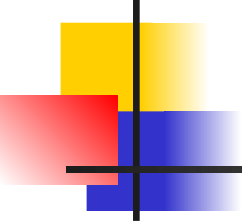


Interpolation and Root finding

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Troy University

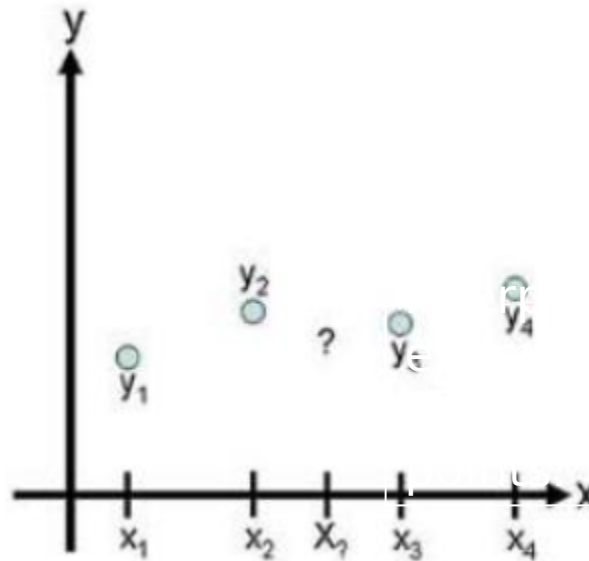


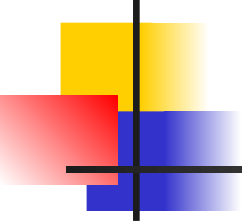
Interpolation

- A dataset consisting of independent data values, x_i and dependent data values, y_i where $i = 1, 2, \dots, n$
- Goal: find an estimation function $\hat{y}$ such that $\hat{y}(x_i) = y_i$ for every point in our dataset.

Interpolation

- Given a new x^* , we can interpolate its function value using $\hat{y}(x^*)$ which is called interpolation function.

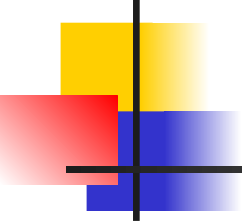




Interpolation

- In linear interpolation, the estimated point is assumed to lie on the line joining the nearest points to the left and right.
- Given x-data points in ascending order ($x_i < x_{i+1}$) and x being a point such that $x_i < x < x_{i+1}$, the linear interpolation at x is

