Numerical Computing:: Project Seven

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```
In [1]:
        from matplotlib import pyplot
           import matplotlib.pyplot as plt
           import numpy as np
           import math
In [2]: ▶ interval = -5, 5
           f = lambda x, theta: 1 / (1 + np.exp(-theta * x))
           xs = np.linspace(interval[0], interval[1], num=8000)
           plt.figure()
           plt.plot(xs, f(xs, 1), label="$\\bf{\\theta=1}$")
           plt.plot(xs, f(xs, 2), label="$\\bf{\\theta=2}$")
           plt.plot(xs, f(xs, 10), label="$\ \")
           plt.xlim([interval[0], interval[1]])
           plt.xlabel("$\\bf{x}$", fontsize='xx-large')
           plt.ylabel("$\\bf{f_{\\theta}(x)}$", fontsize='xx-large')
           plt.legend()
           plt.draw()
```

Figure 1

•

1. Generate training data:

Create a vector with n = 7 evenly spaced points in the interval [-5, 5]. For each point xi in this vector, compute yi = $f\theta(xi)$. You should now have 7 pairs (xi, yi). Make a nice tablewith the seven input/output pairs.

```
\bowtie def f(x, \theta=1):
In [3]:
                 return 1/(1 + math.exp(-\theta*x))
In [4]:
         | x = \text{np.linspace}(-5,5,7) |
            y=[]
            for i in x:
                 y.append(f(i))
            for i in range(len(x)):
                 print("Point {:<3}| {:<23}| {:<23}".format(i, x[i], y[i]))</pre>
            Point 0 | -5.0
                                                   0.0066928509242848554
            Point 1
                      -3.333333333333333
                                                   0.03444519566621118
            Point 2 | -1.666666666666665
                                                  0.15886910488091516
            Point 3 | 0.0
                                                 0.5
                                                 0.8411308951190849
            Point 4 | 1.666666666666667
            Point 5 | 3.33333333333333333
                                                 0.9655548043337889
            Point 6 | 5.0
                                                 0.9933071490757153
```

2. Train the model:

Construct the Vandermonde system and solve for the coefficients of the unique degree-6 interpolating polynomial p6(x). Make a nice table of the 7 coefficients. And make a plot showing both $f\theta(x)$ and p6(x) over the domain [-5, 5]. Does this look like a good approximation? Explain your assessment.

```
In [5]:
           #https://numpy.org/doc/stable/reference/generated/numpy.vander.html
            #Construct the Vandermonde system
            vanderMatrix= np.vander(x, increasing=True) #increasing true so coeff for x^6
            #solve for the coefficients
            coeff = np.linalg.solve(vanderMatrix, y)
            #make a table of the 7 coefficients
            for i in range(len(coeff)):
               print("Coeff {:3}| {:25}| ".format(i, coeff[i]))
               i += 1
                    0
            Coeff
                                            0.5
                   1
            Coeff
                            0.23308408380860865
            Coeff
                       -1.1130791519360287e-16
            Coeff
                          -0.010832133158581564
            Coeff
                   4
                          1.442619596904655e-17
            Coeff
                   5
                         0.00021820907995371755
            Coeff
                        -3.9540246077329687e-19
```

```
p_6(x) = -3.9540246077329687e^{-19}x^6 + 0.00021820907995371755x^5 + 1.4426195969046x^2 + 0.11130791519360287e^{-16}x^2 + 0.23308408380860865x^2
```

◀

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```
In [6]:
            # make a plot showing both f\vartheta(x) and p6(x) over the domain [-5, 5].
            #Does this look like a good approximation? Explain
            p= lambda x: -3.9540246077329687e-19*x**6+0.00021820907995371755*x**5+1.44261
            import matplotlib.pyplot as plt
            f = lambda x, theta: 1 / (1 + np.exp(-theta * x))
            plt.figure()
            plt.subplot(1,1,1)
            plt.plot(xs,f(xs,1),label="$\\bf{f_{(\theta)(x)}$"}
            plt.plot(xs, p(xs), label="$ \ p_{6}(x)")
            plt.title('Nonzeros')
            plt.xlim([interval[0], interval[1]])
            plt.xlabel("$\\bf{x}$", fontsize='xx-large')
            plt.ylabel("$\\bf{f_{\\theta}(x)}$", fontsize='xx-large')
            plt.legend()
            plt.show()
                              p_6(x)
                   0.8
                   0.6
                   0.4
                   0.2
```

