Assignment3

October 20, 2018

1 Assignment 3

1.1 Problem 1.

See attached PDF.

1.2 Problem 2. Simulating your Income.

(a)

```
In [1]: # Import initial packages
        import numpy as np
        import matplotlib.pyplot as plt
        import pandas as pd
        from matplotlib.ticker import MultipleLocator
        from random import randint
        import pylab
        import scipy.stats as stats
```

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

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

            p = {
                'sigma'       : 0.13,       # standard deviation of your income process
                'inc0'        : 80000,      # average initial income
                'rho'         : 0.4,        # the persistence
                'g'           : 0.025,      # the long-run growth rate of income
                'year_start'  : int(2020),  # start year
                'period'      : 40,         # years to work
                'num_draws'   : 10000       # simulations
            }
            """

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

```
        # generate errors
        ln_errors = np.random.normal(0, p['sigma'], (p['period'], p['num_draws']))

        # create a matrix of dim (lf_years, num_draws)
        ln_inc_mat = np.zeros((p['period'], p['num_draws']))

        #fill the matrix
        ln_inc_mat[0, :] = np.log(p['inc0']) + ln_errors[0, :]

        # loop and apply model
        for yr in range(1, p['period']):
            ln_inc_mat[yr, :] = (1 - p['rho']) * (np.log(p['inc0']) + p['g'] * yr) \
            + p['rho'] * ln_inc_mat[yr - 1, :] + ln_errors[yr, :]

        inc_mat = np.exp(ln_inc_mat) # dealing with large numbers so put in terms of 10k's
        return inc_mat
```

```
In [3]: simulation_profile = {
                'sigma'       : 0.13,       # standard deviation of your income process
                'inc0'        : 80000,      # average initial income
                'rho'         : 0.4,        # the persistence
                'g'           : 0.025,      # the long-run growth rate of income
                'year_start'  : int(2020),  # start year
                'period'      : 40,         # years to work
                'num_draws'   : 10000       # simulations
        }

        sim_inc = IncomeSimulate(simulation_profile)
        print(sim_inc)
```

```
[[ 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]]
```

Now, after we simulated the income matrix, we are going to plot one of the income paths.

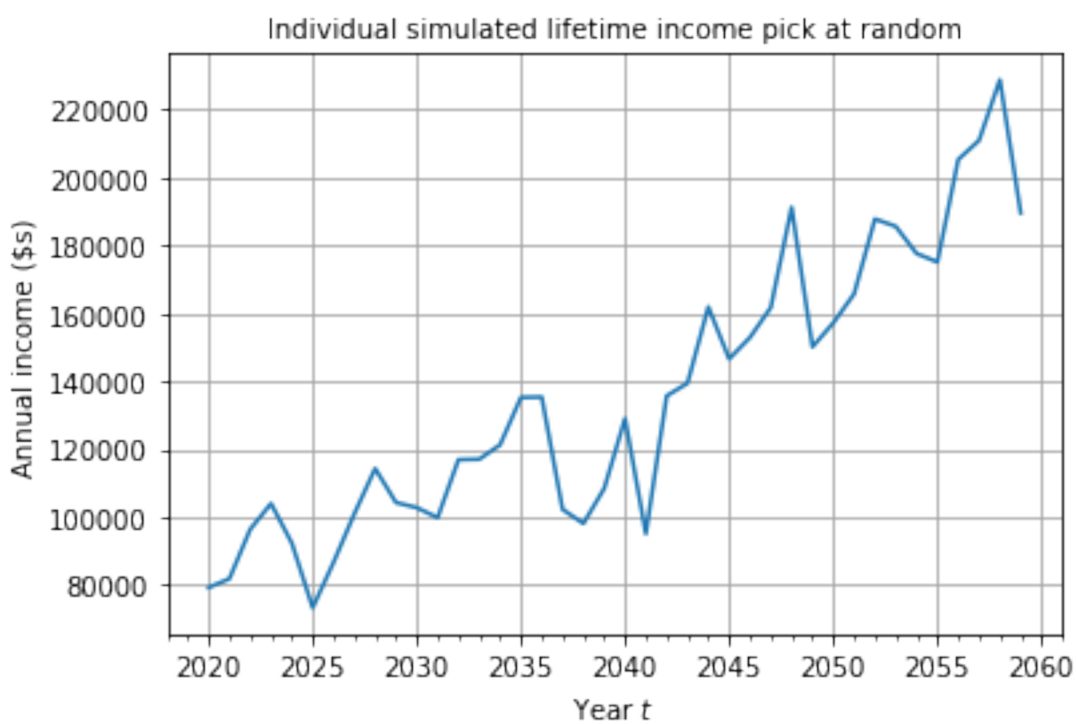
```
In [4]: # Plot one of the income paths at random
        np.random.seed(123)
```

```
random_income = np.array(sim_inc[:, randint(0, simulation_profile['num_draws'] - 1)])
random_income
```

```
Out[4]: array([ 79176.37302043,  81779.65323099,  96362.25149757, 103946.9965005 ,
                92273.24205658,  73238.05454692,  86593.54610353, 100935.8108114 ,
               114279.66730903, 104243.19243207, 102736.96196658,  99789.72394317,
               116889.0829077 , 117009.04738751, 121268.24025042, 135222.18835699,
               135333.95836443, 102225.32858143,  98074.89797281, 108397.47930682,
               129014.64459375,  95061.53295422, 135682.08273827, 139426.08822471,
               161911.46002849, 146572.36751767, 152901.50585761, 161740.0310019 ,
               191265.56786568, 150129.7883697 , 157178.42711608, 165736.79235411,
               187811.33787301, 185644.31213458, 177647.42393792, 175134.0864884 ,
               205355.09154611, 210966.58103084, 228853.31748421, 189600.84825915])
```

```
In [5]: %matplotlib inline
        p = simulation_profile
        year_vec = np.arange(p['year_start'], p['year_start'] + p['period'])
        fig, ax = plt.subplots()
        plt.plot(year_vec, random_income)
        minorLocator = MultipleLocator(1)
        ax.xaxis.set_minor_locator(minorLocator)
        plt.grid(b = True, which = 'major', color = '0.65', linestyle = '-')
        plt.title('Individual simulated lifetime income pick at random', fontsize = 10)
        plt.xlabel(r'Year $t$')
        plt.ylabel(r'Annual income (\$s)')
```

