

Try to implement the functions in fsmc_code.py and complete lines with "###"

```
In [1]: 1 import numpy as np
        2 import nbconvert
        3 import matplotlib.pyplot as plt
        4 import matplotlib as mpl
        5 mpl.rcParams['text.usetex'] = True
        6 mpl.rcParams['text.latex.preamble'] = [r'\usepackage{amsfonts}']
        7 %matplotlib inline
```

executed in 763ms, finished 13:40:05 2019-10-21

▼ 1 Exercise 2.1

What is the distribution of the number of fair coin tosses before one observes 3 heads in a row? To solve this, consider a 4-state Markov chain with transition probability matrix

$$P = \begin{bmatrix} 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0 & 0.5 & 0 \\ 0.5 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

where $X_t = 1$ if the previous toss was tails, $X_t = 2$ if the last two tosses were tails then heads, $X_t = 3$ if the last three tosses were tails then heads twice, and $X_t = 4$ is an absorbing state that is reached when the last three tosses are heads.

- Write a computer program (e.g., in Python) to compute $\Pr(T_{1,4} = m)$ for $m = 1, 2, \dots, 100$ and use this to estimate expected number of tosses $\mathbb{E}[T_{1,4}]$.



```

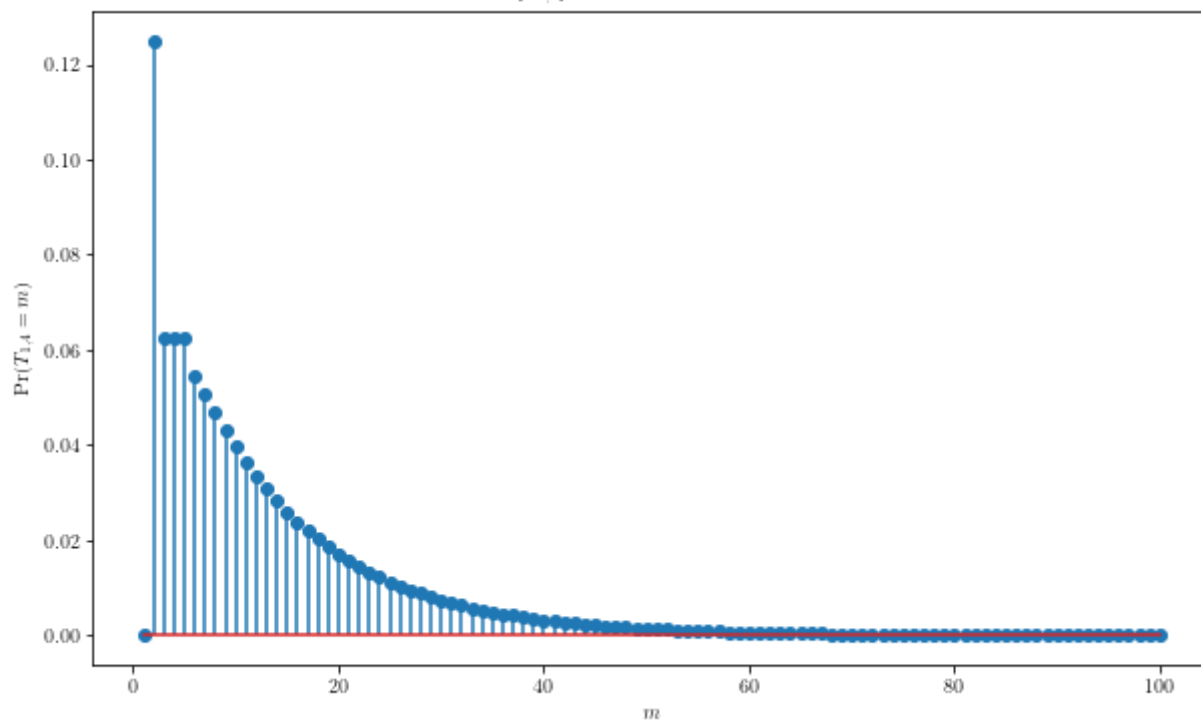
In [4]: 1 ▾ #See compute_Phi_ET in fsmc_code.py
2 ▾ def compute_Phi_ET(P, ns=100):
3     '''
4     Arguments:
5         P {numpy.array} -- n x n, transition matrix of the Markov cha
6         ns {int} -- largest step to consider
7
8     Returns:
9         Phi_list {numpy.array} -- (ns + 1) x n x n, the Phi matrix fo
10        ET {numpy.array} -- n x n, expectedd hitting time approxiamat
11    '''
12    Phi_list = np.zeros([ns+1,P.shape[0],P.shape[1]])
13    Phi_list[0] = P
14 ▾    for i in range(1,ns+1):
15        Phi_list[i] = np.matmul(P, Phi_list[i-1])
16    ET = np.zeros(P.shape)
17 ▾    for i in range(1,ns+1):
18        ET += (i+1)*(Phi_list[i] - Phi_list[i-1])
19    return Phi_list, ET
20
21    P = np.array([[0.5, 0.5, 0, 0], [0.5, 0, 0.5, 0], [0.5, 0, 0, 0.5], [
22    Phi_list, ET = compute_Phi_ET(P, 100)
23
24    m = np.arange(1,101) ### steps to be plotted
25    Pr = Phi_list[m,0,3] - Phi_list[m-1,0,3] ### \Pr(T_{1,4} = m) for all
26    E = ET[0,3] ### \mathbb{E}[T_{1,4}]
27
28    plt.figure(figsize=(10, 6))
29    plt.stem(m, Pr, use_line_collection= True)
30    plt.xlabel(r'$m$')
31    plt.ylabel(r'$\Pr(T_{1,4}=m)$')
32    plt.title(r'$\mathbb{E}[T_{1,4}] = ' + str(E) + ' $')

