

Assignment3_solution

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1 Assignment 3

1.0.1 MACS 30000, Dr. Evans

1.0.2 Ruixi Li

Due Wednesday, Oct. 24 at 11:30 AM

1.1 Question 1

Simulations are widely used in sociology. Techniques like system dynamics, multiagent systems, cellular automata and genetic algorithms have developed in the progress. When constructing a simulation system for mapping theory to practice, the crucial characteristic of the model is matching the real-world, validity in other words. However, some techniques may fail to achieve that.

Two limitations of multiagent system and cellular automata

Multi-agent systems and cellular automata bear some potential weakness in validity.

For multiagent systems, Moretti (2002) believes that the following three aspects need further research. First, using theories and models concerning rationality that are realistic, understandable, and can be applied in the case of limited knowledge. In particular, theories of rationality need to be extended to learning and adaptation. Second, formalizing all the aspects of psychological theories, such as emotions, motivations, desire, intent, consciousness. Third, formalizing all types of knowledge by determine the possibility of it and the best way to achieve that.

For cellular automata, Moretti (2002) proposed two limitations for the approach. Firstly, this approach sync data at the same time. However, agents make decisions and modify their choice at different time. Evidence found that the operation order has great effect on the turnout. Therefore, arbitrarily conclude that actions in the period between two syncing happened together is dangerous. Secondly, the neighborhood of a unit is hard to define. This approach restricts each individual interacts only with a subset of the whole population which is reasonably. The problem is how to define the boundary. Back in old day, we may define the boundary by geographic location. Nowadays, with the invention of Internet, interactions can take place between two individuals on the opposite side of the earth. Consequently, it is difficult to set the line on neighborhood.

Model with feature of dynamic feedback

Except for this two system, there is another system called “genetic algorithm” which present a feature of “dynamic feedback”. That is to say, the result of the initial inputs will be added to inputs for next round of simulation. Genetic algorithm is based on Darwin’s theory of evolution. According to this theory, a species evolves in relation to its own capacity to adapt to the natural and complex environment. In Darwin’s theory of evolution, the result of the initial inputs is stored in the chromosome of a species which can be passed on to next generation. Then, next

generation will behave with the information saved in their chromosome in order to avoid repetitive mistakes. Genetic algorithm is applied to two fields in sociology: game theory and cultural evolution. For further illustration, Moretti (2002) cited a model from cultural evolution. Lustick (2000) apply genetic algorithm model to culture transmission, they study “how cultures emerge and transform out of vast number of micro-interactions entailing the diffusion or disappearance of cultural fragment”.

Example in political science

In political science, examples of dynamic feedback are easy to spot. During elections, advertisements of president candidates is made in different stages. Normally, after the first round advertisement, the candidate group will collect information and feedbacks of the ads. Then, after analyzing the data, they will choose the proper content and position for the second round of advertisement. It is the same with third round and fourth round, etc. That is to say, the current choice is based on the current information, but not the starting-stage information. So the advertisement during elections exhibits dynamic feedback.

Reference

Moretti, Sabrina, "Computer Simulation in Sociology: What Contribution?" Social Science Computer Review, 20:1 (Spring 2002), pp. 43-57.

1.2 Question 2

```
In [1]: # Import initial packages
```

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import MultipleLocator
```

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

```
    """
```

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

```
    p = {
```

```
        'inc0'      : 80000,      #average starting income (t = 2018) for a MACSS s
        'g'         : 0.025,      #income growth rate
        'dep'       : 0.4,        #positive dependence of todays income on last per
        'st_year'   : 2018,      #starting year
        'lf_years'  : 40,         #years to work
        'num_draws' : 10000       #simulations
        'sd'        : 0.13        #standard error
    }
```

```
    """
```

```
    #set random seed
```

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

```
    #create an error term
```

```
    ln_errors = np.random.normal(0, p['sd'], (p['lf_years'], p['num_draws']))
```

```
    #create a matrix of dim (lf_years, num_draws)
```

```

ln_inc_mat = np.zeros((p['lf_years'], p['num_draws']))

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

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

```

(a)

```

In [3]: simulation_profile = {
        'inc0'      : 80000,
        'g'         : 0.025,
        'dep'       : 0.4,
        'st_year'   : 2020,
        'lf_years'  : 40,
        'num_draws' : 10000,
        'sd'        : 0.13
    }

inc_mat = students_income_sim(simulation_profile)
print(inc_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]]

