The Numpy Ecosystem

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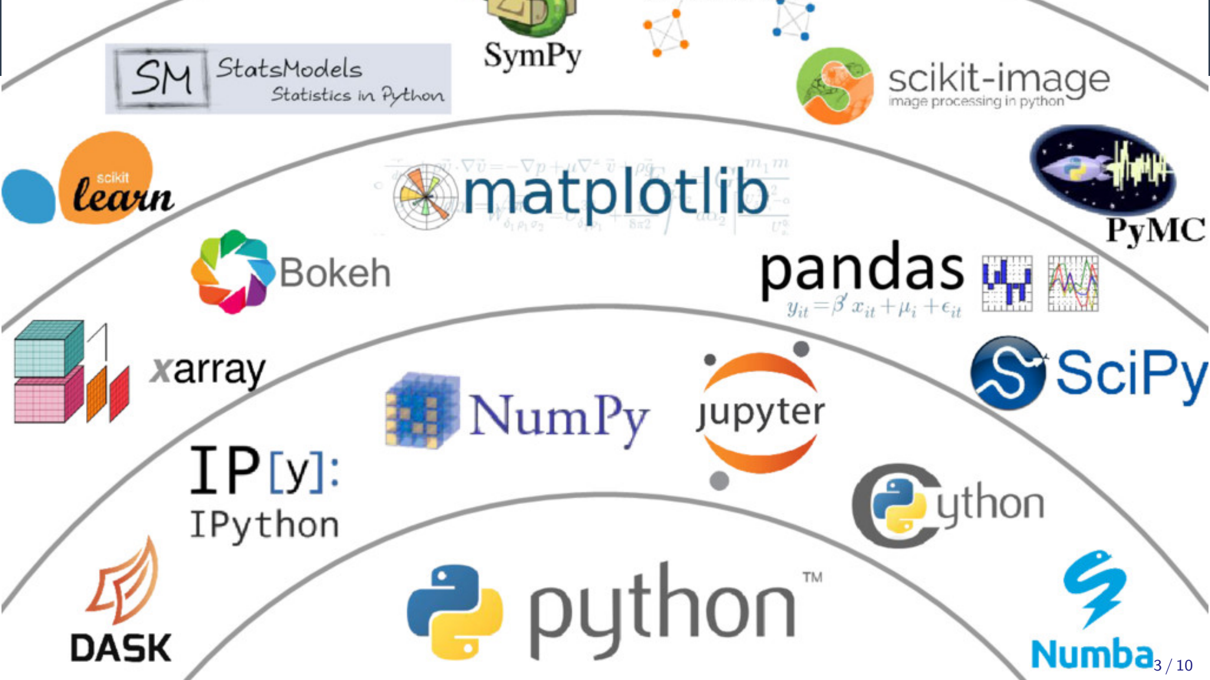
This afternoon, we switch to. . .


StatsModels
Statistics in Python
SymPy
scikit-image
image processing in python
scikit learn
matplotlib
PyMC
Bokeh
pandas
$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$
xarray
SciPy
NumPy
jupyter
IP[y]:
IPython
Cython
DASK
python™
Numba

Specific topics

Statistics tools

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Speeding up code

- **Dask:** parallel processing; Multiple Instructions on Multiple Data (MIMD).
- **Numba:** compile a limited subset of Python, as-is, to C-like speeds.
- **Cython:** compile any Python code, but you have to modify it to make it fast.
- **CuPy:** run any Numpy operations on a GPU.
- **Numba-GPU:** compile limited Python for the GPU.
- **PyCUDA:** interface with raw CUDA through Numpy arrays.
- **ctypes:** cast pointers as Numpy arrays and run code in shared library (`*.so`) files.

Speeding up code

Fast software is not like a fast runner, who has some superior intrinsic ability.
All run at the same rate, but some have more hurdles on the track than others.

Hurdles, from smallest to largest

1. Unnecessary or repeated arithmetic
2. Arithmetic in separate instructions that could be in the same instruction (vectorization)
3. Transcendental functions or division
4. Unnecessary or nonsequential memory access; cache swapping
5. Virtual machine indirection
6. Boxing numbers as objects
7. Type checking at runtime
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Python is guilty of #4, #5, #6, and #7 (Java only #4, #5, and half of #6).

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Example: PyPy, a reimplementation of Python with just-in-time (JIT) compilation. If it works, we'd only use that. It doesn't yet work with all extension modules, though.

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Vertical: use hardware more effectively by removing hurdles.

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Vertical: use hardware more effectively by removing hurdles.

Plateaus as you get close to optimum. More effort yields diminishing returns.

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It's not as fast as Numpy or the other accelerators I'll show, but it benefits from the conciseness of the same Numpythonic mindset.

So without further ado...