1 Contents

- Overview 2
- Example: Plotting a White Noise Process 3
- Example: Variations on Fixed Points 4
- Exercises 5
- Solutions 6

2 Overview

We’re now ready to start learning the Julia language itself.

2.1 Level

Our approach is aimed at those who already have at least some knowledge of programming — perhaps experience with Python, MATLAB, Fortran, C or similar.

In particular, we assume you have some familiarity with fundamental programming concepts such as

- variables
- arrays or vectors
- loops
- conditionals (if/else)

2.2 Approach

In this lecture we will write and then pick apart small Julia programs.

At this stage the objective is to introduce you to basic syntax and data structures.

Deeper concepts—how things work—will be covered in later lectures.

Since we are looking for simplicity the examples are a little contrived

In this lecture, we will often start with a direct MATLAB/FORTRAN approach which often is poor coding style in Julia, but then move towards more elegant code which is tightly connected to the mathematics.
2.3 Set Up

We assume that you’ve worked your way through our getting started lecture already.

In particular, the easiest way to install and precompile all the Julia packages used in QuantEcon notes is to type ] add InstantiateFromURL and then work in a Jupyter notebook, as described here.

2.4 Other References

The definitive reference is Julia’s own documentation.

The manual is thoughtfully written but is also quite dense (and somewhat evangelical).

The presentation in this and our remaining lectures is more of a tutorial style based around examples.

3 Example: Plotting a White Noise Process

To begin, let’s suppose that we want to simulate and plot the white noise process \( \epsilon_0, \epsilon_1, \ldots, \epsilon_T \), where each draw \( \epsilon_t \) is independent standard normal.

3.1 Introduction to Packages

The first step is to activate a project environment, which is encapsulated by Project.toml and Manifest.toml files.

There are three ways to install packages and versions (where the first two methods are discouraged, since they may lead to package versions out-of-sync with the notes)

1. add the packages directly into your global installation (e.g. Pkg.add("MyPackage") or ] add MyPackage)

2. download an Project.toml and Manifest.toml file in the same directory as the notebook (i.e. from the @__DIR__ argument), and then call using Pkg; Pkg.activate(@__DIR__);

3. use the InstantiateFromURL package

In [1]: using InstantiateFromURL

github_project("QuantEcon/quantecon-notebooks-julia", version = "0.5.0")
# github_project("QuantEcon/quantecon-notebooks-julia", version = "0.5.0", instantiate = true) # uncomment to force package installation

If you have never run this code on a particular computer, it is likely to take a long time as it downloads, installs, and compiles all dependent packages.

This code will download and install project files from GitHub, QuantEcon/QuantEconLecturePackages.
We will discuss it more in Tools and Editors, but these files provide a listing of packages and versions used by the code.

This ensures that an environment for running code is reproducible, so that anyone can replicate the precise set of package and versions used in construction.

The careful selection of package versions is crucial for reproducibility, as otherwise your code can be broken by changes to packages out of your control.

After the installation and activation, using provides a way to say that a particular code or notebook will use the package.

In [2]: using LinearAlgebra, Statistics

3.2 Using Functions from a Package

Some functions are built into the base Julia, such as randn, which returns a single draw from a normal distribution with mean 0 and variance 1 if given no parameters.

In [3]: randn()

Out[3]: 0.663006149938107

Other functions require importing all of the names from an external library

In [4]: using Plots
   gr(fmt=:png); # setting for easier display in jupyter notebooks
   n = 100
   ϵ = randn(n)
   plot(1:n, ϵ)

Out[4]:

Let’s break this down and see how it works.

The effect of the statement using Plots is to make all the names exported by the Plots module available.

Because we used Pkg.activate previously, it will use whatever version of Plots.jl that was specified in the Project.toml and Manifest.toml files.

The other packages LinearAlgebra and Statistics are base Julia libraries, but require an explicit using.

The arguments to plot are the numbers 1, 2, ..., n for the x-axis, a vector ϵ for the y-axis, and (optional) settings.

The function randn(n) returns a column vector n random draws from a normal distribution with mean 0 and variance 1.
### 3.3 Arrays

As a language intended for mathematical and scientific computing, Julia has strong support for using unicode characters.

In the above case, the $\epsilon$ and many other symbols can be typed in most Julia editor by providing the LaTeX and `<TAB>`, i.e. `\epsilon<TAB>`.

