```
1 # import packages
2 import matplotlib
3 import matplotlib.pyplot as plt
4 import pylab as PL
5 import random as RD
6 import scipy as SP
7 import numpy as np
8 RD.seed(2020)
9
10 # setting color scheme for latter use
11 coloring = ["red", "green", "blue", "yellow"]
```

→ 1. Single Lane

▼ 1.1. Simulation model

```
1 class TrafficSimulator(object):
 2
    # initilize the parameters
    def init (self, length=100, density=0.1, v max=5, p down=0.5, interactive=False):
 5
      self.interactive = interactive
      self.length = length
      self.density = density
 7
      self.v max = v max
      self.p down = p down
 9
10
      # Arrays for storing the current state and the next state (when we are
11
      # busy doing a state update).
12
13
      self.current state = np.zeros(self.length)
      self.next state = np.zeros(self.length)
14
15
    # setting the 1st state of the road
16
    def initialize(self):
17
18
19
      This will be called by the interactive pycxsimulator whenever the Reset
20
      button is clicked.
```

```
21
      # Set up a random initial state where the fraction of 1s in the array
22
      # equals the density parameter.
23
       self.current state.fill(-1)
24
25
      # setting the cars
26
      for x in range(self.length):
27
        if RD.random() < self.density:</pre>
28
           # each car has initial speed from 1 to v max
29
30
           state = RD.randint(1, self.v max)
           self.current_state[x] = state
31
32
33
       self.time = 0
34
35
    # display using string type
    def display(self):
36
      print(''.join('\cdot' if x == -1 else str(int(x)) for x in self.current state))
37
38
39
    # one step running the similation
40
    def step(self):
41
42
         Update the state of the cellular automaton.
43
        n = self.length
44
45
46
         # initialize next state
        self.next state = np.zeros(self.length)
47
         self.next state.fill(-1)
48
49
        # loop through all cars
50
        for i in range(self.length):
51
52
          # only consider non-empty cells
53
          if self.current state[i] != -1:
54
55
             v = int(self.current state[i])
56
             # checking if we have space to accelerate
57
             for k in range(1, min(v + 1, self.v max) + 1):
58
               # this is the maximum speed we can reach: min(v+1, v max)
59
               current v = min(v + 1, self.v max)
60
               # if there is obstacle: other cars
61
```

```
if self.current state[(i+k)%n] != -1:
62
                 #new max speed
63
                 current v = k-1
64
65
                 break
66
            # randomization in slowing down
67
             if RD.random() < self.p down and current v > 0:
68
               current v -= 1
69
70
            # updating the next state
71
72
             self.next state[(i + current v)%n] = current v
73
        # swapping to update the whole current state
74
        self.current state, self.next state = self.next state, self.current state
75
         self.time += 1
76
77
    # number of cars pass the last bar:
78
    def car pass(self):
79
      for i in range(self.v max):
80
        # if there is a car and has speed > current position -> it must have cross the last bar
81
82
        if self.current state[i] != -1 and self.current state[i] > i:
83
           return True
84
       return False
85
86
    def check density(self, value=None):
87
      The density of cars on the road. Only affects initialization (reset) of
88
      the simulation. The density must be a value between 0 and 1.
89
90
      return np.mean(self.current state != -1)
91
```

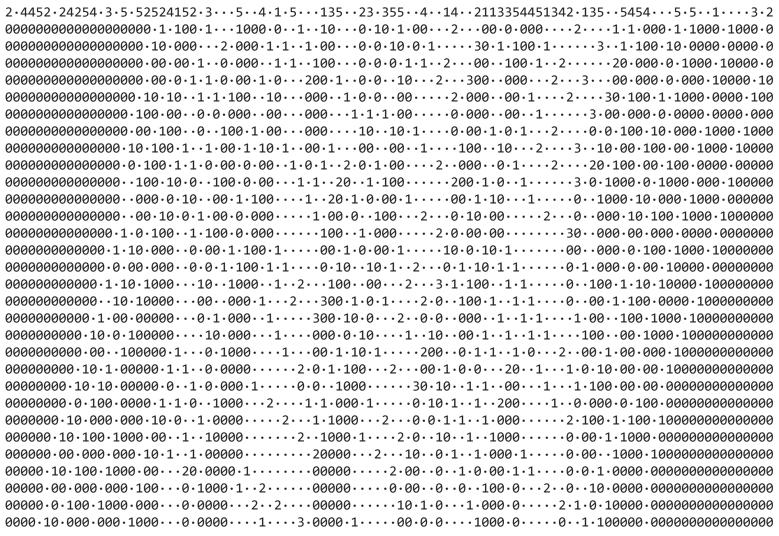
▼ 1.2. Check if the model runs by showing states of this model over time and checking the density over time

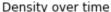
We allow the model to run for 970 steps to avoid the effect of random initialization.

After visualizing the states over time (below) and with three density levels: 0.6, 0.35, 0.5, we see small cluster at low densities, and more prominent clusters in high densities settings, which is because of the velocity fluctuation of the cars. We can see that vehicles coming from the left can comes with peed = 4 or 5 but then has to stop due to congestion. The cars can only get out of traffic jams if the there are no more cars in front of it --> create a backward traveling wave in the road --> traffic jam moves backward as we can see from the figures

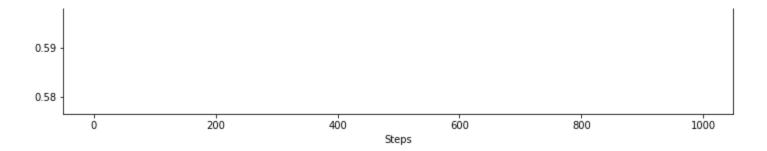
```
1 sim = TrafficSimulator(length=100, density=0.65, v_max=5, p_down=0.5)
 3 # run 1000 times to check if any cars went missing
 4 t = 1000
 5 sim.initialize()
 6 sim.display()
 7 # record the density over time
 8 density = []
 9
10 for i in range(t):
    sim.step()
   if i >= 970:
12
      sim.display()
13
14
    density.append(sim.check_density())
15
16 # plot
17 plt.figure(figsize = (12,6))
18 plt.title("Density over time")
19 plt.xlabel("Steps")
20 plt.ylabel("Density")
21 plt.plot(range(t), density)
22 plt.show()
```

