

# Rare-event simulation: High-performance Python

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Import relevant libraries

```
[1]: # numpy is the 'Numerical Python' package
import numpy as np

# Numpy's methods for pseudorandom number generation
import numpy.random as rnd

# For plotting
import matplotlib.pyplot as plt

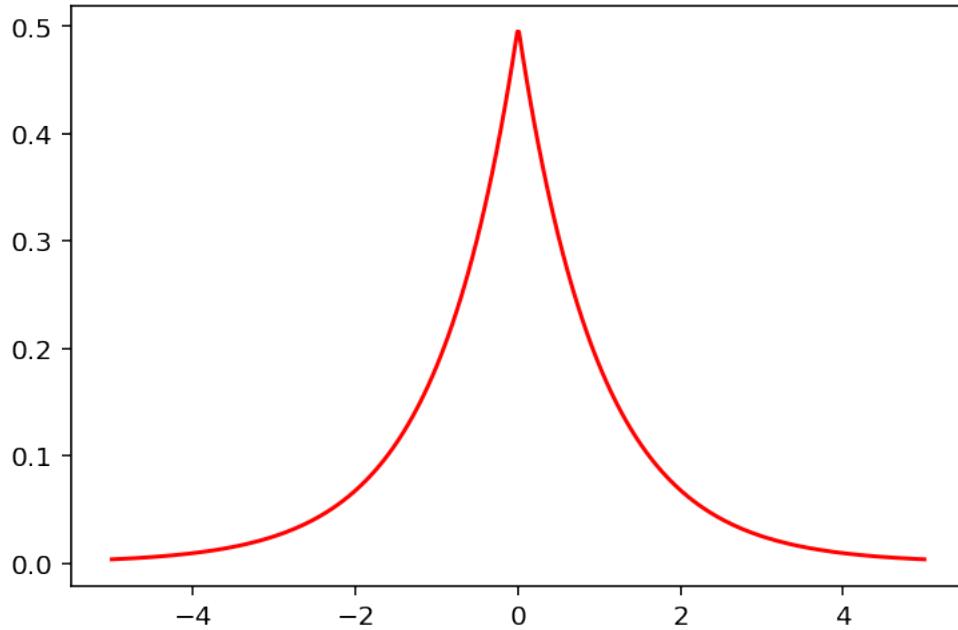
# scipy is the 'Scientific Python' package
# We'll use the stats package to get some p.d.f.s.
from scipy import stats

%config InlineBackend.figure_format = 'retina'
```

## 1 Sampling a Laplace distribution with MCMC

$$X \sim \text{Laplace}(\mu, \lambda) \quad \Rightarrow \quad f_X(x) = \frac{1}{2\lambda} \exp\left\{-\frac{|x - \mu|}{\lambda}\right\}.$$

```
[2]: xs = np.linspace(-5,5, 500)
plt.plot(xs, stats.laplace.pdf(xs), 'r');
```



```
[3]: def sample(R):
    rng = rnd.default_rng(1)

    π = stats.laplace.pdf

    X = np.empty(R)
    X[0] = 0

    for n in range(1, R):
        Y = X[n-1] + rng.normal()

        α = π(Y) / π(X[n-1])

        if rng.uniform() < α:
            X[n] = Y
        else:
            X[n] = X[n-1]

    return X
```

## 1.1 Measure the problem

Before timing any code, put turn off battery saver modes.

```
[4]: %time X = sample(10**2)
```

```
Wall time: 26.5 ms
```

```
[5]: 26.5 / 1000 * 100
```

```
[5]: 2.65
```

```
[6]: %time X = sample(10**4)
```

```
Wall time: 1.68 s
```

```
[7]: 1.68 * 100 / 60
```

```
[7]: 2.8
```

```
[8]: %timeit X = sample(1)
```

```
29.4 µs ± 727 ns per loop (mean ± std. dev. of 7 runs, 10000 loops each)
```

```
[9]: %load_ext line_profiler
```

```
[10]: %lprun -f sample sample(10**4)
```

```
Timer unit: 1e-07 s
```

```
Total time: 2.88904 s
```

```
File: <ipython-input-3-0ab92f3542ac>
```

```
Function: sample at line 1
```