$$\hat{y}(x) = y_i + \frac{(y_{i+1} - y_i)(x - x_i)}{(x_{i+1} - x_i)},$$



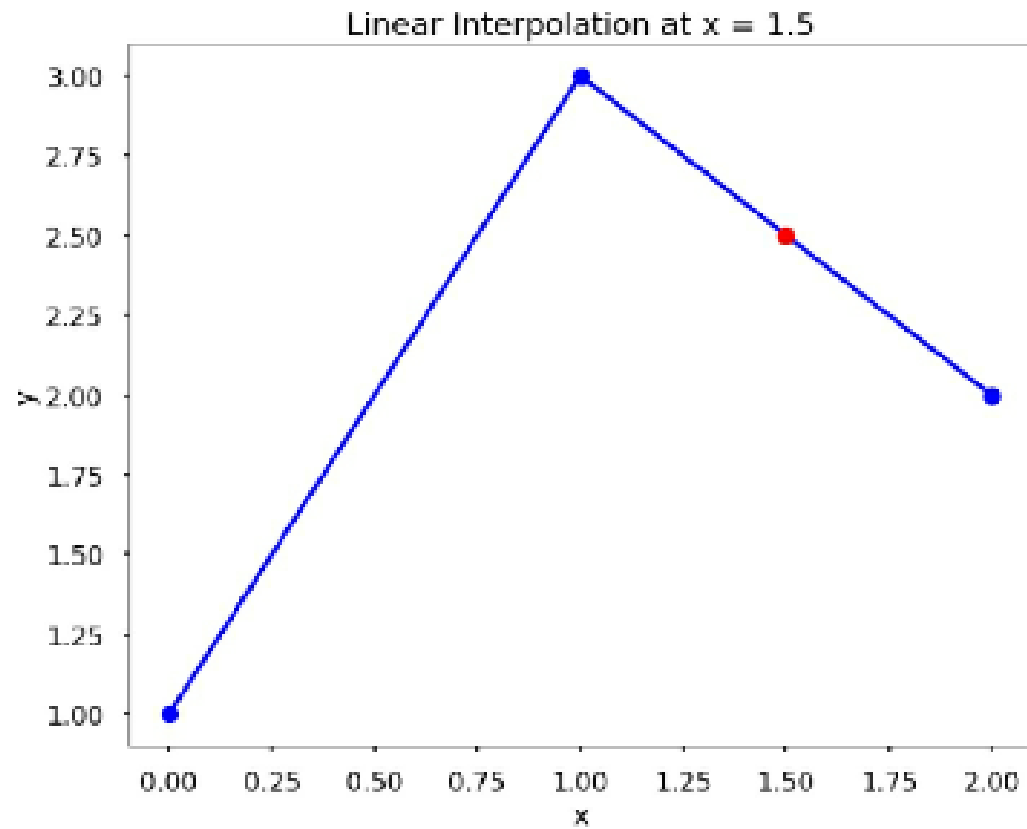
Interpolation

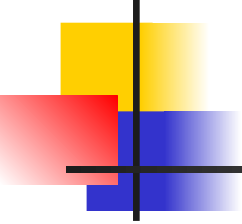
TRY IT! Find the linear interpolation at $x = 1.5$ based on the data $x = [0, 1, 2]$, $y = [1, 3, 2]$. Verify the result using SciPy's function `interp1d`.

Since $1 < x < 2$, we use the second and third data points to compute the linear interpolation. Plugging in the corresponding values gives

$$\hat{y}(x) = y_i + \frac{(y_{i+1} - y_i)(x - x_i)}{(x_{i+1} - x_i)} = 3 + \frac{(2 - 3)(1.5 - 1)}{(2 - 1)} = 2.5.$$

Interpolation





Interpolation

- Python code:

```
In [1]: from scipy.interpolate import interp1d  
import matplotlib.pyplot as plt
```

```
plt.style.use("seaborn-poster")
```

```
In [2]: x = [0, 1, 2]  
y = [1, 3, 2]
```

```
f = interp1d(x, y)  
y_hat = f(1.5)  
print(y_hat)
```

Cubic Spline Interpolation in Python

Use SciPy's function, CubicSpline.

TRY IT! Use CubicSpline to plot the cubic spline interpolation of the dataset $x = [0, 1, 2]$ and $y = [1, 3, 2]$ for $0 \leq x \leq 2$.

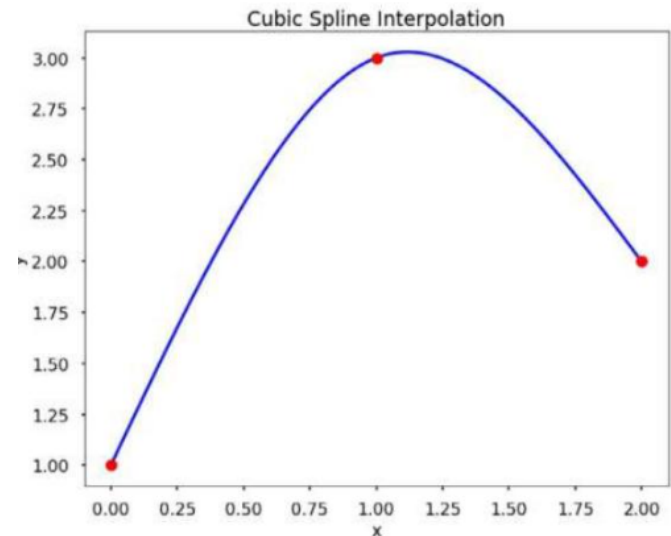
```
In [1]: from scipy.interpolate import CubicSpline
import numpy as np
import matplotlib.pyplot as plt

plt.style.use("seaborn-poster")

In [2]: x = [0, 1, 2]
y = [1, 3, 2]

# use bc_type = "natural" adds the constraints
f = CubicSpline(x, y, bc_type="natural")
x_new = np.linspace(0, 2, 100)
y_new = f(x_new)

In [3]: plt.figure(figsize = (10,8))
plt.plot(x_new, y_new, "b")
plt.plot(x, y, "ro")
plt.title("Cubic Spline Interpolation")
plt.xlabel("x")
plt.ylabel("y")
plt.show()
```

