## 9 Alg. de Horner: Polynomial evaluation

Consider

$$p(x) = \sum_{i=0}^{n} a_i x^i$$

We wish to compute p(k) for a given  $k \in \mathbb{R}$  minimizing the number of operations. Directly computing  $a_0 + a_1 k_1 + \ldots$  leads to n sums. The ith term requires computing  $k^i$ , which means i product operations, for a totall of  $\sum_{i=1}^n i = \frac{n(n+1)}{2}$  products. The total number of operations is then

$$\Theta = n + n(n+1)/2$$

The associated complexity is  $\mathcal{O}(n^2)$ .

Horner's method consists of re-writing p(x) so that the number of products is reduced. One writes

$$p(x) = a_0 + xb_0$$

where  $b_{n-1} = a_n$  and for  $0 \le i < n-1$ :

$$b_{i-1} = a_i + xb_i$$

Let  $p(x) = 3 + 5x - 4x^2 + 0x^3 + 6x^4$ , giving n = 4. Then  $b_3 = 6$  and

$$b_2 = a_3 + xb_3 = 6x,$$
  $b_1 = a_2 + xb_2 = -4 + x(6x),$   $b_0 = a_1 + xb_1 = 5 + x(-4 + x(6x))$ 

This finally gives

$$p(x) = 3 + xb_0 = 3 + x(5 + x(-4 + x(6x)))$$

Here, one must perform n sums again but only n products. Thus, there are  $\Theta = n + n = 2n$  operations, giving a complexity of  $\mathcal{O}(n)$  (in the operation space). See the algorithm below:

```
\begin{aligned} & \textbf{input} \ \ n; a_i, i = 0, \dots, n; x \\ & b_{n-1} \leftarrow a_n \\ & \textbf{for} \ \ i = n-2 \ \ \textbf{to} \ \ i = 0 \\ & b_i = a_{i+1} + x * b_{i+1} \end{aligned} \textbf{od} y \leftarrow a_0 + x * b_0 \textbf{return} \ \ y
```

It is easy to see in this code that the **for** loop performs n-1 iterations, in each of which a single sum and a single product are computed. The nth sum and nth product are performed in the computation of y, the final result.

A more polished version includes the last computation (the one in the assignment of y) within the loop and makes no use of indexes:

$$egin{aligned} \mathbf{input} & n; a_i, i = 0, \dots, n; x \ b \leftarrow a_n \ & \mathbf{for} & i = n-2 & \mathbf{to} & i = -1 \ & b = a_{i+1} + x * b \ & \mathbf{od} \ & \mathbf{return} & b \end{aligned}$$

In Python,

```
def horner(coefs, x):
    n = len(coefs)-1
    b = coefs[n]

for i in reversed(range(-1, n-1)):
    b = coefs[i+1] + x*b

return b
```

It is trivial to adapt the code so that it returns the coefficients  $b_0, \ldots, b_{n-1}$  and not the final result, if needed.

# 10 Error

Let  $r, \overline{r}$  be two real numbers s.t. the latter is an approximation of the first. We define the **error** of the approximation to be  $r - \hat{r}$ , and

$$\Delta r = |r - \overline{r}|, \qquad \delta r = \frac{\Delta r}{|r|}$$

With r unknown the strategy is to work with a known bound of r.

### 11 Non-linear equations

The general problem is to find members of the set  $\mathcal{R}_f$  of roots of  $f \in \mathbb{R} \to \mathbb{R}$ . The numerical strategy is to iteratively approximate some  $r \in \mathcal{R}_f$  until some pre-established threshold in the error of approximation is met.

More formally, the numerical strategy produces a sequence  $\{x_k\}_{k\in\mathbb{N}}$  which satisfies

- $\lim_{k\to\infty} \{x_k\} = r \text{ for some } r \in \mathcal{R}_f$
- Either  $e(x_k) < e(x_{k-1})$  or, more strongly,  $\lim_{k\to\infty} e(x_k) = 0$ , where  $e(x_k)$  is some appropriate measure of the error of approximation.

### 11.1 Bisection

A very simple procedure: if a root exists in [a, b], it iteratively shrinks [a, b] in halves (keeping the halves which contain the root) until the interval is of sufficiently small length.