Line #	Hits	Time	Per Hit	% Time	Line Contents
<hr/>					
1					def sample(R):
2	1	1618.0	1618.0	0.0	rng = rnd.default_rng(1)
3					
4	1	30.0	30.0	0.0	π = stats.laplace.pdf
5					
6	1	66.0	66.0	0.0	X = np.empty(R)
7	1	15.0	15.0	0.0	X[0] = 0
8					
9	10000	42983.0	4.3	0.1	for n in range(1, R):
10	9999	406224.0	40.6	1.4	Y = X[n-1] + rng.normal()
11					
12	9999	27920074.0	2792.3	96.6	α = π(Y) / π(X[n-1])
13					
14	9999	440077.0	44.0	1.5	if rng.uniform() < α:
15	7043	48084.0	6.8	0.2	X[n] = Y
16					else:
17	2956	31274.0	10.6	0.1	X[n] = X[n-1]
18					

```
19      1      3.0      3.0      0.0      return X
```

```
[11]: %lprun -f stats.laplace.pdf sample(10**4)
```

```
Timer unit: 1e-07 s
```

```
Total time: 2.79672 s
```

```
File: C:\Users\patri\Anaconda3\lib\site-packages\scipy\stats\_distn_infrastructure.py
Function: pdf at line 1714
```

Line #	Hits	Time	Per Hit	% Time	Line Contents
1714					def pdf(self, x, *args, **kwds):
1715					"""
1716					Probability density function at x
1717					
1718					Parameters
1719					-----
1720					x : array_like
1721					quantiles
1722					arg1, arg2, arg3,... : array_like
1723					The shape parameter(s) for the
1724					instance object for more info
1725					loc : array_like, optional
1726					location parameter (default=0)
1727					scale : array_like, optional
1728					scale parameter (default=1)
1729					
1730					Returns
1731					-----
1732					pdf : ndarray
1733					Probability density function
1734					
1735					"""
1736	19998	244063.0	12.2	0.9	args, loc, scale = self._parse_ar
1737	19998	805908.0	40.3	2.9	x, loc, scale = map(asarray, (x,
1738	19998	199397.0	10.0	0.7	args = tuple(map(asarray, args))
1739	19998	6459118.0	323.0	23.1	dtyp = np.find_common_type([x.dty
1740	19998	881695.0	44.1	3.2	x = np.asarray((x - loc)/scale, d
1741	19998	1069852.0	53.5	3.8	cond0 = self._argcheck(*args) &
1742	19998	1017517.0	50.9	3.6	cond1 = self._support_mask(x, *ar
1743	19998	580429.0	29.0	2.1	cond = cond0 & cond1
1744	19998	715135.0	35.8	2.6	output = zeros(shape(cond), dtyp)
1745	19998	1573239.0	78.7	5.6	putmask(output, (1-cond0)+np.isnan
1746	19998	2280964.0	114.1	8.2	if np.any(cond):
1747	19998	9581439.0	479.1	34.3	goodargs = argsreduce(cond, *
1748	19998	215533.0	10.8	0.8	scale, goodargs = goodargs[1-

```
1749      19998    2063593.0    103.2     7.4          place(output, cond, self._pdf
1750      19998    141475.0     7.1      0.5
1751      19998    137848.0     6.9      0.5
1752
```

```
        if output.ndim == 0:
            return output[()]
        return output
```

```
[12]: %load_ext heat
```

```
[13]: %%heat
```

```
import numpy as np
import numpy.random as rnd
from scipy import stats

rng = rnd.default_rng(1)
R = 10**4

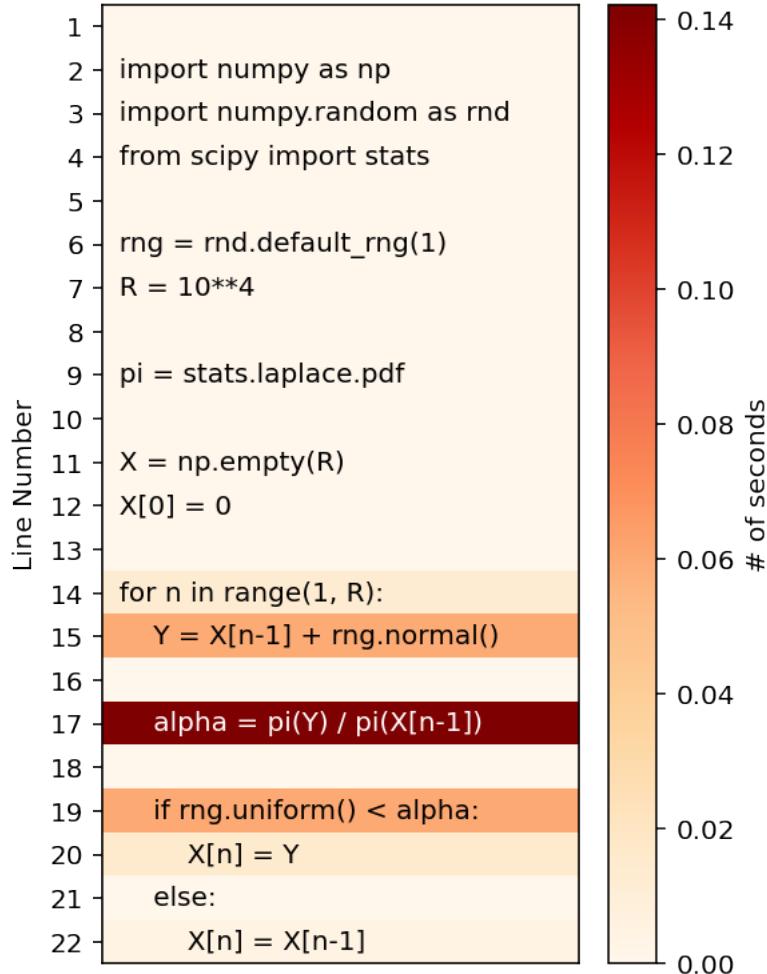
pi = stats.laplace.pdf

X = np.empty(R)
X[0] = 0

for n in range(1, R):
    Y = X[n-1] + rng.normal()

    alpha = pi(Y) / pi(X[n-1])

    if rng.uniform() < alpha:
        X[n] = Y
    else:
        X[n] = X[n-1]
```



```
[14]: %load_ext snakeviz
```

```
[15]: %snakeviz X = sample(10**4)
```

```
*** Profile stats marshalled to file
'C:\\\\Users\\\\patri\\\\AppData\\\\Local\\\\Temp\\\\tmpn9il9v6r'.
Embedding SnakeViz in this document...
<IPython.core.display.HTML object>
```

