Assignment 3- Ying Sun

October 22, 2018

1 Simulation in Sociology, Moretti (2002)

See attached PDF.

2 Simulating your income

2.1 (a) Answer of Question 1

```
In [1]: # Import initial packages
        import numpy as np
        import matplotlib.pyplot as plt
        from matplotlib.ticker import MultipleLocator
```

```
In [2]: def inc_sim(p):

            """
            Requires a simulation profile, p, structured as a dictionary

            p = {
                'inc0'        : integer,    #starting income
                'gr'          : float,      #long-run growth rate of income
                'rho'         : flot,       #postive dependence of today's income on last peri
                'st_year'     : integer,    #start year
                'w_years'     : integer,    #years to work
                'sd'          : float,      #standard deviation of lognormal distribution
                'num_draws'   : integer,    #simulations
                'mu'          : float,      #mean of lognormal distribution
            }
            """

            #set random seed
            np.random.seed(524)

            lognorm_errors = np.random.normal(p['mu'], p['sd'],(p['w_years'], p['num_draws']))

            #create a matrix of dim (w_years, num_draws)
            ln_income_mat = np.zeros((p['w_years'], p['num_draws']))
```

```
        #fill the matrix
        ln_income_mat[0, :] = np.log(p['inc0']) + lognorm_errors[0, :]

        #loop and apply model
        for yr in range(1, p['w_years']):
            ln_income_mat[yr, :] = (1 - p['rho']) * (np.log(p['inc0']) + p['gr'] * (yr)) +\
                                   p['rho'] * ln_income_mat[yr - 1, :]  + lognorm_errors[y
```
```
        #dealing with large numbers so put in terms of 10k's
        income_mat = np.exp(ln_income_mat)
        return income_mat
```

```
In [3]: simulation_profile = {
            'inc0'         : 80000,
            'gr'           : 0.025,
            'rho'          : 0.4,
            'st_year'      : int(2020),
            'w_years'      : 40,
            'sd'           : 0.13,
            'num_draws'    : 10000,
            'mu'           : 0
        }

        income_mat = inc_sim(simulation_profile)
        print(income_mat)
```

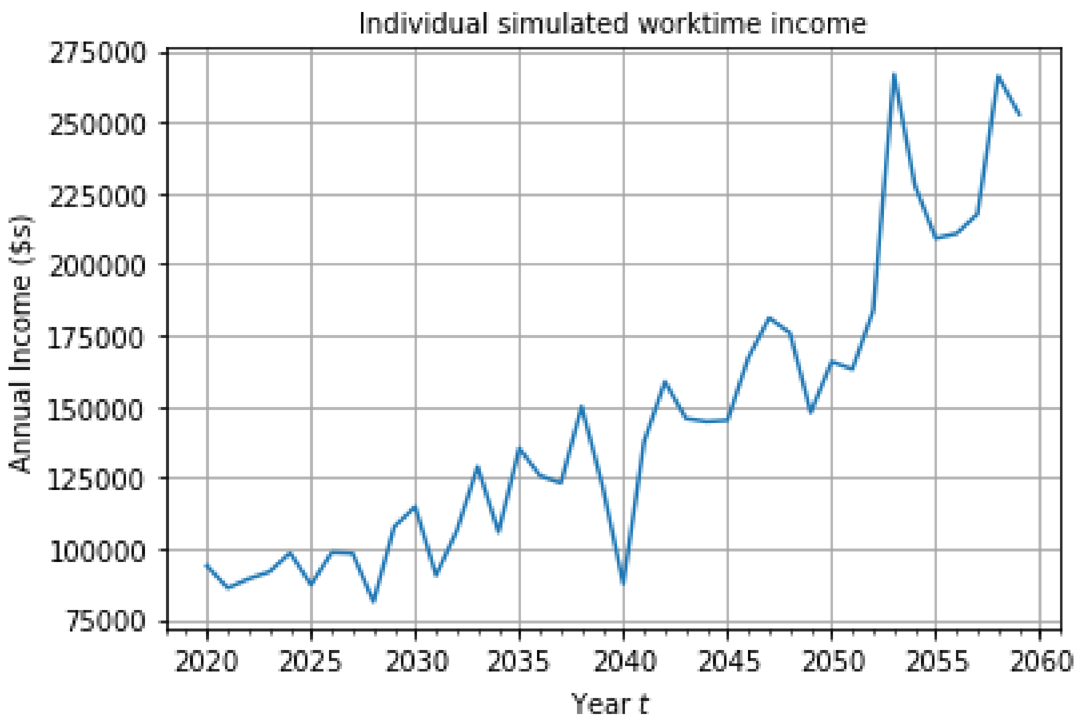
```
[[ 66409.15585396  98274.13534194 101939.81109509 ...  98720.39690442
   72404.51636886  68710.32820307]
 [ 80020.53020329  67383.19350738  84557.85626308 ...  68247.7770509
   74518.33613244  80555.96068584]
 [ 75805.26636606  66134.42494243  91458.20304692 ...  67268.53350159
   90012.42673528  80645.62355527]
 ...
 [272690.56519108 217821.73027242 184724.24512469 ... 159922.45424852
  253961.68337673 209741.55004062]
 [231539.17420799 202509.15149494 197955.96626493 ... 199502.43481758
  210951.71828579 205420.27946389]
 [197895.95201384 165115.10025278 172644.86927513 ... 248654.44847819
  234237.14656466 221566.29879732]]
```

