



Building SciPy kernels with Pythran

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Why we embarked on this journey



SciPy contains a lot of algorithmic code. It needs to be fast. Existing approaches in SciPy were:

- Python: for the glue, and non critical parts
- Cython: for critical parts
- Fortran 77: for very old critical parts
- C & C++: for ultra critical parts :-)

Our goal: make it easier to write fast SciPy kernels!



The Pythran approach



Keep input code portable and high-level:

- takes pure Python code as input
- understands NumPy high-level constructs
- delivers performance by transpiling to C++

But still:

- efficient explicit looping in Python
- without any runtime dependencies



A typical Pythran kernel for SciPy



```
#pythran export _max_len_seq_inner(intp[], int8[], int, int, int8[])
def _max_len_seq_inner(taps, state, nbits, length, seq):
    n_{taps} = taps.shape[0]
    idx = 0
    for i in range(length): \Leftarrow Explicit looping
        feedback = state[idx]
                              Explicit indexing
        seq[i] = feedback
        for ti in range(n_taps):
            feedback ^= state[(taps[ti] + idx) % nbits]
        state[idx] = feedback
        idx = (idx + 1) \% nbits
    return np.roll(state, -idx, axis=0)
```

Understands NumPy function calls



Works in a Jupyter notebook



```
[1]: import numpy as np
     import pythran
     %load ext pythran.magic
[2]: %pythran
     import numpy as np
     # pythran export polynomial matrix(float[:, :], int[:, :])
     def polynomial matrix(x, powers):
         out = np.empty((x.shape[0], powers.shape[0]), dtype=float)
         for i in range(x.shape[0]):
             for j in range(powers.shape[0]):
                 out[i, j] = np.prod(x[i]**powers[j])
         return out
[3]: x = np.random.rand(3, 4)
     powers = np.arange(12).reshape((3, 4))
[4]: %timeit polynomial matrix(x, powers) # pure Python version takes 33 us
     377 ns \pm 3.91 ns per loop (mean \pm std. dev. of 7 runs, 1000000 loops each)
```



Easy build system integration



\$ pythran -E mykernel.py -o mykernel.cpp



Isn't Cython enough?



Cython is a *great* tool

- incremental conversion / mixed mode
- great for gluing existing native code/library with Python
- good portability, no runtime requirements

However, keeping in mind our "easier to write" goal:

- still has a non-negligible learning curve
- tends to be closer to C than Python when performance matters



Then what about Numba?



Numba is a *great* tool

- Just-in-Time compilation
- GPU support
- pure Python syntax

However:

- It has more runtime dependencies
- tends to require lower-level programming for best performance



Comparing Cython, Numba & Pythran

	Cython	Numba	Pythran
Portability	++	+	++
Runtime dependency	++		++
Maturity	++	+	+
Maintenance status	0	+	+
Features	++	+	0
Ease of use		++	+
Debugging & optimization	0	+	0
Size of binaries	-	++	+

For all tools: performance excellent, bus factor is ~ 1-2



When do I use which tool?

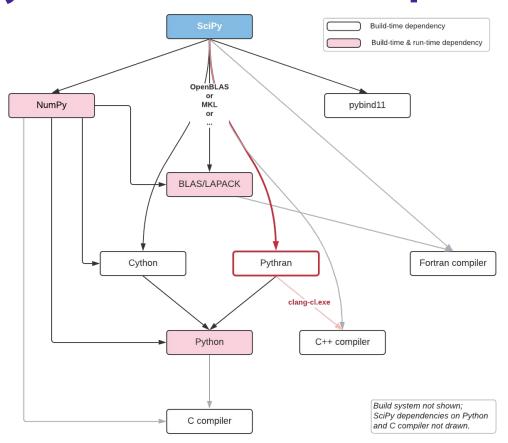


Our advice:

- For higher-level, pure Python packages: use Numba
- If you have any compiled code in your package:
 - Use Pythran for standalone kernels
 - Use Cython for binding C/C++ code, and in case you need to interact with the Python or NumPy C API



SciPy build/run-time dependencies





Current Pythran usage in SciPy



One large extension: RBFInterpolator

Several smaller extensions:

```
$ git grep -l '#pythran'
scipy/optimize/_group_columns.py
scipy/signal/_max_len_seq_inner.py
scipy/signal/_spectral.py
scipy/stats/_hypotests_pythran.py
```

More PRs in progress



GSoC student - Xingyu Liu



Xingyu is going through SciPy's code base, looking for kernels to benchmark and accelerate:

- stats.binned_statistic_dd: 2-30x speedup
- stats.somersd: 4-20x speedup
- spatial.SphericalVoronoi.sort_vertices_of_regions: 3x speedup

With more to come; read the blog of her journey at https://blogs.python-gsoc.org/en/xingyu-lius-blog/



Benefits for SciPy



Key benefit: easiest way to write fast kernels

- Developer experience about as good as with Numba, accessible to almost every contributor
- It's fast typically >= Cython, even without SIMD
- Produced binaries are much smaller than those from Cython
- Pythran itself is easy to contribute to, and has a responsive maintainer
- Build system integration is easy(-ish)



Pythran limitations



There are still gaps in functionality, not all of NumPy is covered:

- numpy.random
- APIs with too much "dynamic behaviour" (e.g., keepdims keyword)
- There is no escape hatch if it's not supported, it must be added to Pythran itself first
- No threading in SciPy. Pythran can use OpenMP, but this is forbidden in SciPy (only custom thread pools allowed).
- Extra constraint on Windows: must build with clang-cl



Integration status



Currently Pythran is:

- enabled by default in the SciPy build
- Still an optional dependency (to disable: export SCIPY_USE_PYTHRAN=0)

Lessons from the recent SciPy 1.7.0 release:

- A small portability issue on AIX (already resolved)
- Status with PyPy unclear (PyPy + SciPy has other issues, so can't test)
- Other than that, mostly smooth sailing

Initial integration required two Pythran releases to fix some build issues



Conclusions



- SciPy contributors like Pythran! "This is very elegant", "Surprised it's that fast"
- Initial goal achieved! Pythran is indeed an easier way to write fast kernels
- The journey continues! Pythran will likely become a hard build-time dependency for or after SciPy 1.8.0

Bonus question: can we combine Pythran with CuPy's Python-to-CUDA JIT? It emits C++ code too, so we could get fast CPU + GPU code like that.