A3-DiTong

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1 Assignment 3

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1. Simulation in Sociology, Moretti (2002)

See the attached PDF at the end of this file

2. Simulating your income

(a)I will use the following codes to Simulate 10,000 different realizations of lifetime income.

```
In [108]: # Import initial packages
          import numpy as np
          import matplotlib.pyplot as plt
          from matplotlib.ticker import MultipleLocator
```

```
In [109]: # Function to do the simulations
          def normal_income_sim(p):

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

              p = {
                  'inc0'          : 80000,      #average initial income
                  'g'             : 0.025,      #growth rate
                  'dep'           : 0.4,        #positive dependence of today's income on
                                                last period's income
                  'work_years'    : 40,         #working years
                  'st_year'       : 2020,       #start year
                  'mean'          : 0,          #mean of normal distribution
                  'sd'            : 0.13,       #standard deviation of normal distribution
                  'size'          : 40,         #size of normal distribution
                  'num_draws'     : 10000       #simulations
              }
              """
```

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

    #create a set of 40 normally distributed errors
    normal_errors = np.random.normal(p['mean'], p['sd'], (p['size'], p['num_draws']))

    #create a matrix of income (work_years, num_draws)
    ln_inc_mat = np.zeros((p['work_years'], p['num_draws']))

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

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


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

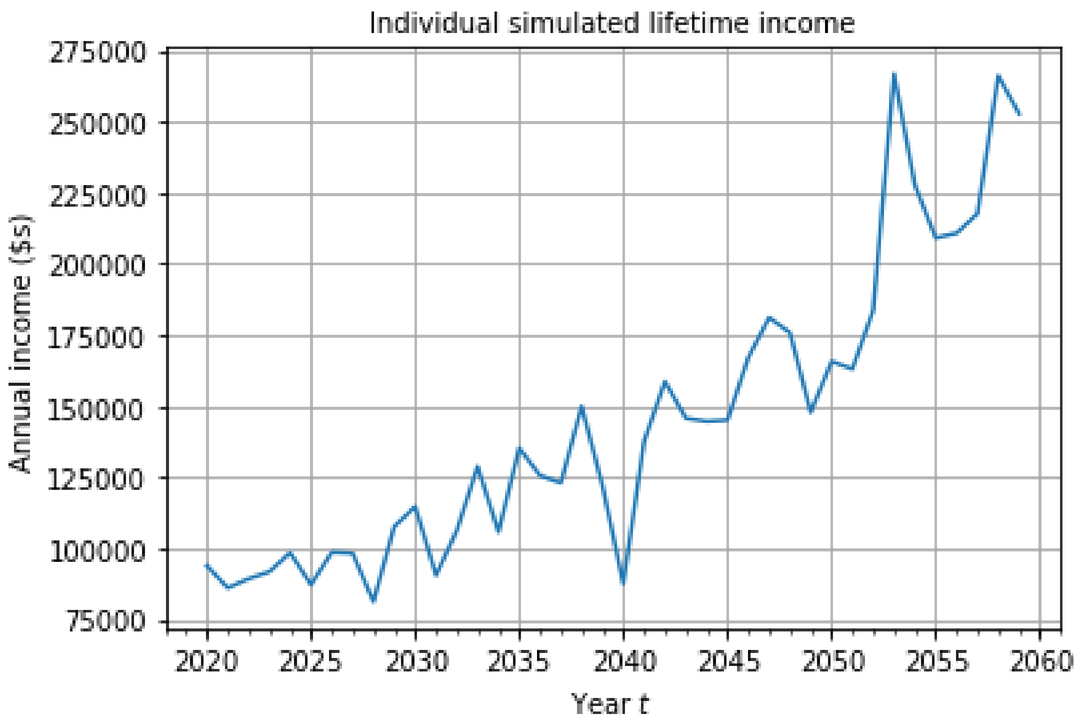
```
In [110]: # Define the simulation profile and plug it in the function
          simulation_profile = {
              'inc0'          : 80000,      #average initial income
              'g'             : 0.025,      #growth rate
              'dep'           : 0.4,        #positive dependence of today's income on
                                            #last period's income
              'work_years'    : 40,         #working years
              'st_year'       : 2020,       #start year
              'mean'          : 0,          #mean of normal distribution
              'sd'            : 0.13,       #standard deviation of normal distribution
              'size'          : 40,         #size of normaldistribution
              'num_draws'     : 10000       #simulations
          }

          inc_mat = normal_income_sim(simulation_profile)
```