 \Box

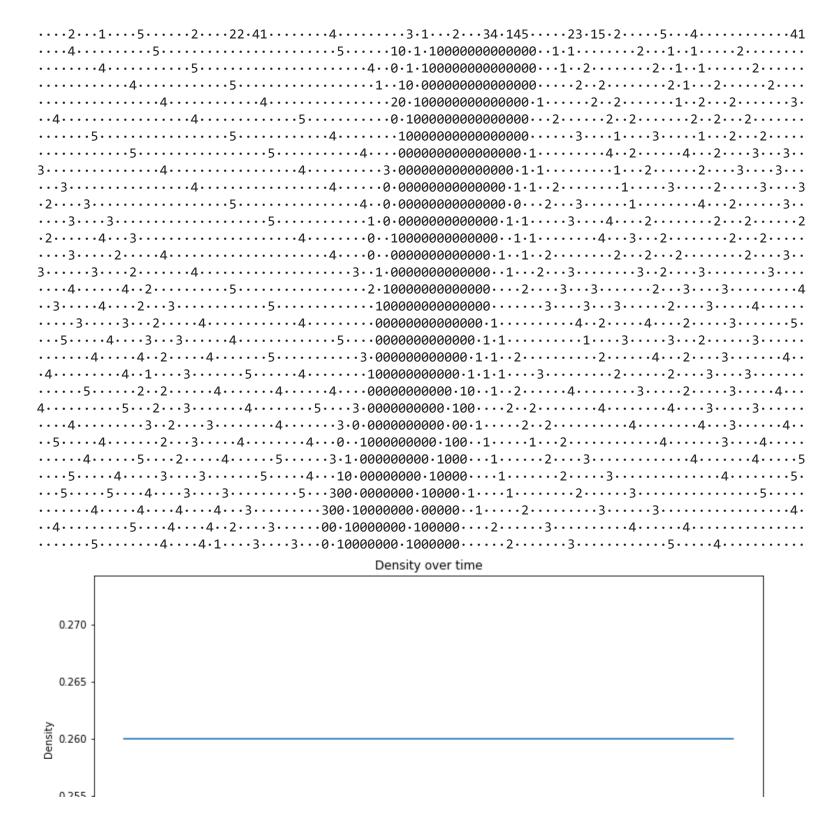


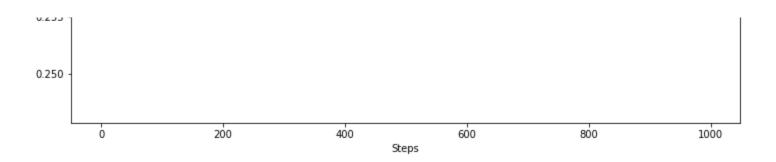




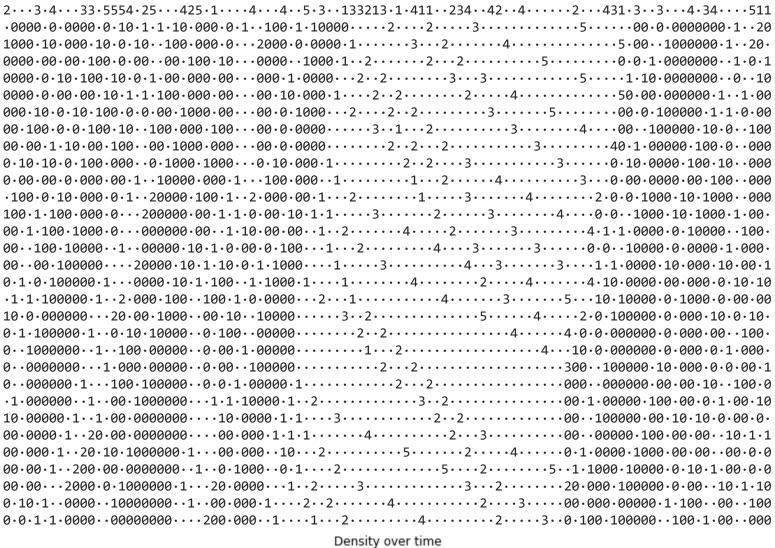


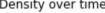
```
1 sim = TrafficSimulator(length=100, density=0.35, v_max=5, p_down=0.5)
 3 # run 1000 times to check if any cars went missing
 4 t = 1000
 5 sim.initialize()
 6 sim.display()
 7 # record the density over time
 8 density = []
10 for i in range(t):
    sim.step()
    if i >= 970:
12
13
       sim.display()
    density.append(sim.check_density())
14
15
16 # plot
17 plt.figure(figsize = (12,6))
18 plt.title("Density over time")
19 plt.xlabel("Steps")
20 plt.ylabel("Density")
21 plt.plot(range(t), density)
22 plt.show()
```

