1 The Wang-Landau algorithm (density of states)

We determine thermodynamic quantities from the partition function by obtaining the density of states from a simulation.

```
import numpy as np
import matplotlib.pyplot as plt
from scipy import interpolate
```

The test system is the 2d Ising model.

```
class Ising:
        def __init__(self, n):
            self.n = n
            self.spins = np.sign(np.random.rand(n, n) - 0.5)
            self.E = self.energy()
            self.Ev = self.E
        def neighbors(self, i, j):
            return np.hstack([self.spins[:,j].take([i-1,i+1], mode='wrap'),
                              self.spins[i,:].take([j-1,j+1], mode='wrap')])
        def energy(self):
10
            return -0.5 * sum(np.sum(s * self.neighbors(i, j))
11
                             for (i, j), s in np.ndenumerate(self.spins))
12
        def propose(self):
13
            i, j = np.random.randint(self.n), np.random.randint(self.n)
            self.i, self.j = i, j
15
            dE = 2 * np.sum(self.spins[i, j] * self.neighbors(i, j))
            self.dE = dE
17
            self.Ev = self.E + dE
        def accept(self):
19
            self.spins[self.i, self.j] *= -1
            self.E = self.Ev
```

Note that this class-based approach adds some overhead. For speed, instances of Ising should be inlined into the simulation method.

A Wang-Landau algorithm, with quantities as logarithms and with montecarlo steps proportional to $f^{-1/2}$ (a "Zhou-Bhat schedule").

```
def flat(H, tol = 0.2):
    """Determines if an evenly-spaced histogram is approximately flat."""
    H\mu = np.mean(H)
    Hf = np.max(H)
    H0 = np.min(H)
    return Hf / (1 + tol) < H\mu < H0 / (1 - tol)
```

```
# def flat(H, tol = 0.2):
           """Determines if an evenly-spaced histogram is approximately flat."""
           H\mu = np.mean(H)
           return not np.any(H < (1 - tol) * H\mu) and np.all(H \neq 0)
    # Note: some parameters are hardcoded for testing
    def density_sim(system):
         randint = np.random.randint
         rand = np.random.rand
4
         exp = np.exp
         # Parameters
         M = 10_000_000 # Monte carlo step scale
         \epsilon = 1e-8
        logftol = np.log(1 + \epsilon)
10
         logf0 = 1
         N = 8**2 + 1 \# Energy bins
12
         E0 = -2 * 8**2
13
         Ef = 2 * 8**2
14
15
         \Delta E = (Ef - E\theta) / (N - 1)
16
         fiters = int(np.ceil(np.log2(logf0) - np.log2(logftol)))
17
         fiter = 0
18
         mciters = 0
19
         Es = np.linspace(E0, Ef, N)
         S = np.zeros(N) # Set all initial g's to 1
21
         H = np.zeros(N, dtype=int)
         logf = logf0
23
         # Linearly bin the energy
24
         i = max(0, min(N - 1, int(round((N - 1) * (system.E - E0) / (Ef - E0)))))
25
         print("ΔE = {}".format(ΔE))
         while logftol < logf:</pre>
27
             H[:] = 0
             logf /= 2
29
             iters = 0
30
             niters = int((M + 1) * exp(-logf / 2))
31
             fiter += 1
32
             while not flat(H[2:-2]) and iters < niters: # Ising-specific histogram</pre>
33
               while not flat(H) and iters < niters:
34
                 system.propose()
35
                 Ev = system.Ev
36
                 j = max(0, min(N - 1, int(round((N - 1) * (Ev - E0) / (Ef - E0)))))
37
                 if E0 - \Delta E/2 \le Ev \le Ef + \Delta E/2 and (S[j] < S[i] \text{ or } rand() < exp(S[i] - S[j])):
38
                      system.accept()
39
                      i = j
40
                 H[i] += 1
```

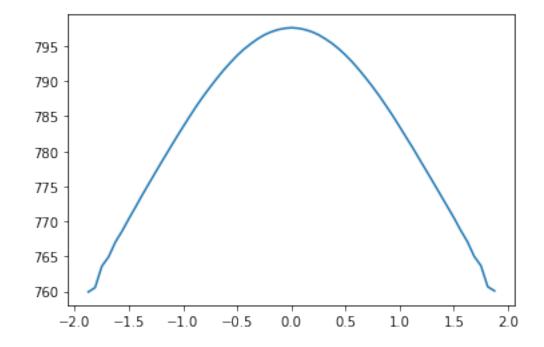
```
S[i] += logf
42
              iters += 1
43
           mciters += iters
44
           print("f: {} / {}\t({} / {})\".format(fiter, fiters, iters, niters))
45
       print("Done: {} total MC iterations.".format(mciters))
47
       return Es, S, H
   isingn = 8
   sys = Ising(isingn)
   Es, S, H = density_sim(sys);
   \Delta E = 4.0
   f: 1 / 27
                (51914 / 7788008)
   f: 2 / 27
                (23763 / 8824969)
   f: 3 / 27
                (28540 / 9394131)
   f: 4 / 27
                (29971 / 9692333)
   f: 5 / 27
                (34174 / 9844965)
   f: 6 / 27
                (47534 / 9922180)
   f: 7 / 27
                (48944 / 9961014)
   f: 8 / 27
                (107754 / 9980488)
   f: 9 / 27
                (179729 / 9990240)
   f: 10 / 27
                (187907 / 9995119)
   f: 11 / 27 (224943 / 9997559)
   f: 12 / 27 (1034768 / 9998780)
   f: 13 / 27 (244301 / 9999390)
   f: 14 / 27 (133628 / 9999695)
   f: 15 / 27 (214968 / 9999848)
   f: 16 / 27 (1293088 / 9999924)
   f: 17 / 27 (420043 / 9999962)
   f: 18 / 27 (551351 / 9999981)
   f: 19 / 27 (253547 / 9999991)
   f: 20 / 27 (394211 / 9999996)
   f: 21 / 27
                (166352 / 9999998)
   f: 22 / 27 (9999999 / 9999999)
   f: 23 / 27 (467290 / 10000000)
   f: 24 / 27 (213657 / 10000000)
   f: 25 / 27 (366069 / 10000000)
    f: 26 / 27 (563593 / 10000000)
   f: 27 / 27 (126259 / 10000000)
```