**Theorem 1** (Intermediate value). If f is continuous in [a, b] and f(a)f(b) < 0, then  $\exists r \in \mathcal{R}_f \text{ s.t. } r \in [a, b].$ 

Assume f is continuous. A root exists in [a, b] if f(a)f(b) < 0 (**Theorem 1**). If that is the case, the midpoint (a+b)/2 is taken as the approximation  $x_0$ . It is also trivial to observe that  $x_0$  is at most at a distance of (b-a)/2 from the real root, so  $e_0 = |x_0 - r| \le (b-a)/2$ .

If  $f(x_0) = 0$  the procedure must end because a root was found. Otherwise, sufficies to find which half of the interval contains a root computing f(a)f(c) and, if needed, f(c)f(b).

The iterations may stop after reaching a maximum number of steps, when |f(c)| is sufficiently close to zero, or when the error bound  $|e_k| \leq (b_k - a_k)/2$  (where  $[a_k, b_k]$  is the interval of this iteration) is sufficiently small.

(!) The algorithm not always converges. Take f(x) = 1/x. Clearly, it has no root. Yet setting a = -1, b = 1 in the initial iteration falsely passes the test. (The problem obviously is that f is not continuous in [-1,1].) If one sets

```
\mathbf{Input}: a, b, \delta, M, f
\mathbf{Output}: Tupla de la forma: (r, \cot de \ error)
f_a \leftarrow f(a)
f_b \leftarrow f(b)
if f_a * f_b > 0
      return?
fi
for i = 1 to i = M do
      c \leftarrow a + (b - a)/2
      f_c \leftarrow f(c)
      if f_c = 0 then
             return (c,0)
      fi
      \epsilon = \frac{b-a}{2}
      if \epsilon < \delta then
            break
      fi
      if f_a * f_c < 0 then
            b \leftarrow c
            f_b = f(b)
      else
            a \leftarrow c
            f_a = f(a)
      fi
od
return (c, \epsilon)
```

```
def bisection(f : callable, a : float, b : float, delta : float, M : int):
 s, e = f(a), f(b) # function values at (s)tart, (e)nd of interval
 if s*e > 0:
   raise ValueError("Interval [a, b] contains no root.")
 for i in range(M):
   c = a + (b-a)/2
   m = f(c) # value of f at (m)idpoint
   if m == 0:
     return c, 0
   e = (b-a)/2
   if e < delta:
     return c, e
   if s*m < 0:
     b = c
     e = f(b)
   else:
     a = c
      s = f(a)
 return c, e
```

**Theorem 2.** If  $\{[a_i, b_i]\}_{i=0}^{\infty}$  are the intervals generated by the bisection method on iterations  $i = 0, 1, \ldots$ , then:

1.  $\lim_{n\to\infty} a_n = \lim_{n\to\infty} b_n$  is a member of  $\mathcal{R}_f$ .

2. If 
$$c_n = \frac{1}{2}(a_n + b_n)$$
,  $r = \lim_{n \to \infty} c_n$ , then  $|r - c_n| \le \frac{1}{2^{n+1}}(b_0 - a_0)$ 

**Proof.** (1) It is clear that  $a_i \leq a_{i+1}$  and  $b_i \geq b_{i+1}$ , since the interval on each iteration shrinks in one direction.

 $\therefore a_n, b_n$  are monotonous.

But clearly  $a_n$  is bounded by  $b_0$  and  $b_n$  is bounded by  $a_0$ .

- $\therefore a_n, b_n$  are monotonous and bounded.
- ... Their limits exist.

It is also clear that the interval shrinks to half its size on each iteration:

$$b_n - a_n = \frac{1}{2}(b_{n-1} - a_{n-1}), \qquad n \ge 1$$
 (1)

By recurrence on (1),

$$b_n - a_n = \frac{1}{2^n}(b_0 - a_0), \qquad n \ge 0$$
 (2)

Then

$$\lim_{n \to \infty} a_n - \lim_{n \to \infty} b_n = \lim_{n \to \infty} (a_n - b_n) = \lim_{n \to \infty} \frac{1}{2^n} (b_0 - a_0) = 0$$
 (3)

