

HW-1-Code-Figgins

January 15, 2021

```
[1]: using Plots, DataFrames, LinearAlgebra, LaTeXStrings, Latexify
```

0.1 Exercise 1

```
[2]: function second_deriv(u::Function, x, h)
      (u(x + h) + u(x - h) - 2*u(x)) / h^2
end
```

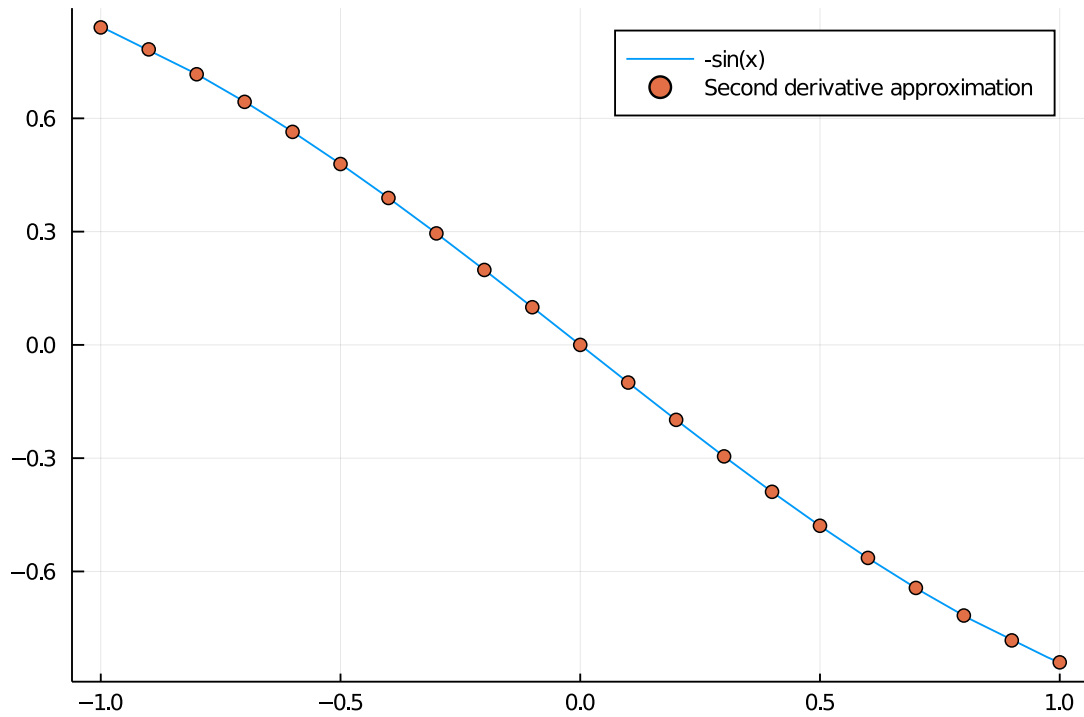
```
[2]: second_deriv (generic function with 1 method)
```

```
[3]: xs = -1:0.1:1
      h = 0.1

      # We can test our approximation using
      # that second derivative of sin is -sin
      sin_xx = [ second_deriv(sin, x, h) for x in xs]

      plot(x -> -1*sin(x), -1, 1, label = "-sin(x)")
      scatter!(xs, sin_xx, label = "Second derivative approximation")
```

```
[3]:
```



```
[4]: hs = [10.0^(-k) for k in 1:16]
x = /6

FDQ = [second_deriv(sin, x, h) for h in hs]
error = abs.(FDQ .+ sin(x)) # True value is -sin(x)
```

```
[4]: 16-element Array{Float64,1}:
 0.00041652780258211175
 4.166652633530443e-6
 4.167449668690537e-8
 3.0387354299499236e-9
 1.1515932100691906e-6
 6.657201129195434e-5
 0.0003996389186794458
 0.6102230246251563
111.52230246251564
 0.49999999999999994
 0.49999999999999994
 0.49999999999999994
 1.1102230246751564e10
 1.1102230246246565e12
 0.49999999999999994
 1.1102230246251566e16
```

```
[5]: df1 = DataFrame(h = hs, FDQ = FDQ, Error = error)
      latexify(df1)
```