Then we plot one of lifetime income paths:

```
In [4]: %matplotlib inline
        p = simulation_profile
        year_vec = np.arange(p['st_year'], p['st_year'] + p['w_years'])
        individual = 500
```

```
fig, ax = plt.subplots()
plt.plot(year_vec, income_mat[:, individual])
minorLocator = MultipleLocator(1)
ax.xaxis.set_minor_locator(minorLocator)
plt.grid(b=True, which='major', color='0.65', linestyle='-')
plt.title('Individual simulated worktime income', fontsize=10)
plt.xlabel(r'Year $t$')
plt.ylabel(r'Annual Income (\$s)')
```

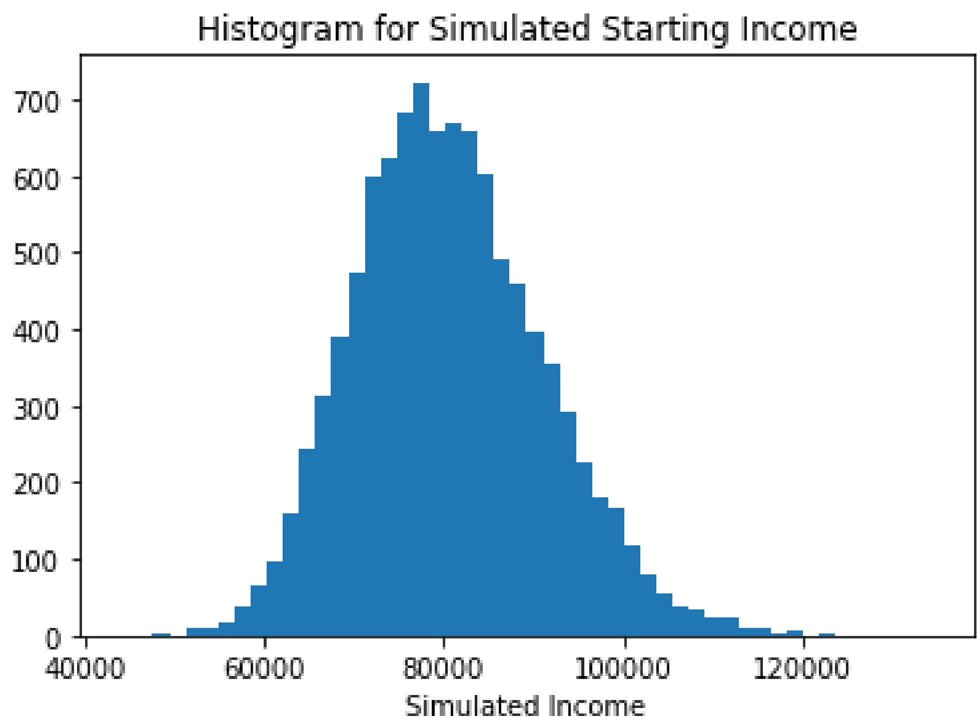
Out[4]: Text(0, 0.5, 'Annual Income (\\$s)')



2.2 (b) Answer of Question 2

In [5]:
```
# plot the histogram
plt.hist(income_mat[0,:], bins=50)
plt.xlabel("Simulated Income")
plt.title("Histogram for Simulated Starting Income")
```

Out[5]: Text(0.5, 1.0, 'Histogram for Simulated Starting Income')



Accroding to the histogram above, the distribution is nearly normal, but it is slightly right skewed.