The return type is one of the most fundamental Julia data types: an array

```julia
In [5]: typeof(ϵ)
```

```
Out[5]: Array{Float64,1}
```

```julia
In [6]: ϵ[1:5]
```

```
Out[6]: 5-element Array{Float64,1}:
    0.24982115675921715
   -0.964862688555342
    0.5371313034198218
    0.6578003667976515
    0.7109426147172597
```

The information from `typeof()` tells us that $\epsilon$ is an array of 64 bit floating point values, of dimension 1.

In Julia, one-dimensional arrays are interpreted as column vectors for purposes of linear algebra.

The $\epsilon[1:5]$ returns an array of the first 5 elements of $\epsilon$.

Notice from the above that

- array indices start at 1 (like MATLAB and Fortran, but unlike Python and C)
- array elements are referenced using square brackets (unlike MATLAB and Fortran)

To get help and examples in Jupyter or other julia editor, use the `?` before a function name or syntax.

```julia
?typeof
```

Get the concrete type of $x$.

Examples

```julia
julia> a = 1//2;

julia> typeof(a)
Rational{Int64}

julia> M = [1 2; 3.5 4];

julia> typeof(M)
Array{Float64,2}
```
3.4 For Loops

Although there’s no need in terms of what we wanted to achieve with our program, for the sake of learning syntax let’s rewrite our program to use a for loop for generating the data.

Note
In Julia v0.7 and up, the rules for variables accessed in for and while loops can be sensitive to how they are used (and variables can sometimes require a global as part of the declaration). We strongly advise you to avoid top level (i.e. in the REPL or outside of functions) for and while loops outside of Jupyter notebooks. This issue does not apply when used within functions.

Starting with the most direct version, and pretending we are in a world where randn can only return a single value

In [7]: # poor style
    n = 100
    ε = zeros(n)
    for i in 1:n
        ε[i] = randn()
    end

Here we first declared ε to be a vector of n numbers, initialized by the floating point 0.0. The for loop then populates this array by successive calls to randn().

Like all code blocks in Julia, the end of the for loop code block (which is just one line here) is indicated by the keyword end.

The word in from the for loop can be replaced by either ∈ or =.

The index variable is looped over for all integers from 1:n – but this does not actually create a vector of those indices.

Instead, it creates an iterator that is looped over – in this case the range of integers from 1 to n.

While this example successfully fills in ε with the correct values, it is very indirect as the connection between the index i and the ε vector is unclear.

To fix this, use eachindex

In [8]: # better style
    n = 100
    ε = zeros(n)
    for i in eachindex(ε)
        ε[i] = randn()
    end

Here, eachindex(ε) returns an iterator of indices which can be used to access ε.

While iterators are memory efficient because the elements are generated on the fly rather than stored in memory, the main benefit is (1) it can lead to code which is clearer and less prone to typos; and (2) it allows the compiler flexibility to creatively generate fast code.

In Julia you can also loop directly over arrays themselves, like so
In [9]: ϵ_sum = 0.0 # careful to use 0.0 here, instead of 0
m = 5
for ϵ_val in ϵ[1:m]
    ϵ_sum = ϵ_sum + ϵ_val
end
ϵ_mean = ϵ_sum / m

Out[9]: -0.0005085942924017539

where ϵ[1:m] returns the elements of the vector at indices 1 to m.

Of course, in Julia there are built in functions to perform this calculation which we can compare against

In [10]: ϵ_mean ≈ mean(ϵ[1:m])
ϵ_mean ≈ sum(ϵ[1:m]) / m

Out[10]: true

In these examples, note the use of ≈ to test equality, rather than ==, which is appropriate for integers and other types.

Approximately equal, typed with \approx<TAB>, is the appropriate way to compare any floating point numbers due to the standard issues of floating point math.

3.5 User-Defined Functions

For the sake of the exercise, let’s go back to the for loop but restructure our program so that generation of random variables takes place within a user-defined function.

To make things more interesting, instead of directly plotting the draws from the distribution, let’s plot the squares of these draws

In [11]: # poor style
function generatedata(n)
    ϵ = zeros(n)
    for i in eachindex(ϵ)
        ϵ[i] = (randn())^2 # squaring the result
    end
    return ϵ
end

data = generatedata(10)
plot(data)

Out[11]:

Here

- function is a Julia keyword that indicates the start of a function definition
- generatedata is an arbitrary name for the function
- return is a keyword indicating the return value, as is often unnecessary
Let us make this example slightly better by “remembering” that `randn` can return a vectors.