I will use the following codes to plot one of the lifetime income paths.

```
In [111]: %matplotlib inline
          p = simulation_profile
          year_vec = np.arange(p['st_year'], p['st_year'] + p['work_years'])
          individual = 500
          fig, ax = plt.subplots()
          plt.plot(year_vec, inc_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 lifetime income', fontsize=10)
plt.xlabel(r'Year $t$')
plt.ylabel(r'Annual income (\$s)')
```

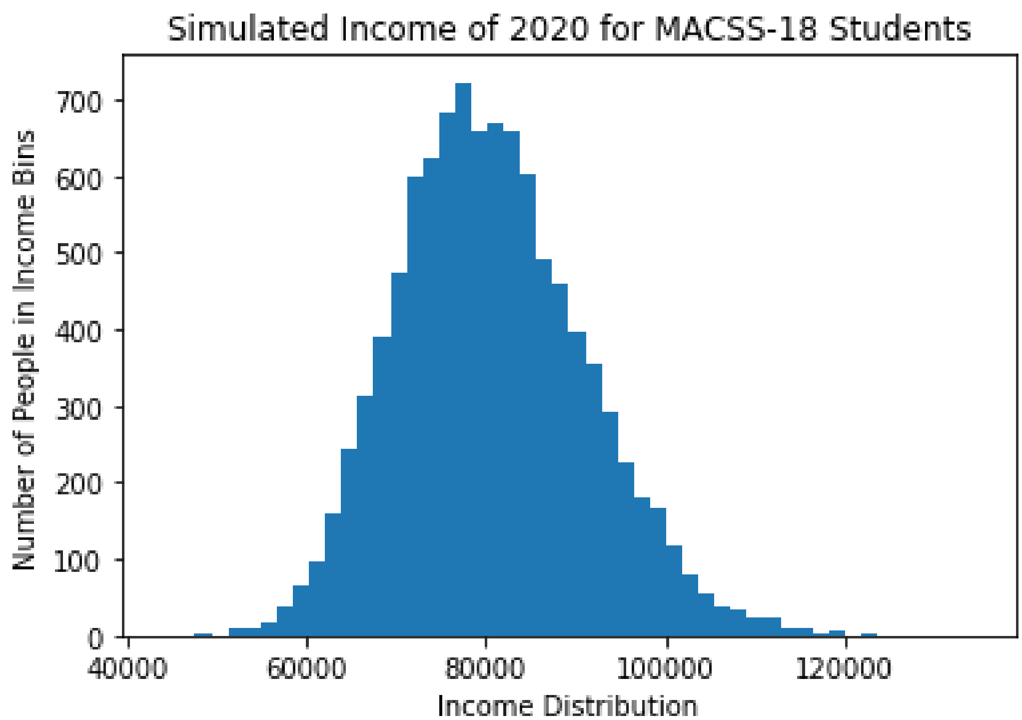
Out[111]: Text(0,0.5,'Annual income (\\$s)')



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

In [112]:
```
plt.hist(inc_mat[0,:], bins=50)
plt.xlabel("Income Distribution")
plt.ylabel("Number of People in Income Bins")
plt.title("Simulated Income of 2020 for MACSS-18 Students")
```

Out[112]: Text(0.5,1,'Simulated Income of 2020 for MACSS-18 Students')