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

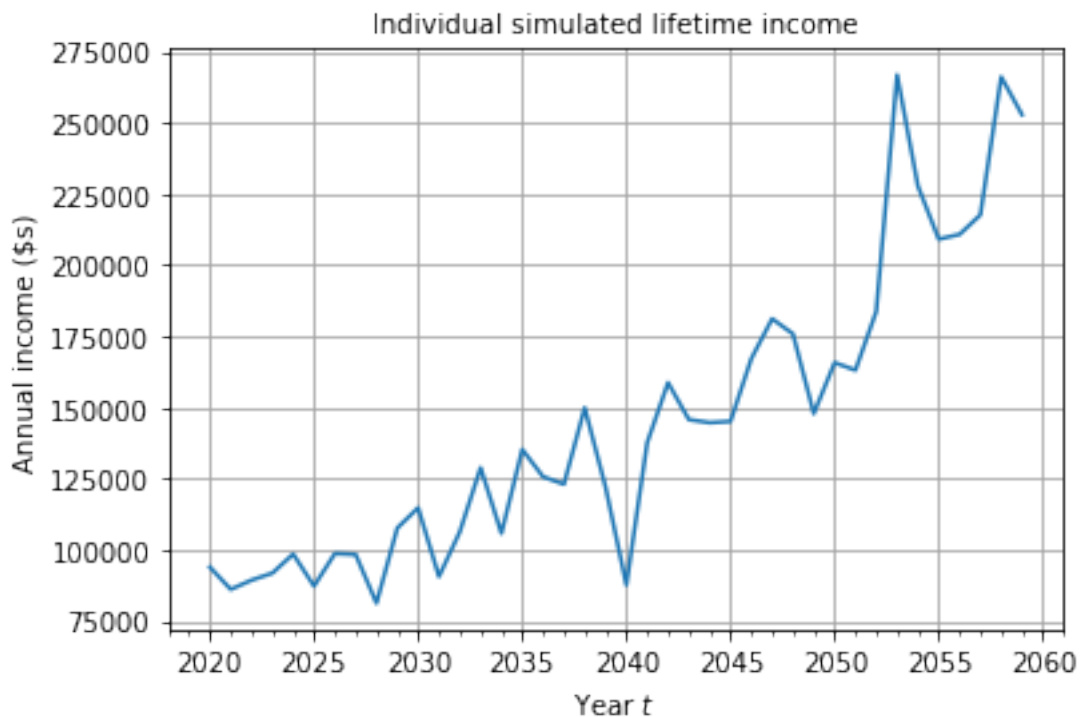
```

```

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



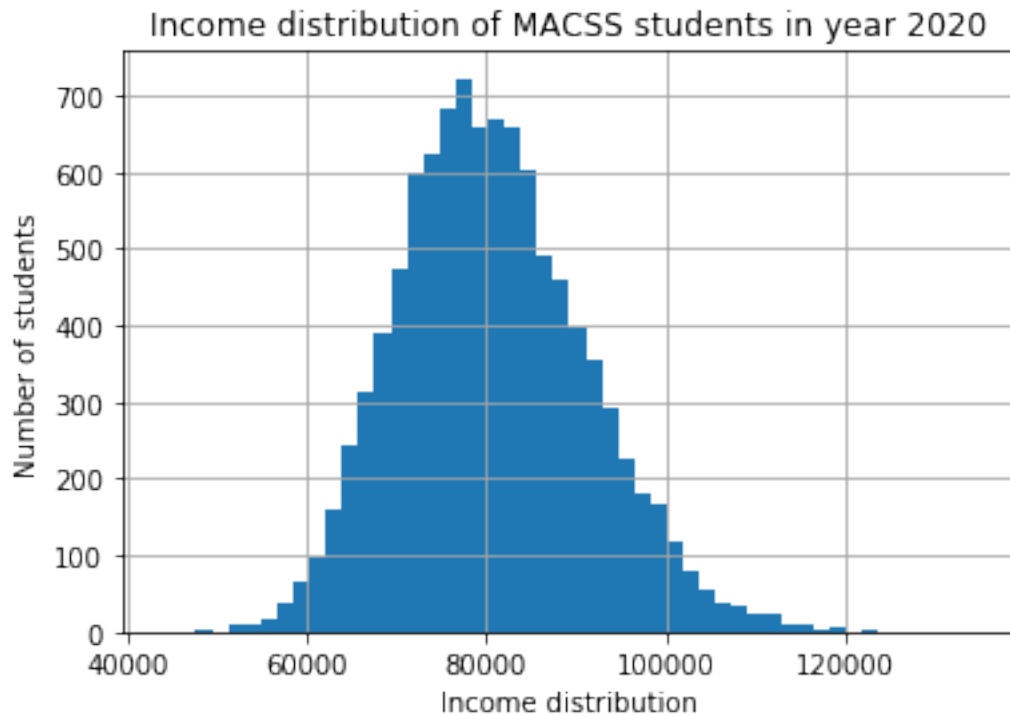
(b)

```

In [5]: plt.hist(inc_mat[0,:], bins=50)
plt.grid(b=True, which='major', color='0.65', linestyle='-')
plt.xlabel("Income distribution")
plt.ylabel("Number of students")
plt.title("Income distribution of MACSS students in year 2020")