[5]:

h	FDQ	Error
0.1	-0.49958347219741783	0.00041652780258211175
0.01	-0.4999958333473664	$4.166652633530443e-6$
0.001	-0.49999995832550326	$4.167449668690537e-8$
0.0001	-0.4999999969612645	$3.0387354299499236e-9$
$1.0e-5$	-0.50000115159321	$1.1515932100691906e-6$
$1.0e-6$	-0.499933427988708	$6.657201129195434e-5$
$1.0e-7$	-0.4996003610813205	0.0003996389186794458
$1.0e-8$	-1.1102230246251563	0.6102230246251563
$1.0e-9$	111.02230246251564	111.52230246251564
$1.0e-10$	0.0	0.49999999999999994
$1.0e-11$	0.0	0.49999999999999994
$1.0e-12$	0.0	0.49999999999999994
$1.0e-13$	$1.1102230246251564e10$	$1.1102230246751564e10$
$1.0e-14$	$-1.1102230246251565e12$	$1.1102230246246565e12$
$1.0e-15$	0.0	0.49999999999999994
$1.0e-16$	-1.1102230246251566e16	$1.1102230246251566e16$

```
[6]: plot(hs, error, scale = :log10,
      label = false,
      xlabel = L"h",
      ylabel = "Absolute Error",
      title = "Exercise 1 Error")
```

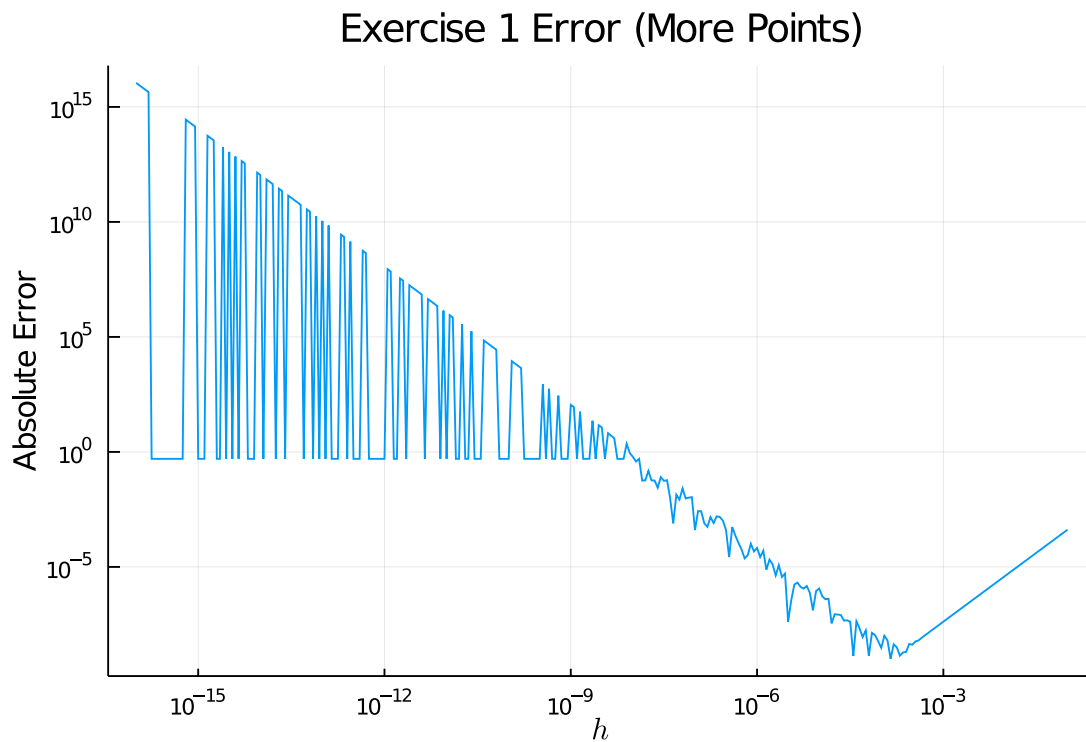


```
[7]: hs = [10.0^(-k) for k in 1:0.05:16]
      x = /6

      FDQ = [second_deriv(sin, x, h) for h in hs]
      error = abs.(FDQ .+ sin(x)) # True value is -sin(x)

      plot(hs, error, scale = :log10,
            label = false,
            xlabel = L"h",
            ylabel = "Absolute Error",
            title = "Exercise 1 Error (More Points)")
```

[7]:



There are significant issues once we go smaller than $h \approx 10e - 7$

0.2 Exercise 2

```
[8]: function RE(u, x, h, approx, order = 2, t = 2)
      ( t^order * approx(u, x, h / t) - approx(u, x, h) ) / (t^order - 1)
      end
```