This is a relatively good approximation, which is surprising because from lecutre I remember that if xi are equally then Vandermone is ill conditioned since interpolating is unstable at equally spaced points, so I was expecting this to be a poor approximation

3. Generate testing data:

Create a new vector with 101 evenly spaced points in [-5, 5]. For each point x'i, compute y'i = $\theta(x'i)$

```
In [7]:
         morex = np.linspace(-5,5,101)
            y=[]
            for i in morex:
                y.append(f(i,1))
            #showing the first 5 and last 5 points
            for i in range(5):
                print("Point {:<3}| {:<23}| {:<23}".format(i, morex[i], y[i]))</pre>
                i += 1
            print("...")
            for e in range(96,101):
                print("Point {:<3}| {:<23}| .format(e, morex[e], y[e]))</pre>
                e += 1
            Point 0 | -5.0
                                              0.0066928509242848554
            Point 1 | -4.9
                                              0.007391541344281971
            Point 2 | -4.8
                                              0.008162571153159897
            Point 3 | -4.7
                                              0.009013298652847822
            Point 4 | -4.6
                                              0.009951801866904324
                                              0.9900481981330957
            Point 96 | 4.6000000000000001
            Point 97 | 4.7000000000000001
                                              0.990986701347152
            Point 98 | 4.8000000000000001
                                              0.9918374288468401
```

4.Compute the testing error:

Point 99 | 4.9

Point 100 5.0

Compute and report the the absolute testing error: error = error θ =1,n=7 = maximum

0.9926084586557181

0.9933071490757153

The absolute testing error is : 0.025163852153648192

5. Repeat steps 1-4 with θ = 10.

How does the error change? What does that tell you about the quality of the polynomial approximation for the two functions?

```
In [9]:
          ▶ #1. Generate training data
             theta10x = np.linspace(-5,5,7)
             theta10y=[]
             for i in x:
                 theta10y.append(f(i,10))
             for i in range(len(theta10x)):
                 print("Point {:<3}| {:<23}| .format(i, theta10x[i], theta10y[i]))</pre>
                 i += 1
             Point 0 | -5.0
                                                1.928749847963918e-22
             Point 1
                      -3.333333333333333
                                                3.338237795365011e-15
             Point 2 | -1.666666666666665
                                               5.777748185595394e-08
             Point 3 | 0.0
                                               0.5
             Point 4 | 1.66666666666667
                                               0.9999999422225181
             Point 5 | 3.33333333333333333
                                               0.999999999999967
             Point 6 | 5.0
                                               1.0
In [10]:
             #2. Train the model
             vanderMatrix= np.vander(theta10x, increasing=True) #increasing true so coeff
             #solve for the coefficients
             theta10coeff = np.linalg.solve(vanderMatrix, theta10y)
             #make a table of the 7 coefficients
             for i in range(len(coeff)):
                 print("Coeff {:3}| {:25}| ".format(i, theta10coeff[i]))
                 i += 1
             ptheta10= lambda x: -9.55036237717536e-19*x**6+0.0006479998128009668*x**5+3.4
                               0.4999999999999999
             Coeff
                     0
             Coeff
                     1
                               0.3699999480002668
             Coeff
                     2
                          -2.5646310240750854e-16
             Coeff
                            -0.026999993240034843
                     3 l
             Coeff
                    4
                            3.413443003923874e-17
             Coeff
                            0.0006479998128009668
                     5
             Coeff
                            -9.55036237717536e-19
                     6
          np.linalg.cond(vanderMatrix)
In [11]:
```

