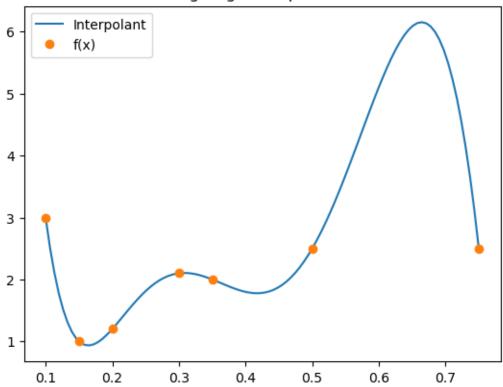
Homework4

March 10, 2024

```
[1]: import numpy as np
     import matplotlib.pyplot as plt
[2]: def list_prod(l):
         ret = 1
         for x in 1: ret *= x
         return ret
     def list_sum(l):
         ret = 0
         for x in 1: ret += x
         return ret
[3]: x_{hat} = [0.1, 0.15, 0.2, 0.3, 0.35, 0.5, 0.75]
     y_hat = [3.0, 1.0, 1.2, 2.1, 2.0, 2.5, 2.5]
     def lagrange_interpolant(x_hat, y_hat):
         phis = []
         for i,x_i in enumerate(x_hat):
             tmps = [lambda x, x_i = x_i, x_j = x_j: (x - x_j)/(x_i - x_j)  for j, x_j  in_u
      ⇒enumerate(x_hat) if i != j]
             phis.append(lambda x, tmps=tmps: list_prod([g(x) for g in tmps]))
         L = lambda x, y_hat=y_hat, phis=phis: list_sum([y_hat[i] * phis[i](x) for__
      →i,phi in enumerate(phis)])
         return lambda x: L(x), phis
    L_1, phis = lagrange_interpolant(x_hat, y_hat)
[4]: xs = np.linspace(0.1, 0.75, 100)
     plt.plot(xs, [L_1(x) for x in xs], label="Interpolant")
     plt.plot(x_hat, y_hat, 'o', label="f(x)")
     plt.title("Lagrange interpolation")
     plt.legend()
     plt.plot()
```

[4]: []

Lagrange interpolation

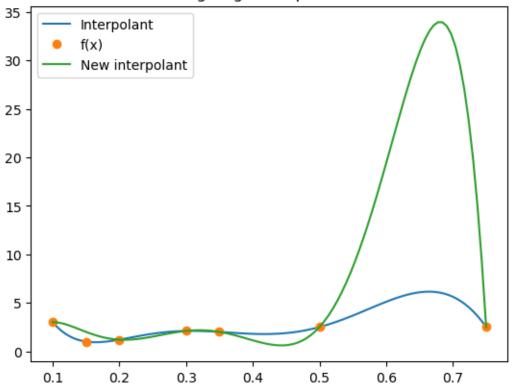


```
[5]: x_hat_new = [0.1, 0.15, 0.2, 0.3, 0.35, 0.5, 0.75]
y_hat_new = [3.0, 2.0, 1.2, 2.1, 2.0, 2.5, 2.5]
L_2, _ = lagrange_interpolant(x_hat_new, y_hat_new)
```

```
[6]: xs = np.linspace(0.1, 0.75, 100)
  plt.plot(xs, [L_1(x) for x in xs], label="Interpolant")
  plt.plot(x_hat, y_hat, 'o', label="f(x)")
  plt.plot(xs, [L_2(x) for x in xs], label="New interpolant")
  plt.title("Lagrange interpolation")
  plt.legend()
  plt.plot()
```

[6]: []

Lagrange interpolation



Difference at x* = 0.7 is 26.6666666666675

Since
$$L_n(x) = \sum_{i=1}^n f(x_i) \phi_i(x),$$
 and $y_2 = f(x_2),$

$$\frac{\partial L_n(x)}{\partial y_2} = \phi_2(x)$$

Then, the gradient at $x^* = 0.7$ is $\phi_2(0.7)$, which evaluates to

[8]: print(phis[1](0.7))

26.666666666667

To check numerically,

Gradient of polynomial with respect to old y2: 26.66666887307656 Gradient of polynomial with respect to new y2: 26.66666887307656

Since the gradient with respect to y_2 is constant, we have that

$$\frac{\Delta L_n(x)}{\Delta y_2} = \phi_2(x) \Delta L_n(x) = \phi_2(x) \Delta y_2$$

Since in parts b and c we have that $\Delta y_2 = 1$, we get

$$\Delta L_n(x) = \phi_2(x) \Delta L_n(x^*) = \phi_2(x^*) = 1$$

Which is exactly the change in $L(x^*)$ which we found in part c.