```

executed in 1.77s, finished 13:41:08 2019-10-21

Out[4]: Text(0.5, 1.0, '\$\mathbb{E}[T_{1,4}] = 13.972692578968473 \$')

$$\mathbb{E}[T_{1,4}] = 13.972692578968473$$



- Write a computer program that generates 500 realizations from this Markov chain and uses them to plots a histogram of $T_{1,4}$.

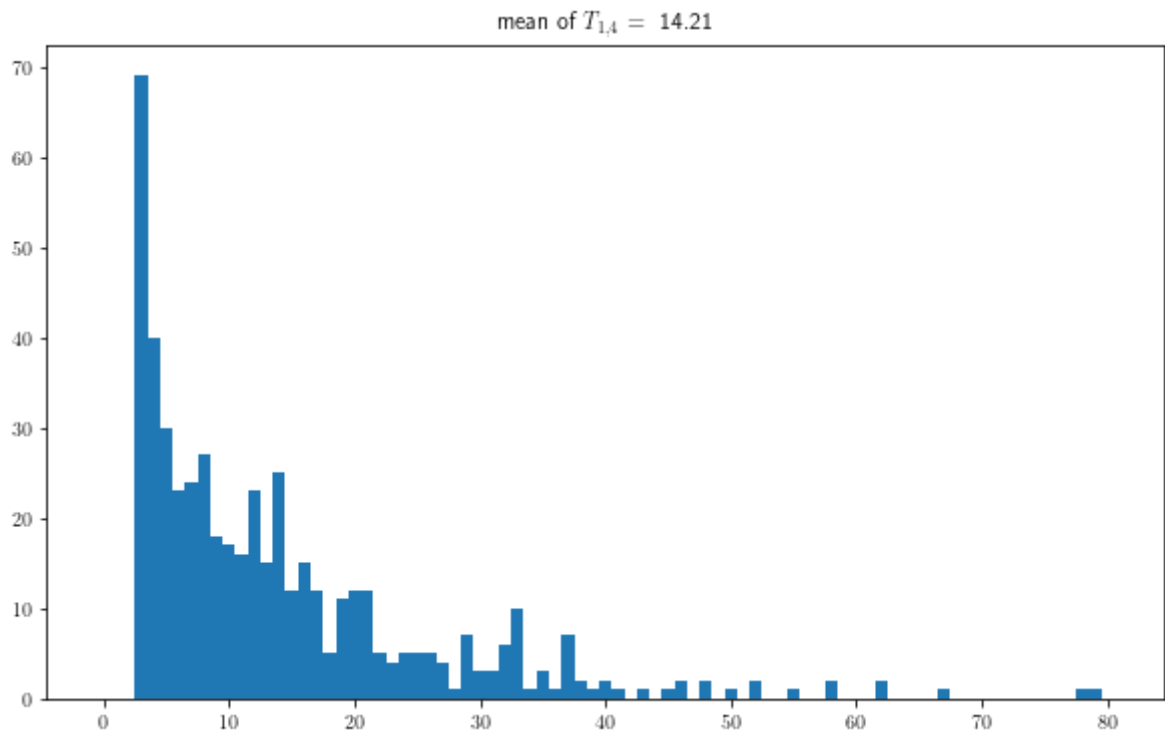
```

In [5]: 1 ▾ # implement simulate_hitting_time(P, states, nr) in fsmc_code.py
2
3 ▾ def vector(index, m):
4     m = np.zeros(m.size)
5     m[index] = 1
6     return m
7
8     # General function to simulate hitting time for Exercise 2.1
9 ▾ def simulate_hitting_time(P, states, nr):
10     '''
11 ▾     Arguments:
12         P {numpy.array} -- n x n, transition matrix of the Markov cha
13         states {list[int]} -- the list [start state, end state], inde
14         nr {int} -- largest step to consider
15
16 ▾     Returns:
17         T {list[int]} -- a size nr list contains the hitting time of
18     '''
19     # Add code here to simulate following quantities:
20     # T[i] = hitting time of the i-th run (i.e., realization) of proc
21     # Notice in python the index starts from 0
22     start, end = states
23     if start == end: return [0] * nr
24     T = np.zeros(nr)
25 ▾     for k in range(nr):
26         curr_state = start
27         step = 0
28         next_state = start
29         q = np.zeros(P.shape[0])
30 ▾         while(curr_state != end):
31             i = 0
32             u = np.random.random_sample()
33             curr_vec = vector(curr_state, q)
