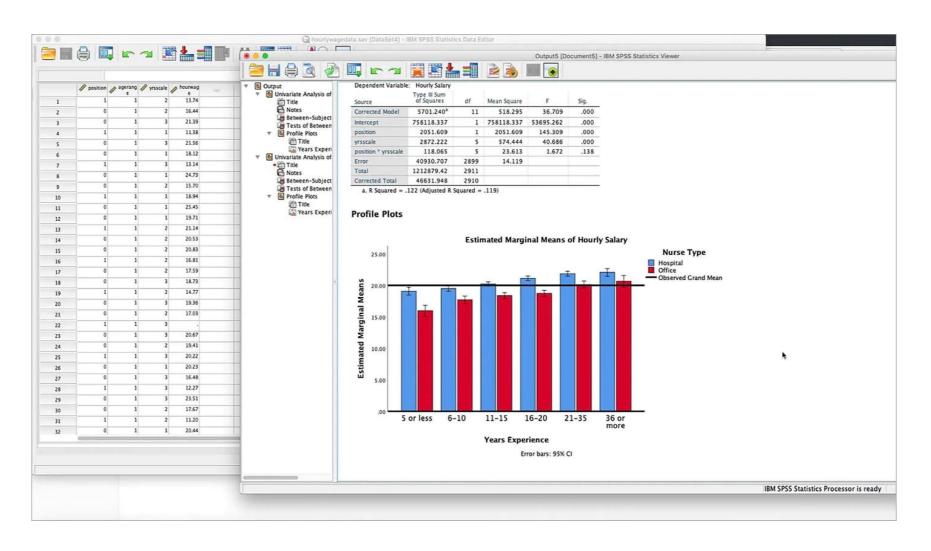
Julia for Scientists

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Why learn a programming language?



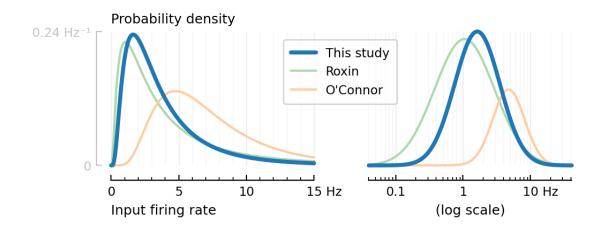
Why program?

- Automate analyses
 - → less error-prone

..which goes hand in hand with:

- Reproducibility
- Customize:
 - Special plots
 - Tweak analyses
- Run simulations
- For fun

An example custom plot:

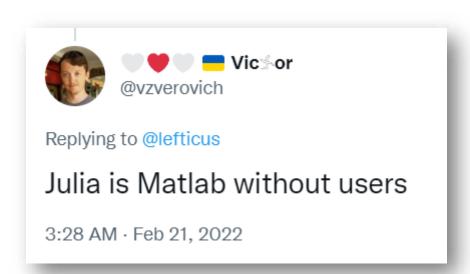


Choosing a programming language

as a researcher

	First released	Free & open?	Online community
	(The new builds on & learns from the old)	(Hackable, "own your code- running environment")	(→ Learning resources & documentation iterations)
Main choices:			•
R	1995 / 1976 (S)	Yes	Huge
Python	1991	Yes	Huge
Others			
Julia	2012	Yes	Medium
Matlab	1979	No	Large

..is also choosing a community





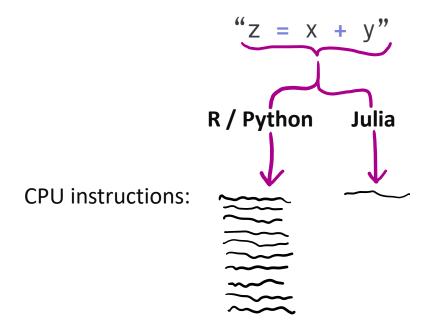
Julia syntax

```
using Unitful: M\Omega, pF, mV # Import names from a package
11 11 11
Simulate a simple leaky-integrate-and-fire (LIF) neuron, given
input current 'I' and a timestep '\Deltat'.
Return when the neuron fires its first spike.
The neuron's input resistance 'R' and time constant 'τ' can be
customized by keyword argument.
function first_spike(I, \Delta t; R = 100M\Omega, \tau = 200pF)
    N = length(I)
                                # Number of samples
                                       # Resting membrane potential
    V = -70 \text{mV}
    for i in 1:N
        dv = -v + R*I[i] # Leaky current integration v += dv/\tau * \Delta t # Euler integration of ODE
         if V > -55mV
                                    # Spike!
             return time = i * Δt
         end
    end
    return nothing
                                      # Never spiked
end
```