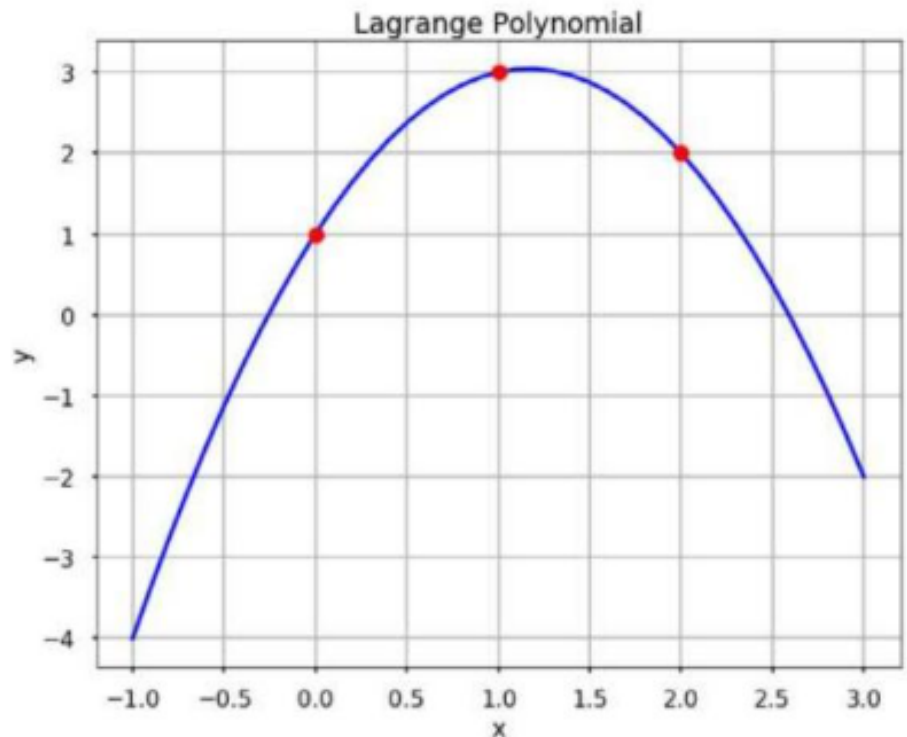


Lagrange Polynomial Interpolation in Python using Lagrange Function from Scipy

```
In [4]: from scipy.interpolate import lagrange
```

```
In [5]: f = lagrange(x, y)
```

```
In [6]: fig = plt.figure(figsize = (10, 6))  
plt.plot(x_new, f(x_new), "b")  
plt.title("Lagrange Polynomia")  
plt.grid()  
plt.xlabel("x")  
plt.ylabel("y")  
plt.show()
```



Newton's Polynomial Interpolation in Python

TRY IT! Calculate the divided difference table for $x = [-5, -1, 0, 2], y = [-2, 6, 1, 3]$.

```
In [1]: import numpy as np
import matplotlib.pyplot as plt

plt.style.use("seaborn-poster")

%matplotlib inline
```

```
In [2]: def divided_diff(x, y):
    """
    function to calculate the divided
    difference table
    """
    n = len(y)
    coef = np.zeros([n, n])
    # the first column is y
    coef[:,0] = y

    for j in range(1,n):
        for i in range(n-j):
            coef[i][j] = (coef[i+1][j-1]-coef[i][j-1])/(x[i+j]-x[i])

    return coef

def newton_poly(coef, x_data, x):
    """
    evaluate the Newton polynomial
    at x
    """
    n = len(x_data) - 1
    p = coef[n]
```

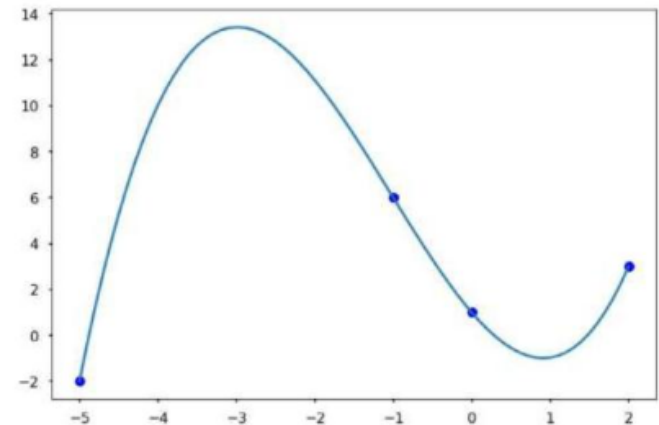
```
    for k in range(1,n+1):
        p = coef[n-k] + (x - x_data[n-k])*p
    return p
```

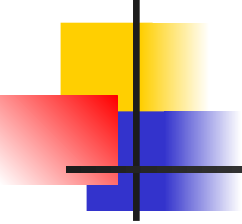
```
In [3]: x = np.array([-5, -1, 0, 2])
y = np.array([-2, 6, 1, 3])
# get the divided difference coef
a_s = divided_diff(x, y)[0, :]

# evaluate on new data points
x_new = np.arange(-5, 2.1, .1)
y_new = newton_poly(a_s, x, x_new)

plt.figure(figsize = (12, 8))
plt.plot(x, y, "bo")
plt.plot(x_new, y_new)
```

