### Lecture11

March 7, 2019

# 1 Lecture 11: Simple Random Systems

# take steps

**Overview:** \* Random walk in 1D. \* Random walk in 2D and entropy. **Next Lecture:** \* Intro to Monte Carlo, integrating functions in high dimensions. —

#### 1.1 Tasks

- Modify randwalk() to use purely numpy arrays i.e. remove the loop over nsamples. What sort
  of performance gain do you achieve with this? Hint: np.random.randint() can generate array's
  of arbitrary shape.
- Modify randwalk() to take random step sizes between 0 and 1. Does the slope of  $\langle x^2 \rangle$  vs n change?

```
In [1]: %matplotlib notebook
        import numpy as np
        import matplotlib.pyplot as plt
        # we will use numba again
        from numba import jit
        import matplotlib.cm as cm
In [2]: def randwalk(nsteps = 100, nsamples = 1000):
            nsteps = int(nsteps)
            nsamples = int(nsamples)
            rms = np.zeros(nsteps)
            trajectories = np.zeros([nsamples, nsteps])
            for ii in range(nsamples):
                # draw a random integer between -1 and 1 for each step, and scale to -0.5 - 0.
                # exclude first point, because we want to start at 0
                x0 = 2*np.random.randint(0,1+1, nsteps-1) -1
                # always start at 0
                x0 = np.insert(x0,0,0,axis= 0)
```

```
traj = np.cumsum(x0)

# update trajectories array and displacement squared array
trajectories[ii,:] = traj
rms+=traj**2

trajectories = np.array(trajectories)
return rms/nsamples, trajectories
```

 Once you have created a randwalk method using only numpy array methods and no for loops, use the %%timeit function in the cell below to benchmark any performance enhancement.

```
In [16]: %%timeit
                    # run some timing routines on the current cell, only uncomment for testing
        nsteps = 500
         nsamples = 2e4
         rms, trajectories = randwalk(nsteps, nsamples)
630 ms ś 33.7 ms per loop (mean ś std. dev. of 7 runs, 1 loop each)
In [4]: fig = plt.figure()
        ax = fig.add_subplot(111)
        # plot every 20th trajectory, so the plot is not too crowded
        for ii in np.arange(0,len(rms),20):
            ax.plot(trajectories[ii,:],'.-')
        # put a horizontal line at y=0
        ax.hlines(0,0,1.1*nsteps, linestyles = 'dashed', zorder = 10) #zorder sets the layer o
        ax.set_xlim([0,nsteps])
        ax.set_xlabel('Step number', fontsize =14)
        ax.set_ylabel('$x$', fontsize = 14)
<IPython.core.display.Javascript object>
<IPython.core.display.HTML object>
Out[4]: Text(0, 0.5, '$x$')
```

## 1.1.1 Examine the statistics: mean = $\langle x \rangle$ and variance = $\langle x^2 \rangle$

Below I have set up the a figure with two axes.

- On the first axis ax1 plot the mean trajectory.
- On the second axis ax2 plot the root mean squared (rms) trajectory.

• Find the slope of the rms trajectory by eye.

```
In [20]: fig = plt.figure(figsize = (8,4))
         ax1 = fig.add_subplot(121)
         ax2 = fig.add_subplot(122)
         # function to make a straight line
         # lambda is a special constructor to create functions on the fly
         linear = lambda D, x : 2*D*x
         # the above could also be written as
         # def linear(D,x):
         # return 2*D*x
         steps = np.arange(len(rms))
         # First plot
         ax1.plot(steps, np.mean(trajectories, axis =0))
         ax1.set_ylim([-0.25,0.25])
         ax1.set_xlabel('Step number', fontsize =14)
         ax1.set_ylabel('$<x>$', fontsize = 14)
         # second plot
         ax2.plot(steps, rms, 'o')
         ax2.set_xlabel('Step number', fontsize =14)
         ax2.set_ylabel('$<x^2>$', fontsize = 14)
         fig.subplots_adjust(left = 0.12, right = 0.96, bottom = 0.14, top = 0.86, wspace = 0.45,
         plt.show()
<IPython.core.display.Javascript object>
<IPython.core.display.HTML object>
```

### 1.1.2 Examine the probability distributions for 1D random walk

```
In [9]: # let's look at the distribution of x for 3 different timepoints
# define a Gaussin function for plotting, use the lambda constructor again
Gaussian = lambda Dt, x : 1/np.sqrt(4*np.pi*Dt)*np.exp(-x**2/(4*Dt))
```

```
fig = plt.figure()
        ax = fig.add_subplot(111)
        # plot P(x) for three differnt timepoints
        for ts in [50,100,200]:
           Dt = 0.5*ts
            # P(x) is obtained from the histogram over all trajectories at a fixed time point
           n, bins = np.histogram(trajectories[:,ts], bins = 'auto', density = True)
            # histogram returns bin edges, need to extract bin centers for plotting purposes
            bin_center = np.diff(bins)+bins[:-1]
            sf = np.max(n)*np.sqrt(4*np.pi*Dt) # correct scaling for histogram normalization
            # make a bar chart
            ax.bar(bin_center,n)
            # also plot points
            # assign the plot object to a variable so we can 'grab' its color
            points, = ax.plot(bin_center,n ,'o', mfc = 'white', label = 't = {} steps'.format(
            # plot exact Gaussian with sigma = sqrt(2Dt)
            ax.plot(bin_center, sf*Gaussian(Dt, bin_center), lw = 2, color = points.get_color(
        ax.set_ylabel('Probablity')
        ax.set_xlabel('x')
        ax.legend()
       plt.show()
<IPython.core.display.Javascript object>
<IPython.core.display.HTML object>
```

