) - tthe expected time to find the k-median in an array of length n

$$exp-time(n) = max_k exp-time(n, k)$$

Since we are interested in the worst case analysis, we assume that the recursive call chooses always the longest subarray.

Recall that
$$E(CB) < \frac{3}{4}$$

It follows that the expected length of the longest subarray is at most $\frac{3}{4}n$.

randSelect: analysis 2/3

Lemă

The expected length of the array after i call is at most $\left(\frac{3}{4}\right)^i$ n.

Proof

 L_i the random variable that returns the length of the array after i calls.

 P_j the random variable that returns the fraction of the elements preserved at the level j

 X_j the random variable that returns the length of the longest subarray at the level j

We have:
$$L_i = n \prod_{j=1}^i P_j$$
, $P_j = \frac{X_j}{n}$, $E(P_j) = E\left(\frac{X_j}{n}\right) = \frac{E(X_j)}{n} \le \frac{\frac{3}{4}n}{n} = \frac{3}{4}$, P_1, \ldots, P_n are independent,

$$E(L_i) = E(n \prod_{j=1}^i P_j) = n \prod_{j=1}^i E(P_j) \le \left(\frac{3}{4}\right)^i n$$

Now the lemma is proved.



randSelect: analysis 3/3

At the levell i, the number of operations is liniar, let say $\leq aX_i + b$ (recal that X_i is the length of the longest subarray).

Let $r \le n$ be the number of recursive calls. The the expected time is:

exp-time(n) =
$$E\left(\sum_{i=1}^{r} (aX_i + b)\right)$$

= $\sum_{i=1}^{r} E(aX_i + b)$
 $\leq \sum_{i=1}^{n} (aE(X_i) + b)$
 $\leq \sum_{i=1}^{n} \left(a\left(\frac{3}{4}\right)^i n + b\right)$
= $an\sum_{i=1}^{n} \left(\frac{3}{4}\right)^i + bn$
 $\leq 3an + bn$
= $O(n)$