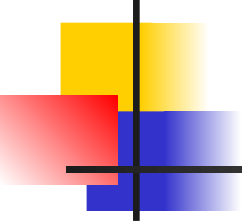
Out[3]: [<matplotlib.lines.Line2D at 0x11bd4e630>]





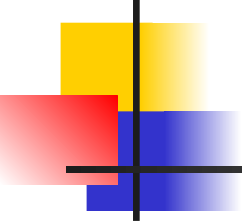
Root Finding

- The root or zero of a function, $f(x)$: x_r such that $f(x_r) = 0$.
 - For some functions, it is clear finding the root of a function.
 $f(x) = x^2 - 9 \rightarrow$ the roots are 3 and -3
 - For some functions, determining an analytic or exact solution for the roots of functions can be difficult. $f(x) = \cos(x) - x$



Root Finding

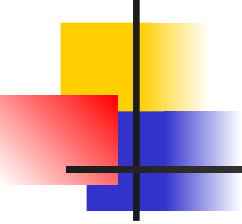
- **Error**: a deviation from an expected or computed value.
- **Tolerance**: the level of error that is acceptable for an engineering application.
- “Computer program has **converged** to a solution when it has found a solution with an error smaller than the tolerance.”
- For computing roots, we want an x_r such that $f(x_r)$ is very close to zero.



Root Finding

- Newton's Method starts with a guess and repeatedly improves it.
- The update formula is:

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



Root Finding

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

Where:

- x_n = current guess
- x_{n+1} = better guess
- $f(x)$ = function
- $f'(x)$ = derivative

Root Finding

Example

Solve:

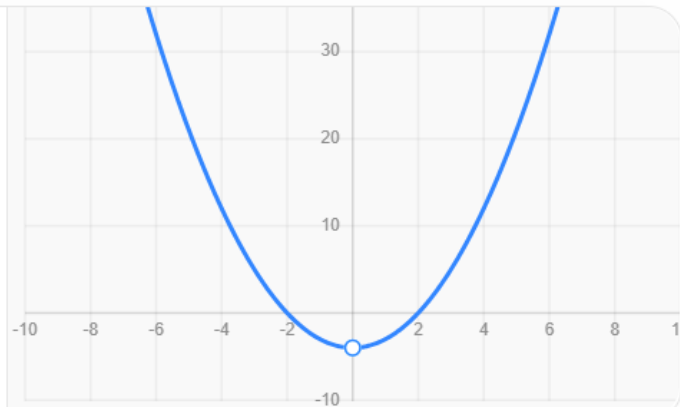
$$x^2 - 4 = 0$$

Function:

×

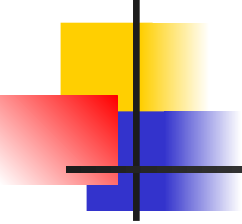


$$y = x^2 - 4$$



Derivative:

$$f'(x) = 2x$$



Root Finding

Step 1 — Initial Guess

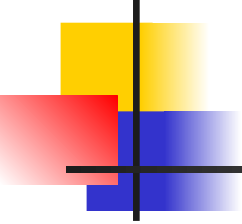
Choose:

$$x_0 = 3$$

Step 2 — Apply Formula

Newton formula:

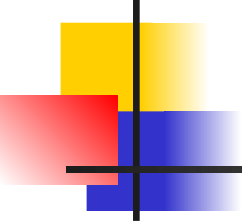
$$x_{n+1} = x_n - \frac{x_n^2 - 4}{2x_n}$$



Root Finding

Iteration 1

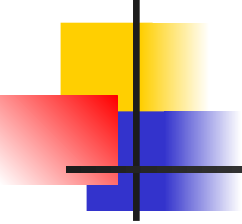
$$\begin{aligned}x_1 &= 3 - \frac{3^2 - 4}{2(3)} \\&= 3 - \frac{5}{6} \\&= 2.1667\end{aligned}$$



Root Finding

Iteration 2

$$x_2 = 2.1667 - \frac{2.1667^2 - 4}{2(2.1667)}$$
$$\approx 2.0064$$



Root Finding

Iteration 3

$$x_3 \approx 2.00001$$

Very close to the exact root:

$$x = 2$$



Root Finding

Python Example

</> Python

```
def f(x):  
    return x**2 - 4  
  
def df(x):  
    return 2*x  
  
x = 3  
  
for i in range(5):  
    x = x - f(x)/df(x)  
    print(x)
```

Output:

</> Python

```
2.1666666666666665  
2.0064102564102564  
2.0000102400262145  
2.000000000026214  
2.0
```