In [12]: # still poor style
   function generatedata(n)
       ϵ = randn(n) # use built in function
       for i in eachindex(ϵ)
           ϵ[i] = ϵ[i]^2 # squaring the result
       end
       return ϵ
   end
   data = generatedata(5)

Out[12]: 5-element Array{Float64,1}:
    3.0314182055887295
    0.2491413025408233
    0.01462288100789602
    0.09492839808385116
    2.780676714847063

While better, the looping over the i index to square the results is difficult to read.
Instead of looping, we can broadcast the ^2 square function over a vector using a ..
To be clear, unlike Python, R, and MATLAB (to a lesser extent), the reason to drop the for is not for performance reasons, but rather because of code clarity.
Loops of this sort are at least as efficient as vectorized approach in compiled languages like Julia, so use a for loop if you think it makes the code more clear.

In [13]: # better style
   function generatedata(n)
       ϵ = randn(n) # use built in function
       return ϵ.^2
   end
   data = generatedata(5)

Out[13]: 5-element Array{Float64,1}:
    1.1870920477774138
    0.3832789351122684
    0.7766197808266485
    0.969668710447312
    1.1746653292495337

We can even drop the function if we define it on a single line.

In [14]: # good style
   generatedata(n) = randn(n).^2
   data = generatedata(5)

Out[14]: 5-element Array{Float64,1}:
    0.07808657771609412
    0.20634082447356386
    0.99237301919782522
    0.8357488492361947
    0.004425557660323686
Finally, we can broadcast any function, where squaring is only a special case.

In [15]: # good style
   f(x) = x^2 # simple square function
   generatedata(n) = f.(randn(n)) # uses broadcast for some function `f`
   data = generatedata(5)

Out[15]: 5-element Array{Float64,1}:
   8.103229248537597
   1.4017698921298563
   0.6486409332143371
   0.6368112444084437
   0.8604275775254652

As a final – abstract – approach, we can make the `generatedata` function able to generically apply to a function.

In [16]: generatedata(n, gen) = gen.(randn(n)) # uses broadcast for some function `gen`
   f(x) = x^2 # simple square function
   data = generatedata(5, f) # applies f

Out[16]: 5-element Array{Float64,1}:
   4.64493699255591
   0.1003228999746721
   0.13556102535386344
   4.2535226808712156e-5
   0.10377239355284992

Whether this example is better or worse than the previous version depends on how it is used. High degrees of abstraction and generality, e.g. passing in a function `f` in this case, can make code either clearer or more confusing, but Julia enables you to use these techniques with no performance overhead.

For this particular case, the clearest and most general solution is probably the simplest.

In [17]: # direct solution with broadcasting, and small user-defined function
   n = 100
   f(x) = x^2
   x = randn(n)
   plot(f.(x), label="x^2")
   plot!(x, label="x") # layer on the same plot

Out[17]:

While broadcasting above superficially looks like vectorizing functions in MATLAB, or Python ufuncs, it is much richer and built on core foundations of the language.

The other additional function `plot!` adds a graph to the existing plot.

This follows a general convention in Julia, where a function that modifies the arguments or a global state has a `!` at the end of its name.
3.5.1 A Slightly More Useful Function

Let’s make a slightly more useful function.

This function will be passed in a choice of probability distribution and respond by plotting a histogram of observations.

In doing so we’ll make use of the Distributions package, which we assume was instantiated above with the project.

Here’s the code

In [18]: using Distributions

    function plothistogram(distribution, n)
        ϵ = rand(distribution, n)  # n draws from distribution
        histogram(ϵ)
    end

    lp = Laplace()
plothistogram(lp, 500)

Out[18]:

Let’s have a casual discussion of how all this works while leaving technical details for later in the lectures.

First, \( lp = \text{Laplace()} \) creates an instance of a data type defined in the Distributions module that represents the Laplace distribution.

The name \( lp \) is bound to this value.

When we make the function call \( \text{plothistogram}(lp, 500) \) the code in the body of the function \( \text{plothistogram} \) is run with

- the name \( \text{distribution} \) bound to the same value as \( lp \)
- the name \( n \) bound to the integer \( 500 \)

3.5.2 A Mystery

Now consider the function call \( \text{rand}(\text{distribution}, n) \).

This looks like something of a mystery.

The function \( \text{rand()} \) is defined in the base library such that \( \text{rand}(n) \) returns \( n \) uniform random variables on \([0, 1)\).

In [19]: rand(3)

Out[19]: 3-element Array{Float64,1}:
0.7416584556338026
0.6763219485764944
0.4258199710488886
On the other hand, *distribution* points to a data type representing the Laplace distribution that has been defined in a third party package.

So how can it be that *rand()* is able to take this kind of value as an argument and return the output that we want?