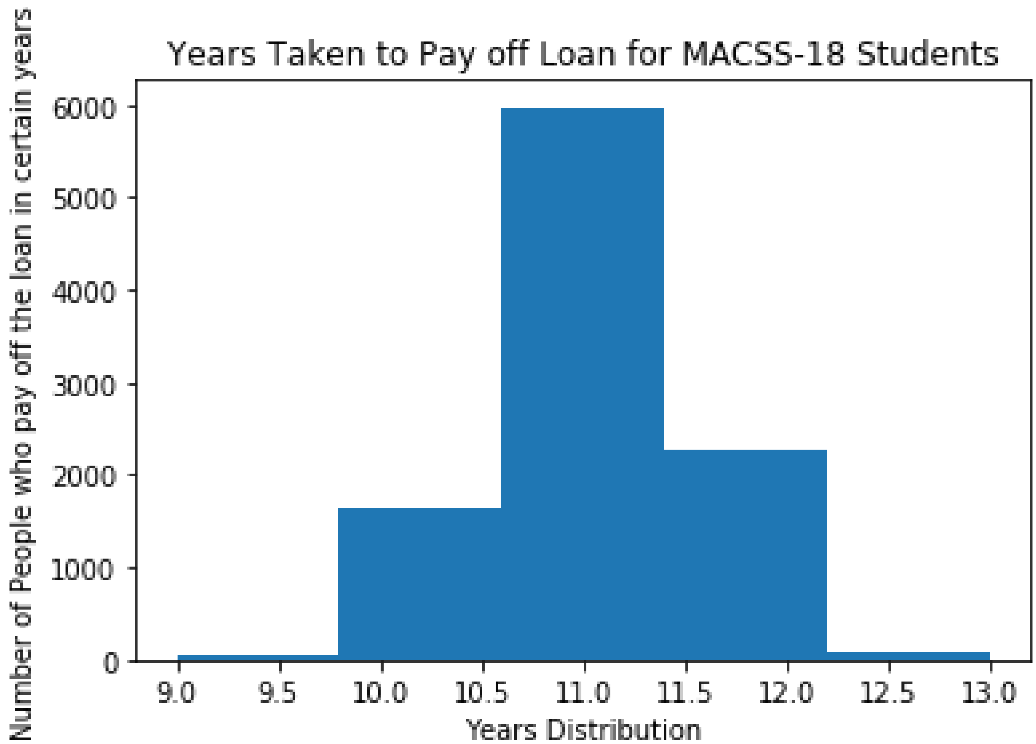



```
In [113]: #calculate the percentage of people in my class that will earn more
          #than $100,000 in the first year out of the program
          num = 0
          for d in inc_mat[0]:
              if d > 100000:
                  num +=1
          percentage = num / 10000
          print("percentage of people that earn more than $100000 =", percentage)

          #calculate the percentage of people in my class that will earn less
          #than $70,000 in the first year out of the program
          num = 0
          for d in inc_mat[0]:
              if d < 70000:
                  num +=1
          percentage = num / 10000
          print("percentage of people that earn less than $70000 =", percentage)

percentage of people that earn more than $100000 = 0.0417
percentage of people that earn less than $70000 = 0.1512
```

From the histogrm above, we can see that the distribution largely follows a normal distribution pattern, though it is a bit right skewed.

(c) I will use the following codes to calculate the years needed to pay off the loan for all simulations, plot the histogram and calculate the percentage.

```
In [114]: # create a list of years needed to pay off debt for all simulations
          inc_mat = normal_income_sim(simulation_profile)
          def calculate_year(inc_mat):
              """
              Calculate the years needed to pay off debt

              """
              years = []
              for column in inc_mat.T:
                  paid_debt = 0
                  for i in range(len(column)):
                      if paid_debt < 95000:
                          paid_debt += 0.1 * column[i]
                      else:
                          years.append(i)
                          break
              return years

          # remove the duplicate elements in the list years and calculate
          #unique years in which people pay off the debt
          years = calculate_year(inc_mat)

          def remove(duplicate):
              final_list = []
              for num in duplicate:
                  if num not in final_list:
                      final_list.append(num)
              return final_list
          non_duplicate_years = remove(years)
          n = len(non_duplicate_years)

In [115]: plt.hist(years[:], bins = n)
          plt.xlabel("Years Distribution")
          plt.ylabel("Number of People who pay off the loan in certain years")
          plt.title("Years Taken to Pay off Loan for MACSS-18 Students")

Out[115]: Text(0.5,1,'Years Taken to Pay off Loan for MACSS-18 Students')
```




```
In [117]: # Calculate the percentage of the simulations that I am able to
          #pay off the debt in ten years
          count = 0
          for t in years:
              if t <= 10:
                  count +=1
          percentage = count / 10000
          print("percentage of the simulations that I am able to \
              pay off the debt in ten years =", percentage)

percentage of the simulations that I am able to pay off the debt in ten years = 0.1678
```