 $\therefore \lim_{n\to\infty} a_n = \lim_{n\to\infty} b_n.$ 

Since the limit of  $a_n, b_n$  exists and f is by assumption continuous, the composition limit theorem applies and:

$$\lim_{n \to \infty} (f(a_n) \cdot f(b_n))$$

$$= \lim_{n \to \infty} f(a_n) \cdot \lim_{n \to \infty} f(b_n)$$
 {Product of limits}
$$= f\left(\lim_{n \to \infty} a_n\right) \cdot f\left(\lim_{n \to \infty} b_n\right)$$
 {Composition limit theorem}
$$= [f(r)]^2$$
 
$$\left\{r = \lim_{n \to \infty} a_n\right\}$$
 (4)

The invariant of the algorithm is  $f(a_n)f(b_n) < 0$ . But due to the last result,

$$\lim_{n \to \infty} f(a_n) f(b_n) \le 0 \iff [f(r)]^2 \le 0 \iff f(r) = 0$$

- $\therefore r = \lim_{n \to \infty} a_n = \lim_{n \to \infty} b_n$  is a root.
- (2) Follows directly from result (2)

$$|r - c_n| = \left| r - \frac{1}{2} (b_n - a_n) \right|$$

$$\leq \left| \frac{1}{2} (b_n - a_n) \right|$$

$$= \left| \frac{1}{2^{n+1}} (b_0 - a_0) \right|$$
 {Result (2)}

#### 11.2 Newton's method

**Taylor: repasito.** El desarrollo de una f suficientemente diferenciable alrededor de un punto r espa

$$f(x) = f(r) + f'(r)(x - r) + \frac{f''(r)}{2!}(x - r)^2 + \ldots + \frac{f^{(n)}(r)}{n!}(x - r)^n + R_n(x)$$

donde  $R_n(x)$  es el resto.

Usualmente, queremos tomar r = x + h, donde x es una aproximación de r y h el error de aproximación. Entonces es provechoso expandir f(r) alreededor de su estimación x:

$$f(r) = f(x+h) = f(x) + f'(x)h + \frac{f''(x)}{2!}h^2 + \dots + \frac{f^{(n)}(x)}{n!}h^n + R_n(h)$$

Esto es **recontra** útil porque nos dice cuánto se diferencia f(r) de nuestra aproximación f(x) (pues expresa f(r) como f(x) más algo).

Usualmente r, h son desconocidos pero h puede acotarse.

El resto  $R_n$  del teorema puede expresarse como sigue:

$$f(r) = f(x+h) = f(x) + f'(x)h + \frac{f''(x)}{2!}h^2 + \ldots + \frac{f^{(n)}(x)}{n!}h^n + \frac{f^{(n+1)}(\zeta)}{(k+1)!}h^{n+1}$$

para algún  $\zeta \in (x, h)$ . Esta forma de expresar el error de aproximación con el polinomio de Taylor se usará mucho.

Assume  $r \in \mathcal{R}_f$  and r = x + h, with x an approximation of r and h its error. Assume f'' exists and is continuous in some I around x s.t.  $r \in I$ . What we explained on Taylor expansions around a point gives:

$$0 = f(r) = f(x+h) = f(x) + f'(x)h + \mathcal{O}(h^2)$$

If x is sufficiently close to r, h is small and  $h^2$  even smaller, so that  $\mathcal{O}(h^2)$  is unconsiderable:

$$0 \approx f(x) + hf'(x)$$

Therefore,

$$h \approx -\frac{f(x)}{f'(x)} \tag{5}$$

From this follows that r = x + h is approximated by

$$r \approx x - \frac{f(x)}{f'(x)}$$

Since the approximation in (5) truncated the terms of  $\mathcal{O}(h^2)$  complexity, this new approximation is closer to r than x originally was. In other words, x - f(x)/f'(x) is a better approximation to r than x itself.

Thus, if  $x_0$  is an original approximation, we can define

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \tag{6}$$

to produce a sequence of approximations. This is the fundamental idea of Newton's method.

Input: 
$$x_0, M, \delta, \epsilon$$
;  $v \leftarrow f(x_0)$  if  $|v| < \epsilon$  then return  $x_0$  fi for  $k = 1$  to  $k = M$  do  $x_1 \leftarrow x_0 - \frac{v}{f'(x_0)}$   $v \leftarrow f(x_1)$  if  $|x_1 - x_0| < \delta \lor v < \epsilon$  then return  $x_1$  fi  $x_0 \leftarrow x_1$  od

The predicate  $|x_1 - x_0| < \delta$  checks whether our algorithm is adjusting x in a negligible degree. If that is the case, we should stop.