34             cdf_vec = np.cumsum(np.matmul(curr_vec, P))
35 ▾             if(u < cdf_vec[0]):
36                 next_state = 0
37 ▾             while(u >= cdf_vec[i]):
38 ▾                 if(u < cdf_vec[i+1]):
39                     next_state = i+1
40                     i += 1
41                 step = step + 1
42                 curr_state = next_state
43             T[k] = step
44         return T
45
46     T = simulate_hitting_time(P, [0, 3], 500)
47     plt.figure(figsize=(10, 6))
48     plt.hist(T, bins=np.arange(max(T))-0.5)
49     plt.title(r'mean of $ T_{1,4} = \sim $' + str(np.mean(T)))

```

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Out[5]: Text(0.5, 1.0, 'mean of \$ T_{1,4} = \sim \$14.21')



▼ 2 Exercise 2.2

Consider the miniature chutes and ladders game shown in Figure 1. Assume a player starts on the space labeled 1 and plays by rolling a fair four-sided die and then moves that number of spaces. If a player lands on the bottom of a ladder, then they automatically climb to the top. If a player lands at the top of a slide, then they automatically slide to the bottom. This process can be modeled by a Markov chain with $n = 16$ states where each state is associated with a square where players can start their turn (e.g., players never start at the bottom of a ladder or the top of a slide). To finish the game, players must land exactly on space 20 (moves beyond this are not taken).

- Compute the transition probability matrix P of the implied Markov chain.

