

1)

a)

For each interpolating point x_j in $[a,b]$, we can define an equation

$$P(x_j) = c_n + c_{(n-1)}(x_j) + c_{(n-2)}(x_j)^2 + \dots + c_1(x_j)^{(n-1)}$$

which lets us define the linear system that one would need to solve as

$$V \cdot c = y$$

where

V is the main matrix we need to invert, written as

$$\begin{bmatrix} 1, x_0, x_0^2, \dots, x_0^n, \\ 1, x_1, x_1^2, \dots, x_1^n, \\ \dots \\ 1, x_n, x_n^2, \dots, x_n^n \end{bmatrix}$$

,
 c is the vector of unknown c_i values from i in $\{0,1,\dots,n\}$, written as

$$[c_n, c_{(n-1)}, c_{(n-2)}, \dots, c_1]^T$$

,
and y is the vector of n th Lagrange Interpolating Polynomial evaluated at each x_j , written as

$$[P(x_0), P(x_1), \dots, P(x_n)]^T = [f(x_0), f(x_1), \dots, f(x_n)]^T \quad (\text{by construction})$$

The code that would solve for the coefficients would be solving the linear system, which we could do by simply multiplying the inverse of V against vector y , which is full of knowns as for each interpolating point x_j , $P(x_j) = f(x_j)$.

Code:

```
# create interpolating nodes, and vector y by evaluate f at those nodes
x = np.zeros(N)
for i in range(1, N + 1):
    x[i - 1] = -1 + (i - 1) * h
y = f(x)

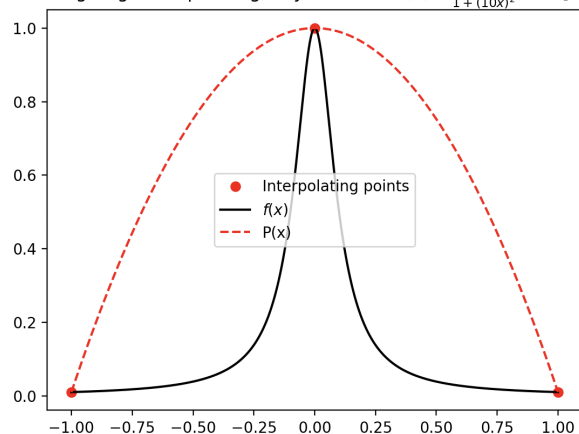
# create matrix Vandermonde matrix
V = np.zeros((N, N))
for i, x_j in enumerate(x):
    for j in range(N):
        V[i][j] = x_j**j

# solve for c vector
c = np.matmul(np.linalg.inv(V), y)
```

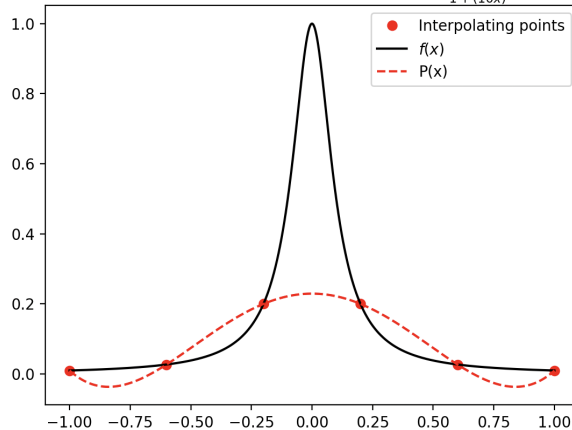
b)

Below, we plot $P(x)$ with solved c coefficients for several N as directed. As N increases, we can see the error gets worse at endpoints. We can also see that odd N predicts better at the midpoint while even N is better at the endpoints, which is caused by a difference in where the interpolating points lie over the interval $[a,b]$.

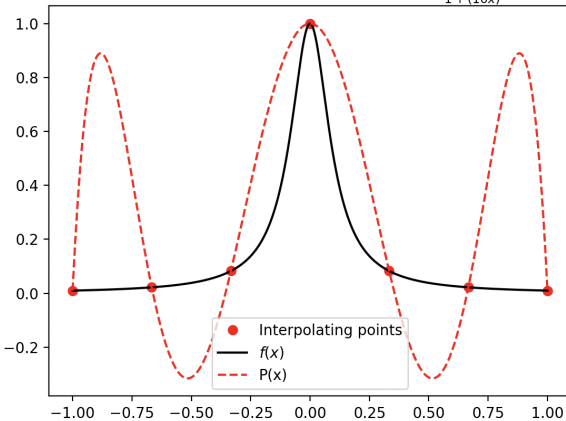
3rd Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