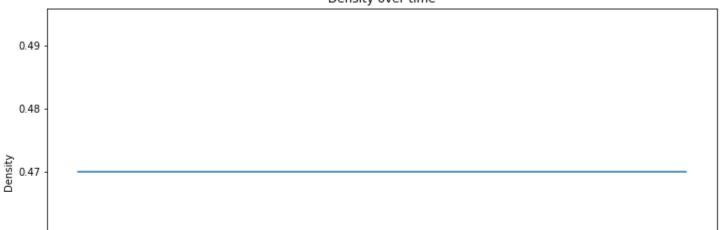


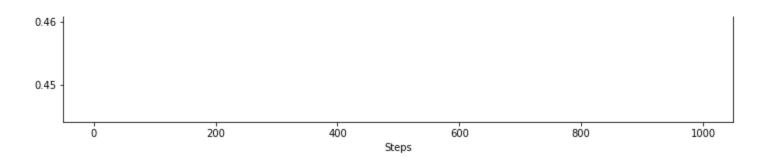


```
1 sim = TrafficSimulator(length=100, density=0.5, v_max=5, p_down=0.5)
 3 # run 1000 times to check if any cars went missing
 4 t = 1000
 5 sim.initialize()
 6 sim.display()
 7 # record the density over time
 8 density = []
10 for i in range(t):
    sim.step()
11
    if i >= 970:
12
      sim.display()
13
    density.append(sim.check_density())
14
15
16 # plot
17 plt.figure(figsize = (12,6))
18 plt.title("Density over time")
19 plt.xlabel("Steps")
20 plt.ylabel("Density")
21 plt.plot(range(t), density)
22 plt.show()
```









▼ 1.3. Average car flow with respect to density

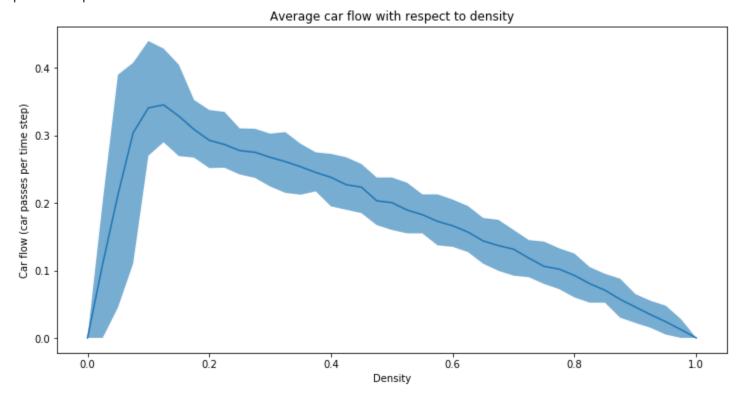
I use the average car flow levels to evaluate the traffic: number of cars passing through the last bar (the end of the road) per time step to compare different scenarios. I run the model for 100 initializing steps to avoid possible effects of random initialization. Then, I record the steps for 200 steps, with 50 different initial configurations.

The result is shown in the graph below. As we can see, the car flow amount increases linearly from 0 to 0.1. This result is because the density is low, which makes all cars flow freely. However, as we see the peak at 0.1 and then a decrease from there (from 0.1 to 1), this result is due to traffic jams when the density is high enough and velocity differences between cars. The 95% interval for the peak is especially more significant because of the high dependency on the initial random configuration. For other regions, the 95% interval is smaller because the patterns are more set: flow freely if low density and traffic jams if high density.

```
1 # empty list to record results
2 track_mean, track_low, track_high = [], [], []
3
4 # seting the density levels
5 densities = np.linspace(0, 1, 41)
6
7 # initializing steps to avoid the effect of random initialization
8 init_steps = 100
9 steps = 200
10 simulations = 50
11
12 for p in densities:
13 # set the simulation
14 sim = TrafficSimulator(length=100, density = p, v_max = 5, p_down = 0.5)
15 tracking = []
```

```
for i in range(simulations):
16
      total = 0
17
      sim.initialize()
18
      # running simulations
19
      for i in range(steps + init_steps):
20
21
        sim.step()
        # only record values after the init steps to avoid effects of random initialization
22
23
        if i >= init steps:
          total += sim.car pass()
24
25
        # get average number
26
      tracking.append(total/steps)
27
    # attach to the list
    track mean.append(np.mean(tracking))
28
    track low.append(np.quantile(tracking, 0.05))
29
    track high.append(np.quantile(tracking, 0.95))
30
1 print("peak at: p =", densities[track mean.index(max(track mean))])
2 # Plotting the results
3 plt.figure(figsize = (12,6))
4 plt.plot(densities, track mean)
5 plt.fill between(densities, track low, track high, alpha=0.6)
7 # store it to new variables to compare later on
8 single_lane_mean, single_lane_low, single_lane_high = track_mean, track_low, track_high
10 plt.title("Average car flow with respect to density")
11 plt.xlabel("Density")
12 plt.ylabel("Car flow (car passes per time step)")
13 plt.show()
```

peak at: p = 0.125



1

▼ 2. Multi lanes (standard model)

▼ 2.1. Simulation model

optimal: when cars can reach the max_speed or able to accelerate

Multi-lanes model rules:

• First, avoid changing lanes: only change lanes when the optimal scenarios (max achievable speed) are not on the same lane but can occur by changing to the next lane. Function: look_ahead_same: check what is the optimal speed cars can move in the same lane and if it is optimal.

- Second, when changing lanes: only change if the optimal scenarios are reached (reach max_speed or can accelerate). Function: look_ahead_other: check what is the optimal speed cars can move in the other lane and if it is optimal.
- Also, with checking if cars can speed up: also check the obstacles behind to make sure we do not block any cars. Function: look_behind_other: check v_max blocks behind to make sure that the behind path is empty. Or else a crash could happen.
- Third, cars prefer left lanes over right: hence, if we can change to both lanes, prefer the left one.
- Finally, there is a probability of changing lanes and slowing down, apply to the speed at any given step.

The flow of the rules: The model check for all optimal cases for either staying in the same lane or changing to 2 next by lanes. Then, if staying in the same lane is not optimal, only change lane if other lanes are optimal, and no obstacle behind and pass the p_change level. Else, staying in the same lane and update as the 1-lane model.

