AI505

Optimization

Bracketing

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Outline

Bracketing

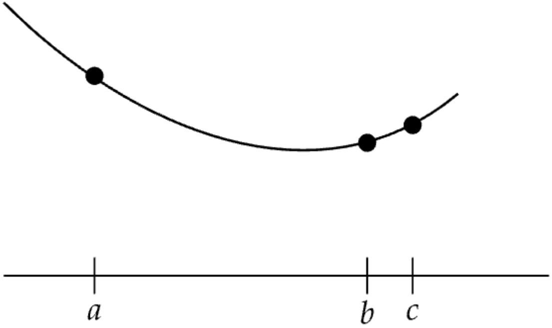
A derivative-free method to identify an interval containing a local minimum and then successively shrinking that interval

Unimodality

There exists a unique optimizer $\boldsymbol{x}^*$ such that f is monotonically decreasing for $\boldsymbol{x} \leq \boldsymbol{x}^*$ and monotonically increasing for $\boldsymbol{x} \geq \boldsymbol{x}^*$

Finding an Initial Bracket

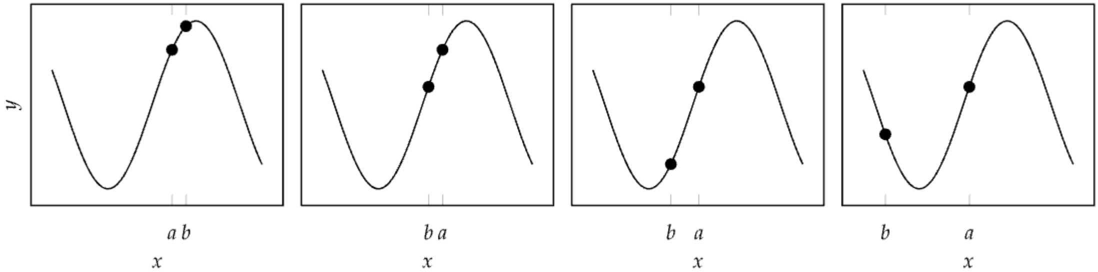
Given a unimodal function, the global minimum is guaranteed to be inside the interval $[a, c]$ if $f(a) > f(b) < (c)$




```
function bracket_minimum(f, x=0; s=1e-2, k=2.0)
    a, ya = x, f(x)
    b, yb = a + s, f(a + s)
    if yb > ya
        a, b = b, a
        ya, yb = yb, ya
        s = -s
    end
    while true
        c, yc = b + s, f(b + s)
        if yc > yb
            return a < c ? (a, c) : (c, a)
        end
        a, ya, b, yb = b, yb, c, yc
        s *= k
    end
end
```

Finding an Initial Bracket

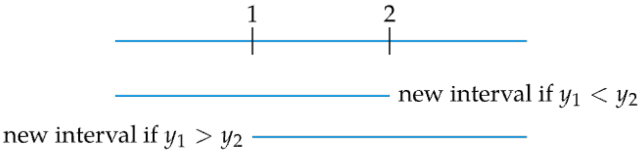
Example of `bracket_minimum` on a function



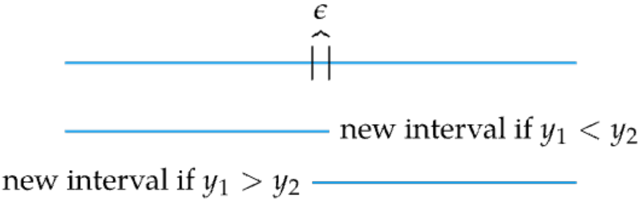
reverses direction between the first and second iteration and expands until a minimum is bracketed in the fourth iteration.

For unimodal functions, when function evaluations are limited, what is the maximal shrinckage we can achieve?

When restricted to only 2 function evaluations (queries) the most we can guarantee to shrink our interval is by just under a factor of 2.