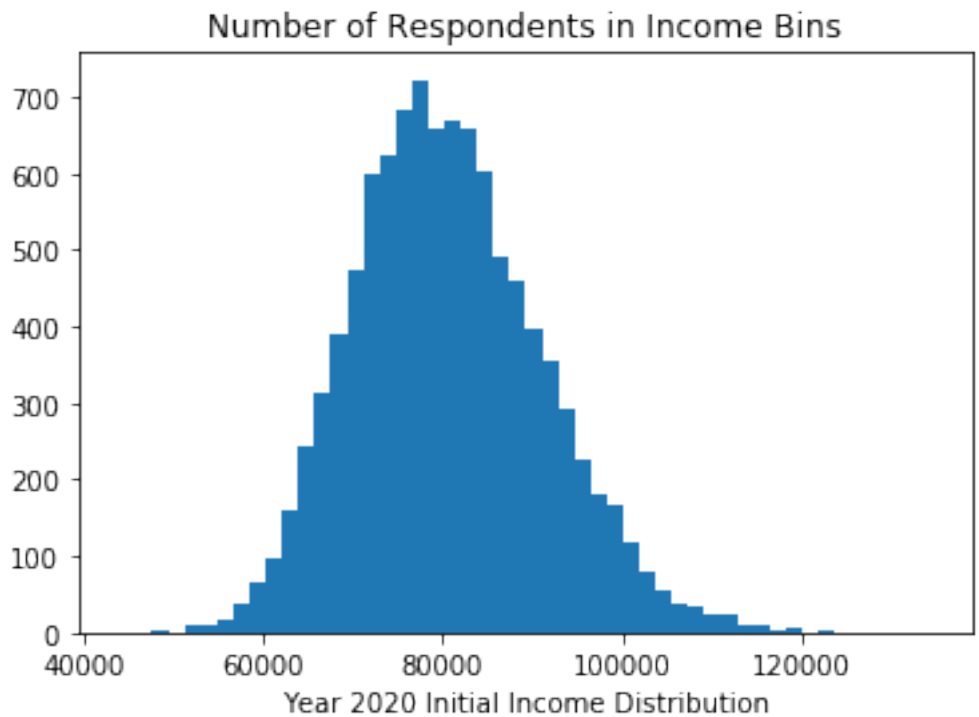
```
Out[5]: Text(0, 0.5, 'Annual income (\\$s)')
```