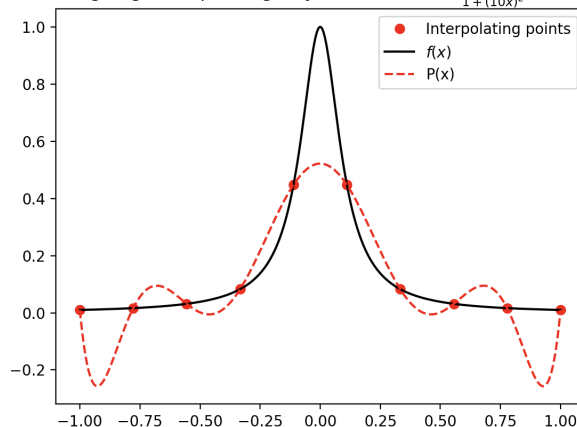
6th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



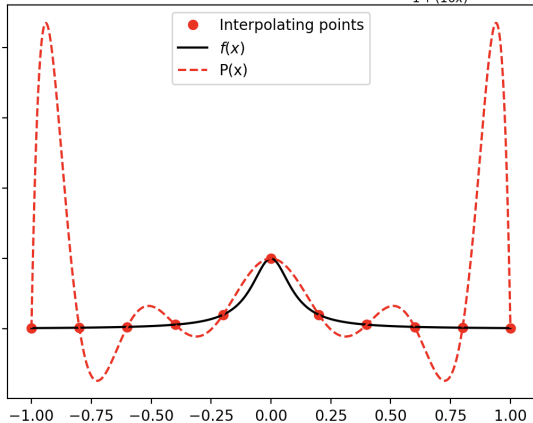
7th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



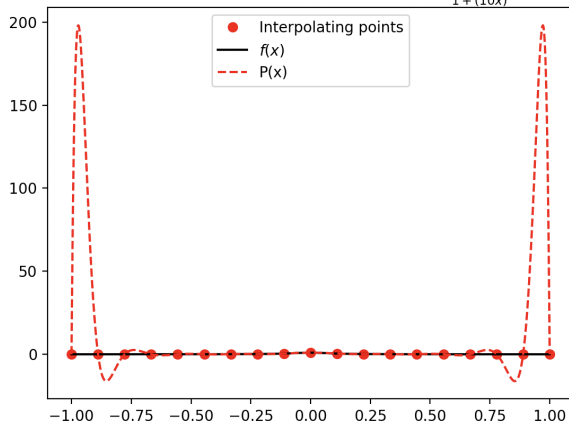
10th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