[8]: RE (generic function with 3 methods)

```
[9]: hs = [0.05, 0.1, 0.2]
x = /6

# No Richardson extrapolation
raw_FDQ = [second_deriv(sin, x, h) for h in hs]
raw_error = raw_FDQ .+ sin(x) # True value is -sin(x)
```

```
[9]: 3-element Array{Float64,1}:
 0.00010415798651314256
 0.00041652780258211175
 0.0016644460310434872
```

```
[10]: # One step of Richardson extrapolation
RE_1_FDQ = [RE(sin, x, h, second_deriv) for h in hs]
RE_1_error = RE_1_FDQ .+ sin(x) # True value is -sin(x)
```

```
[10]: 3-element Array{Float64,1}:
 2.170097102016655e-9
 3.471449017133921e-8
 5.550597616532649e-7
```

```
[11]: ## RE on the RE
RE_1(u, x, h) = RE(u, x, h, second_deriv)

# Two steps of Richardson extrapolation
RE_2_FDQ = [ RE(sin, x, h, RE_1, 4,2) for h in hs]
RE_2_error = RE_2_FDQ .+ sin(x) # True value is -sin(x)
```

```
[11]: 3-element Array{Float64,1}:
 -5.636047184509607e-13
 4.709010958947601e-13
 2.4805379972292485e-11
```

```
[12]: df2 = DataFrame(h = hs,
                    NoRE = raw_FDQ,
                    Richardson1 = RE_1_FDQ,
                    Richardson2 = RE_2_FDQ)
df2[1,[3,4]] .= NaN
latexify(df2)
```

```
[12]:
```

h	NoRE	Richardson1	Richardson2
0.05	-0.4998958420134868	NaN	NaN
0.1	-0.49958347219741783	-0.4999999652855098	-0.49999999999952904
0.2	-0.49833555396895646	-0.4999994449402383	-0.49999999997519456

```
[13]: df2Errors = DataFrame(h = hs,
                          NoRE_Error = raw_error,
```

```

Richardson1_Error = RE_1_error,
Richardson2_Error = RE_2_error)
df2Errors[1,[3,4]] .= NaN
latexify(df2Errors)

```

[13]:

h	NoRE_Error	Richardson1_Error	Richardson2_Error
0.05	0.00010415798651314256	<i>NaN</i>	<i>NaN</i>
0.1	0.00041652780258211175	$3.471449017133921e-8$	$4.709010958947601e-13$
0.2	0.0016644460310434872	$5.550597616532649e-7$	$2.4805379972292485e-11$

```

[14]: hs = [10.0^(-k) for k in 0.5:0.01:5]

# No Richardson extrapolation
raw_FDQ = [second_deriv(sin, x, h) for h in hs]
raw_error = abs.(raw_FDQ .+ sin(x)) # True value is -sin(x)

# One step of Richardson extrapolation
RE_1_FDQ = [RE(sin, x, h, second_deriv) for h in hs]
RE_1_error = abs.(RE_1_FDQ .+ sin(x)) # True value is -sin(x)

# Two steps of Richardson extrapolation
RE_2_FDQ = [RE(sin, x, h, RE_1, 4,2) for h in hs]
RE_2_error = abs.(RE_2_FDQ .+ sin(x)) # True value is -sin(x)

plot(hs, raw_error, scale = :log10,
     label = "No RE",
     xlabel = L"h",
     ylabel = "Absolute Error",
     title = "Exercise 2 Error")

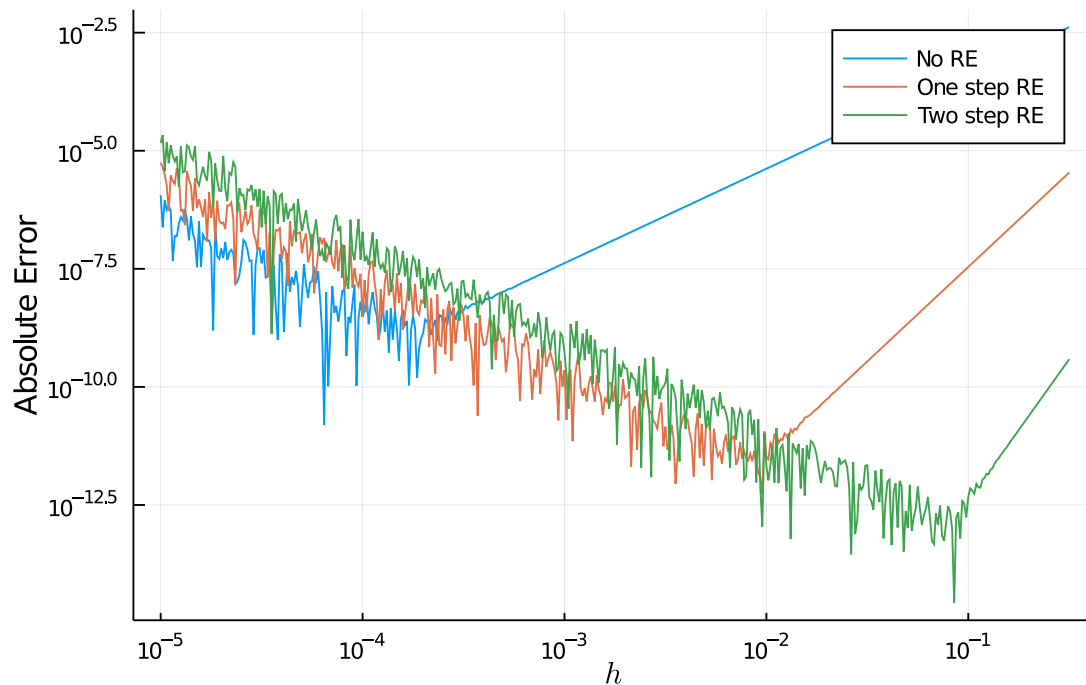
plot!(hs, RE_1_error, scale = :log10,
      label = "One step RE")

plot!(hs, RE_2_error, scale = :log10,
      label = "Two step RE")