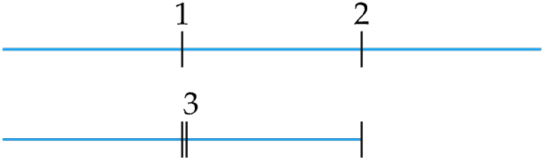


yeilds a factor of 3.



for $\epsilon \to 0$ yields a factor of just less than 2

When restricted to only 3 function evaluations (queries) the most we can guarantee to shrink our interval is by a factor of 3.

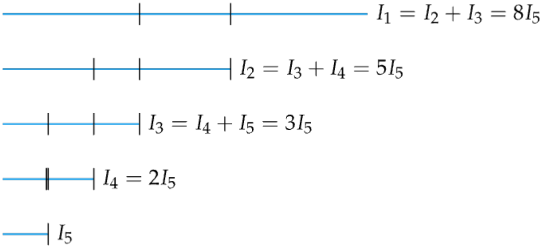


Fibonacci Search

When restricted to n functions evaluations following the previous strategy, we are guaranteed to shrink our interval by a factor of F_{n+1}.

Fibonacci numbers: sum of previous two,
$1, 1, 2, 3, 5, 8, 13, \dots$

$$F_n = \begin{cases} 0 & \text{if } n = 0 \\ 1 & \text{if } n = 1, 2 \\ F_{n-1} + F_{n-2} & \text{otherwise} \end{cases}$$



The length of every interval constructed can be expressed in terms of the final interval times a Fibonacci number.
- final, smallest interval has length I_n,
- second smallest interval has length $I_{n-1} = F_3 I_n$
- third smallest interval has length $I_{n-2} = F_4 I_n$,
and so forth.

Fibonacci Search Algorithm

For a unimodal function f in the interval $[a, b]$, we want to shrink the interval within n iterations. (At each iteration we want to shrink by a factor ϕ).

$$b_{k+1} - a_{k+1} = \frac{F_{n-k+1}}{F_{n-k+2}}(b_k - a_k)$$

Therefore:

$$\begin{aligned} b_n - a_n &= \frac{F_2}{F_3}(b_{n-1} - a_{n-1}) \\ &= \frac{F_2}{F_3}\frac{F_3}{F_4}\cdots\frac{F_n}{F_{n+1}}(b_1 - a_1) \\ &= \frac{1}{F_{n+1}}(b_1 - a_1) \end{aligned}$$

Closed-form expression (Binet's formula):

$$F_n = \frac{\phi^n - (1-\phi)^n}{\sqrt{5}},$$

$\phi = (1+\sqrt{5})/2 \approx 1.61803$ is the golden ratio.

$$\frac{F_{n+1}}{F_n} = \phi\frac{1 - s^{n+1}}{1 - s^n}, \quad s = (1-\sqrt{5})(1+\sqrt{5}) \approx -0.38$$

Suppose we have a unimodal function f in the interval $[a, b]$ and a tolerance $\epsilon = 0.01$. Let $k = 1$.

1. $d_k = a_k + \frac{F_{n-k+1}}{F_{n-k+2}}(b_k - a_k)$

$$\rho = \frac{F_n}{F_{n+1}} = \frac{1 - s^n}{\phi(1 - s^{n+1})}$$

2. if $k = n - 1$:

$$c_k = a_k + \left(1 - \frac{F_{n-k+1}}{F_{n-k+2}}\right)(b_k - a_k)$$

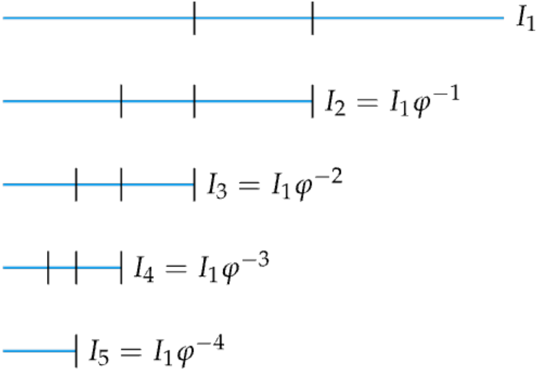
   Otherwise: $c_k = a_k + (1 - \epsilon)(b_k - a_k)$