Assumptions:

- All cars follow the same rules
- All cars drive safely not to have accidents (from the look_nehind_other function).
- All cars are cautious of their environment and update from left to right. The model can avoid cases like having two cars: car A in the traffic jam and the other car (B) is approaching the traffic spam with speed = v and decided to change lane. If A change lane, it could crash with the intended path of B. Hence, we update from the back (left to right) to avoid such caveats.

```
1 class TrafficSimulator(object):
    # initialize the parameters. Only work for multi-lanes
    def init (self, length=100, density=0.1, v max=5, p down=0.5, p change = 1, interactive=False, lanes = 4):
      self.interactive = interactive
 4
      self.length = length
      self.density = density
 6
      self.v max = v max
 7
 8
      self.p_down = p_down
      self.p_change = p_change
 9
      # only work for multi lanes
10
      if lanes <= 1:
11
        raise ValueError("Lanes must be larger than 1")
12
13
       self.lanes = lanes
14
      # Arrays for storing the current state and the next state (when we are
15
      # busy doing a state update).
16
      self.lane = np.zeros((lanes, self.length))
17
       self next lane = nn zeros((lanes self length))
12
```

```
SCITTHEAC_TAIL - HPTZCI OS((IAHCS) SCITTICHECHI))
TO
19
20
    # setting up the 1st state
    def initialize(self):
21
22
23
       This will be called by the interactive pycxsimulator whenever the Reset
24
       button is clicked.
       111
25
26
       # Set up a random initial state where the fraction of 1s in the array
      # equals the density parameter.
27
       self.lane.fill(-1)
28
29
30
      # looping through each node
      for x in range(self.lanes):
31
        for y in range(self.length):
32
          if RD.random() < self.density:</pre>
33
             # assigning random initial speed
34
35
             state = RD.randint(1, self.v max)
             self.lane[x,y] = state
36
       self.time = 0
37
38
39
    # simple display using string
40
    def display 1(self):
      print(''.join('\cdot' if x == -1 else str(int(x)) for x in self.lane[0]))
41
42
    def display_all(self):
43
      for i in range(self.lanes):
44
45
         print(''.join('.' if x == -1 else str(int(x)) for x in self.lane[i]))
46
47
    # look ahead check function for the current lane
48
    # takes in the current lane and current position and output should we stay in lane and best speed can achieve
49
50
    def look ahead same(self, cur lane, cur pos):
      # get the current speed
51
       speed = cur lane[cur pos]
52
53
54
       # optimal = True represents best to stay in same lane
55
      optimal = True
56
57
      # max speed can get
      n speed = min(speed + 1, self.v max)
58
50
       #chack obstacle on the way
```

```
#CHECK ODSCACTE OH THE WAY
ンン
      for i in range(int(min(speed + 1, self.v max))):
60
        if cur lane[(cur pos + i + 1)%len(cur lane)] != -1:
61
62
          # not optimal
          optimal = False
63
          # new_speed
64
           n \text{ speed} = i
65
           break
66
67
      return optimal, n speed
68
69
    # look ahead check function for the other lane
70
    # takes in the next lane and current position and output should we stay change lane and best speed can achieve
71
    def look ahead other(self, cur lane, other lane, cur pos):
72
      speed = cur_lane[cur_pos]
73
      # optimal means should change lane
74
      optimal = True
75
76
77
      # max speed can get
      n speed = min(speed + 1, self.v max)
78
79
      # check the ahead path in the next lane
80
      for i in range(int(min(speed + 1, self.v max)) + 1):
81
82
        if other lane[(cur pos + i + 1)%len(other lane)] != -1:
83
           #not optimal
           optimal = False
84
85
           n \text{ speed} = i
           break
86
87
       return optimal, n speed
88
89
    # look behind and check function for the other lane
    # takes in the next lane and current position and output can we change lane so that no car behind that can crash us
90
    def look behind other(self, other lane, cur pos):
91
92
93
      # optimal: no obstacle
      obstacle = False
94
      for i in range(self.v max + 1):
95
        # check all path: if there is obstacle: return True
96
97
        if other lane[(cur pos - i)%len(other lane)] != -1:
98
           obstacle = True
99
       return obstacle
```