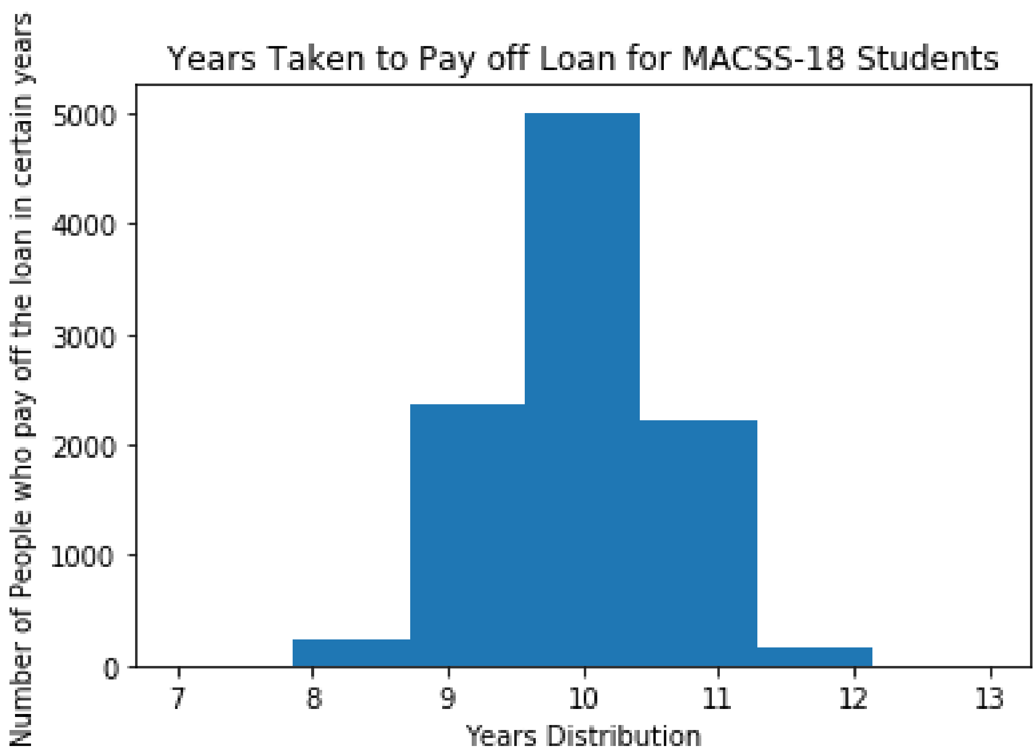
(d) I will use the following codes to calculate the years needed to pay off the loan for all simulations, plot the histogram and calculate the percentage.

```
In [118]: new_simulation_profile = {
              'inc0'          : 90000,      #average initial income
              'g'             : 0.025,      #growth rate
              'dep'           : 0.4,        #positive dependence of today's income
                                            #on last period's income
              'work_years'    : 40,         #working years
              'st_year'       : 2020,       #start year
```

```
    'mean'          : 0,          #mean of normal distribution
    'sd'            : 0.17,       #standard deviation of normal distribution
    'size'          : 40,         #size of normaldistribution
    'num_draws'     : 10000       #simulations
}

inc_mat = normal_income_sim(new_simulation_profile)
new_years = calculate_year(inc_mat)
new_n_dup_years = remove(new_years)
p = len(new_n_dup_years)
```

In [119]:
```
plt.hist(new_years[:], bins = p)
plt.xlabel("Years Distribution")
plt.ylabel("Number of People who pay off the loan in certain years")
plt.title("Years Taken to Pay off Loan for MACSS-18 Students")
```

Out[119]:
```
Text(0.5,1,'Years Taken to Pay off Loan for MACSS-18 Students')
```



In [120]:
```
#Calculate the percentage of the simulations that I am able to
#pay off the debt in ten years
new_count = 0
for t in new_years:
    if t <= 10:
```

```python
            new_count +=1
    new_percentage = new_count / 10000
    print("percentage of the simulations that I am able to \
        pay off the debt in ten year =", new_percentage)
```

```
percentage of the simulations that I am able to pay off the debt in ten year = 0.7602
```

For multi-agent systems, some potential weaknesses regarding validity lie in the formalization of psychological theories (emotions, motivations, desire, intent, consciousness) and knowledge, which are important elements to set up the rules of human interaction for modelling. Since these theories and the related concepts involve lots of interpretations, and hence, could not be easily operationalized, models based on formalization of them might have the risk of not representing the real situation.

For cellular automata, the first potential weakness in validity concerns the use of synchronous updating of states. Since in real social processes, individuals might not change their attitudes and opinions simultaneously, a simulation model based on this assumption may lose the validity to reflect the real world. Another potential weakness of cellular automata in validity is related to the restrictions imposed by spatial structures, which confines the interactions of each individual within a subset of the whole population. Since it is difficult to define and constantly update the "neighborhood" each individuals interact with, a model with spatial structures restrictions might not hold plausible regarding its ability to furnish a realistic account of social processes.

The author cites a model of population growth from Forrester's (1971) *World Dynamics* that exhibits the characteristic of "dynamic feedback": a new unforeseen technological innovation could change the relationship between natural resources and population growth, and hence, affect the population growth.

An example research question where the underlying system exhibits dynamic feedback can be: what is the effect of online discussion of certain political activism on the participation of it? An initial increase in online discussion can get the potential participants of that activism informed of its existence and then participate in it. When the number of participants increase, more online discussion and other forms of media coverage of the activism can be triggered, and hence make it possible for the activists organization to reach out to more potential participants and absorb them into the activism.