In Python / R / Matlab: "Avoid for-loops"
"Write vectorized code"

Compilation: Your code we the CPU

- If one line of Julia code corresponds to just a few CPU instructions
- ..then the same line in base Python / R / Matlab will often correspond to an order of magnitude more CPU instructions
 - ..That's why the code that does the 'real' numeric work in these languages is actually written in C / C++ NumPy, PyTorch, Tensorflow, dplyr, ...: all have their core written in a different language
 - ..That's why, to have your code run fast, you're discouraged from writing for-loops for numeric code ..
 - .. and instead use the provided library functions
 e.g. np.where(...)
 - Python is often used as "glue-code" (see next slide)
 - If you want a custom numeric algorithm that's not provided by the libraries, you need to learn C / C++ The "two languages-problem"



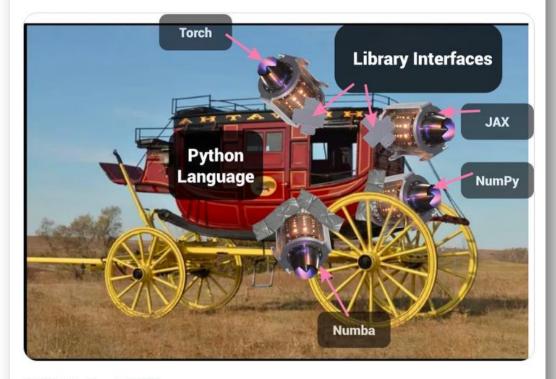
Python can have JIT compilation via the fantastic **Numba** package. (But you can only use base Python with Numba, not arbitrary other packages).

Matlab added JIT compilation in 2015 (but it's rather opaque)



The more I use Julia, the more Python and its numeric libraries look like a Victorian-era stagecoach with jet engines duct-taped to it, each pointing a different direction (=mutually incompatible).

It's such a weird ecosystem, and makes it so much harder for users to contribute.



5:50 PM · Nov 7, 2022

JIT compilation

- If **one line** of Julia code corresponds to just a few CPU instructions
- ..then the same line in base Python / R / Matlab* will often correspond to an order of magnitude more CPU instructions
- Why is this ↑?
 - The same line of code (say, z = x + y) does different things, based on the **type** of X and y
 - If they're integers (8 + 3), use the `leaq` CPU instruction
 - If one is a float (8 + 3.3), call 'convert' and use the floating point processor unit
 - If they're both plots, call subroutines, to compose the plots together into a bigger figure
 - •
 - Python, R, and Matlab need to check the types of X and Y every time the line is run, and then call the appropriate subroutines
 - Hence all these extra CPU instructions
 - Julia will *infer* the types of x and y
 - When? The first time the function that contains our line of code is called
 - It does this type inference based on the arguments that the function was called with (more specifically, their types), and by analyzing the function's source code you wrote
 - I then compiles a fast version of the function This is just-in-time (JIT) compilation

Data analysis in Julia

- DataFrames.jl
 - Tidyverse's dplyr & Python's Pandas equivalent
 - Better API than Pandas, imho
 - In the very capable hands of Bogumił Kamiński
 - Check out his tutorials: github.com/bkamins/Julia-DataFrames-Tutorial
- Work in <u>Jupyter</u> notebooks
 - Via IJulia.jl
 - Ju stands for Julia (r for R).
- missing datatype is built-in in Julia
 - distinct from nothing
- I plot using Python's matplotlib 😩
 - Via PyPlot.jl
 - There's also Makie.jl
 - ..and Gadfly.jl, which is ggplot-inspired