```

[14]:

Exercise 2 Error



0.3 Exercise 6

```
[15]: M = 25 # Number of grid points
      h = 1/M # Step size
```

```
[15]: 0.04
```

```
[16]: ## Guess  $f$  given a  $u$ 
```

```
function make_matrix(M)
    # Step size
    h = 1/M

    # Xjs of interest
    xjs = [j*h for j in 1:M]

    # Defining diagonal
    diagA = [ -(1 + (xj + h/2)^2) - (1 + (xj - h/2)^2) for xj in xjs]
    diagB = [ (1 + (xj + h/2)^2) for xj in xjs[1:M-1]]

    ##Building Matrix
    A = Array{Tridiagonal}(diagB, diagA, diagB)
    A[end, [M, M-1, M-2]] .= 3*h/2, -2*h, h/2
```

```

    A = A ./ h^2

    return A
end

# Generate MxM approximation
A = make_matrix(M)

```

[16]: 25×25 Array{Float64,2}:

```

-1252.5   627.25    0.0      0.0  ...    0.0      0.0      0.0
 627.25 -1258.5   631.25    0.0      0.0      0.0      0.0
 0.0     631.25 -1268.5   637.25    0.0      0.0      0.0
 0.0      0.0   637.25 -1282.5    0.0      0.0      0.0
 0.0      0.0    0.0   645.25    0.0      0.0      0.0
 0.0      0.0    0.0    0.0  ...    0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0  ...    0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0  ...    0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0      0.0      0.0      0.0
 0.0      0.0    0.0    0.0  ...    0.0      0.0      0.0
 0.0      0.0    0.0    0.0      1131.25    0.0      0.0
 0.0      0.0    0.0    0.0     -2308.5   1177.25    0.0
 0.0      0.0    0.0    0.0     1177.25 -2402.5   1225.25
 0.0      0.0    0.0    0.0      12.5     -50.0     37.5

```

```

[17]: # Define test function
u(x) = (1 - x)^2

```

[17]: u (generic function with 1 method)

```

[18]: # Define true solution for test function
true_f(x) = 2*(3*x^2 - 2*x + 1)

```

[18]: true_f (generic function with 1 method)

```

[19]: function guess_f(u, M)
    h = 1 / M

```



```

# Discretize u
xjs = [j*h for j in 1:M]
U = u.(xjs)

# Approximate the F vector
F_approx = make_matrix(M)*U

# End points will be funky due to boundary conditions

## First end point has extra term
F_approx[1] += (1+ (h/2)^2)/h^2

## Last is a derivative and isn't needed
return F_approx[1:(M-1)]
end

f_approx = guess_f(u, M)

```

[19]: 24-element Array{Float64,1}:

```

1.8504000000000036
1.719199999999546
1.607199999999807
1.5144000000001938
1.44079999999974
1.3864000000000942
1.351199999999489
1.335200000000043
1.338399999999787
1.3608000000001539
1.4024
1.463200000000029
1.5432000000000414
1.642400000000066
1.760799999999038
1.8984000000000094
2.0552000000000845
2.231199999999443
2.426399999999987
2.6408000000000059
2.874399999999517
3.127199999999984
3.399200000000002
3.690399999999985