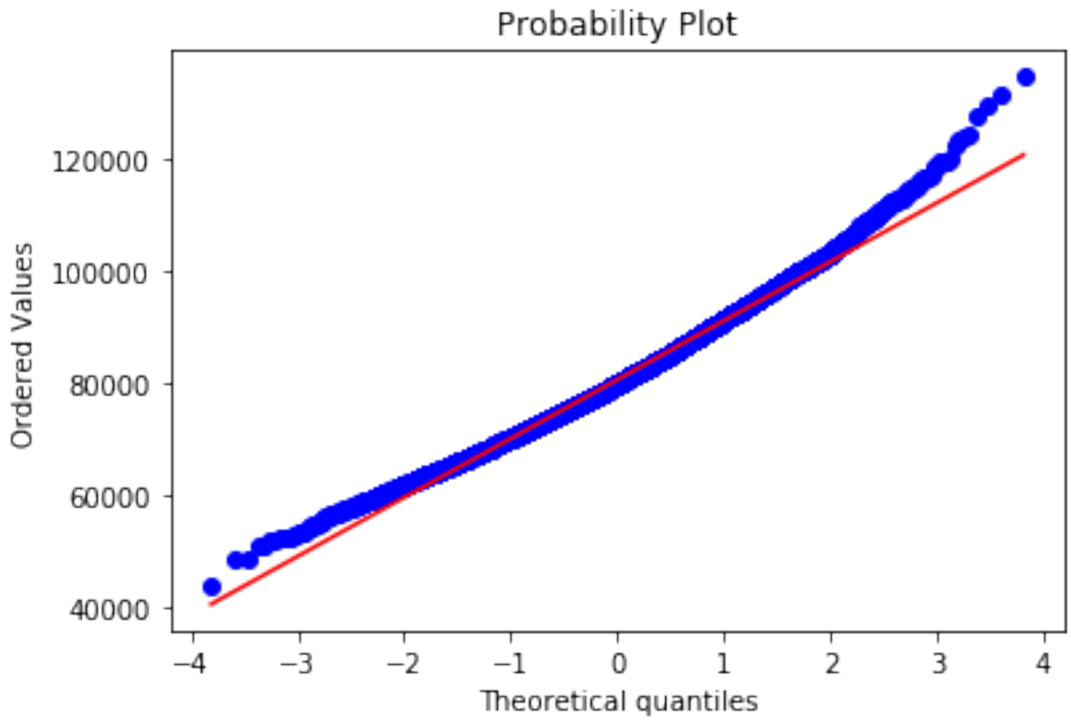
(b)

```
In [6]: plt.hist(sim_inc[0,:], bins = 50)
        plt.xlabel("Year 2020 Initial Income Distribution")
        plt.title("Number of Respondents in Income Bins")
```

```
Out[6]: Text(0.5, 1.0, 'Number of Respondents in Income Bins')
```




```
In [7]: stats.probplot(sim_inc[0,:], dist = "norm", plot = pylab)
        pylab.show()
```



As we can see from the histogram, the distribution is roughly normal, although it is a little bit right skewed (concave up); it is just a minor issue.

Now, calculate the percentage of earn more than \$100,000 in the first year.

```
In [8]: # percentage more than 100,000
        len(sim_inc[0, :][sim_inc[0, :] > 100000]) / len(sim_inc[0, :])
```

```
Out[8]: 0.0417
```

As we can see that 4.17% of the class will earn more than 100,000\$ in the first year.

Next, we will calculate the percentage of earn less than \$70,000.

```
In [9]: # percentage more than 70,000
        len(sim_inc[0, :][sim_inc[0, :] < 70000]) / len(sim_inc[0, :])
```

```
Out[9]: 0.1512
```

As we can see that 15.12% of the class will earn less than 70,000\$ in the first year.

(c)

```
In [10]: '''
         Find the cumulative sum of 10% of the annual income and calculate
         the number of year to pay the debt
         '''
```

```
yr_debt = []
for i in range(p['num_draws']):
    cum = np.cumsum(sim_inc[:, i] * 0.1)
    # the true number of years should be the index plus 1
    a = np.where(cum >= 95000)[0][0] + 1
    yr_debt.append(a)
yr_debt = np.array(yr_debt)
yr_debt
```

