Assignment 3

Ellen Hsieh

1. Simulation in Sociology, Moretti (2002)

In the article the author discusses about the potential weaknesses in validity regarding to multi-agent systems and cellular automata that is the feature of synchronism and the connection with the empirical word. Even though multi-agent systems and cellular automata can better simulate the social phenomena, using the synchronous updating of states might not be able to perfectly represent the real world since the behavior of individual would not updated simultaneously. In addition, computation simulations in general derive the verified behavior of agents from the theory, and theory might not be an accurate representation of reality. In other words, the consequence of the simulation is only based on the changes of variables or assumptions of the theory. Therefore, the simulations produced by multi-agent systems and cellular automata are still not able to perfectly represent the social phenomena in the real world.

To illustrate the characteristics of dynamic feedback in computer simulation, the author mentions some researches such as the model of dynamic social impact, which explores the necessary and sufficient conditions for the clustering and the polarization of opinions. In this study, the author, Latané, proposes that individual differs and each individual tends to have a stable location in space. Based on those propositions, he points out that social influence depends on the strength of the influential individual and physical distances among people. For instance, people are more likely to be influenced by their neighbor rather than a stranger, which will lead to a spatial clustering. Due to the phenomena of clustering, the number of minorities in the society will decline but still be able to survive. Even though the incremental influence will lead to convergence, nonlinear influence will maintain the diversity within a society. The researchers in this study attain this result from computer simulation by getting the dynamic feedback.

Within Political Science, theories of international relations are difficult to test. For example, the topic on the preference of a country towards cooperation when a strong military country starts building up its military power would be hard to experiment. Therefore, using the dynamic feedback here would be helpful to discourse the possible outcomes. Assuming there are three countries which possess different level of military power, one is strong (country A), one is not so strong (country B), and the last one is least strong (country C). If today country A, the strongest one, decides to enhance their military power, then country C might choose to cooperate with other stronger country, either A or B. In response to this cooperation, if country C cooperates with country A, then country B might become nervous and try to join the alliance. However, if country C chooses to cooperate with country B, country A might reconsider about its strategy of enhancing its military power. Apparently, one's decision might influence others' decisions to cooperate. In order to study on the complex interactions between these three countries, using the dynamic feedback in computer simulation can help the researchers to better evaluate the possible outcome of this political topic.

Assignment3_EH

October 23, 2018

1 Assignment 3

1.0.1 MACSS 3000, Dr. Evans

1.0.2 Ellen Hsieh

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

1.0.3 2. Simulating your income

(a) Simulate 10,000 different realizations of my lifetime income

$$\ln(inc_{2020}) = \ln(inc_0) + \ln(\varepsilon_{2020})$$
$$\ln(inc_t) = (1-\rho)[\ln(inc_0) + g(t-2020)] + \rho\ln(inc_{t-1}) + \ln(\varepsilon_t) \ \ \forall 2021 \le t \le 2059$$

In [2]:
```
# create a simulation model for MACSS students lifetime income
def macss_income_sim(p):

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

    p = {
        'inc'         : 80000,      #starting income
        'rho'         : 0.4,        #dependence of todays income on last periods incom
        'mu'          : 0,          #mean
        'sd'          : 0.13,       #standard deviation
        'gr'          : 0.025,      #growth rate
        'st_year'     : int(2020),  #start year
        'wr_years'    : 40,         #years to work
        'num_draws'   : 10000       #simulations
    }
    """

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

```
        inc_errors = np.random.normal(p['mu'], p['sd'] , (p['wr_years'], p['num_draws']))

        #create a matrix of dim (wr_years, num_draws)
        ln_macss_inc = np.zeros((p['wr_years'], p['num_draws']))

        #fill the matrix
        ln_macss_inc[0, :] = np.log(p['inc']) + inc_errors[0, :]

        #loop and apply model
        for yr in range(1, p['wr_years']):
            ln_macss_inc[yr, :] = ((1- p['rho']) * (np.log(p['inc']) + p['gr']* yr) +
                                            p['rho'] * ln_macss_inc[yr - 1, :] + inc