3. if $f(c_k) < f(d_k)$: $\quad b_{k+1} = d_k, \quad d_{k+1} = c_k, \quad a_{k+1} = a_k$
   otherwise: $a_{k+1} = b_k, \quad b_{k+1} = c_k, \quad d_{k+1} = d_k$

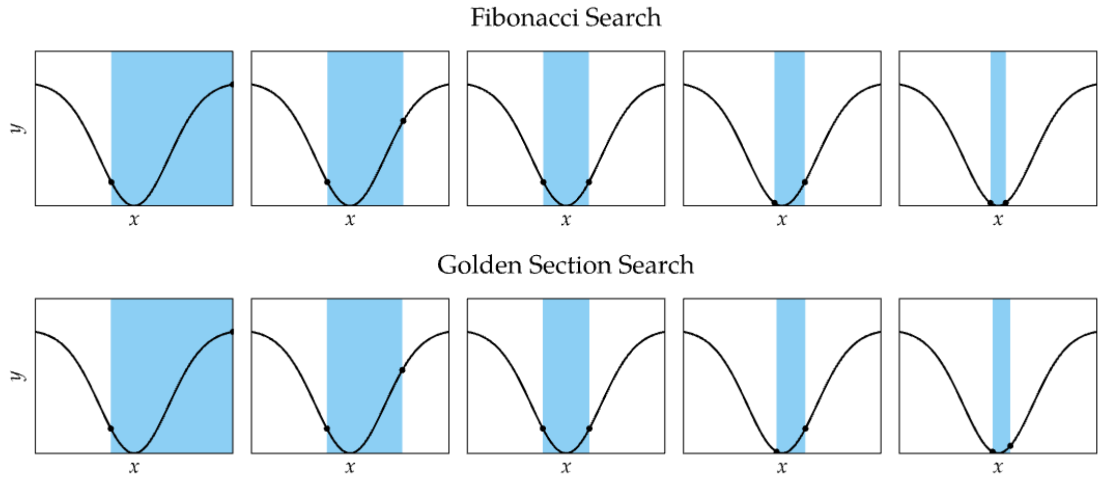
4. $k = k + 1$, go to step 2

Golden Section Search

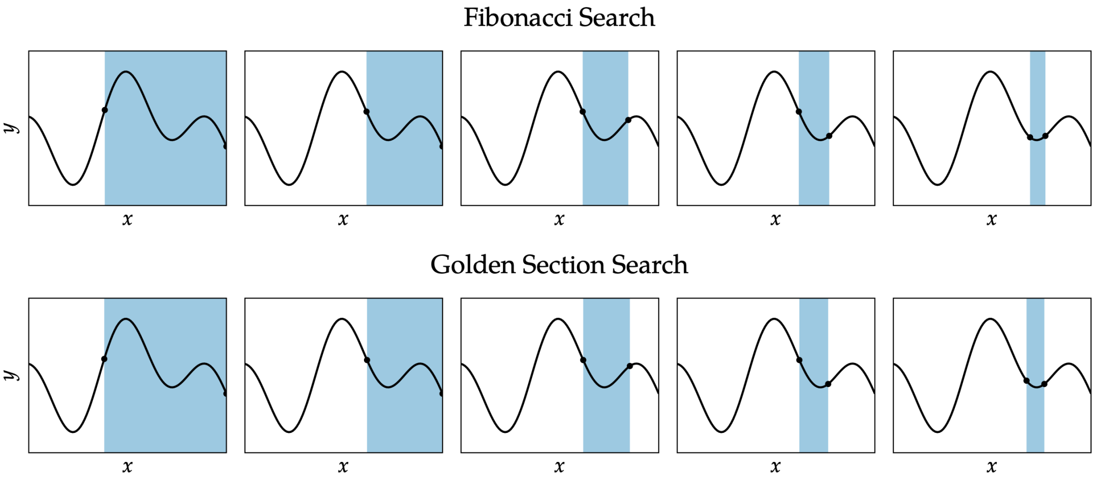
$$\lim_{n\to\infty} \frac{F_{n+1}}{F_n} = \phi \frac{1 - s^{n+1}}{1 - s^n} = \phi$$