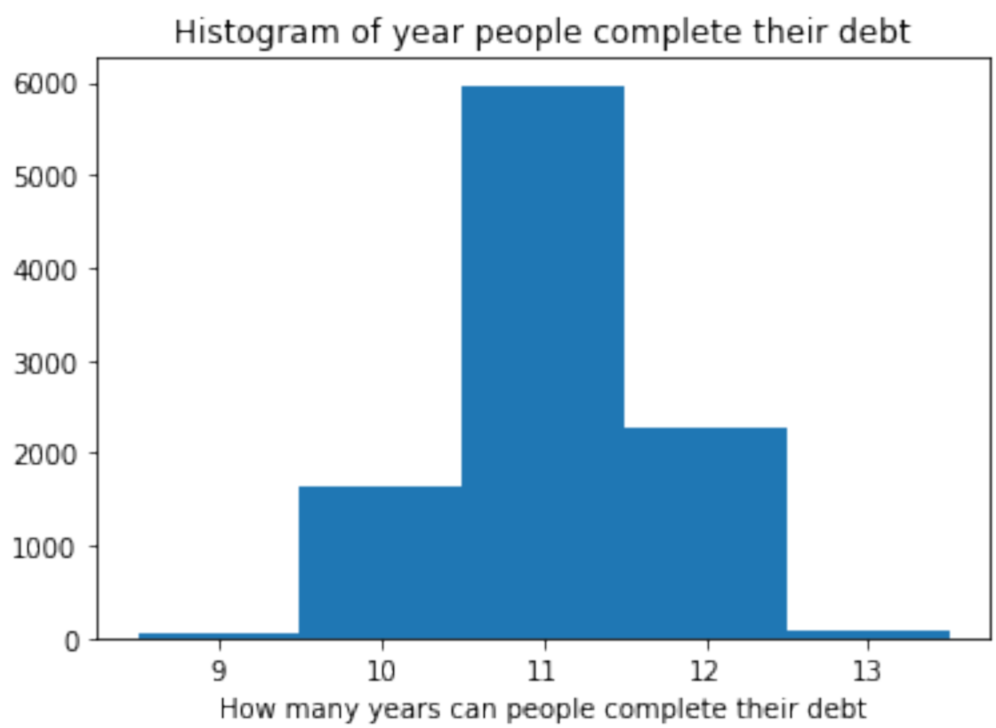
```
Out[10]: array([11, 11, 10, ..., 12, 11, 11])
```

```
In [11]: # find how many unique number of years in the array
         s = set(yr_debt)
         s
```

```
Out[11]: {9, 10, 11, 12, 13}
```

```
In [12]: plt.hist(yr_debt, bins = np.arange(min(s) - 0.5, max(s) + 1.5))
         plt.xlabel("How many years can people complete their debt")
         plt.title("Histogram of year people complete their debt")
```

```
Out[12]: Text(0.5, 1.0, 'Histogram of year people complete their debt')
```



Next, we will calculate the percentage of the simulations are able to pay off the loan in 10 years:

```
In [13]: # Find percentage
         p = len(yr_debt[yr_debt  <= 10]) / len(yr_debt)
         p

Out[13]: 0.1678
```

As we can see from the output, 16.78% of the simulations are able to pay off their debt.

(d)

```
In [14]: new_sim_profile = {
                 'sigma'       : 0.17,       # standard deviation of your income process
                 'inc0'        : 90000,      # average initial income
                 'rho'         : 0.4,        # the persistence
                 'g'           : 0.025,      # the long-run growth rate of income
                 'year_start'  : int(2020),  # start year
                 'period'      : 40,         # years to work
                 'num_draws'   : 10000       # simulations
         }

         new_sim_inc = IncomeSimulate(new_sim_profile)
         print(new_sim_inc)

[[ 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 [15]: '''
         Find the cumulative sum of 10\% of the annual income and calculate
         the number of year to pay the debt
         '''
         new_yr_debt = []
         for i in range(new_sim_profile['num_draws']):
             cum = np.cumsum(new_sim_inc[:, i] * 0.1)
             # the true number of years should be the index plus 1
             a = np.where(cum >= 95000)[0][0] + 1
             new_yr_debt.append(a)
         new_yr_debt = np.array(new_yr_debt)
         new_yr_debt
```