11th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$

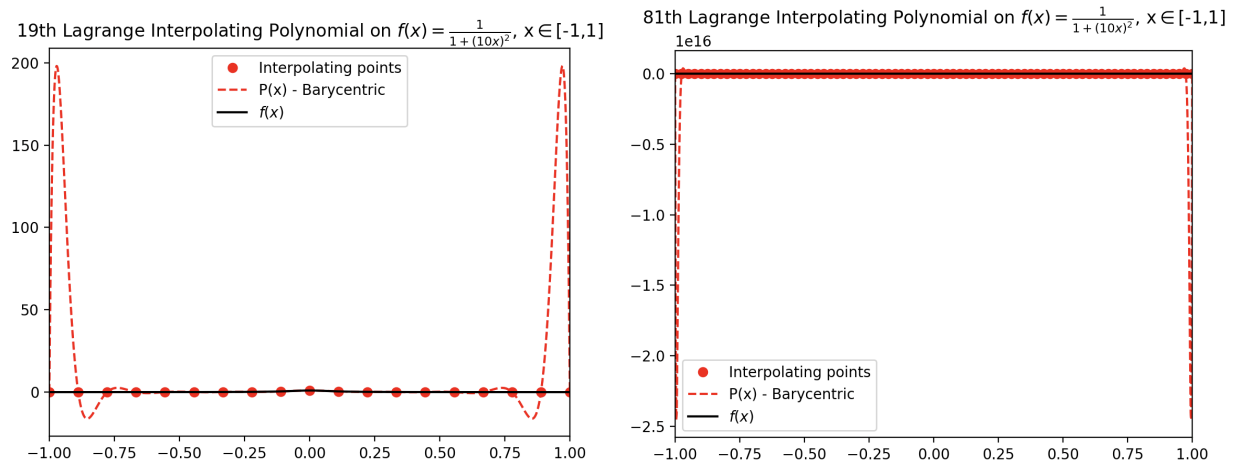


19th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



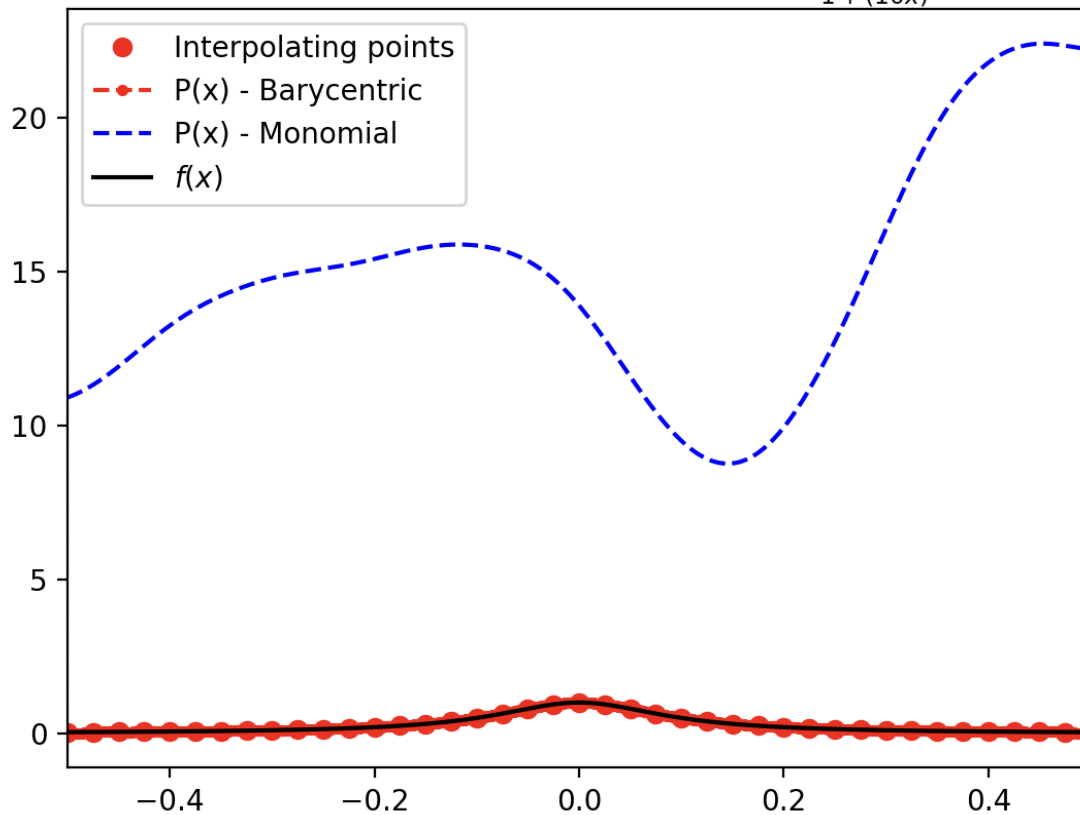
2)

Here, we see the graph for $P(x)$ using the barycentric Lagrange interpolation formula. We see we still get bad behavior towards endpoints, which is especially apparent for high (and odd) N .



However, compared to the Monomial basis of problem 1, we see that the Barycentric polynomial is much more accurate/stable with small x for large number of interpolating points, N .

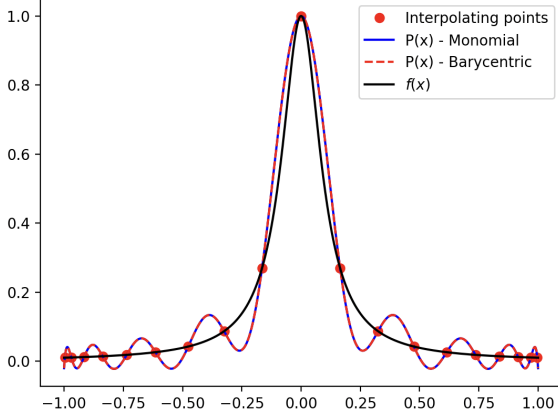
81th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-0.5, 0.5]$



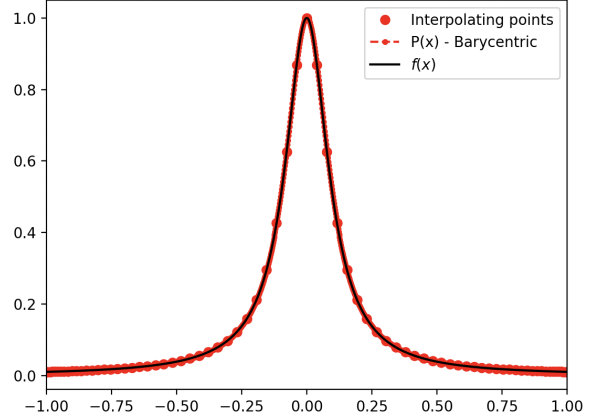
3)

Using the Chebyshev points that are clustered towards endpoints, we get far better approximations near endpoints for large N , as seen below.

19th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



81th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$



We can still get the interpolation to fail, however, if we use the Monomial basis for large N . This is because the method itself is very ill-conditioned for large N (matrix inversion). We show the difference between the Monomial and Barycentric method for $N=81$ below.

81th Lagrange Interpolating Polynomial on $f(x) = \frac{1}{1+(10x)^2}$, $x \in [-1,1]$