#### 1.2 Random walk in Two-Dimensions

- using numba jit to speed up critical components, there are many loops and simple conditionals here, numba can result in a significant speed up.
- try commenting out the jit decorator around step\_2d and see how fast the code runs.

```
In [10]: @jit(nopython=True)
    def step_2d():
        # step for random walk on 2D square lattice
        d = np.random.randint(1,5)
        if d == 1:
```

```
x_s, y_s = 1, 0
                                   if d == 2:
                                             x_s, y_s = 0, 1
                                   if d == 3:
                                             x_s, y_s = -1, 0
                                   if d == 4:
                                              x_s, y_s = 0, -1
                                   return [x_s, y_s]
                        @jit(nopython=True)
                        def randwalk_2d(nsteps, wall = 1e6):
                                 # trajectory for a single 2D random walk
                                   x = np.zeros(nsteps+1, np.double)
                                   y = np.zeros(nsteps+1, np.double)
                                   for i in range(nsteps):
                                              s = step_2d()
                                              x[i+1] = x[i] + s[0]
                                              if abs(x[i+1]) > wall: x[i+1] = x[i]
                                              y[i+1] = y[i] + s[1]
                                              if abs(y[i+1]) > wall: y[i+1] = y[i]
                                   return x, y
                        @jit(nopython=True)
                        def ensemble_2d(N,t_max, wall = 1e6):
                                    #generate an ensemble or random walkers
                                   xh = np.zeros(N, np.double)
                                   yh = np.zeros(N, np.double)
                                   for i in range(N):
                                              x, y = randwalk_2d(t_max, wall)
                                              xh[i] = x[-1]
                                              yh[i] = y[-1]
                                   return xh, yh
In [11]: x,y = randwalk_2d(100, wall = 8)
                        fig = plt.figure()
                        ax = fig.add_subplot(111)
                        colormap = cm.Reds
                        #ax.scatter(x, y, c=np.arange(101), cmap='Reds')
                        ax.plot(x,y, marker = 'o', ls = 'None', mfc = 'w', mec = 'k')
                        ax.plot(x[0],y[0], marker = 'o', ls = 'None', mfc = 'None', mew = 2, mec = 'darkblue',
                        ax.plot(x[-1],y[-1], marker = 'o', ls = 'None', mfc = 'None', mec = 'r', mew = 2, ms = 2, ms = 2, ms = 3, ms
                        ax.quiver(x[:-1],y[:-1], x[1:]-x[:-1], y[1:]-y[:-1], np.arange(101), cmap = 'Blues',
```

```
ax.axis('equal')
         \#ax.set\_xlim([-8,8])
         \#ax.set\_ylim([-8,8])
         ax.set xlabel('x')
         ax.set_ylabel('y')
         ax.set_title('Radom walk on 2D square lattice')
<IPython.core.display.Javascript object>
<IPython.core.display.HTML object>
Out[11]: Text(0.5, 1.0, 'Radom walk on 2D square lattice')
1.2.1 Generate an ensemble of 2D walkers and coarse-grain to calculate entropy
In [22]: S = []
         ts = np.arange(10,5000,100)
         # create coarse grained grid for calculating Probabilities
         bin_edge = np.arange(-100,110,10)
         # loop over different max times
         for t in ts:
             xh, yh = ensemble_2d(N = 500, t_max = t, wall = 200)
             # h is counts/bin/total/Area, multiply h by bin area to get a probability
             h, x_edges, y_edges = np.histogram2d(xh,yh, bins = [bin_edge, bin_edge], normed =
             # calculate entropy, taking care of log(0) with a small number
             S.append(-1*np.sum(100*h*np.log(100*h+1e-40)))
In [23]: fig = plt.figure()
         ax = fig.add_subplot(111)
         ax.plot(ts,S, lw = 2)
         ax.set_xlabel('time step')
         ax.set_ylabel('Entropy')
         ax.set_title("Entropy in 2D square lattice")
<IPython.core.display.Javascript object>
<IPython.core.display.HTML object>
Out[23]: Text(0.5, 1.0, 'Entropy in 2D square lattice')
In [24]: # Check that we have a proper probability, should be 1
         np.sum(h)*100
Out[24]: 1.0000000000000000000002
In []:
```

scale = 1, units = 'xy', scale\_units = 'xy', width = 0.075, headwidth = 4)