```

[20]: plot(true_f, 0, 1,
label = "True f",

```

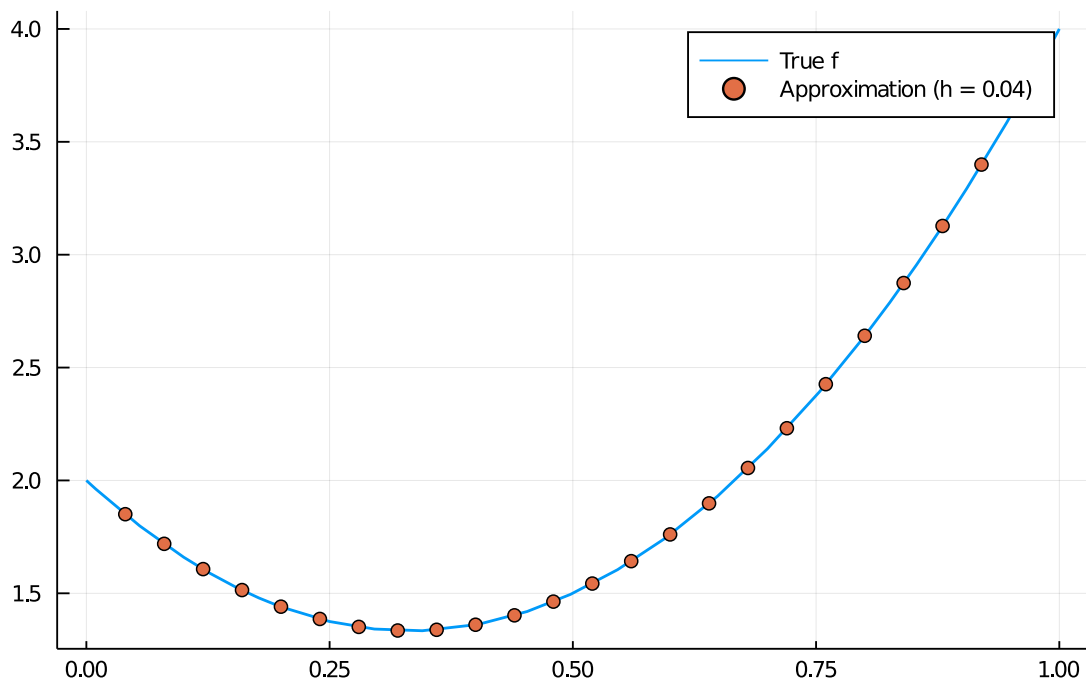
linewidth = 1.5)

scatter!([j*h for j in 1:(M-1)],
        f_approx,
        label = "Approximation (h = $h)",
        title = "Exercise 6 approximation")

```

[20]:

Exercise 6 approximation



```

[21]: function get_infinity_error(M)
        # Discretize True Solution
        xjs = [j/M for j in 1:(M-1)]
        true_f_val = true_f.(xjs)
        f_approx = guess_f(u, M)

        return maximum( abs.(true_f_val .- f_approx) )
    end

```

[21]: get_infinity_error (generic function with 1 method)

```
[22]: get_infinity_error(1000)
```

[22]: 5.007842034387977e-7

```
[23]: M_vec = [2^k for k in 2:12]

error_vec = []
for M in M_vec
    push!(error_vec, get_infinity_error(M))
end
```

Here's a simple attempt to plot the infinity norm error on our approximations. This is difficult to do for very small values of h since the size of the linear system grows as h increases.

```
[24]: scatter(1 ./ M_vec, error_vec, scale = :log10,
    xlabel = L"h",
    ylabel = "Error",
    title = "Exercise 6 Error",
    label = false)
```

[24]:



```
[25]: error_vec
```

```
[25]: 11-element Array{Any,1}:
 0.03125
 0.0078125
 0.001953125
 0.00048828125
```

```
0.0001220703125
3.0517578125e-5
7.62939453125e-6
1.9073486328125e-6
4.76837158203125e-7
1.1920928955078125e-7
2.9802322387695312e-8
```

```
[26]: 1 ./ M_vec
```

```
[26]: 11-element Array{Float64,1}:
 0.25
 0.125
 0.0625
 0.03125
 0.015625
 0.0078125
 0.00390625
 0.001953125
 0.0009765625
 0.00048828125
 0.000244140625
```