100

```
TOO
     # to NOT use period lanes (leftmost lane can turn left to go to rightmost lane):
101
     # a function to output all nearby lanes
102
     # for edge lane, will do the next lane twice (would change a bit of the result because the probability for edge lanes
103
104
     # to change is not p anymore, but 1 - (1-p)^2 = 2p - p^2.
     def next_lanes(self, cur_lane):
105
106
       # leftmost
       if cur lane == 0:
107
         return [1,1]
108
109
       #rightmost
       elif cur lane == self.lanes - 1:
110
         return [self.lanes - 2, self.lanes - 2]
111
       # left + right
112
113
       else:
114
         return [cur lane - 1, cur lane + 1]
115
116
     # updating step
117
     def step(self):
118
119
         Update the state of the cellular automaton.
          111
120
         n = self.length
121
122
         lanes = self.lanes
123
124
         # initialize next state
         self.next lane.fill(-1)
125
126
         # loop through all cars
127
         for x in range(self.lanes):
128
129
           for i in range(self.length):
             # only consider non-empty cells
130
             if self.lane[x][i] != -1:
131
               v = int(self.lane[x][i])
132
133
134
               # check the same lane first
               opt ahead same, n v same = self.look ahead same(self.lane[x], i)
135
136
               # check the nextby lanes
137
               left lane, right lane = self.next lanes(x)
138
139
140
                # optimal status and best speed
                ant about other 1 m w other 1 calf last shoot other/calf langful calf langflaft land :)
```

```
opt_anead_other_i, n_v_other_i = Seit.iook_anead_other(Seit.iane[x], Seit.iane[iett_iane], i)
141
                               opt ahead other 2, n v other 2 = self.look ahead other(self.lane[x], self.lane[right lane], i)
142
                               opt_ahead_other_3, n_v_other_3 = self.look_ahead_other(self.lane[x], self.next_lane[left_lane], i)
143
                               opt ahead other 4, n v other 4 = self.look ahead other(self.lane[x], self.next lane[right lane], i)
144
145
                               # check obstacle
146
                               obstacle 1 = self.look behind other(self.lane[left lane], i)
147
                               obstacle 2 = self.look behind other(self.lane[right lane], i)
148
                               obstacle 3 = self.look behind other(self.next lane[left lane], i)
149
                               obstacle 4 = self.look behind other(self.next lane[right lane], i)
150
151
152
                               # if moving in same lane is not optimal and we have better option in the left lanes (optimal + no obstacle):
                               if opt_ahead_same == False and opt_ahead_other_1 == True and opt_ahead_other_3 == True and obstacle_1 == False and obst
153
154
                                   # random slow down
155
                                   if RD.random() < self.p down and n v other 1 > 0:
156
                                       n \ v \ other \ 1 \ -= \ 1
                                   # updating next lane
157
                                   self.next_lane[left_lane][int(i + n_v_other_1)%n] = n_v_other_1
158
159
160
                               # if moving in same lane is not optimal and we have better option in the right lanes (optimal + no obstacle):
                               elif opt ahead same == False and opt ahead other 2 == True and opt ahead other 4 == True and obstacle 2 == False and ob
161
162
                                   # random slowdown
                                   if RD.random() < self.p down and n v other 2 > 0:
163
                                       n \ v \ other \ 2 \ -= \ 1
164
165
                                   # updating next lane
                                   self.next lane[right lane][int(i + n v other 2)%n] = n v other 2
166
167
168
                               # other cases: stay in the same lane
169
                               else:
170
                                   # random slowdown
171
                                   if RD.random() < self.p_down and n_v_same > 0:
172
                                       n v same -= 1
                                   # updating current lane
173
                                   self.next_lane[x][int(i + n_v_same)%n] = n_v_same
174
175
                   # for all lanes, swap to update
176
                   for x in range(self.lanes):
177
                       self.lane[x], self.next lane[x] = self.next lane[x], self.lane[x]
178
179
                   self.time += 1
180
181
           # count the number of car pass the bar at each step
         THE COLUMN TRANSPORT OF THE PARTY OF THE PAR
```

```
# return a list of which lane has a car pass the bar
183
     def car pass(self):
       result = []
184
       # loop through each lane
185
       for x in range(self.lanes):
186
187
         added = False
188
         for i in range(self.v max):
           # if there is a car with speed > current position -> it passes the bar
189
190
           if self.lane[x][i] != -1 and self.lane[x][i] > i:
              added = True
191
              result.append(added)
192
193
              break
         if not added:
194
           result.append(False)
195
196
        return result
197
198
     def check density(self, value=None):
199
       The density of cars on the road. Only affects initialization (reset) of
200
       the simulation. The density must be a value between 0 and 1.
201
202
203
       return np.mean(self.lane != -1)
```


I allow the model to run for 970 steps to avoid the effect of random initialization.

I have 2 types of display: display all lanes or only the 1st lane.

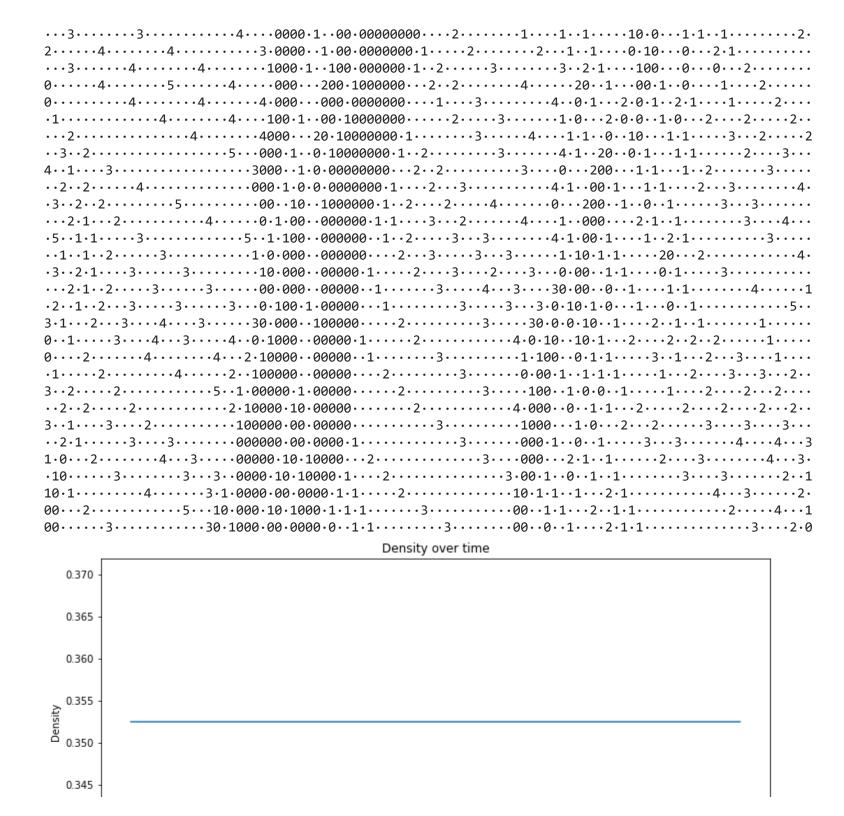
For the 1st lane, the behaviors are similar to the single lane model.