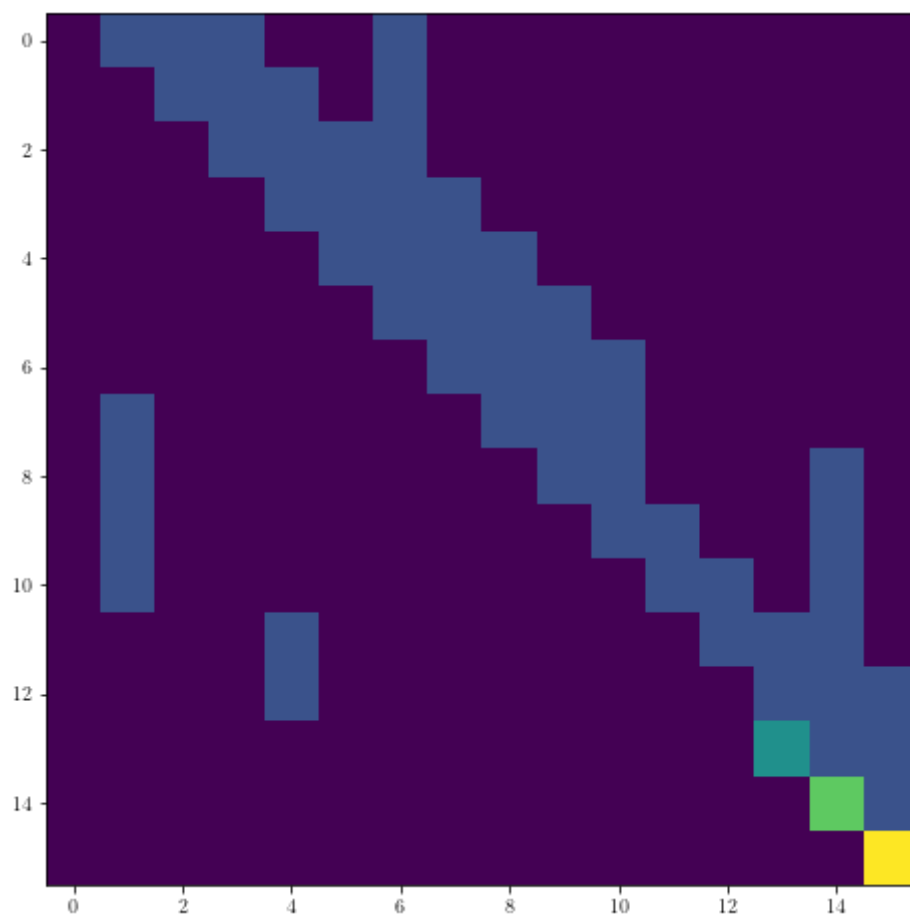
```

In [6]: 1 # You can either do this by hand (e.g., look at picture and write down
2
3 # By hand
4 #P = np.asarray([[[...],[...],[...],...]])
5 # Or automated general function for Chutes and Ladders games
6 def construct_P_matrix(n, dice, chutes, ladders):
7     '''
8     Arguments:
9         n {int} -- size of the state space
10        dice {numpy.array} -- probability distribution of the dice outcomes
11        chutes {list[(int, int)]} -- the list of chutes, in pairs of (source, destination)
12        ladders {list[(int, int)]} -- the list of ladders, in pairs of (source, destination)
13
14    Returns:
15        P {numpy.array} -- n x n, transition matrix of the Markov chain
16    '''
17
18    # Add code here to build matrix
19    c = len(chutes)
20    l = len(ladders)
21    P = np.zeros((n+c+l,n+c+l))
22    for i in range(n+c+l):
23        if(i<len(dice)):
24            P[i,i+1:i+len(dice)+1] = dice[i:i+len(dice)]
25        else:
26            P[i,i+1:n+c+l] = dice[0:(n+c+l-i-1)]
27            P[i,i] = 1 - sum(dice[0:(n+c+l-i-1)])
28    delete_row = [0]*(l+c)
29    for i in range(c):
30        P[:,chutes[i][1]-1] += P[:,chutes[i][0]-1]
31        delete_row[i] = chutes[i][0]-1
32    for i in range(l):
33        P[:,ladders[i][1]-1] += P[:,ladders[i][0]-1]
34        delete_row[i+c] = ladders[i][0]-1
35
36    P = np.delete(P,delete_row,0)
37    P = np.delete(P,delete_row,1)
38    P[n-1,n-1] = 1
39    return P
40
41
42 n = 16 ### number of states
43 dice = np.array([0.25,0.25,0.25,0.25]) ### probability distribution of the dice
44 chutes = [(13,2), (17,6)] ### (source, destination) pairs of chutes
45 ladders = [(4,8),(14,19)] ### (source, destination) pairs of ladders
46 P = construct_P_matrix(n, dice, chutes, ladders)
47
48 # Plot transition matrix
49 plt.figure(figsize=(8, 8))
50 plt.imshow(P)

```

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Out[6]: <matplotlib.image.AxesImage at 0x10b64ada0>