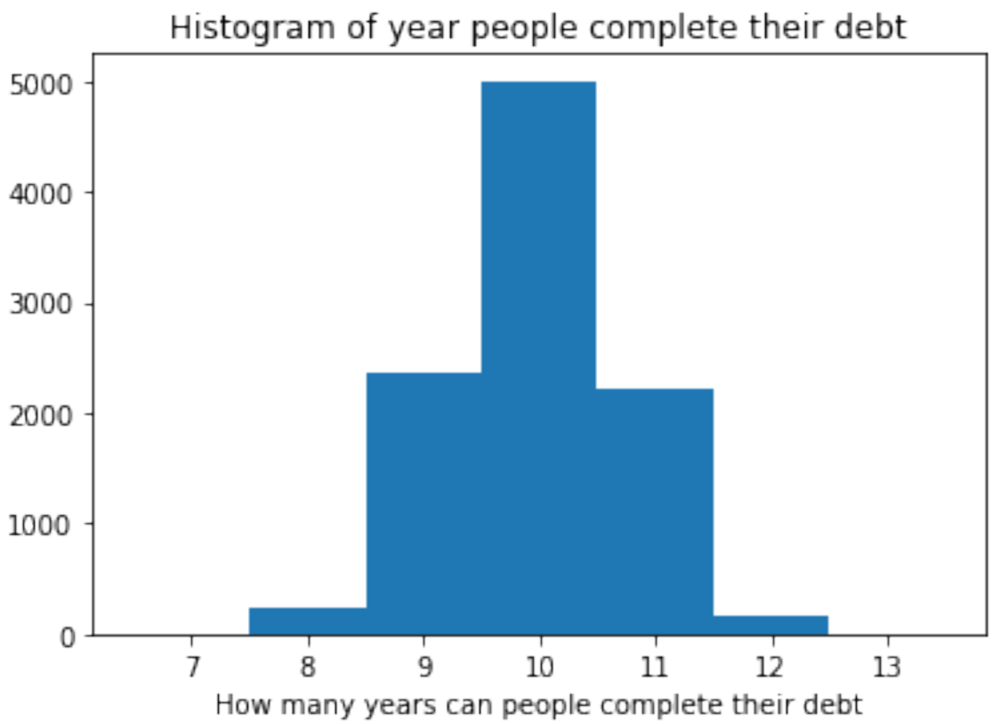
```
Out[15]: array([10, 10,  9, ..., 11, 10, 10])
```

```
In [16]: # find how many unique number of years in the array
         s = set(new_yr_debt)
         s
```

```
Out[16]: {7, 8, 9, 10, 11, 12, 13}
```

```
In [17]: plt.hist(new_yr_debt, bins = np.arange(min(s) - 0.5, max(s) + 1.5))
         plt.xlabel("How many years can people complete their debt")
         plt.title("Histogram of year people complete their debt")
```

```
Out[17]: Text(0.5, 1.0, 'Histogram of year people complete their debt')
```



Next, we will calculate the percentage of the simulations are able to pay off the loan in 10 years:

```
In [18]: # Find percentage
         p = len(new_yr_debt[new_yr_debt  <= 10]) / len(new_yr_debt)
         p
```

```
Out[18]: 0.7602
```

As we can see from the output, 76.02% of the simulations are able to pay off their debt.

Assignment 3

Problem 1

(a) The author discussed the role of simulation as a tool for sociology research and its contribution to the sociology field. In the paper, she highlighted the importance of establishing "validity" of simulative model of the theory. Both multiagent systems and cellular automata have some weakness on validity. The validity problem stems from the fact the simulative models are inherently a virtual world lacking the material senses of the real world.

For multiagent systems, the primary weakness in validity with regard to multiagent systems is the difficulties of adopting and adapting theories and models properly while as completely as possible when designing each individual decision maker. First of all, the models of rationality should be extended to learning and adaptation to be more realistic. In addition, aside from the properties of individuals that currently are included in multiagent system models, there are many other aspects of psychological theories that should be incorporated, such as emotions, motivations, desire, intent, and consciousness. Another major challenge in the development of multiagent systems is the formalization of knowledge. What kinds of knowledge are formalizable and how to best formalize knowledge still remain for future research.

For cellular automata, a limitation is the use of synchronous updating of states; we assume that there is a global clock according to which all cells are updated simultaneously. This assumption may not be found in real social processes, because individuals modify their attitudes and opinions at different moments. In physics and natural sciences, this assumption is considered very dangerous. Another important limitation regards the restrictions imposed by spatial structures, establishing that each individual interacts only with a subset of the whole population. While this type of restriction may be acceptable, 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 another. Furthermore, the neighborhood can change over time. Thus, we should consider if cellular automata is plausible before using it.

(b) The author gives some examples from Sociology to demonstrate "dynamic feedback". The model in Hanneman, Collins, & Mordt (1995) is one of them. In this model, the motivation of rulers to initiate external conflict is directly proportional to the difference between their current legitimacy and the goal of maximum legitimacy. After the conflict is initiated, the result of it leads to change in prestige in the status order of political communities, which in turn changes the current legitimacy level. Then the difference between the current legitimacy and the goal of maximum legitimacy is changed, so that a new conflict may be initiated.

To give an example of a research question on a political science topic where the underlying system exhibits dynamic feedback, I would say that sequential game theory with more than two series of actions will be one of the examples. The action of the person will depend on the former action of another person. For instance, president election can be seen as a game theory with dynamic feedback. Two candidates' behaviors will highly depend on the behaviors of each other.