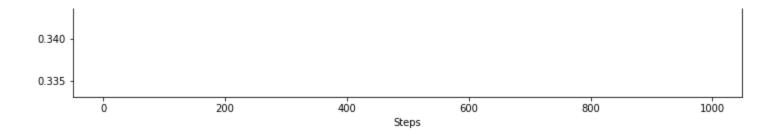
One difference is that: for multi-lanes, sometimes, the traffic jam reduces in size because some cars were able to perform lane change. However, that does not resolve the traffic jam because the condition for lane changing is strict, and the density over each lane is quite similar.

After visualizing the states over time (below) and with three density levels: 0.6, 0.35, 0.5, we see small cluster at low densities, and more prominent clusters in high densities settings, which is because of the velocity fluctuation of the cars. We can see that vehicles coming from the left can comes with peed = 4 or 5 but then has to stop due to congestion. The cars can only get out of traffic jams if the there are no more cars in front of it --> create a backward traveling wave in the road --> traffic jam moves backward as we can see from the figures.

```
3 # initil
 4 sim.initialize()
 5 density = []
 6 t = 1000
7 for i in range(t):
    sim.step()
    if i >= 970:
      sim.display_1()
10
11
    density.append(sim.check_density())
12
13 plt.figure(figsize = (12,6))
14 plt.title("Density over time")
15 plt.xlabel("Steps")
16 plt.ylabel("Density")
17 plt.plot(range(t), density)
18 plt.show()
```

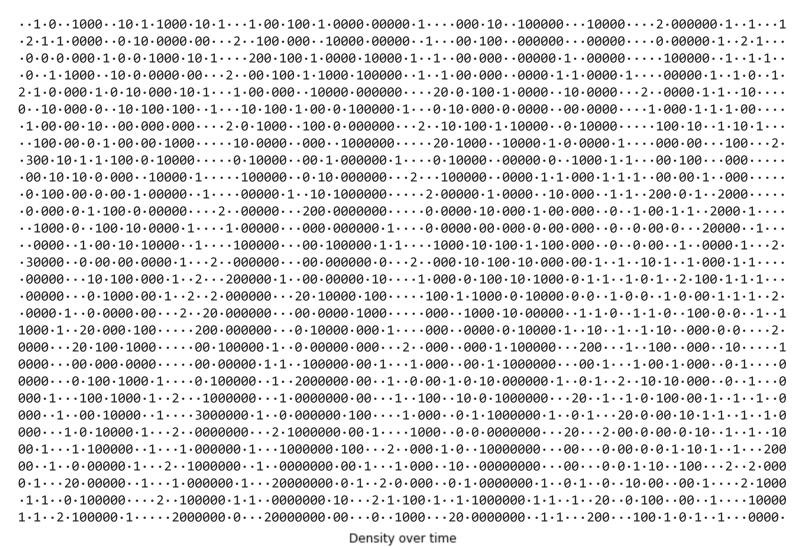
С⇒



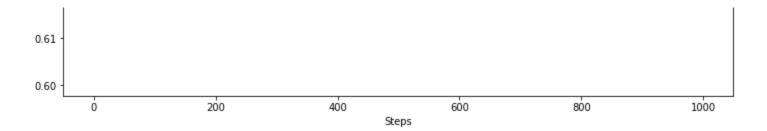


```
1 sim = TrafficSimulator(length=100, density=0.65, v_max=5, p_down=0.5)
 2
 3 # initil
 4 sim.initialize()
 5 density = []
 6 t = 1000
 7 for i in range(t):
    sim.step()
    if i >= 970:
       sim.display_1()
10
    density.append(sim.check_density())
11
12
13 plt.figure(figsize = (12,6))
14 plt.title("Density over time")
15 plt.xlabel("Steps")
16 plt.ylabel("Density")
17 plt.plot(range(t), density)
18 plt.show()
```