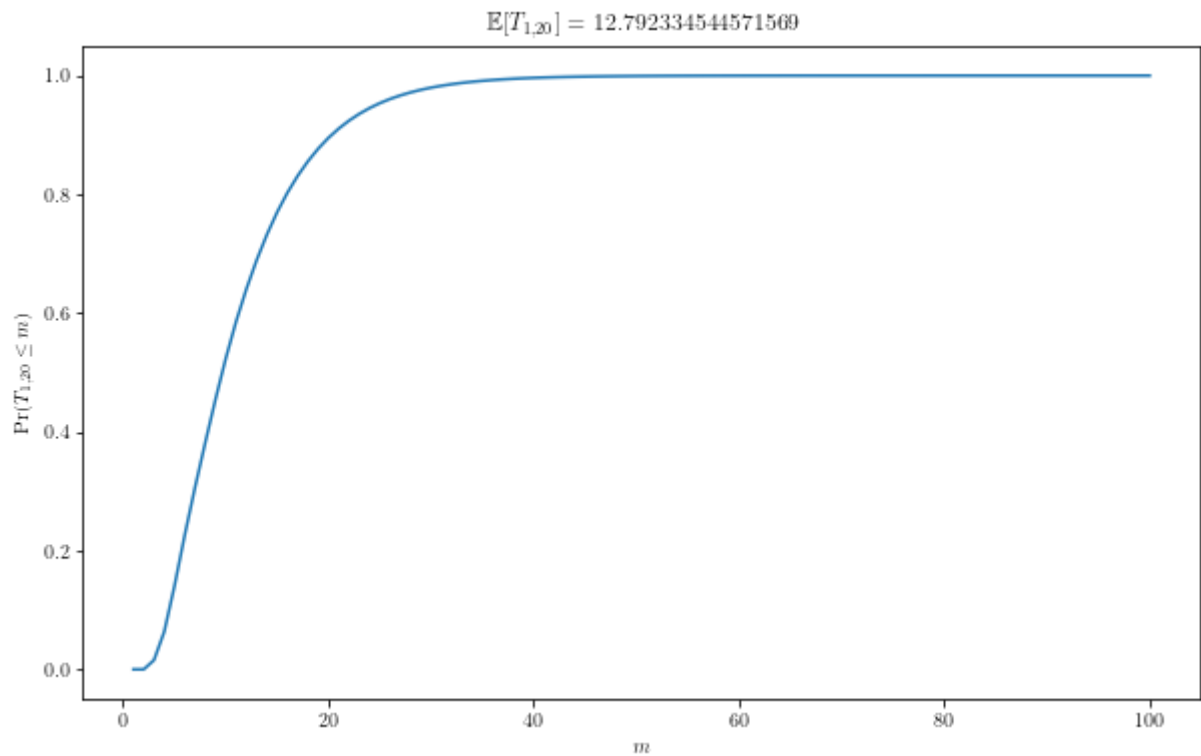
- For this Markov chain, write a computer program (e.g., in Python) to compute the cumulative distribution of the number turns a player takes to finish (i.e., the probability $\Pr(T_{1,20} \leq m)$ where $T_{1,20}$ is the hitting time from state 1 to state 20).

```

In [8]: 1 # Use previous functions to complete this exercise
2 Phi_list, ET = compute_Phi_ET(P, ns=100)
3 m = np.arange(1,101) ### steps to be plotted
4 Pr = Phi_list[m,0,15] ### \Pr(T_{1,4} = m) for all m
5 E = ET[0,15]
6 plt.figure(figsize=(10, 6))
7 plt.plot(m ,Pr)
8 plt.xlabel(r'$ m $')
9 plt.ylabel(r'$ \Pr(T_{1,20} \leq m) $')
10 plt.title(r'$ \mathbb{E}[T_{1,20}] = ' + str(E) + ' $');

```

executed in 370ms, finished 13:41:46 2019-10-21



- Write a computer program that generates 500 realizations from this Markov chain and uses them to plot a histogram of $T_{1,20}$.