Example of working with a DataFrame containing missing values, in a Jupyter notebook

(loading data from Arrow, which is useful for data interchange with R or Python):

Out[30]: 3×4 DataFrame

Row	Α	В	C	D
	Bool	Int64?	String?	Char?
1	true	1	missing	a
2	false	2	b	missing
3	true	missing	С	С

Source: https://github.com/bkamins/Julia-
DataFrames-Tutorial/blob/master/04 loadsave.ipynb

Julia likes

Unicode variable names & operators

- Some code is read much more than it is written. There, readability counts!
- For throwaway / exploratory code, not worth the slower input though
- Real-life example from my own code:

```
izh() = begin
    # Conductance-based synaptic current
    I_{syn} = g_e * (v - E_e) + g_i * (v - E_i)
    # Izhikevich 2D system
    \Delta \cdot v = (k*(v-v_1)*(v-v_t) - u - I_syn) / C # Membrane potential
    \Delta.u = a*(b*(v-v_r) - u)
                                          # Adaptation current
    # Synaptic conductance decay
    \Delta \cdot g_e = -g_e / \tau \# (g_e \text{ is sum over all exc synapses})
    \Delta \cdot g_i = -g_i / \tau
end
has_spiked() = (v ≥ v<sub>s</sub>) ←----- Compact operator :)
on_self_spike() = begin
    V = V_T
    u += \Delta u
end
```

Julia likes

Community

- Discourse forum & Slack
- Scientists
- Contribute to ecosystem (open source, build upon others)

As close-to-the-metal as you like

 Look under the hood. Understand why something is slow/fast, and how it works

"data structures + functions" design style

- Decoupling is good
- Versus: when you're designing software in Python, you're often pushed towards a coupled OOP design, with inheritance

Keyword argument syntax sugar:

```
options = [some object]
simulate(x, options = options) # Python
simulate(x; options) # Julia
```

Inspectability

- @edit to jump to source code of anything... amazing
- @code_native to see cpu instructions
- ? for documentation

Dependency management

- Single, ergonomic tool (↔ Python)
 - Pkg.jl, with `]`REPL mode
- Easy **reproducibility** via thin environments
 - Project.toml & Manifest.toml
- Not just for Julia code, for e.g. data too!
 - Artifacts.jl, DataDeps.jl
 - And for binaries: Yggdrasil & BinaryBuilder.jl

• Macro's

Lisp-like. 'Code as data'

Julia annoyances

- Package startup time ("time-to-first-plot")
 - Language developers are working hard this year to improve this
- No winning plotting package yet
- `name.<tab>` autocompletion (API discovery) not as good as Python
 - <u>"Power of the dot"</u> in OOP languages
- Getting floats to print with lower precision is way more difficult than it should be for new users
- Traits / interfaces (lack of)
- Error handling is underdeveloped / under-practiced ("→ silent fails & crashes")
- See also:
 - yuri.is/not-julia
 - danluu.com/julialang
 - <u>viralinstruction.com/posts/badjulia</u>

"Julia has a correctness problem"

- (i.e. there's nasty hidden bugs everywhere)
- Not true for Base Julia:
 - every line there is pored over by many language developers
 - automatic test coverage is very comprehensive
- For other people's packages:
 - Not a problem in my experience.
 - But you have to inspect the packages that you use, if they're not in Julia Base; and make a value judgement about their quality
 - A lot of Julia packages are of *very* high quality in my experience
 - Except for the lack of error checking (of inputs and outputs)
 - Julia doesn't hold your hand: you gotta know what you're doing mathematically / numerically / statistically

Why did I switch to Julia?