**Theorem 3.** If f'' continuous around  $r \in \mathcal{R}_f$  and  $f'(r) \neq 0$ , then there is some  $\delta > 0$  s.t. if  $|r - x_0| \leq \delta$ , then:

- $|r x_n| \le \delta$  for all  $n \ge 1$ .
- $\{x_n\}$  converges to r
- The convergence is quadratic, i.e. there is a constant  $c(\delta)$  and a natural N s.t.  $|r x_{n+1}| \le c |r x_n|^2$  for all  $n \ge N$ .

**Proof.** Let  $e_n = r - x_n$  be the error in the *n*th approximation. Assume f'' is continuous and f(r) = 0,  $f'(r) \neq 0$ . Then

$$e_{n+1} = r - x_{n+1}$$

$$= r - \left(x_n - \frac{f(x_n)}{f'(x_n)}\right)$$

$$= r - x_n + \frac{f(x_n)}{f'(x_n)}$$

$$= \frac{e_n f'(x_n) + f(x_n)}{f'(x_n)}$$
(8)

Thus, the error at any given iteration is a function of the error at the previous iteration. Now consider the expression of f(r) as

$$f(r) = f(x_n - e_n) = f(x_n) + e_n f'(x_n) + \frac{e_n^2 f''(\zeta_n)}{2}$$
(9)

for  $\zeta_n$  between  $x_n$  and r. This equation gives

$$e_n f'(x_n) + f(x_n) = -\frac{1}{2} f''(\zeta_n) e_n^2$$
(10)

The expression in (10) is the numerator in (8), whereby we obtain via substitution:

$$e_{n+1} = -\frac{1}{2} \frac{f''(\zeta_n) e_n^2}{f'(x_n)} \tag{11}$$

Equation (11) ensures that the error scales quadratically. Now we wish to bound the error expression in (11).

The continuity of f', f'' ensures that these functions reach their extreme values in a closed and bounded interval around r. Take  $\delta > 0$  to define a neighbourhood of length  $\delta$  around r. Define

$$c(\delta) = \frac{1}{2} \frac{\max_{|x-r| \le \delta} |f''(x)|}{\min_{|x-r| \le \delta} |f'(x)|}$$

Here,  $c(\delta)$  is the maximum value which  $e_{n+1}$  can take if  $\zeta_n, x_n$  are assumed to belong to the neighbourhood, according to equation (11). Now we make two assumptions:

- 1.  $x_0$  belongs to the neighbourhood, i.e.  $|x_0 r| \le \delta$
- 2.  $\delta$  is sufficiently small so that  $\rho := \delta c(\delta) < 1$ .

Note that, since  $\zeta_0$  is between  $x_0$  and r, assumption (1) ensures that  $\zeta_0$  is also in the neighbourhood, i.e.  $|r - \zeta_0| \leq \delta$ . Then we have:

$$\frac{1}{2} |f''(\zeta_0)/f'(x_0)| \le c(\delta) \tag{12}$$

Therefore, using the recurrent definition of  $e_{n+1}$  in (11),

$$|x_{1} - r| = |e_{1}|$$

$$= \left| \frac{1}{2} f''(\zeta_{0}) / f'(x_{0}) e_{0}^{2} \right|$$

$$\leq |e_{0}^{2}| c(\delta)$$

$$\leq |e_{0}| \varrho \qquad \{|e_{0}| \leq \delta\}$$

$$< |e_{0}| \qquad \{\varrho < 1\}$$

 $|e_1| < |e_0| \le \delta$ , which means the error decreases. This argument may be repeated inductively, giving:

$$|e_1| \le \varrho |e_0|$$
  
 $|e_2| \le \varrho |e_1| \le \varrho^2 |e_0|$   
 $|e_3| \le \varrho |e_2| \le \varrho^3 |e_0|$   
:

In general,  $|e_n| \leq \varrho^n |e_0|$ . And since  $0 \leq \varrho < 1$ , we have  $\varrho^n \to 0$  when  $n \to \infty$ , entailing that  $|e_n| \to 0$  when  $n \to \infty$ .