Counting the percent of the class who earn more than 100000:

```
In [6]: income_above = np.mean(income_mat[0, :] > 100000)
        print(income_above)
```

```
0.0417
```

So 4.17% of my class will earn more than $100000 in the first year out of the program.

Counting the percent of the class who earn less than 70000:

```
In [7]: income_below = np.mean(income_mat[0, :] < 70000)
        print(income_below)
```

```
0.1512
```

And 15.12% of the class will earn less than $70000 in the first year out of the program.

2.3 (c) Answer of Question 3

```
In [8]: def repay_sim(p,income_mat):
            '''
```

```
        Simulate the amount of repay

        Inputs: p: simulation profile
                income_matrix:a matrix of income
        Returns: a matrix of the amount of repay

        '''
        repay = np.zeros((p['w_years'], p['num_draws']))
        repay[0, :] = income_mat[0,:] * 0.1
        for yr in range(1,p['w_years']):
            repay[yr,:] = repay[yr - 1,:] + income_mat[yr, :] * 0.1
        return repay
```

```
In [9]: def repay_yr(p,income_mat):
        '''
        Calculate the year when I can payoff the loan
        Inputs: p: simulation profile
                income_matrix:a matrix of income

        Returns: a list of the year when I can payoff the loan
        '''
        repay_yr = [0] * p['num_draws']
        repay = repay_sim(p, income_mat)
        for i in range(p['num_draws']):
            for yr in range(p['w_years']):
                if repay[yr,i] >= 95000:
                    repay_yr[i] = yr + 1
                    break
        return repay_yr
```

```
In [10]: def cal_percent(p, ls):
         '''
         Calculate the percent of the simulations that I am able to pay off the loan
         Inputs: p: simulation profile
                 repay_yr:a list of the year when I can payoff the loan
         Returns: the percent of the simulations that I am able to pay off the loan

         '''
         num=0
         for i in range(p['num_draws']):
             if ls[i] <= 10:
                 num = num + 1
         percent = num/p['num_draws']
         return percent
```

Calculate the percent of simulation that I am able to pay off the loan in 10 year:

```
In [11]: repay_yrs= repay_yr(simulation_profile, income_mat)
         percent = cal_percent(simulation_profile, repay_yrs)
         print(percent)
```

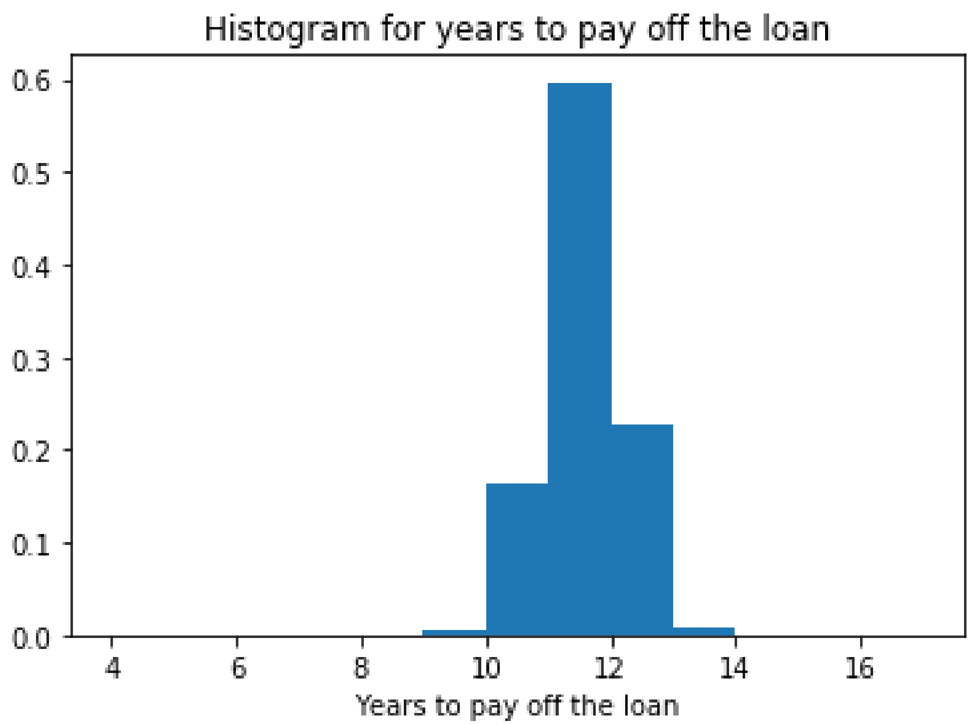
```
0.1678
```

So in 16.78% of the simulation I am able to pay off the loan in 10 years.