## 1.2 Check improvements one-by-one

Replace built-in Laplace p.d.f. with a version we have made.

```
[16]: xs = np.linspace(-5, 5, 11)
old = stats.laplace.pdf(xs)
new = np.exp(-np.abs(xs))/2
old - new
```

```
[16]: array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.])
```

```
[17]: xs = np.linspace(-5, 5, 10**5)
%timeit stats.laplace.pdf(xs)
%timeit np.exp(-np.abs(xs)) # Don't need normalising constant
```

5.58 ms ± 315 µs per loop (mean ± std. dev. of 7 runs, 100 loops each)  
1.2 ms ± 35 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)

```
[18]: 5.58 / 1.2
```

```
[18]: 4.65
```

```
[19]: xs = np.linspace(-5, 5, 10**5)
%timeit [stats.laplace.pdf(x) for x in xs]
%timeit [np.exp(-np.abs(x)) for x in xs]
```

7.37 s ± 211 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)  
233 ms ± 1.83 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

```
[20]: 7.37 / 0.233
```

```
[20]: 31.630901287553648
```

```
[21]: samplePrev = sample
```

```
[22]: def sample(R):
    rng = rnd.default_rng(1)

    π = lambda x: np.exp(-np.abs(x))

    X = np.empty(R)
    X[0] = 0

    for n in range(1, R):
        Y = X[n-1] + rng.normal()

        α = π(Y) / π(X[n-1])

        if rng.uniform() < α:
            X[n] = Y
        else:
```

```
X[n] = X[n-1]
```

```
return X
```

```
[23]: print(samplePrev(5))
print(sample(5))
```

```
[ 0.          0.          0.          0.         -0.53695324]
[ 0.          0.          0.          0.         -0.53695324]
```

```
[24]: %time X = samplePrev(10**5)
%time X = sample(10**5)
```

```
Wall time: 16.3 s
Wall time: 987 ms
```

```
[25]: 16.3 / 0.987
```

```
[25]: 16.51469098277609
```

```
[26]: %lprun -f sample sample(10**5)
```

```
Timer unit: 1e-07 s
```

```
Total time: 1.38244 s
File: <ipython-input-22-2f3c9d85c13d>
Function: sample at line 1
```