The answer in a nutshell is *multiple dispatch*, which Julia uses to implement **generic programming**.

This refers to the idea that functions in Julia can have different behavior depending on the particular arguments that they’re passed.

Hence in Julia we can take an existing function and give it a new behavior by defining how it acts on a new type of value.

The compiler knows which function definition to apply to in a given setting by looking at the types of the values the function is called on.

In Julia these alternative versions of a function are called **methods**.

## 4 Example: Variations on Fixed Points

Take a mapping $f : X \to X$ for some set $X$.

If there exists an $x^* \in X$ such that $f(x^*) = x^*$, then $x^*$ is called a “fixed point” of $f$.

For our second example, we will start with a simple example of determining fixed points of a function.

The goal is to start with code in a MATLAB style, and move towards a more **Julian** style with high mathematical clarity.

### 4.1 Fixed Point Maps

Consider the simple equation, where the scalars $p, \beta$ are given, and $v$ is the scalar we wish to solve for

$$v = p + \beta v$$

Of course, in this simple example, with parameter restrictions this can be solved as $v = p/(1 - \beta)$.

Rearrange the equation in terms of a map $f(x) : \mathbb{R} \to \mathbb{R}$

$$v = f(v)$$

where

$$f(v) := p + \beta v$$

Therefore, a fixed point $v^*$ of $f(\cdot)$ is a solution to the above problem.
4.2 While Loops

One approach to finding a fixed point of (1) is to start with an initial value, and iterate the map

\[ v^{n+1} = f(v^n) \]  

(2)

For this exact \( f \) function, we can see the convergence to \( v = p/(1 - \beta) \) when \( |\beta| < 1 \) by iterating backwards and taking \( n \to \infty \)

\[ v^{n+1} = p + \beta v^n = p + \beta p + \beta^2 v^{n-1} = p \sum_{i=0}^{n-1} \beta^i + \beta^n v_0 \]

To implement the iteration in (2), we start by solving this problem with a while loop.

The syntax for the while loop contains no surprises, and looks nearly identical to a MATLAB implementation.

In [20]: # poor style
    p = 1.0 # note 1.0 rather than 1
    \beta = 0.9
    maxiter = 1000
    tolerance = 1.0E-7
    v_iv = 0.8 # initial condition

    # setup the algorithm
    v_old = v_iv
    normdiff = Inf
    iter = 1
    while normdiff > tolerance && iter <= maxiter
        v_new = p + \beta * v_old # the f(v) map
        normdiff = norm(v_new - v_old)

        # replace and continue
        v_old = v_new
        iter = iter + 1
    end
    println("Fixed point = $v_old, and |f(x) - x| = $normdiff in $iter iterations")

Fixed point = 9.999999173706609, and |f(x) - x| = 9.181037796679448e-8 in 155 iterations

The while loop, like the for loop should only be used directly in Jupyter or the inside of a function.

Here, we have used the norm function (from the LinearAlgebra base library) to compare the values.

The other new function is the println with the string interpolation, which splices the value of an expression or variable prefixed by $ into a string.

An alternative approach is to use a for loop, and check for convergence in each iteration.
In [21]: # setup the algorithm
v_old = v_iv
normdiff = Inf
iter = 1
for i in 1:maxiter
  v_new = p + β * v_old # the f(v) map
  normdiff = norm(v_new - v_old)
  if normdiff < tolerance # check convergence
    iter = i
    break # converged, exit loop
  end
  # replace and continue
  v_old = v_new
end
println("Fixed point = $v_old, and |f(x) - x| = $normdiff in $iter iterations")

Fixed point = 9.999999081896231, and |f(x) - x| = 9.181037796679448e-8 in 154 iterations

The new feature there is break, which leaves a for or while loop.

4.3 Using a Function

The first problem with this setup is that it depends on being sequentially run – which can be easily remedied with a function.

In [22]: # better, but still poor style
function v_fp(β, p, v_iv, tolerance, maxiter)
  # setup the algorithm
  v_old = v_iv
  normdiff = Inf
  iter = 1
  while normdiff > tolerance && iter <= maxiter
    v_new = p + β * v_old # the f(v) map
    normdiff = norm(v_new - v_old)
  # replace and continue
    v_old = v_new
    iter = iter + 1
  end
  return (v_old, normdiff, iter) # returns a tuple
end

# some values
p = 1.0 # note 1.0 rather than 1
β = 0.9
maxiter = 1000
tolerance = 1.0E-7
v_initial = 0.8 # initial condition

v_star, normdiff, iter = v_fp(β, p, v_initial, tolerance, maxiter)
println("Fixed point = $v_star, and |f(x) - x| = $normdiff in $iter iterations")
Fixed point = 9.999999173706609, and |f(x) - x| = 9.181037796679448e-8 in 155 iterations

While better, there could still be improvements.