Comparison

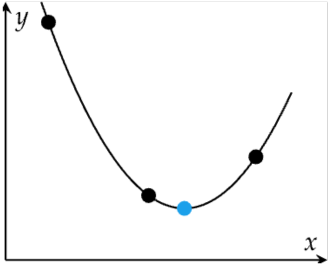


Comparison



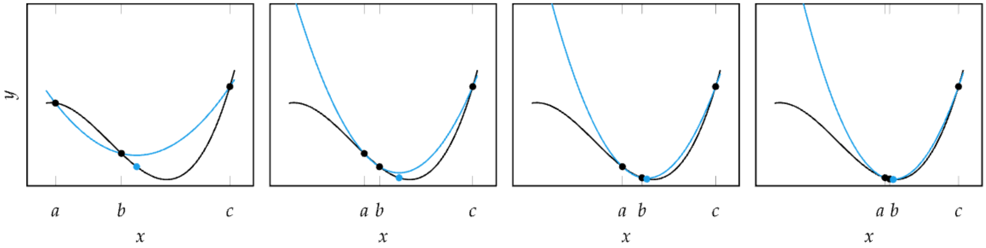
Quadratic Fit Search

- Leverages ability to analytically minimize quadratic functions
- Iteratively fits quadratic function to three bracketing points



Quadratic Fit Search

- If a function is locally nearly quadratic, the minimum can be found after several steps



Using Linear Algebra

- We assume that the variable y is related to $\boldsymbol{x} \in \mathbb{R}^n$ quadratically, so for some constants b_0, b_1, b_2:

$$y = b_0 + b_1 x + b_2 x^2$$

- Given the set of m points $(y_1, x_1,), \ldots, (y_3, x_3)$ in the ideal case, we have that $y_i = b_0 + b_1 x_i + b_2 x_i^2$, for all $i = 1, 2, 3$. In matrix form:

$$\begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \\ b_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

This can be written as $A\boldsymbol{z} = \boldsymbol{y}$ to emphasize that $\boldsymbol{z}$ are our unknowns and A and $\boldsymbol{y}$ are given.

In Python

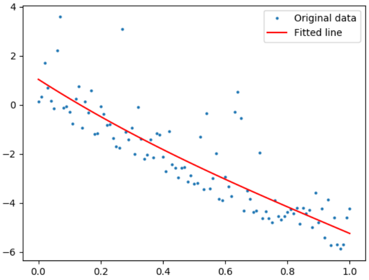
In polynomial regression, the $m \times (n+1)$ matrix A is called a **Vandermonde matrix** (a matrix with entries $a_{ij} = x_i^{n+1-j}$, $j = 1..n+1$).
NumPy's `np.vander()` is a convenient tool for quickly constructing a Vandermonde matrix, given the values x_i, $i = 1..m$, and the number of desired columns $(n+1)$.

```
>>> print(np.vander([2, 3, 5], 2))
[[2 1]                                # [[2**1, 2**0]
 [3 1]                                #  [3**1, 3**0]
 [5 1]]                               #  [5**1, 5**0]]

>>> print(np.vander([2, 3, 5, 4], 3))
[[ 4  2  1]                           # [[2**2, 2**1, 2**0]
 [ 9  3  1]                           #  [3**2, 3**1, 3**0]
 [25  5  1]                           #  [5**2, 5**1, 5**0]
 [16  4  1]]                          #  [4**2, 4**1, 4**0]
```

In Python

```
A = np.vander(x,4)

coeff = np.linalg.solve(A,y) ## Error!! Why?

B = A.T @ A
z = np.linalg.inv(B) @ A.T @ y

coeff = np.linalg.lstsq(A, y)[0]
np.allclose(z,coeff)

f=np.poly1d(coeff)
plt.plot(x, y, 'o', label='Original data', ↪
    ↪markersize=2)
plt.plot(x, f(x), 'r', label='Fitted line')
plt.legend()
plt.show()
```