Then we plot the histogram of how many years it takes to pay off the loan in each of 10000 simulations:

```
In [12]: plt.hist(repay_yrs, density = True, bins = np.arange(min(repay_yrs) -5, max(repay_yrs
         plt.xlabel("Years to pay off the loan")
         plt.title("Histogram for years to pay off the loan")
```

```
Out[12]: Text(0.5, 1.0, 'Histogram for years to pay off the loan')
```



2.4 (d) Answer of Question 4

```
In [13]: new_simulation_profile = {
             'inc0'          : 90000,
             'gr'            : 0.025,
             'rho'           : 0.4,
             'st_year'       : int(2020),
             'w_years'       : 40,
             'sd'            : 0.17,
             'num_draws'     : 10000,
             'mu'            : 0
```

```
}

income_mat = inc_sim(new_simulation_profile)
print(income_mat)
```

```
[[ 70550.46142451 117783.33011091 123561.20729139 ... 118483.24080508
   78992.81966812  73764.25171169]
 [ 89615.63768821  71575.56495871  96317.75493523 ...  72778.88084775
   81644.3347736   90400.57899801]
 [ 82955.30101689  69396.06916251 106035.55593099 ...  70956.3661129
  103848.93176006  89949.09077038]
 ...
 [338309.11761165 252187.52025149 203293.03644369 ... 168361.21927259
  308250.29858492 240024.49205936]
 [271061.07048342 227502.32436192 220836.5697397  ... 223095.32811759
  239983.96514044 231788.44418303]
 [219057.46748997 172865.33333479 183245.71710131 ... 295275.8618388
  273090.00167035 253934.86273481]]
```

In [14]:
```
new_inc = inc_sim(new_simulation_profile)
new_repay_yr = repay_yr(new_simulation_profile,new_inc)
new_percent = cal_percent(new_simulation_profile,new_repay_yr)
print(new_percent)
```

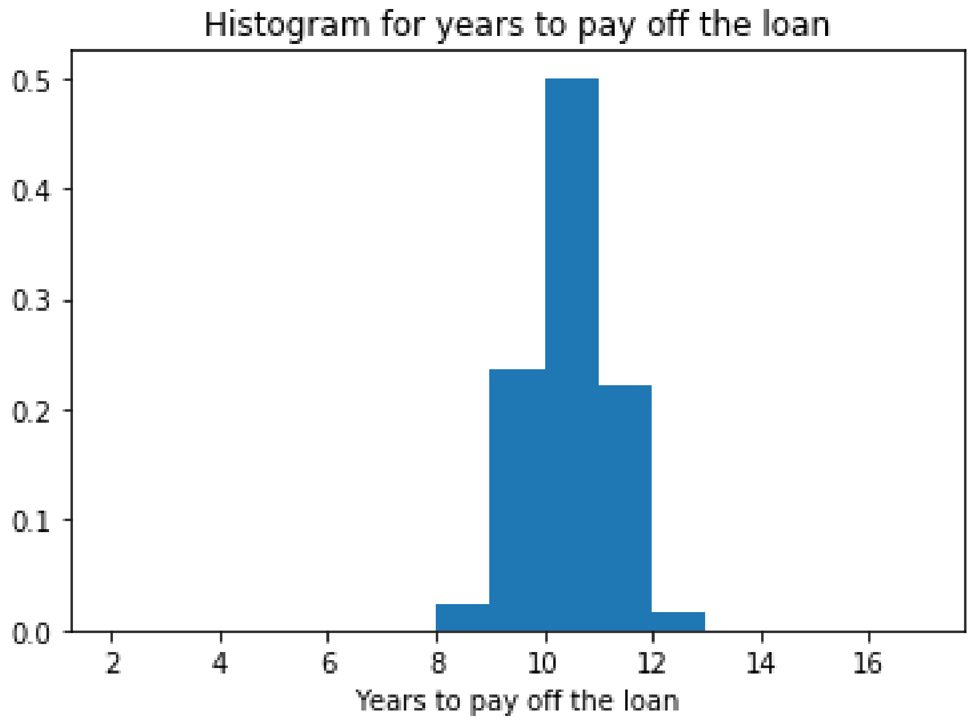
```
0.7602
```

Accodring to the result, in 76.02% of the simulations that I am able to pay off the loan in 10 years.