4.4 Passing a Function

The chief issue is that the algorithm (finding a fixed point) is reusable and generic, while the function we calculate $p + \beta \cdot v$ is specific to our problem.

A key feature of languages like Julia, is the ability to efficiently handle functions passed to other functions.

In [23]: # better style
   function fixedpointmap(f, iv, tolerance, maxiter)
      # setup the algorithm
      x_old = iv
      normdiff = Inf
      iter = 1
      while normdiff > tolerance && iter <= maxiter
         x_new = f(x_old) # use the passed in map
         normdiff = norm(x_new - x_old)
         x_old = x_new
         iter = iter + 1
      end
      return (x_old, normdiff, iter)
   end

   # define a map and parameters
   p = 1.0
   \(\beta\) = 0.9
   f(v) = p + \beta \cdot v # note that p and \(\beta\) are used in the function!

   maxiter = 1000
   tolerance = 1.0E-7
   v_initial = 0.8 # initial condition

   v_star, normdiff, iter = fixedpointmap(f, v_initial, tolerance, maxiter)
   println("Fixed point = \$v_star, and |f(x) - x| = \$normdiff in \$iter iterations")

   Fixed point = 9.999999173706609, and |f(x) - x| = 9.181037796679448e-8 in 155 iterations

   Much closer, but there are still hidden bugs if the user orders the settings or returns types wrong.

4.5 Named Arguments and Return Values

To enable this, Julia has two features: named function parameters, and named tuples
In [24]: # good style

```python
function fixedpointmap(f; iv, tolerance=1E-7, maxiter=1000)
    # setup the algorithm
    x_old = iv
    normdiff = Inf
    iter = 1
    while normdiff > tolerance && iter <= maxiter
        x_new = f(x_old)  # use the passed in map
        normdiff = norm(x_new - x_old)
        x_old = x_new
        iter = iter + 1
    end
    return (value = x_old, normdiff=normdiff, iter=iter)  # A named tuple
end
```

# define a map and parameters
p = 1.0
β = 0.9
f(v) = p + β * v  # note that p and β are used in the function!

sol = fixedpointmap(f, iv=0.8, tolerance=1.0E-8)  # don't need to pass
println("Fixed point = 
\$(sol.value), and |f(x) - x| = 
\$(sol.normdiff) in $\"(sol.iter)"
\" iterations")

Fixed point = 9.999999918629035, and |f(x) - x| = 9.041219328764782e-9 in 177 iterations

In this example, all function parameters after the ; in the list, must be called by name.

Furthermore, a default value may be enabled – so the named parameter iv is required while tolerance and maxiter have default values.

The return type of the function also has named fields, value, normdiff, and iter – all accessed intuitively using ..

To show the flexibilty of this code, we can use it to find a fixed point of the non-linear logistic equation, \( x = f(x) \) where \( f(x) := rx(1 - x) \).

In [25]: r = 2.0
    \( f(x) = r * x * (1 - x) \)

sol = fixedpointmap(f, iv=0.8)
println("Fixed point = 
\$(sol.value), and |f(x) - x| = 
\$(sol.normdiff) in $\"(sol.iter)"
\" iterations")

Fixed point = 0.4999999999999968, and |f(x) - x| = 3.97933237546819e-8 in 7 iterations

4.6 Using a Package

But best of all is to avoid writing code altogether.
In [26]: # best style
    using NLsolve

    p = 1.0
    β = 0.9
    f(v) = p .+ β * v  # broadcast the +
    sol = fixedpoint(f, [0.8])
    println("Fixed point = $(sol.zero), and |f(x) - x| = "
           "$(norm(f(sol.zero) - sol.zero)) in "
           "$(sol.iterations) iterations")

Fixed point = [9.999999999999972], and |f(x) - x| = 3.552713678800501e-15 in 3 iterations

The fixedpoint function from the NLsolve.jl library implements the simple fixed point iteration scheme above.

Since the NLsolve library only accepts vector based inputs, we needed to make the \( f(v) \) function broadcast on the + sign, and pass in the initial condition as a vector of length 1 with \([0.8]\).

While a key benefit of using a package is that the code is clearer, and the implementation is tested, by using an orthogonal library we also enable performance improvements.