Out[11]: 25066.919613708356

```
In [12]:
             #graph
             import matplotlib.pyplot as plt
             f = lambda x, theta: 1 / (1 + np.exp(-theta * x))
             plt.figure()
             plt.subplot(1,1,1)
             plt.plot(xs,f(xs,10),label="$\bf{f_{(\theta=10)(x)}$"})
             plt.plot(xs, ptheta10(xs),label="$\bf{p_{6,theta=10}(x)}$")
             plt.title('Nonzeros')
             plt.xlim([interval[0], interval[1]])
             plt.xlabel("$\\bf{x}$", fontsize='xx-large')
             plt.ylabel("$\\bf{f_{\\theta}(x)}$", fontsize='xx-large')
             plt.legend()
             plt.show()
                    0.8
                    0.6
                    0.4
                    0.2
                    0.0
```

```
In [13]:
          ▶ ## 3.Generate testing data:
             #Create a new vector with 101 evenly spaced points in [-5, 5]
             morex = np.linspace(-5,5,101)
             ##For each point x'i, compute y'i = f\partial(x'i)
             y=[]
             for i in morex:
                 y.append(f(i,10))
             #showing the first 5 and last 5 points
             for i in range(5):
                 print("Point {:<3}| {:<23}| {:<23}".format(i, morex[i], y[i]))</pre>
                 i += 1
             print("...")
             for e in range(96,101):
                 print("Point {:<3}| {:<23}| {:<23}|".format(e, morex[e], y[e]))</pre>
                 e += 1
             Point 0 | -5.0
                                                 1.928749847963918e-22
             Point 1 | -4.9
                                                 5.242885663363464e-22
             Point 2 | -4.8
                                                 1.4251640827409352e-21
             Point 3 | -4.7
                                                 3.873997628687187e-21
             Point 4 | -4.6
                                                 l 1.0530617357553813e-20
             Point 96 | 4.6000000000000001
                                                 1.0
             Point 97 | 4.7000000000000001
                                                 1.0
             Point 98 | 4.8000000000000001
                                                 1.0
             Point 99 | 4.9
                                                 1.0
             Point 100 5.0
                                                 1.0
In [14]:
          \mid #compute p6(x')
             yp=[]
             for i in morex:
                 yp.append(ptheta10(i))
             #find max error
             error=0
             for i in range(len(y)):
                 temperror=abs(y[i]-yp[i])
                 if (error<temperror):</pre>
                      error=temperror
             print("The absolute testing error is :" , error)
```

The absolute testing error is: 0.3423015676002892

Thus the error is about 10x larger when theta=10 vs. when theta=1.

After seeing that the approximation is not as good, I was expecting this error to be larger, however I am still unsure why. I could not find anything online or in the book related to this, which makes me even more curious.

I originally hypothesized that the approximation and error would be near since we are using equally spaced points in both cases. I expected both to be equally ill conditioned, which was true, however this does not help explain why the approximation is not as good and error is higher for theta==10

References

- Lectures were informative although brief for this section, so I relied primarily on my best friend, the numpy docs and google
- https://numpy.org/doc/stable/index.html https://numpy.org/doc/stable/index.html (https://numpy.org/doc/stable/index.html)
- https://sites.google.com/site/sscnumericalanalysis/interpolation-and-polynomialapproximation/vandermonde-matrix
 (https://sites.google.com/site/sscnumericalanalysis/interpolation-and-polynomial-approximation/vandermonde-matrix)
- https://cu-numcomp.github.io/spring22/slides/2022-03-02-interpolation.html#vandermonde-matrices-can-be-ill-conditioned (https://cu-numcomp.github.io/spring22/slides/2022-03-02-interpolation.html#vandermonde-matrices-can-be-ill-conditioned)
- https://www.cs.purdue.edu/homes/wxg/selected_works/section_01/118.pdf (https://www.cs.purdue.edu/homes/wxg/selected_works/section_01/118.pdf)