```

Out[5]: Text(0.5,1,'Income distribution of MACSS students in year 2020')



```
In [6]: #Transform Numpy Arrays Into Useful Dataframe
import pandas as pd
```

```
years = np.arange(p['st_year'], p['st_year'] + p['lf_years']).tolist()
df = pd.DataFrame(inc_mat).T
df.columns = years
df = df.T
df['year'] = df.index
df = pd.melt(df, id_vars='year', var_name='id')
df.head()
```

```
Out[6]:
```

	year	id	value
0	2020	0	66409.155854
1	2021	0	80020.530203
2	2022	0	75805.266366
3	2023	0	88075.026534
4	2024	0	106861.634158

```
In [7]: df_year = df.loc[df['year'] == 2020]
df_year['value'].describe()
```

```
Out[7]:
```

	count	mean	std
count	10000.000000		
mean		80653.274318	
std		10541.874277	

```

min      43891.472511
25%      73182.442566
50%      79865.114586
75%      87363.900030
max      134596.691453
Name: value, dtype: float64

```

```

In [8]: #Calculate percentile of given earnings
from scipy import stats
percentile_more_than_100000 = 100 - stats.percentileofscore(df_year['value'], 100001,
print(percentile_more_than_100000)

```

```
4.1700000000000002
```

The percent of my class will earn more than \$100,000 in the first year out of the program is 4.17%.

```

In [9]: percentile_less_than_70000 = stats.percentileofscore(df_year['value'], 70001, 'strict')
print(percentile_less_than_70000)

```

```
15.120000000000001
```

The percent of my class will earn less than \$70,000 in the first year out of the program is 15.1%.

```

In [10]: # Check if the distribution normally distributed
stats.normaltest(df_year['value'])

```

```
Out[10]: NormaltestResult(statistic=290.481782626689, pvalue=8.369169350300544e-64)
```

From the normal test with such a small p-value, we believe that the income of MACSS student is normal. It is symmetric and bell-curved.

(c)

```

In [11]: # Calculate the year of paying off the loan
inc_mat_loan = 0.1 * inc_mat
inc_mat_loan_count = inc_mat_loan.cumsum(axis=0)
df_count = pd.DataFrame(inc_mat_loan_count).T
df_count['payoff_year'] = df_count.apply(lambda x: (x<95000).sum() + 2020, axis=1)
df_count.head()

```

```

Out[11]:
      0      1      2      3      4  \
0  6640.915585  14642.968606  22223.495242  31030.997896  41717.161311
1  9827.413534  16565.732885  23179.175379  31525.852192  41258.618848
2  10193.981110  18649.766736  27795.587041  36777.439151  45797.855445
3  10233.704639  18946.540346  27524.243572  37661.664339  47253.827953
4  10124.798322  17686.536303  25482.631147  33616.286403  40848.363562

```

	5	6	7	8	9 \
0	52676.693530	61802.183208	72777.802094	81851.561040	90545.655033
1	48916.052326	58145.237557	68716.189449	79366.460690	89201.898695
2	55903.458803	66055.526545	76675.919178	87577.596683	97206.692550
3	57876.950873	68924.709523	79103.893255	88773.587840	97722.872590
4	47363.138501	54752.099691	63622.606918	71769.940539	82510.675309

	...	31	32	33	34 \
0	...	401320.070822	416826.041658	431634.560790	448494.207843
1	...	370901.093848	385737.661666	404338.083038	428022.431760
2	...	384172.593397	403016.624248	421111.319671	443370.331011
3	...	373251.374256	391183.734099	411393.734102	431922.235539
4	...	398451.017414	420788.974503	438703.481476	458197.910693