- Advent of Code :) (2021)
- Physical units in neuron simulations:

- I could keep using:
 - my Jupyter notebook workflow
 - my Matplotlib experience

```
parameters = (
    # Izhikevich neuron
    C = 100 * pF
    k = 0.7 * (nS/mV)
    V_1 = -60 \times mV
    v_t = -40 * mV
    a = 0.03 / ms
    b = -2 * nS
    v_s = 35    * mV
    V_r = -50 \times mV
    \Delta u = 100 \times pA
    # Synapses
    E_e = 0 * mV
    E_i = -80 * mV
    \tau = 7 * ms
    # Inputs
    N_e = 40
    N_i = 10
    N = N_e + N_i
    \Delta g_e = 60 \text{nS} / N_e
    \Delta g_i = 60 \text{nS} / N_i
    # Integration
    \Delta t = 0.1 ms
    T = 10seconds
```



- Code must be type-inferable ("type-stable")
 - Put everything in (small) functions
 - If using globals: `const`, or typed
- Read the manual
 - Especially the "Performance tips" section, if you're wondering why your code is not as fast as promised. Also:
- Ask questions on the forum
 - discourse.julialang.org
 - People are very eager to help, and the community managers do a great job
- Use Revise.jl (Use all of Tim Holy's packages actually).
 - This minizes nr. of times you have to restart the Julia session (re: time-to-first-X problem)
 - Plus:
 - If using VS Code, there's a plugin for Julia. Also: the JuliaMono font:) Example: ------
 - On Windows, use the Julia REPL in the Windows Terminal
 - Put commonly used snippets in your startup.jl
- Don't load unnecessary packages
 - Julia Base has no real latency (time-to-first-X) problem.
 It's loading many packages that gets you
 - Especially packages that have many dependencies themselves (looking at you SciML ecosystem :P)
 - Do you really need this package?
 Can you just implement it yourself / copy the relevant part?
- Learn by doing
 - Like by doing some Advent of Code puzzles!

```
# Code excerpt from the
# JuliaMono homepage.
# Original by Zygmunt Szpak
\otimes = kron
N = length(\mathcal{D}[1])
\mathcal{M}, \mathcal{M}' = \mathcal{D}
\Lambda_1, \Lambda_2 = C
e_1 = @SMatrix [1.0; 0.0; 0.0]
e_2 = @SMatrix [0.0; 1.0; 0.0]
for n = 1:N
       index = SVector(1,2)
       \Lambda_{n}[1:2,1:2] = \Lambda_{1}[n][index, in]
       \Lambda_n[3:4,3:4] = \Lambda_2[n][index,i]
                 = hom(\mathcal{M}[n])
                = hom(\mathfrak{M}'[n])
                = (m \otimes m')
       \partial_{\mathsf{x}} \mathbf{u}_{\mathsf{n}} = [(\mathbf{e}_{\mathsf{1}} \otimes \mathbf{m}') \ (\mathbf{e}_{\mathsf{2}} \otimes \mathbf{m}')]
                = \partial_x u_n * \Lambda_n * \partial_x u_n'
       \Sigma_n = \theta' * B_n * \theta
       \Sigma_n^{-1} = inv(\Sigma_n)
end
```

Should you use Julia?

- Do you 'just' need data analysis, automation, and pretty, customized plots?
 - Then, no
- Or do you also write custom numeric algorithms / simulations?
 - Then, yes:)
 - ..Unless you already know Matlab and don't have the time
 - ..Plus, Python and R have huge ecosystems of packages that might already do your custom thing
 - A concrete example in computational neuroscience: **Brian** Python package for spiking neural network simulations (core written in C++)
 - Also, Python has **Numba** for JIT-optimization of hot inner loops (<u>numba.pydata.org</u>). That might be enough for your use case

Links

- <u>"Seven Lines of Julia"</u>: examples of Julia, in different applications.
 - "What cool thing can you do in seven lines of code?"
- tfiers.github.io/phd
 - made with <u>JupyterBook</u>
 - auto-built and -published <u>with GitHub Actions on GitHub Pages</u>
- github.com/schluppeck/ng-data-club
 - Repo of the Lunchtime data club
- Discussion of these slides on Julia Discourse
 - (woah meta)