In [27]: # best style
    p = 1.0
    β = 0.9
    iv = [0.8]
    sol = fixedpoint(v -> p .+ β * v, iv)
    println("Fixed point = $(sol.zero), and |f(x) - x| = "
           "$(norm(f(sol.zero) - sol.zero)) in "
           "$(sol.iterations) iterations")

Fixed point = [9.999999999999972], and |f(x) - x| = 3.552713678800501e-15 in 3 iterations

Note that this completes in 3 iterations vs 177 for the naive fixed point iteration algorithm.

Since Anderson iteration is doing more calculations in an iteration, whether it is faster or not would depend on the complexity of the \( f \) function.

But this demonstrates the value of keeping the math separate from the algorithm, since by decoupling the mathematical definition of the fixed point from the implementation in (2), we were able to exploit new algorithms for finding a fixed point.

The only other change in this function is the move from directly defining \( f(v) \) and using an anonymous function.

Similar to anonymous functions in MATLAB, and lambda functions in Python, Julia enables the creation of small functions without any names.

The code \( v -> p .+ β * v \) defines a function of a dummy argument, \( v \) with the same body as our \( f(x) \).
### 4.7 Composing Packages

A key benefit of using Julia is that you can compose various packages, types, and techniques, without making changes to your underlying source.

As an example, consider if we want to solve the model with a higher-precision, as floating points cannot be distinguished beyond the machine epsilon for that type (recall that computers approximate real numbers to the nearest binary of a given precision; the *machine epsilon* is the smallest nonzero magnitude).

In Julia, this number can be calculated as

In \[28\]: `eps()`

Out\[28\]: `2.220446049250313e-16`

For many cases, this is sufficient precision – but consider that in iterative algorithms applied millions of times, those small differences can add up.

The only change we will need to our model in order to use a different floating point type is to call the function with an arbitrary precision floating point, `BigFloat`, for the initial value.

In \[29\]:

```julia
# use arbitrary precision floating points
p = 1.0
β = 0.9
iv = [BigFloat(0.8)] # higher precision

# otherwise identical
sol = fixedpoint(v -> p * v + β * v, iv)
println("Fixed point = ", sol, ", and \|f(x) - x\| = ", norm(f(sol) - sol.zero)) in 

"$sol.iterations" iterations"
```

Here, the literal `BigFloat(0.8)` takes the number 0.8 and changes it to an arbitrary precision number.

The result is that the residual is now **exactly 0.0** since it is able to use arbitrary precision in the calculations, and the solution has a finite-precision solution with those parameters.

### 4.8 Multivariate Fixed Point Maps

The above example can be extended to multivariate maps without any modifications to the fixed point iteration code.

Using our own, homegrown iteration and simply passing in a bivariate map:
In 

\[
p = [1.0, 2.0] \\
\beta = 0.9 \\
iv = [0.8, 2.0] \\
f(v) = p .+ \beta * v \quad \# \text{note that } p \text{ and } \beta \text{ are used in the function!}
\]

sol = fixedpointmap(f, iv = iv, tolerance = 1.0E-8)
println("Fixed point = $(sol.value), and |f(x) - x| = $(sol.normdiff) in \\
\$((sol.iter)) iterations")

Fixed point = [9.9999999961080519, 19.999999923853192], and |f(x) - x| = 9.501826248250528e-9 in 184 iterations

This also works without any modifications with the fixedpoint library function.

In 

using NLsolve

\[
p = [1.0, 2.0, 0.1] \\
\beta = 0.9 \\
iv = [0.8, 2.0, 51.0] \\
f(v) = p .+ \beta * v
\]

sol = fixedpoint(v -> p .+ \beta * v, iv)
println("Fixed point = $(sol.zero), and |f(x) - x| = $(norm(f(sol.zero) - \\
\$\text{sol.zero}) in \\
\$\text{sol.iterations}) iterations")

Fixed point = [9.999999999999998, 20.0, 1.0], and |f(x) - x| = 0.0 in 3 iterations

Finally, to demonstrate the importance of composing different libraries, use a StaticArrays.jl type, which provides an efficient implementation for small arrays and matrices.

In 

using NLsolve, StaticArrays

\[
p = @SVector [1.0, 2.0, 0.1] \\
\beta = 0.9 \\
iv = @SVector [0.8, 2.0, 51.0] \\
f(v) = p .+ \beta * v
\]

sol = fixedpoint(v -> p .+ \beta * v, iv)
println("Fixed point = $(sol.zero), and |f(x) - x| = $(norm(f(sol.zero) - \\
\$\text{sol.zero}) in \\
\$\text{sol.iterations}) iterations")

Fixed point = [9.999999999999998, 20.0, 1.0], and |f(x) - x| = 0.0 in 3 iterations

The @SVector in front of the \([1.0, 2.0, 0.1]\) is a macro for turning a vector literal into a static vector.