ex2.py



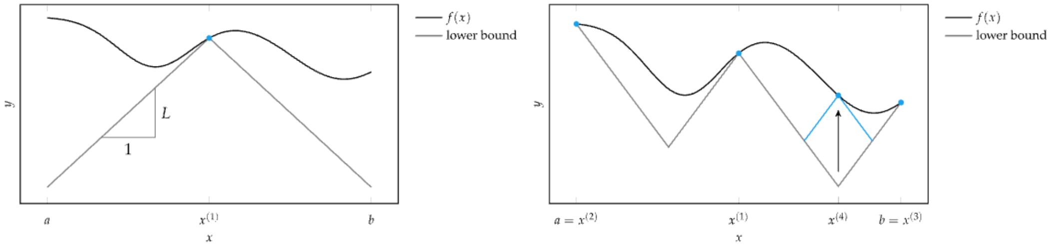
Shubert-Piyavskii Method

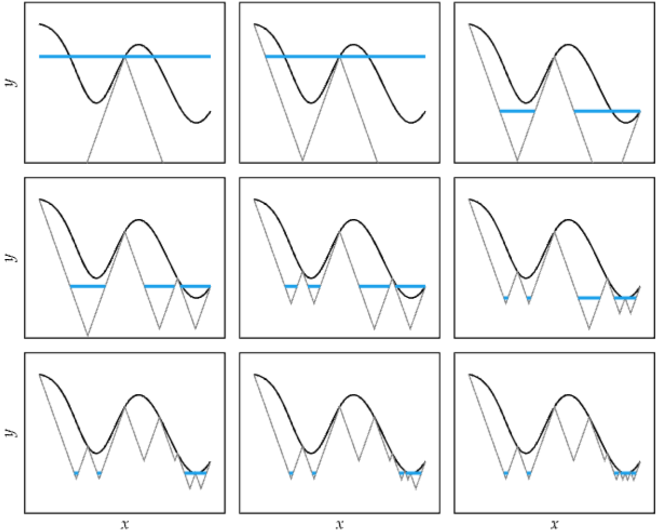
- The Shubert-Piyavskii method is guaranteed to find the global minimum of any bounded function

- but requires that the function be Lipschitz continuous

- A function is **Lipschitz continuous** if there is an upper bound on the magnitude of its derivative. A function f is Lipschitz continuous on $[a, b]$ if there exists an $\ell > 0$ such that:

$$|f(x) - f(y)| \leq \ell |x - y|, \quad \forall x, y \in [a, b]$$

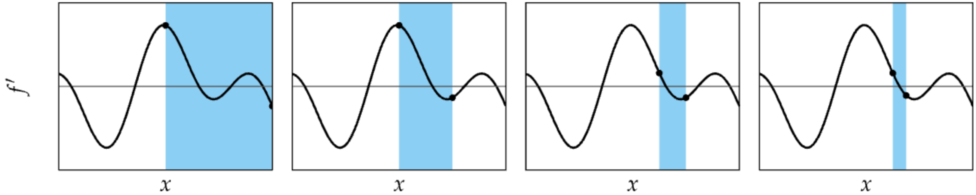




y
y
y
x
x
x

Bisection Method

- **Intermediate value theorem**: If f is continuous on $[a, b]$, and there is some $y \in [f(a), f(b)]$, then there exists at least one $x \in [a, b]$, such that $f(x) = y$.
- Used in root-finding methods
- When applied to $f'(x)$, can be used to find minimum of f
- if $\text{sign}(f'(a)) \neq \text{sign}(f'(b))$, or equivalently, $f'(a)f'(b) \leq 0$ then $[a, b]$ is guaranteed to contain a zero.



Bisection method

- Cut the bracketed region $[a, b]$ in half with every iteration
- Evaluate the midpoint $(a + b)/2$
- form a new bracket from the midpoint and whichever side that continues to bracket a zero.
- Terminate after a fixed number of iterations.
- Guaranteed to converge within ϵ of x^* within $\lg_2(|b - a|/\epsilon)$

Summary

- Many optimization methods shrink a bracketing interval, including Fibonacci search, golden section search, and quadratic fit search

- The Shubert-Piyavskii method outputs a set of bracketed intervals containing the global minima, given the Lipschitz constant

- Root-finding methods like the bisection method can be used to find where the derivative of a function is zero