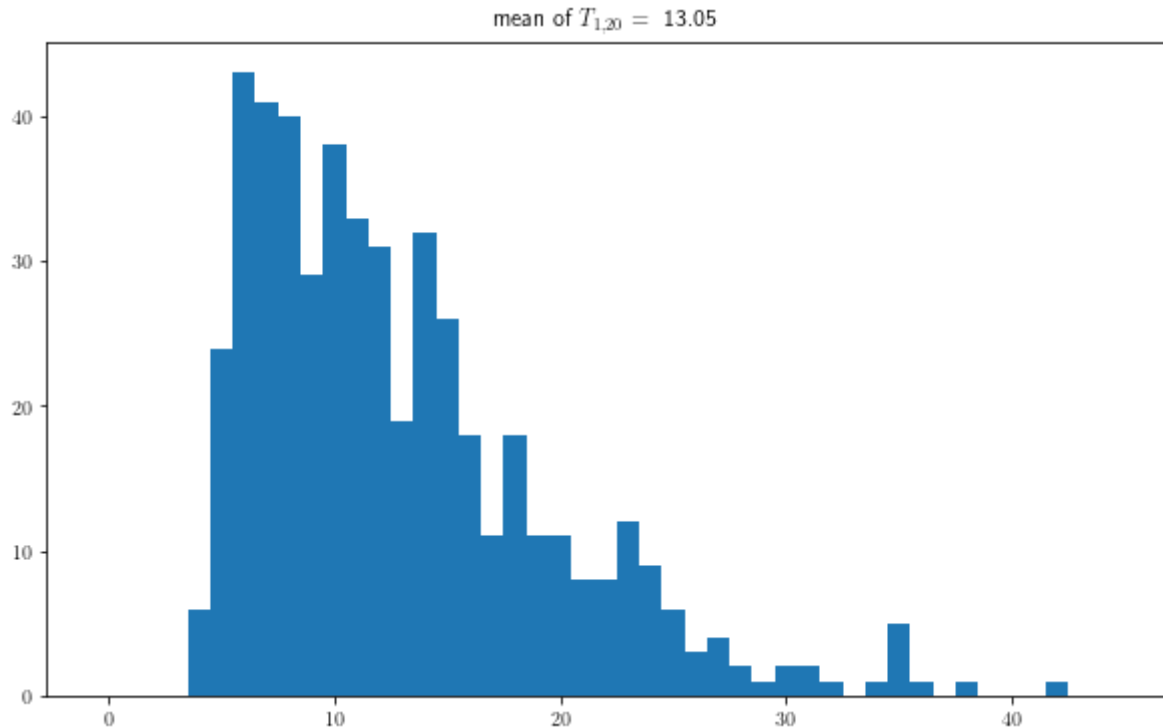

```

In [9]: 1 ▾ # Use previous functions to complete this exercise
        2 T = simulate_hitting_time(P, [0, n-1], 500)
        3 plt.figure(figsize=(10, 6))
        4 plt.hist(T, bins=np.arange(max(T))-0.5)
        5 plt.title(r'mean of $ T_{1,20} = \sim $' + str(np.mean(T)))

```

executed in 913ms, finished 13:41:55 2019-10-21

Out[9]: Text(0.5, 1.0, 'mean of \$ T_{1,20} = \sim \$13.05')



- Optional Challenge: If the first player rolls 4 and climbs the ladder to square 8, then what is the probability that the second player will win.

```

In [ ]: 1 ▾ # Use previous functions to complete this exercise
        2
        3 ### compute Pr_win
        4

```

executed in 5ms, finished 16:14:10 2018-10-21

▼ 3 Example 2.3

In a certain city, it is said that the weather is rainy with a 90% probability if it was rainy the previous day and with a 50% probability if it not rainy the previous day. If we assume that only the previous

day's weather matters, then we can model the weather of this city by a Markov chain with $n = 2$ states whose transitions are governed by

$$P = \begin{bmatrix} 0.9 & 0.1 \\ 0.5 & 0.5 \end{bmatrix}$$

Under this model, what is the steady-state probability of rainy weather?

```
In [10]: 1 # implement stationary_distribution(P) in fsmc.py
2 def nullspace(A, atol=1e-13, rtol=0):
3     A = np.atleast_2d(A)
4     u, s, vh = np.linalg.svd(A)
5     tol = max(atol, rtol * s[0])
6     nnz = (s >= tol).sum()
7     ns = vh[nnz:].conj().T
8     return ns
9
10
11
12 # General function to approximate the stationary distribution of a Ma
13 def stationary_distribution(P):
14     '''
15     Arguments:
16         P {numpy.array} -- n x n, transition matrix of the Markov cha
17
18     Returns:
19         pi {numpy.array} -- length n, stationary distribution of the
20         ...
21
22     # Add code here: Think of pi as column vector, solve linear equat
23     #     P^T pi = pi
24     #     sum(pi) = 1
25     I = np.identity(P.shape[0])
26     Transf = (I-P).T
27     A = nullspace(Transf)
28     A = A/sum(A)
29     return A
30
31
32 P = np.array([[0.9, 0.1], [0.5, 0.5]])
33 stationary_distribution(P)
```