Done: 17408297 total MC iterations.

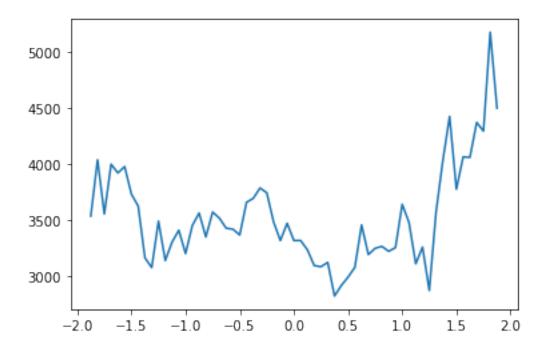
Н

```
array([4027, 0, 3534, 4035, 3553, 3996, 3918, 3975, 3729, 3624, 3162, 3075, 3489, 3138, 3301, 3408, 3200, 3450, 3561, 3348, 3570, 3515, 3426, 3417, 3365, 3656, 3692, 3784, 3741, 3482, 3316, 3470, 3316, 3316, 3233, 3093, 3083, 3121, 2822, 2915, 2990, 3077, 3455, 3191, 3247, 3264, 3220, 3253, 3639, 3477, 3109, 3258, 2871, 3571, 4028, 4422, 3773, 4061, 4057, 4368, 4291, 5172, 4495, 0, 6085])
```

plt.plot(Es[2:-2] / isingn**2, S[2:-2]);



plt.plot(Es[2:-2] / isingn**2, H[2:-2]);

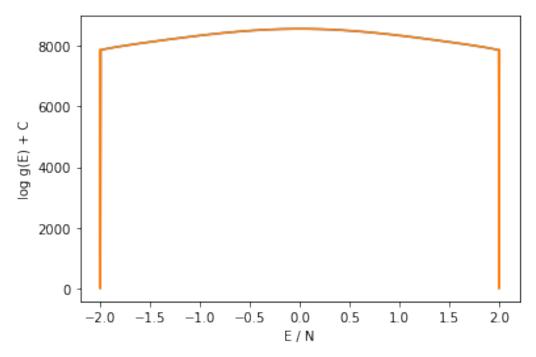


1.1 Calculating canonical ensemble averages

```
gspl = interpolate.splrep(Es, S, s=2*np.sqrt(2))
gs = np.exp(interpolate.splev(Es, gspl) - min(S))

<ipython-input-414-d6b1add1a212>:2: RuntimeWarning: overflow encountered in exp
gs = np.exp(interpolate.splev(Es, gspl) - min(S))

plt.plot(Es / isingn**2, S)
plt.plot(Es / isingn**2, interpolate.splev(Es, gspl))
plt.xlabel("E / N")
plt.ylabel("log g(E) + C");
```



Translate energies to have minimum zero so that Z is representable.

```
nEs = Es - min(Es)

Z = lambda β: np.sum(gs * np.exp(-β * nEs))

Ensemble averages

βs = [np.exp(k) for k in np.linspace(-5, 0, 200)]

Eμ = lambda β: np.sum(nEs * gs * np.exp(-β * nEs)) / Z(β)

E2 = lambda β: np.sum(nEs**2 * gs * np.exp(-β * nEs)) / Z(β)

CV = lambda β: (E2(β) - Εμ(β)**2) * β**2

F = lambda β: -np.log(Z(β)) / β

Sc = lambda β: β*Εμ(β) + np.log(Z(β))

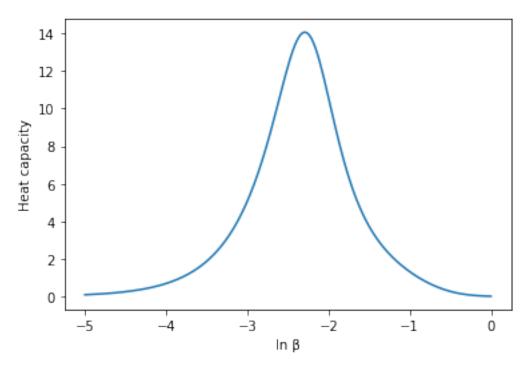
Heat capacity

plt.plot(np.log(βs), [CV(β) for β in βs])

plt.xlabel("ln β")

plt.ylabel("Heat capacity")

plt.show()
```



Entropy

```
plt.plot(np.log(\betas), [Sc(\beta) for \beta in \betas]) plt.xlabel("ln \beta")
```

- plt.ylabel(" $S(\beta) + C$ ")
- plt.show()