All macros in Julia are prefixed by @ in the name, and manipulate the code prior to compilation.

We will see a variety of macros, and discuss the “metaprogramming” behind them in a later lecture.
5 Exercises

5.1 Exercise 1

Recall that \( n! \) is read as “\( n \) factorial” and defined as \( n! = n \times (n - 1) \times \cdots \times 2 \times 1 \).

In Julia you can compute this value with `factorial(n)`.

Write your own version of this function, called `factorial2`, using a `for` loop.

5.2 Exercise 2

The binomial random variable \( Y \sim Bin(n, p) \) represents

- number of successes in \( n \) binary trials
- each trial succeeds with probability \( p \)

Using only `rand()` from the set of Julia’s built-in random number generators (not the `Distributions` package), write a function `binomial_rv` such that `binomial_rv(n, p)` generates one draw of \( Y \).

Hint: If \( U \) is uniform on \((0, 1)\) and \( p \in (0, 1) \), then the expression \( U < p \) evaluates to `true` with probability \( p \).

5.3 Exercise 3

Compute an approximation to \( \pi \) using Monte Carlo.

For random number generation use only `rand()`.

Your hints are as follows:

- If \( U \) is a bivariate uniform random variable on the unit square \((0, 1)^2\), then the probability that \( U \) lies in a subset \( B \) of \((0, 1)^2\) is equal to the area of \( B \).
- If \( U_1, \ldots, U_n \) are iid copies of \( U \), then, as \( n \) gets larger, the fraction that falls in \( B \) converges to the probability of landing in \( B \).
- For a circle, area = \( \pi \times \text{radius}^2 \).

5.4 Exercise 4

Write a program that prints one realization of the following random device:

- Flip an unbiased coin 10 times.
- If 3 consecutive heads occur one or more times within this sequence, pay one dollar.
- If not, pay nothing.

Once again use only `rand()` as your random number generator.

5.5 Exercise 5

Simulate and plot the correlated time series

\[ x_{t+1} = \alpha x_t + \epsilon_{t+1} \quad \text{where} \quad x_0 = 0 \quad \text{and} \quad t = 0, \ldots, n \]

The sequence of shocks \( \{\epsilon_t\} \) is assumed to be iid and standard normal.

Set \( n = 200 \) and \( \alpha = 0.9 \).
5.6 Exercise 6

Plot three simulated time series, one for each of the cases $\alpha = 0$, $\alpha = 0.8$ and $\alpha = 0.98$.

(The figure will illustrate how time series with the same one-step-ahead conditional volatilities, as these three processes have, can have very different unconditional volatilities)

5.7 Exercise 7

This exercise is more challenging.

Take a random walk, starting from $x_0 = 1$

$$x_{t+1} = \alpha x_t + \sigma \epsilon_{t+1} \quad \text{where} \quad x_0 = 1 \quad \text{and} \quad t = 0, \ldots, t_{\text{max}}$$

- Furthermore, assume that the $x_{t_{\text{max}}} = 0$ (i.e. at $t_{\text{max}}$, the value drops to zero, regardless of its current state).
- The sequence of shocks $\{\epsilon_t\}$ is assumed to be iid and standard normal.
- For a given path $\{x_t\}$ define a **first-passage time** as $T_a = \min\{t \mid x_t \leq a\}$, where by the assumption of the process $T_a \leq t_{\text{max}}$.

Start with $\sigma = 0.2$, $\alpha = 1.0$

1. calculate the first-passage time, $T_0$, for 100 simulated random walks – to a $t_{\text{max}} = 200$ and plot a histogram
2. plot the sample mean of $T_0$ from the simulation for $\alpha \in \{0.8, 1.0, 1.2\}$

5.8 Exercise 8(a)

This exercise is more challenging.

The root of a univariate function $f(\cdot)$ is an $x$ such that $f(x) = 0$.

One solution method to find local roots of smooth functions is called Newton’s method.

Starting with an $x_0$ guess, a function $f(\cdot)$ and the first-derivative $f'(\cdot)$, the algorithm is to repeat

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

until $|x_{n+1} - x_n|$ is below a tolerance

1. Use a variation of the **fixedpointmap** code to implement Newton’s method, where the function would accept arguments $f, f_{\text{prime}}, x_0, \text{tolerance}, \text{maxiter}$.
2. Test it with $f(x) = (x - 1)^3$ and another function of your choice where you can analytically find the derivative.
5.9 Exercise 8(b)

For those impatient to use more advanced features of Julia, implement a version of Exercise 8(a) where \( f'_\text{prime} \) is calculated with auto-differentiation.