executed in 18ms, finished 13:42:02 2019-10-21

```
Out[10]: array([[0.83333333],
               [0.16666667]])
```

▼ 4 Exercise 2.4

Consider a game where the gameboard has 8 different spaces arranged in a circle. During each turn, a player rolls two 4-sided dice and moves clockwise by a number of spaces equal to their sum. Define the transition matrix for this 8-state Markov chain and compute its stationary probability distribution.

```
In [11]: 1 # Use previous functions to complete this exercise
2      ### construct the transition matrix
3      P = np.zeros((8,8))
4      P[0,:] = [1/16,0,1/16,2/16,3/16,4/16,3/16,2/16]
5      for i in range(1,8):
6          P[i,:] = np.roll(P[i-1,:],1)
7      print(P)
8      stationary_distribution(P)
```

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```
[ [0.0625 0.      0.0625 0.125  0.1875 0.25   0.1875 0.125 ]
  [0.125  0.0625 0.      0.0625 0.125  0.1875 0.25   0.1875]
  [0.1875 0.125  0.0625 0.      0.0625 0.125  0.1875 0.25   ]
  [0.25   0.1875 0.125  0.0625 0.      0.0625 0.125  0.1875]
  [0.1875 0.25   0.1875 0.125  0.0625 0.      0.0625 0.125 ]
  [0.125  0.1875 0.25   0.1875 0.125  0.0625 0.      0.0625]
  [0.0625 0.125  0.1875 0.25   0.1875 0.125  0.0625 0.      ]
  [0.      0.0625 0.125  0.1875 0.25   0.1875 0.125  0.0625]]
```

```
Out[11]: array([[0.125],
                [0.125],
                [0.125],
                [0.125],
                [0.125],
                [0.125],
                [0.125],
                [0.125]])
```

Next, suppose that one space is special (e.g., state-1 of the Markov chain) and a player can only leave this space by rolling doubles (i.e., when both dice show the same value). Again, the player moves clockwise by a number of spaces equal to their sum. Define the transition matrix for this 8-state Markov chain and compute its stationary probability distribution.

```

In [12]: 1 ▾ # Use previous functions to complete this exercise
          2 ### construct the transition matrix
          3 P = np.zeros((8,8)) ### construct the transition matrix
          4 P[0,:] = [13/16,0,1/16,0,1/16,0,1/16,0]
          5 P[1,:] = np.roll([1/16,0,1/16,2/16,3/16,4/16,3/16,2/16],1)
          6 ▾ for i in range(2,8):
          7     P[i,:] = np.roll(P[i-1,:],1)
          8 print(P)
          9 stationary_distribution(P)

```

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```

[[0.8125 0.      0.0625 0.      0.0625 0.      0.0625 0.    ]
 [0.125  0.0625 0.      0.0625 0.125  0.1875 0.25   0.1875]
 [0.1875 0.125  0.0625 0.      0.0625 0.125  0.1875 0.25   ]
 [0.25   0.1875 0.125  0.0625 0.      0.0625 0.125  0.1875]
 [0.1875 0.25   0.1875 0.125  0.0625 0.      0.0625 0.125   ]
 [0.125  0.1875 0.25   0.1875 0.125  0.0625 0.      0.0625]
 [0.0625 0.125  0.1875 0.25   0.1875 0.125  0.0625 0.    ]
 [0.      0.0625 0.125  0.1875 0.25   0.1875 0.125  0.0625]]

```

```

Out[12]: array([[0.41836864],
                [0.08285234],
                [0.10176963],
                [0.07092795],
                [0.09311176],
                [0.0625555 ],
                [0.09593429],
                [0.07447989]])

```

```

In [ ]: 1

```