        macss_inc = np.exp(ln_macss_inc)
        return macss_inc
```

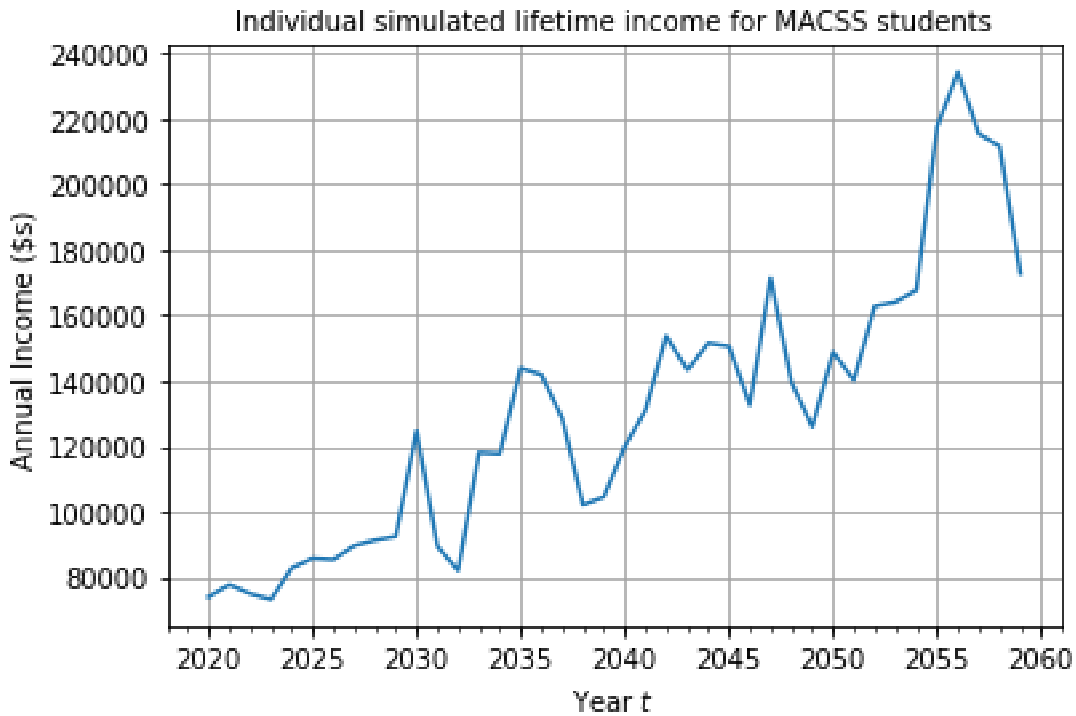
In [3]:
```
# simulate the lifetime income with initial income = 80000, mu = 0, sd = 0.13, g = 0.0
simulation_profile = {
    'inc'          : 80000,
    'rho'          : 0.4,
    'mu'           : 0,
    'sd'           : 0.13,
    'gr'           : 0.025,
    'st_year'      : int(2020),
    'wr_years'     : 40,
    'num_draws'    : 10000
    }

macss_inc = macss_income_sim(simulation_profile)
print(macss_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]]
```

In [4]:
```
# plot the lifetime income path of individual 214
%matplotlib inline
```

```
p = simulation_profile
year_vec = np.arange(p['st_year'], p['st_year'] + p['wr_years'])
individual = 214
fig, ax = plt.subplots()
plt.plot(year_vec, macss_inc[:, individual])
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 for MACSS students', fontsize=10)
plt.xlabel(r'Year $t$')
plt.ylabel(r'Annual Income (\$s)')
```

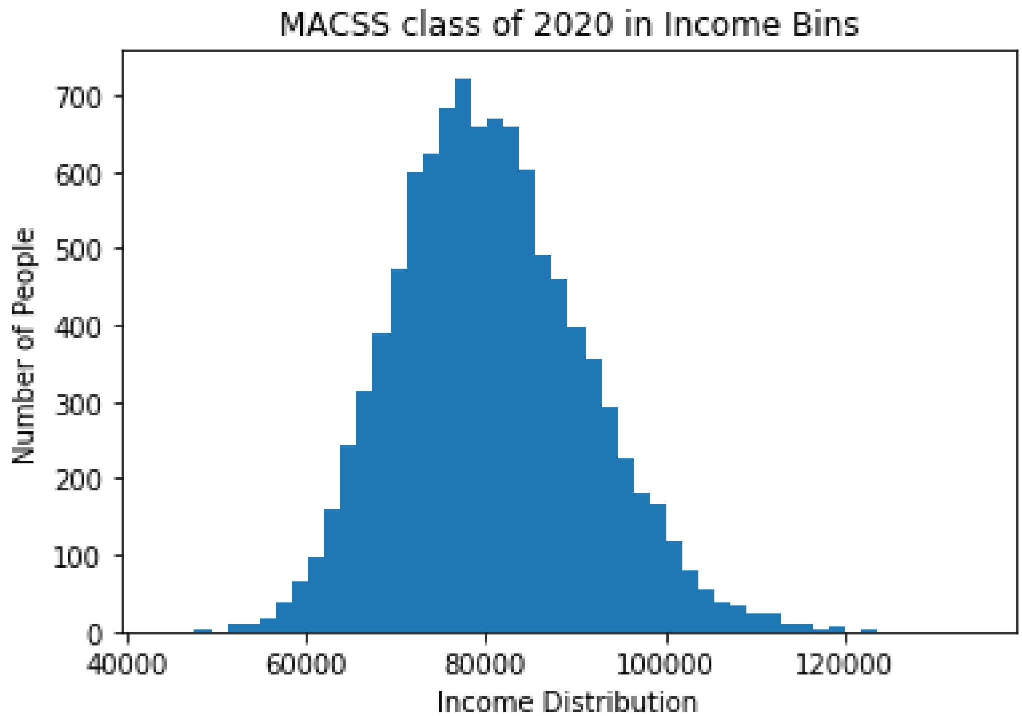
Out[4]: Text(0,0.5,'Annual Income (\\$s)')



(b) Plot a histogram with 50 bins of year t = 2020 initial income for each of the 10,000 simulations

In [5]:
```
# plot the histogram
plt.hist(macss_inc[0,:], bins=50)
plt.xlabel("Income Distribution")
plt.ylabel("Number of People")
plt.title("MACSS class of 2020 in Income Bins")
```

Out[5]: Text(0.5,1,'MACSS class of 2020 in Income Bins')



This distrincution is normally distributed but a little bit skewed to the right.