 \Box







С⇒

```
1 sim = TrafficSimulator(length=100, density=0.5, v_max=5, p_down=0.5)
2
3 # initil
4 sim.initialize()
5 density = []
6 t = 1000
7 for i in range(t):
8  sim.step()
9  if i >= 970:
10  sim.display_all()
11  print("")
```

```
\cdots 0 \cdot 1 \cdot 10 \cdot 100 \cdot \cdots \cdot 2 \cdot \cdots 2 \cdot \cdots 2 \cdot \cdots 0000 \cdot 0 \cdot 00 \cdot 1 \cdot \cdots 00 \cdot 1 \cdot \cdots 1 \cdot \cdots 1 \cdot \cdots 1 \cdot 0 \cdot \cdots 100 \cdot 100 \cdot \cdots 20 \cdot \cdots 100 \cdot 100 \cdot 000 \cdot \cdots 2 \cdot \cdots 3 \cdot \cdots 100 \cdot 100
0 \cdots 1 \cdots 0000 \cdot 10000 \cdot 1 \cdot 1 \cdots \cdots 4 \cdot 10 \cdots 0 \cdot 0 \cdots 1 \cdots 1 \cdots 1 \cdots 1 \cdots 0 \cdot 0 \cdots 100 \cdot 1 \cdots 2 \cdots 100 \cdot 0 \cdots 00 \cdot 000 \cdot 000 \cdot 0 \cdots 00 \cdot 1 \cdots 1 \cdots 2 \cdots 000
 \cdot 3 \cdot 1 \cdot 100 \cdot 00 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 2 \cdot \cdots \cdot 2 \cdot \cdots \cdot 2 \cdot \cdots \cdot 100 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 100 \cdot 100 \cdot 1 \cdot \cdots \cdot 100 \cdot 
0 \cdot \cdot \cdot \cdot 1 \cdot 000 \cdot 100000 \cdot 0 \cdot \cdot \cdot 2 \cdot \cdot \cdot \cdot \cdot \cdot 10 \cdot 1 \cdot \cdot 1 \cdot 1 \cdot \cdot 1 \cdot \cdot 1 \cdot \cdot \cdot 2 \cdot \cdot 1 \cdot \cdot \cdot 2 \cdot 0 \cdot 0 \cdot 000 \cdot 1 \cdot \cdot \cdot 200 \cdot 10 \cdot 000 \cdot 10 \cdot 000 \cdot 1 \cdot \cdot \cdot 20 \cdot 0 \cdot 10 \cdot 000 \cdot 10 
30 \cdot 0 \cdot 000 \cdot 0 \cdot 1 \cdot 1 \cdot \cdots \cdot 2 \cdot 1 \cdot \cdots \cdot 3 \cdot 000 \cdot 0 \cdot 1 \cdot 1 \cdot 1 \cdot 000 \cdot \cdots \cdot 2 \cdot 2 \cdot 2 \cdot 0 \cdot 0 \cdot 0 \cdot 0 \cdot 000 \cdot \cdots \cdot 20 \cdot 1 \cdot \cdots 1 \cdot 0 \cdot 1000 \cdot 000 \cdot \cdots 2 \cdot \cdots \cdots 
 \cdots 1 \cdots 2 \cdot 10000 \cdots 2 \cdots 2000 \cdot 0 \cdots 1 \cdot 0 \cdots \cdots 0000000 \cdots 1 \cdot 00 \cdot 1000 \cdot 10000 \cdots \cdots 2 \cdots 2 \cdot \cdots 2 \cdot 0.000 \cdot 000 \cdots 1 \cdot 0 \cdots 10 \cdot 000 \cdot 10 \cdot 1
\cdots 2 \cdots 000 \cdot 1000000 \cdot 0 \cdots \cdots \cdots 3 \cdots 1 \cdot 10 \cdot 0 \cdots 1 \cdots 2 \cdots 2 \cdots 0 \cdot 0 \cdot 000 \cdots \cdots 200 \cdot 100 \cdot 0 \cdot 1000 \cdots 0 \cdot 10 \cdot 100 \cdots 0 \cdot 1 \cdot 100 \cdots 0 \cdot 1 \cdot 100 \cdots 0 \cdot
\cdots 0 \cdot 0 \cdot 10000000 \cdot 1 \cdot 1 \cdot \cdots \cdots 10 \cdot 0 \cdot 1 \cdots 2 \cdots 3 \cdot 1 \cdot 10 \cdots 1 \cdot 000 \cdots 1 \cdots 000 \cdot 00 \cdot 1 \cdot 100 \cdot 1 \cdots 2 \cdot 100 \cdot 00 \cdots 2 \cdot 0 \cdot 0000
 \cdots \cdots 100000000 \cdots 1 \cdot 1 \cdot 1 \cdot 1 \cdots \cdots \cdots 0 \cdot 1 \cdots 2 \cdots 3 \cdots 3 \cdot 0 \cdot 000 \cdots 000 \cdot 1 \cdots 1 \cdots 00 \cdot 10 \cdots 100 \cdot 1 \cdot 1 \cdot 0 \cdot 000 \cdot 000 \cdots 0 \cdot 000000
```

A 4 4 AA 4 AA A 4 AA A 4

0 0 000 0 4

200 24 00 40000 4

00 4 4000

```
00 \cdot 00 \cdot 1 \cdot 1 \cdot 1 \cdot 000 \cdot \cdot 10 \cdot 1 \cdot \cdot 2 \cdot \dots \cdot 3 \cdot 10 \cdot 0000 \cdot 0000 \cdot \dots 2 \cdot 1 \cdot \dots 2 \cdot 1 \cdot \cdot 1 \cdot 1 \cdot 1 \cdot 00 \cdot \cdot 1000 \cdot 10 \cdot 00 \cdot 000 \cdot 00 \cdot 1 \cdot \dots \cdot 10 \cdot 0 \cdot 1 \cdot 1
1 \cdot 0000 \cdot \cdots \cdot 0000 \cdot \cdots \cdot 0000 \cdot \cdots \cdot 10 \cdot \cdots \cdot 2 \cdot \cdots \cdot 10000 \cdot 00 \cdot 1 \cdot 0 \cdot 1000 \cdot 1 \cdot 1000 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 0 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots \cdot 2 \cdot \cdots \cdot 200000 \cdot 10 \cdot 1 \cdot \cdots \cdot 2 
\cdot 000 \cdot 1 \cdot 1 \cdot 000 \cdot \dots \cdot 20000 \cdot \dots \cdot 0 \cdot \dots \cdot 2 \cdot \cdot 10000 \cdot 10 \cdot 1 \cdot 10 \cdot 000 \cdot 1 \cdot 000 \cdot \cdot 1 \cdot \dots \cdot 2 \cdot \dots \cdot 100000 \cdot \dots \cdot 10 \cdot \dots \cdot 2 \cdot \dots \cdot 10000 \cdot 10 \cdot \dots \cdot 1 \cdot 000 \cdot \dots \cdot 10 \cdot \dots \cdot 10
```

```
0 \cdot 1 \cdot \dots \cdot 10 \cdot \dots \cdot 2 \cdot \dots \cdot 1 \cdot 0 \cdot \dots \cdot 0 \cdot 1 \cdot \dots \cdot 20 \cdot 00 \cdot \dots \cdot 00 \cdot 1 \cdot \dots \cdot 2 \cdot 
\cdots 1 \cdot 00 \cdot 0 \cdots 10 \cdots 10 \cdot 1 \cdots 2 \cdots \cdots 3 \cdot 00 \cdot 100000 \cdot 0 \cdots 20 \cdots 1 \cdots 00 \cdots 100 \cdots 200000 \cdot 1 \cdot 100 \cdot 10 \cdot 10 \cdot 10 \cdot 1 \cdots 00 \cdot 0 \cdot 1 \cdots 10000
```