Line #	Hits	Time	Per Hit	% Time	Line Contents
<hr/>					
1					def sample(R):
2	1	1803.0	1803.0	0.0	rng = rnd.default_rng(1)
3					
4	1	10.0	10.0	0.0	π = lambda x: np.exp(-np.abs(x))
5					
6	1	160.0	160.0	0.0	X = np.empty(R)
7	1	15.0	15.0	0.0	X[0] = 0
8					
9	100000	425389.0	4.3	3.1	for n in range(1, R):
10	99999	3331726.0	33.3	24.1	Y = X[n-1] + rng.normal()
11					
12	99999	6631665.0	66.3	48.0	α = π(Y) / π(X[n-1])
13					
14	99999	2774220.0	27.7	20.1	if rng.uniform() < α:
15	70184	421547.0	6.0	3.0	X[n] = Y
16					else:
17	29815	237841.0	8.0	1.7	X[n] = X[n-1]
18					

```
19          1          3.0        3.0        0.0      return X
```

Let's try vectorising the random number generation

```
[27]: samplePrev = sample
```

```
[28]: def sample(R):
    rng = rnd.default_rng(1)

    π = lambda x: np.exp(-np.abs(x))

    X = np.empty(R)
    X[0] = 0

    jumps = rng.normal(size=R-1)
    uniforms = rng.uniform(size=R-1)

    for n in range(1, R):
        Y = X[n-1] + jumps[n-1]

        α = π(Y) / π(X[n-1])

        if uniforms[n-1] < α:
            X[n] = Y
        else:
            X[n] = X[n-1]

    return X
```

```
[29]: print(samplePrev(5))
print(sample(5))
```

```
[ 0.          0.          0.          0.         -0.53695324]
[ 0.          0.34558419  1.16720234  1.16720234 -0.1359549 ]
```

```
[30]: %time X = samplePrev(10**6)
%time X = sample(10**6)
```

```
Wall time: 9.98 s
Wall time: 6.14 s
```

```
[31]: 9.98 / 6.14
```

```
[31]: 1.6254071661237786
```

```
[32]: %lprun -f sample sample(10**6)
```

```
Timer unit: 1e-07 s
```

```

Total time: 9.0506 s
File: <ipython-input-28-f0fc8c08d600>
Function: sample at line 1

Line #      Hits          Time  Per Hit   % Time  Line Contents
=====
1           1           1906.0    1906.0     0.0    def sample(R):
2           1           21.0      21.0      0.0      rng = rnd.default_rng(1)
3
4           1           406.0     406.0     0.0      π = lambda x: np.exp(-np.abs(x))
5
6           1           21.0      21.0      0.0      X = np.empty(R)
7           1           0.0       0.0       0.0      X[0] = 0
8
9           1           224605.0   224605.0    0.2      jumps = rng.normal(size=R-1)
10          1           109040.0   109040.0    0.1      uniforms = rng.uniform(size=R-1)
11
12          1000000     4178819.0   4.2       4.6      for n in range(1, R):
13         999999      9092839.0   9.1      10.0      Y = X[n-1] + jumps[n-1]
14
15         999999      64142919.0  64.1     70.9      α = π(Y) / π(X[n-1])
16
17         999999      6992107.0   7.0       7.7      if uniforms[n-1] < α:
18         700380      3681116.0   5.3       4.1      X[n] = Y
19
20         299619      2082243.0   6.9       2.3      else:
21
22           1           3.0       3.0       0.0      X[n] = X[n-1]
23
24           1           0.0       0.0       0.0      return X

```

Let's try getting rid of the exponential in the p.d.f.

[33]: samplePrev = sample

[34]:

```

def sample(R):
    rng = rnd.default_rng(1)

    logπ = lambda x: -np.abs(x)

    X = np.empty(R)
    X[0] = 0

    jumps = rng.normal(size=R-1)
    exponentials = np.log(rng.uniform(size=R-1)) # Seems faster than rng.
    ↵exponential

    for n in range(1, R):

```

```

Y = X[n-1] + jumps[n-1]

logα = logπ(Y) - logπ(X[n-1])

if exponentials[n-1] < logα:
    X[n] = Y
else:
    X[n] = X[n-1]

return X

```

[35]: `print(samplePrev(5))  
print(sample(5))`

```
[ 0.          0.34558419  1.16720234  1.16720234 -0.1359549 ]
[ 0.          0.34558419  1.16720234  1.16720234 -0.1359549 ]
```