	35	36	37	38	39 \
0	470080.410935	489583.886535	516852.943054	540006.860475	559796.455676
1	448057.333219	470661.887333	492444.060360	512694.975510	529206.485535
2	468386.636542	490570.416678	509042.841190	528838.437817	546102.924744
3	454122.307209	474466.476564	495085.866389	513470.490072	532248.706033
4	477064.734821	490432.584758	509769.914805	530601.811995	547182.885692

	payoff_year
0	2030
1	2030
2	2029
3	2029
4	2030

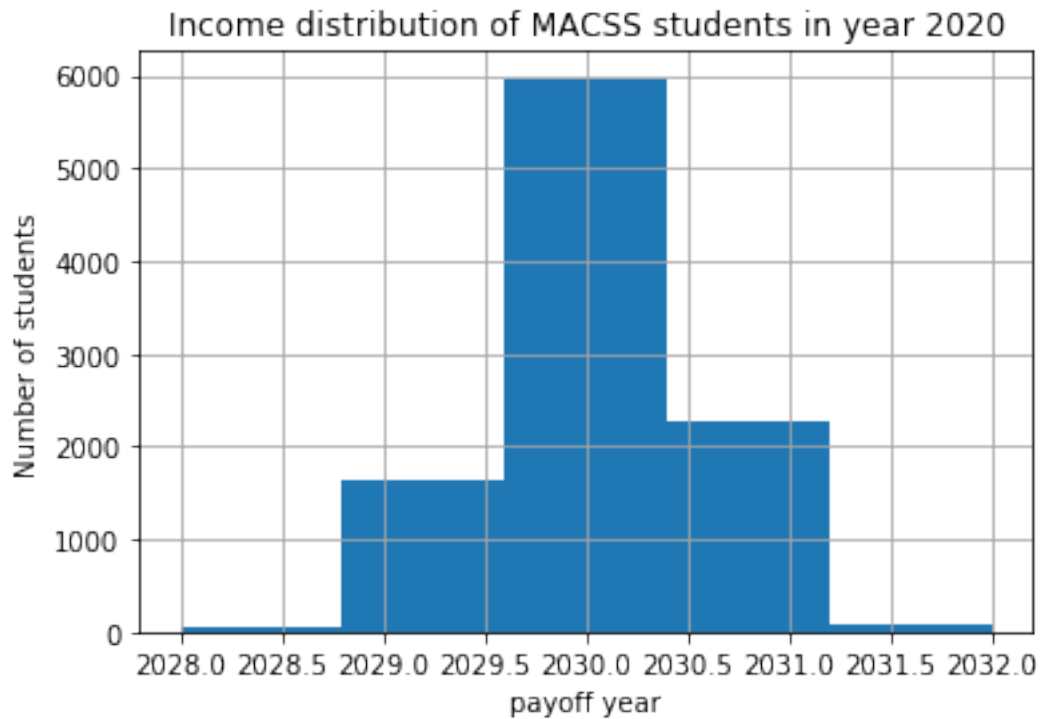
[5 rows x 41 columns]

```
In [12]: # Calculate number of bins by calculate number of unique years
len(df_count['payoff_year'].unique())
```

Out[12]: 5

```
In [13]: # Plot the histogram of how many years it takes to pay off the loan
plt.hist(df_count['payoff_year'], bins=5)
plt.grid(b=True, which='major', color='0.65', linestyle='-')
plt.xlabel("payoff year")
plt.ylabel("Number of students")
plt.title("Income distribution of MACSS students in year 2020")
```

Out[13]: Text(0.5,1,'Income distribution of MACSS students in year 2020')



```
In [14]: percentile_10yr = stats.percentileofscore(df_count['payoff_year'], 2030, 'strict')
         print(percentile_10yr)
```

16.78

16.8% percent of the simulations are able to pay off the loan in 10 years.

(d)

```
In [15]: # New simulation
         simulation_profile1 = {
             'inc0'      : 90000,
             'g'         : 0.025,
             'dep'       : 0.4,
             'st_year'   : 2020,
             'lf_years'  : 40,
             'num_draws' : 10000,
             'sd'        : 0.17
         }

         inc_mat1 = students_income_sim(simulation_profile1)
         print(inc_mat1)
```



```

[[ 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 [16]: # Calculate the year of paying off the loan
inc_mat_loan1 = 0.1 * inc_mat1
inc_mat_loan1_count = inc_mat_loan1.cumsum(axis=0)
df_count1 = pd.DataFrame(inc_mat_loan1_count).T
df_count1['payoff_year'] = df_count1.apply(lambda x: (x<95000).sum()+2020, axis=1)
df_count1.head()