In [33]: using ForwardDiff

    # operator to get the derivative of this function using AD
    D(f) = x -> ForwardDiff.derivative(f, x)

    # example usage: create a function and get the derivative
    f(x) = x^2
    f_prime = D(f)

    f(0.1), f_prime(0.1)

Out[33]: (0.010000000000000002, 0.2)

1. Using the \( D(f) \) operator definition above, implement a version of Newton’s method that does not require the user to provide an analytical derivative.

2. Test the sorts of \( f \) functions which can be automatically integrated by ForwardDiff.jl.

6 Solutions

6.1 Exercise 1

In [34]: function factorial2(n)
    k = 1
    for i in 1:n
        k *= i  # or \( k = k \times i \)
    end
    return k
end

factorial2(4)

Out[34]: 24

In [35]: factorial2(4) == factorial(4)  \# built-in function

Out[35]: true

6.2 Exercise 2

In [36]: function binomial_rv(n, p)
    count = 0
    U = rand(n)
    for i in 1:n
        if U[i] < p
6.3 Exercise 3

Consider a circle with diameter 1 embedded in a unit square.

Let $A$ be its area and let $r = 1/2$ be its radius.

If we know $\pi$ then we can compute $A$ via $A = \pi r^2$.

But the point here is to compute $\pi$, which we can do by $\pi = A / r^2$.

Summary: If we can estimate the area of the unit circle, then dividing by $r^2 = (1/2)^2 = 1/4$ gives an estimate of $\pi$.

We estimate the area by sampling bivariate uniforms and looking at the fraction that fall into the unit circle.

```python
7, 3, 7, 5, 5, 6, 5, 4, 5, 4, 5, 8, 8, 2, 6, 4, 7, 2, 6, 3, 5, 5, 6, 3,
```

6.4 Exercise 4

In [38]: payoff = 0
   count = 0

   print("Count = ")

   for i in 1:10
       U = rand()
       if U < 0.5
count += 1

else
  count = 0
end

print(count)

if count == 3
  payoff = 1
end

println("\npayoff = $payoff")

Count = 1010010010
payoff = 0

We can simplify this somewhat using the **ternary operator**. Here are some examples

In [39]: a = 1 < 2 ? "foo" : "bar"

Out[39]: "foo"

In [40]: a = 1 > 2 ? "foo" : "bar"

Out[40]: "bar"

Using this construction:

In [41]: payoff = 0.0
count = 0.0

print("Count = ")

for i in 1:10
  U = rand()
  count = U < 0.5 ? count + 1 : 0
  print(count)
  if count == 3
    payoff = 1
  end
end
println("\npayoff = $payoff")

Count = 1.0010100000
payoff = 0.0

6.5 Exercise 5

Here’s one solution
In [42]: using Plots
   gr(fmt=:png); # setting for easier display in jupyter notebooks
   α = 0.9
   n = 200
   x = zeros(n + 1)

   for t in 1:n
       x[t+1] = α * x[t] + randn()
   end
   plot(x)

Out[42]:

6.6 Exercise 6

In [43]: αs = [0.0, 0.8, 0.98]
   n = 200
   p = plot() # naming a plot to add to

   for α in αs
       x = zeros(n + 1)
       x[1] = 0.0
       for t in 1:n
           x[t+1] = α * x[t] + randn()
       end
       plot!(p, x, label = "alpha = $α") # add to plot p
   end
   p # display plot

Out[43]:

6.7 Exercise 7: Hint

As a hint, notice the following pattern for finding the number of draws of a uniform random number until it is below a given threshold

In [44]: function drawsuntilthreshold(threshold; maxdraws=100)
   for i in 1:maxdraws
       val = rand()
       if val < threshold # checks threshold
           return i # leaves function, returning draw number
       end
   end
   return Inf # if here, reached maxdraws
end

draws = drawsuntilthreshold(0.2, maxdraws=100)

Out[44]: 9

Additionally, it is sometimes convenient to add to just push numbers onto an array without indexing it directly
In [45]: vals = zeros(0) # empty vector

    for i in 1:100
        val = rand()
        if val < 0.5
            push!(vals, val)
        end
    end
println("There were $(length(vals)) below 0.5")

    There were 45 below 0.5