[36]: `%time X = samplePrev(10**6)  
%time X = sample(10**6)`

```
Wall time: 6.06 s
Wall time: 3.5 s
```

[37]: `6.06 / 3.5`

[37]: `1.7314285714285713`

### 1.3 Sample from a truncated Laplace distribution

[38]: `def sample(R):
 rng = rnd.default_rng(1)

 π = lambda x: (x > -1) * (x < 1) * np.exp(-np.abs(x))

 X = np.empty(R)
 X[0] = 0

 jumps = rng.normal(size=R-1)
 uniforms = rng.uniform(size=R-1)

 for n in range(1, R):
 Y = X[n-1] + jumps[n-1]

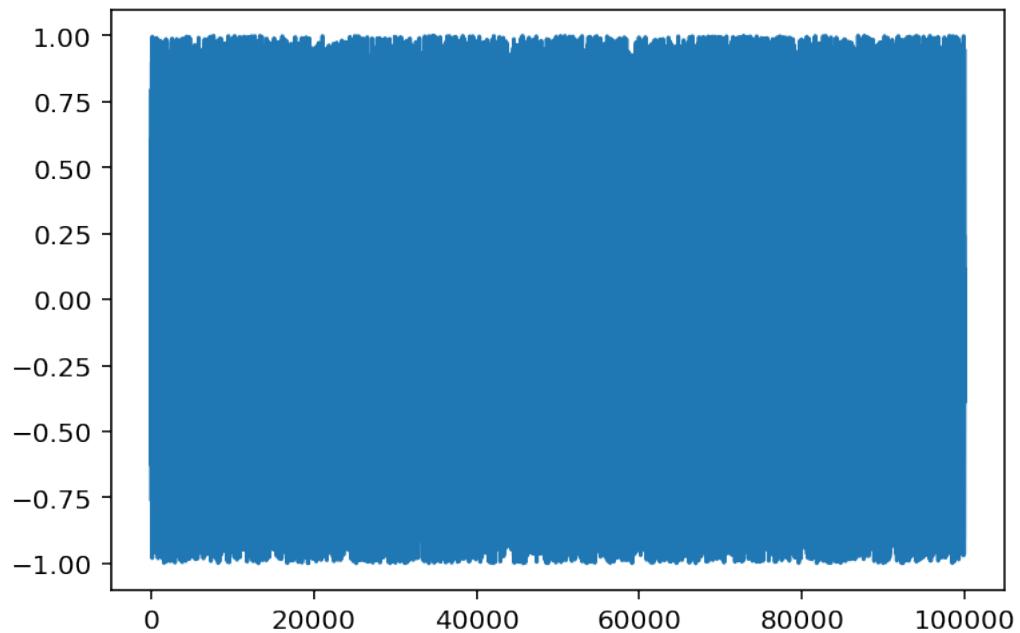
 α = π(Y) / π(X[n-1])

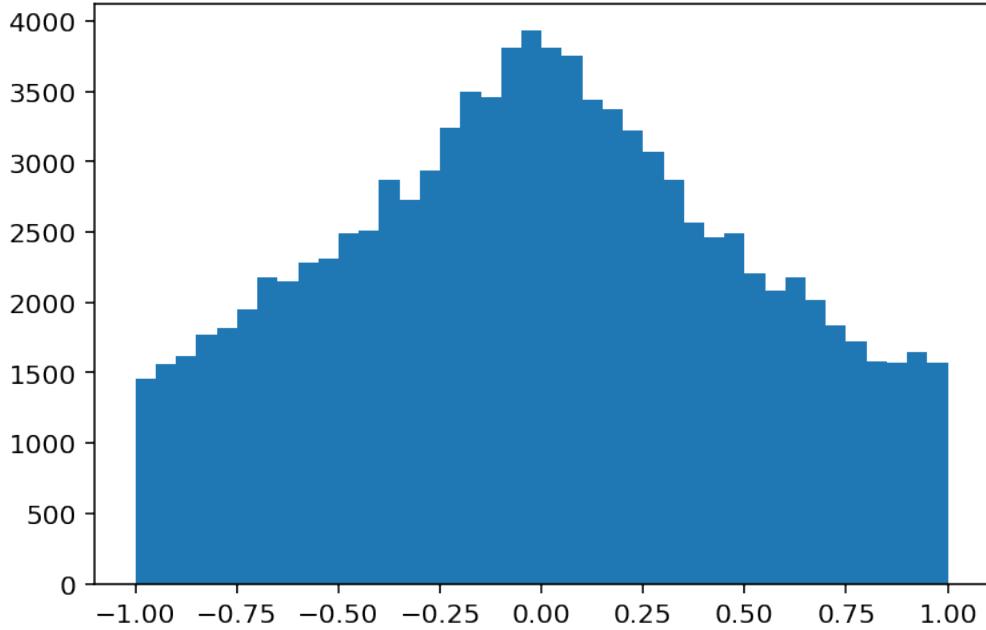
 if uniforms[n-1] < α:
 X[n] = Y`

```
    else:  
        X[n] = X[n-1]  
  
    return X
```

```
[39]: %time X = sample(10**5)  
  
plt.plot(X)  
plt.show()  
  
plt.hist(X, 40);
```