```

```

Out[16]:
      0      1      2      3      4 \
0  7055.046142 16016.609911 24312.140013 34333.296161 47140.911566
1  11778.333011 18935.889507 25875.496423 35216.582126 46550.888080
2  12356.120729 21987.896223 32591.451816 42872.807107 53134.720879
3  12419.122357 22435.567638 32186.140501 44230.528342 55351.190956
4  12246.576993 20568.831331 29174.187992 38204.750454 45891.409034

      5      6      7      8      9 \
0  60278.250807 70538.832110 83501.014229 93530.289712 102941.709379
1  54771.198811 65184.514942 77525.312299 89891.909093 100950.693669
2  64949.829434 76745.318015 89161.647500 101911.366268 112667.740724
3  67963.700504 81138.195166 92884.345976 103783.561489 113557.846084
4  52545.816626 60331.417932 70143.066774 78854.839154 91263.186075

      ...      31      32      33      34 \
0  ...      461907.029993 478710.884413 494412.014189 512873.278455
1  ...      415136.337440 430997.912532 452152.620044 480946.075180
2  ...      435560.458455 457244.366269 477650.088915 504198.845312
3  ...      418926.251938 439248.634289 462828.475331 486711.019972
4  ...      457203.348438 484288.814926 504429.220114 526750.916183

      35      36      37      38      39 \
0  538182.129208 560176.382415 594007.294176 621113.401225 643019.147974
1  503903.201069 530578.622378 555797.374404 578547.606840 595834.140173
2  534890.908317 560918.860780 581248.164425 603331.821399 621656.393109
3  512965.151441 536207.314368 559680.244528 579728.470866 600181.868244

```

```
4  547973.678153  561394.580288  582977.478421  606584.965040  623966.797805
```

```
payoff_year
0      2029
1      2029
2      2028
3      2028
4      2030
```

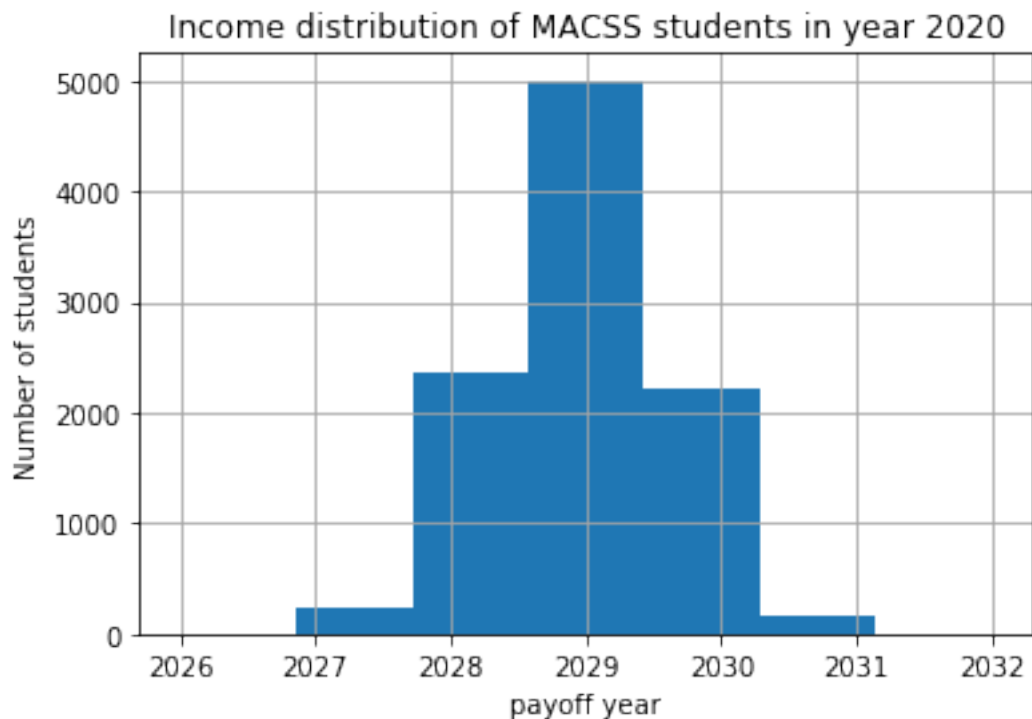
```
[5 rows x 41 columns]
```

```
In [17]: # Calculate number of bins by calculate number of unique years
len(df_count1['payoff_year'].unique())
```

```
Out[17]: 7
```

```
In [18]: # Plot the histogram of how many years it takes to pay off the loan
plt.hist(df_count1['payoff_year'], bins=7)
plt.grid(b=True, which='major', color='0.65', linestyle='-')
plt.xlabel("payoff year")
plt.ylabel("Number of students")
plt.title("Income distribution of MACSS students in year 2020")
```

```
Out[18]: Text(0.5,1,'Income distribution of MACSS students in year 2020')
```



```
In [19]: percentile_10yr1 = stats.percentileofscore(df_count1['payoff_year'], 2030, 'strict')
         print(percentile_10yr1)
```

76.02

76.0%percent of the simulations are able to pay off the loan in 10 years.