```
In [6]: income = macss_inc[0, :]
        len(income [income > 100000]) / len(income)
```

```
Out[6]: 0.0417
```

4.17% of the class will earn more than $100,000 in the first year.

```
In [7]: income = macss_inc[0, :]
        len(income [income < 70000]) / len(income)
```

```
Out[7]: 0.1512
```

15.12% of class will earn less than 70,000 in the first year.

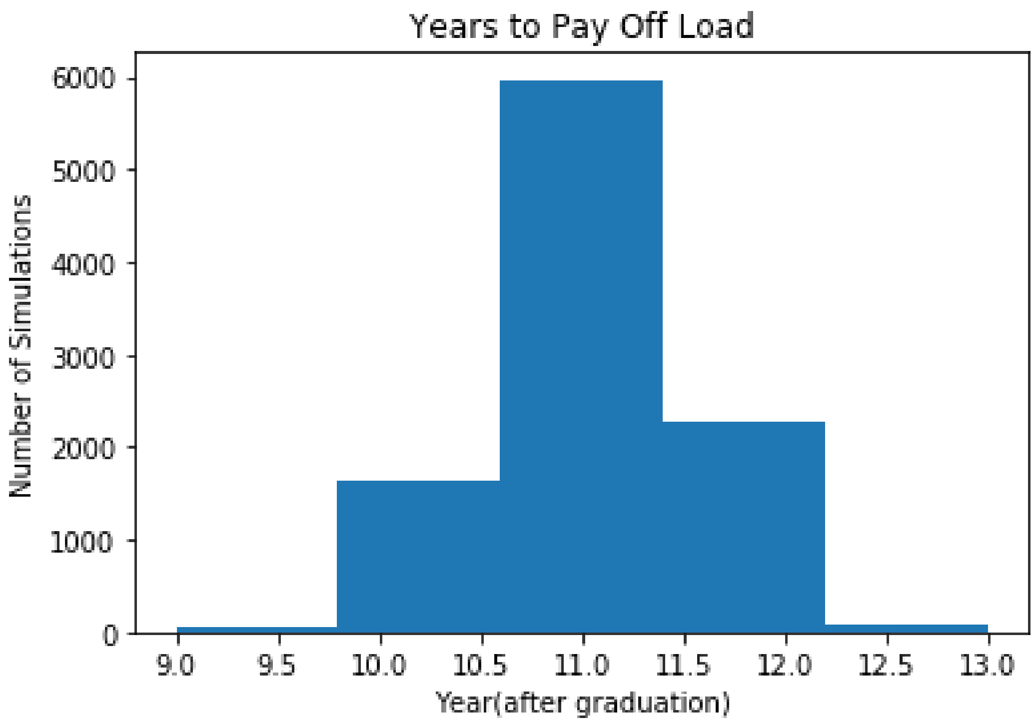
(c) Plot the histogram of how many years it takes to pay the loan in each of your 10,000 simulations

```
In [8]: # calculate the number of years to pay off the loan
        loan = 0.1 * macss_inc

        year_to_payoff = []
        for i in range(10000):
            paid=loan[:,i][0]
```