Wall time: 1.45 s





```
[40]: np.mean(np.diff(X) == 0)
```

```
[40]: 0.4680446804468045
```

```
[41]: samplePrev = sample
```

```
[42]: def sample(R):
    rng = rnd.default_rng(1)

    piUn = lambda x: np.exp(-np.abs(x))

    X = np.empty(R)
    X[0] = 0

    jumps = rng.normal(size=R-1)
    uniforms = rng.uniform(size=R-1)

    for n in range(1, R):
        Y = X[n-1] + jumps[n-1]

        # Check the constraint first
        if Y <= -1 or Y >= 1:
            X[n] = X[n-1]
            continue

        # Then, if a valid proposal,
```

```

# calculate the acceptance prob.
α = πUn(Y) / πUn(X[n-1])

if uniforms[n-1] < α:
    X[n] = Y
else:
    X[n] = X[n-1]

return X

```

[43]: `print(samplePrev(5))  
print(sample(5))`

```
[ 0.          0.34558419  0.34558419  0.34558419 -0.95757304]  
[ 0.          0.34558419  0.34558419  0.34558419 -0.95757304]
```

[44]: `%time X = samplePrev(10**6)  
%time X = sample(10**6)`

```
Wall time: 14.6 s  
Wall time: 4.11 s
```

[45]: `14.6 / 4.11`

[45]: `3.552311435523114`

## 1.4 Try compiling the algorithm with numba

[46]: `from numba import njit`

[47]: `samplePrev = sample`

```

@njit
def sample(R):
    rng = rnd.default_rng(1)

    πUn = lambda x: np.exp(-np.abs(x))

    X = np.empty(R)
    X[0] = 0

    jumps = rng.normal(size=R-1)
    uniforms = rng.uniform(size=R-1)

    for n in range(1, R):
        Y = X[n-1] + jumps[n-1]

```

```

# Check the constraint first
if Y <= -1 or Y >= 1:
    X[n] = X[n-1]
    continue

# Then, if a valid proposal,
# calculate the acceptance prob.
α = πUn(Y) / πUn(X[n-1])

if uniforms[n-1] < α:
    X[n] = Y
else:
    X[n] = X[n-1]

return X

```

[49]: sample(5)

```

█
↳-----

TypingError                                     Traceback (most recent call █)
↳last()

    <ipython-input-49-dfc5eee7c6c4> in <module>
----> 1 sample(5)

    ~\Anaconda3\lib\site-packages\numba\dispatcher.py in █
↳_compile_for_args(self, *args, **kws)
    399             e.patch_message(msg)
    400
--> 401         error_rewrite(e, 'typing')
    402     except errors.UnsupportedError as e:
    403         # Something unsupported is present in the user code,█
↳add help info

    ~\Anaconda3\lib\site-packages\numba\dispatcher.py in error_rewrite(e, █
↳issue_type)
    342             raise e
    343         else:
--> 344             reraise(type(e), e, None)
    345
    346     argtypes = []

```

```

~\Anaconda3\lib\site-packages\numba\six.py in reraise(tp, value, tb)
666         value = tp()
667     if value.__traceback__ is not tb:
--> 668         raise value.with_traceback(tb)
669     raise value
670

TypingError: Failed in numpy mode pipeline (step: numpy
↳ frontend)
    Unknown attribute 'default_rng' of type Module(<module 'numpy.random'>
↳ from 'C:
↳ \\\Users\\\patri\\\Anaconda3\\\lib\\\site-packages\\\numpy\\\random\\\__init__.
↳ py'>)

File "<ipython-input-48-bced36de9aed>", line 3:
def sample(R):
    rng = rnd.default_rng(1)
    ^