Then we plot the new histogram of how many years it takes to pay off my loan of $95,000 in my new 10,000 simulations with the new standard deviation and the new average initial salary

In [15]:
```
plt.hist(new_repay_yr, density = True, bins = np.arange(min(new_repay_yr) -5, max(new_
plt.xlabel("Years to pay off the loan")
plt.title("Histogram for years to pay off the loan")
```

Out[15]:
```
Text(0.5, 1.0, 'Histogram for years to pay off the loan')
```


Histogram for years to pay off the loan
0.5
0.4
0.3
0.2
0.1
0.0
2
4
6
8
10
12
14
16
Years to pay off the loan

Simulation in Sociology

This paper mainly answers the question that what contribution does computer simulation bring to the process of sociological research. In order to answer this question, Sabrina Moretti introduces four techniques of simulation have developed: system dynamics, multiagent systems, cellular automata and genetic algorithms. The author also discusses the role of simulation as a tool for exploring theory. It can be concluded as follows: firstly, simulation is a language for expressing theories; secondly, simulation is a tool for studying complex systems; thirdly, it is a tool for experimenting on theory.

The author highlights the importance of validity which means the degree to which theoretical constructs and their computational implementation are representative of the real world. However, there are some potential weakness in validity when we use simulations. As for multi-agent systems, because the point of departure in agent-based modeling is the individual so the definition of a multiagent systems includes a detailed list of rules of agents' behavior, that is, protocols of communication and decision-making procedures that consider environmental changes and all interactions with other agents in that system. But in practical application, this definition can be difficult to form. The transformation of the rules of agents' behavior, environmental changes and all other interactions in that system to computational expressions which can apply to simulation is very difficult in some cases. Aside from this, theories of rationality need to be extended to learning and adaptation. Besides, in some specific area, such as psychological theories, the difficulty of formalization of all the aspects of psychological theories is another concern and potential weakness of this system. Another one of the principal challenges is the incorporation and formalization of knowledge, more specifically, what kind of knowledge can be formalized and how to best formalize still remain to be solved in the future.

In terms of cellular automata, the potential weakness in validity is the use of synchronous updating of states. In other words, we assume that all cells are updated simultaneously. But this assumption may not be found in the real social processes because individuals modify their attitudes and opinions at different moments. Another potential weakness is the restrictions imposed by spatial structures, establishing that each individual interacts only with a subset of the whole population. But it is very difficult to define the neighborhood of a unit. In the real world, interactions can also take place among individuals who are not "physically" close to one other. Furthermore, the neighborhood can change over time.

Dynamic feedback is a key characteristic that computer simulation is good at modeling, which means some initial stimulus changes behavior and then that change in behavior creates new stimuli which in turn cause further behavior change. One example of dynamic feedback that the author cites from sociology is the model came up by Hanneman, Collins, & Mordt (1995). In this legitimacy and conflict model, the motivation of governors to initiate external conflict is directly proportional to the legitimacy deficit compared with the maximum legitimacy. Then the conflict has an impact on the prestige and legitimacy of political communities, which further changes the current legitimacy level. So, the current legitimacy deficit is changed and new conflict will emerge.

In the area of political science, although political science research often views public policy as the outcome of political processes, the policy feedback approach incorporates existing policies as inputs into the policymaking process. Existing policies fundamentally reshape the political environment and, therefore, subsequent policy outcomes in a dynamic manner. Policies through their designs and implementation affect a variety of actors in the political system, including both members of the public and political elites. At the elite level, policies can confer resources on some interest groups over others, shape views about what constitute good policies, impose budget constraints, and affect institutional capacity. Among the public, they can influence individuals' attitudes about the role of government and toward societal groups, and they can enhance or undermine rates of political participation, which will further influence the policy makers. So here one research question is how policy changes made by policy communities have influence on public's attitude and political participation and in return, how the public's attitude and political participation will influence policy communities.

Reference:

1. Moretti, Sabrina, "Computer Simulation in Sociology: What Contribution?" *Social Science Computer Review*, 20:1 (Spring 2002), pp. 43-57.
2. Hanneman, R., Collins, R., & Mordt, G. (1995). Discovering theory dynamics by computer simulation: Experiments on state legitimacy and imperialist capitalism. Sociological Methodology, 25, 1-46.