```
        for j in range(1,40):
            if paid < 95000:
                paid = paid + loan[:,i][j]
            else:
                year_to_payoff.append(j)
                break
```

In [9]:
```
# plot the histogram
plt.hist(year_to_payoff, bins=5)
plt.xlabel("Year(after graduation)")
plt.ylabel("Number of Simulations")
plt.title("Years to Pay Off Load")
```

Out[9]: `Text(0.5,1,'Years to Pay Off Load')`



In [10]:
```
# calculate the percentage of the simulations which can pay off the loan in 10 years
perc_before_10y = 0

for i in range(10000):
    if year_to_payoff[i] <= 10:
        perc_before_10y += 1

perc_before_10y/10000
```

Out[10]: `0.1678`

16.78% of the simulations are able to pay off the loan in 10 years.

(d) Plot the new histogram of how many years it takes to pay your loan of according to new income and standard deviation

```
In [11]: # new prifile to simulate
         new_simulation_profile = {
             'inc'          : 90000,
             'rho'          : 0.4,
             'mu'           : 0,
             'sd'           : 0.17,
             'gr'           : 0.025,
             'st_year'      : int(2020),
             'wr_years'     : 40,
             'num_draws'    : 10000
             }

         new_macss_inc = macss_income_sim(new_simulation_profile)
         print(new_macss_inc)
```

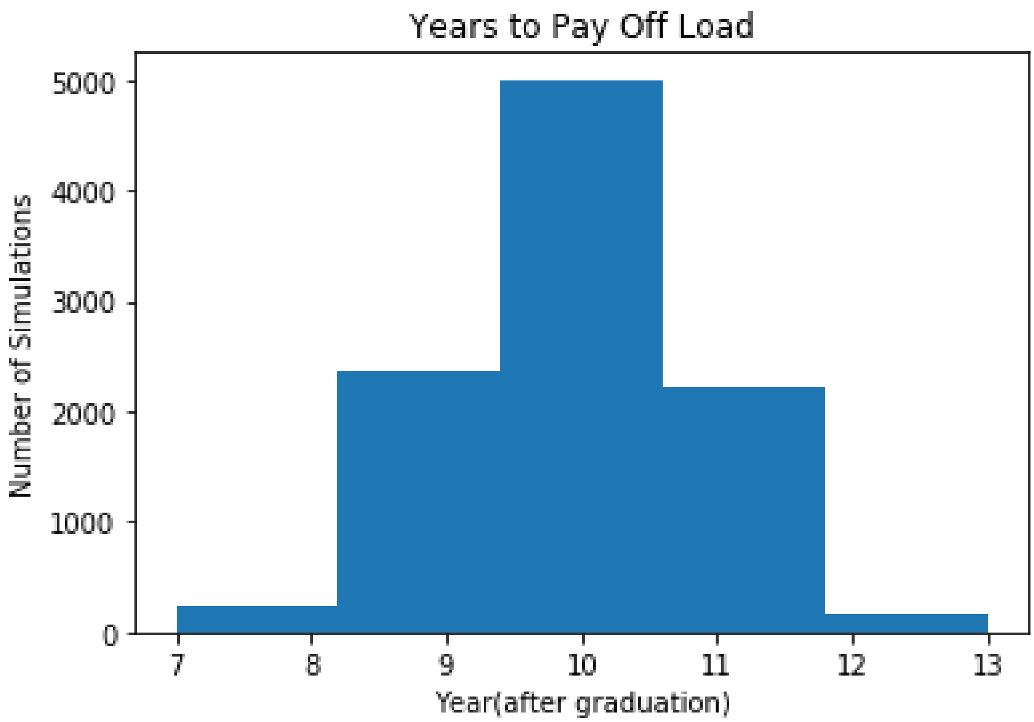
```
[[ 70550.46142451 117783.33011091 123561.20729139 ... 118483.24080508
   78992.81966812  73764.25171169]
 [ 89615.63768821  71575.56495871  96317.75493523 ...  72778.88084775
   81644.3347736   90400.57899801]
 [ 82955.30101689  69396.06916251 106035.55593099 ...  70956.3661129
  103848.93176006  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 [12]: # calculate the new number of years to pay off the loan
         loan = 0.1 * new_macss_inc

         new_year_to_payoff = []
         for i in range(10000):
             paid=loan[:,i][0]
             for j in range(1,40):
                 if paid < 95000:
                     paid = paid + loan[:,i][j]
                 else:
                     new_year_to_payoff.append(j)
                     break
```

```
In [13]: # plot the new histogram
         plt.hist(new_year_to_payoff, bins=5)
         plt.xlabel("Year(after graduation)")
```

```
plt.ylabel("Number of Simulations")
plt.title("Years to Pay Off Load")
```

Out[13]: Text(0.5,1,'Years to Pay Off Load')




```
In [14]: # new percentage of simulations which can pay off the loan in 10 years
         new_perc_before_10y = 0

         for i in range(10000):
             if new_year_to_payoff[i] <= 10:
                 new_perc_before_10y += 1

         new_perc_before_10y/10000
```

Out[14]: 0.7602

76.02% of the simulations are able to pay off the loan in 10 years.