```

[1] During: typing of get attribute at <ipython-input-48-bced36de9aed> (3)

```

File "<ipython-input-48-bced36de9aed>", line 3:
def sample(R):
    rng = rnd.default_rng(1)
    ^

```

```

[50]: def sample(R):
        rng = rnd.default_rng(1)

        X = np.empty(R)
        X[0] = 0

        jumps = rng.normal(size=R-1)
        uniforms = rng.uniform(size=R-1)

        sample_jit(X, jumps, uniforms)

        return X

@njit
def sample_jit(X, jumps, uniforms):
    R = len(X)

```

```

πUn = lambda x: np.exp(-np.abs(x))

for n in range(1, R):
    Y = X[n-1] + jumps[n-1]

    # Check the constraint first
    if Y <= -1 or Y >= 1:
        X[n] = X[n-1]
        continue

    # Then, if a valid proposal,
    # calculate the acceptance prob.
    α = πUn(Y) / πUn(X[n-1])

    if uniforms[n-1] < α:
        X[n] = Y
    else:
        X[n] = X[n-1]

```

[51]: %time X = sample(10\*\*6)  
%time X = sample(10\*\*6)

Wall time: 242 ms  
Wall time: 41 ms

[52]: print(samplePrev(5))  
print(sample(5))

```
[ 0.          0.34558419  0.34558419  0.34558419 -0.95757304]
[ 0.          0.34558419  0.34558419  0.34558419 -0.95757304]
```

[53]: %time X = samplePrev(10\*\*6)  
%time X = sample(10\*\*6)

Wall time: 4.67 s  
Wall time: 41.9 ms

[54]: 4.67 / 0.0419

[54]: 111.45584725536993

[55]: from numba import int64, float64

[56]: samplePrev = sample

[57]: @njit(float64[:,](int64))
def sample(R):

```

rnd.seed(123)
X = np.empty(R)
X[0] = 0
for n in range(1, R):
    Y = X[n-1] + rnd.normal(0, 1)

    α = (Y > -1) * (Y < 1) * np.exp(-np.abs(Y)+np.abs(X[n-1]))

    if rnd.uniform(0, 1) < α:
        X[n] = Y
    else:
        X[n] = X[n-1]

return X

```

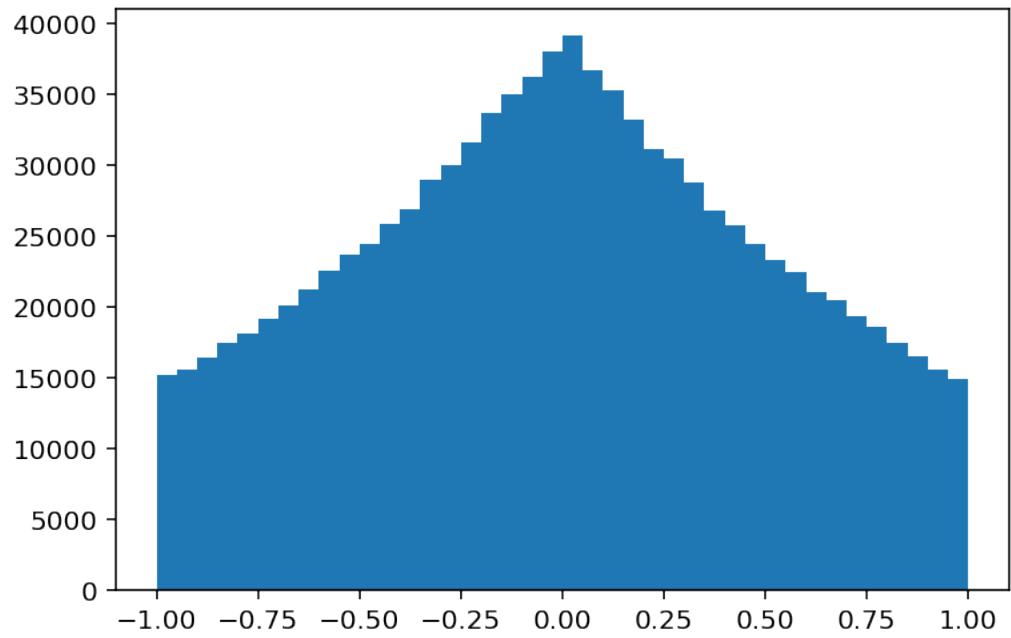
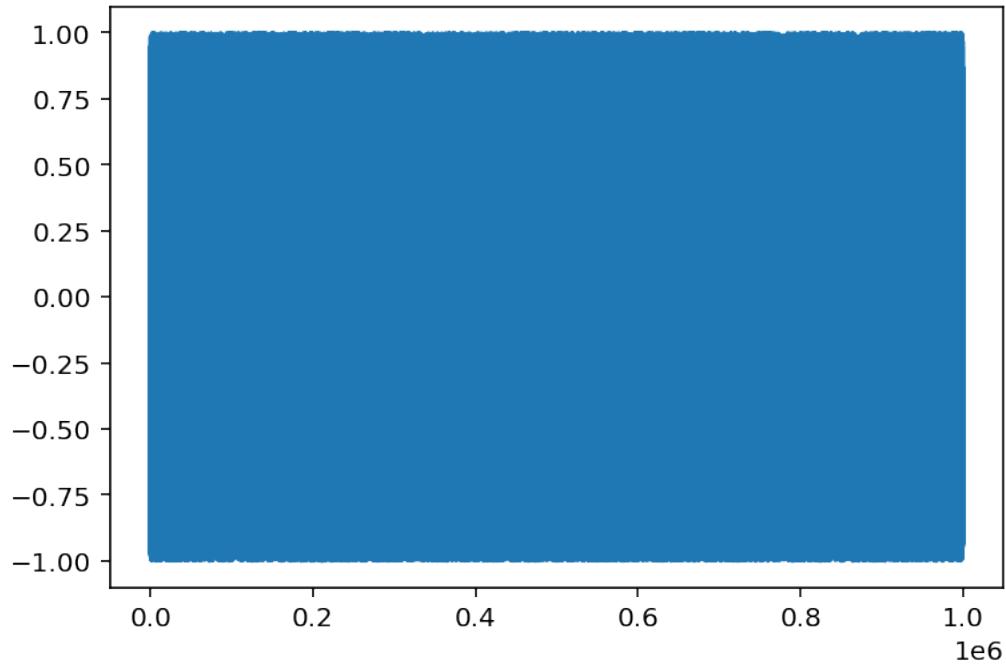
[58]: %time X = sample(10\*\*7)  
%time X = sample(10\*\*7)

Wall time: 572 ms  
Wall time: 584 ms

[59]: %timeit X = samplePrev(10\*\*7)  
%timeit X = sample(10\*\*7)

400 ms ± 8.55 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)  
578 ms ± 31 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)

[60]: plt.plot(X[:10\*\*6])  
plt.show()  
plt.hist(X[:10\*\*6], 40);



Can get a little faster by noticing that each  $\pi$  function call is called (at least) twice with the same arguments. If the result is stored/cached, then we get faster but uglier code, so I'll stop here. Similarly, one can try to [simulate using a truncated proposal](#) so that invalid points are never proposed.

## 1.5 Keep in mind

Improvements to the algorithm and your choice of hyperparameters are often a better starting point than going down a rabbit-hole of performance optimisations!

Updating Python and its packages may give you a free small speed boost (or maybe it will slow things down). With this numpy update, I tested CMC before and after and the time went from 5m 4s down to 3m 54s.

```
[61]: from IPython.display import Image  
Image("numpy_update.png")
```

[61]:

## NumPy 1.18.2 Release Notes

This small release contains a fix for a performance regression in numpy/random and several bug/maintenance updates.

The Python versions supported in this release are 3.5-3.8. Downstream developers should use Cython >= 0.29.15 for Python 3.8 support and OpenBLAS >= 3.7 to avoid errors on the Skylake architecture.

## Contributors

A total of 5 people contributed to this release. People with a "+" by their names contributed a patch for the first time.

- Charles Harris
- Ganesh Kathiresan +
- Matti Picus
- Sebastian Berg
- przemb +

## Pull requests merged

A total of 7 pull requests were merged for this release.

- [#15675](#): TST: move \_no\_tracing to testing.\_private
- [#15676](#): MAINT: Large overhead in some random functions
- [#15677](#): TST: Do not create gfortran link in azure Mac testing.
- [#15679](#): BUG: Added missing error check in ndarray.\_\_contains\_\_
- [#15722](#): MAINT: use list-based APIs to call subprocesses