2.3. Average car flow with respect to density

Based on the graph, there are three key findings:

- Based on the figure, the best traffic flow still holds at p = 0.1 for all models (single vs. multi-lane).
- The multi-lanes models seem to create a better car flow rate, with approximately 0.04 car/step more than a single-lane model (12% increase) at the peak (p = 0.1). Between p = 0.1 and p = 0.5, there is a significant increase in car flow rate from single lane model to 2-lane model, whereas there are only slight increases from 2-lane to 5-lane or 10-lane models. Outside the range [0.1, 0.5], the behaviors are quite similar (as either all car flow freely or traffic jams on all lanes)
- One interesting observation is that: for multi-lane models, the 95% interval seems narrower as the number of lanes increases, which implies multi-lane models are less affected by random initialization. This observation makes sense because more lanes would allow flexible lane-changing, which after the long run, will create balances and adequate car flow on all lanes, which reduce the effect of random initialization.

```
1 # 3 different number of lanes
2 lanes_values = [2, 5, 10]
3 # keep track list
4 track_man__track_law__track_bish___[[] for i in mange(lan(lanes_values))]. [[] for i in mange(lan(lanes_values))]. [[] for i in mange(lan(lanes_values))].
```

```
4 track_mean, track_iow, track_nign = [[] for i in range(ien(ianes_values))], [[] for i in range(ien(ianes_values))], [[] for i in range(ien(ianes_values))],
 5 densities = np.linspace(0, 1, 41)
 6 # running first few steps to avoid effect by random initialization
7 \text{ init steps} = 50
8 \text{ steps} = 100
 9 \text{ simulations} = 30
10
11 # looping through each number of lane
12 for k in range(len(lanes values)):
    num lanes = lanes values[k]
13
    for p in densities:
14
15
      # initialize the mode;
       sim = TrafficSimulator(length=100, density = p, v max = 5, p down = 0.5, lanes = num lanes)
16
17
      tracking = []
18
19
       # start simulation
20
       for i in range(simulations):
21
         total = 0
         sim.initialize()
22
         for i in range(steps + init steps):
23
           sim.step()
24
           # only record after the first few steps
25
26
           if i >= init steps:
             total += np.sum(sim.car pass())
27
28
         # take the average
29
         tracking.append(total/num lanes/steps)
30
       # record it into list
       track mean[k].append(np.mean(tracking, axis = 0))
31
       track low[k].append(np.quantile(tracking, 0.05, axis = 0))
32
       track high[k].append(np.quantile(tracking, 0.95, axis = 0))
33
1 plt.figure(figsize = (12,6))
 3 # plot the single lane to compare
 4 plt.plot(densities, single lane mean, label = "1 lane", color = coloring[3], linewidth = 3)
5 plt.fill between(densities, single lane low, single lane high, alpha=0.1, color = coloring[3])
7 # plot the multi-lanes
8 for i in range(len(track mean)):
    print(str(lanes values[i]) + " lane peak at: p =", densities[track mean[i].index(max(track mean[i]))])
    plt.plot(densities, track mean[i], label = str(lanes values[i]) + " lane", color = coloring[i], linewidth = 3)
```

```
plt.fill_between(densities, track_low[i], track_high[i], alpha=0.1, color = coloring[i])

# multiple lanes - same cars - the value:
# multi_same_mean, multi_same_low, multi_same_high = track_mean, track_low, track_high

plt.legend()

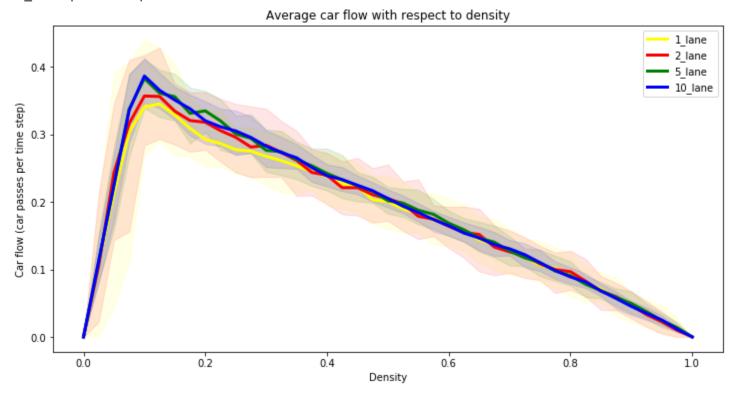
plt.title("Average car flow with respect to density")

plt.xlabel("Density")

plt.ylabel("Car flow (car passes per time step)")

plt.show()
```

2_lane peak at: p = 0.1
5_lane peak at: p = 0.1
10_lane peak at: p = 0.1



→ 3. Stretch goal: Good & Bad driver (chaotic model)

▼ 3.1. Simulation model

The traffic rules are similar to the multi-lane model, except each car has a different configuration (instead of all vehicles follow the same rule).

For each car, I initialize a different slowdown property, different possible max speed, accelerating steps, changing lane property. This model is more complicated as we cannot only store the velocity in the road, but we have to store the whole car because each car has different properties. The p_down also reflects bad drivers as they are more likely to slow down randomly. Also, this model increases the velocity differences between cars (as some cars have different max_speed and different accelerating steps).

```
1 # Each location will be an independent car settings, to depict random driving behavior
 2 class Car(object):
    # few basic parameters
    def __init__(self, v_max = 5, p_down = 0.5, acce = 1, v = 3, p_change = 0.5):
 5
      acce: the speed up step: some car can move 2 steps at a time
 6
      v max: each car has different max speed
 7
      p down: each car has different probability slowing down
 8
 9
      p change: each car has different probability changing lanes
      v: current speed
10
11
12
      self.acce = acce
      self.v max = v max
13
14
      self.p down = p down
15
      self.v = v
16
      self.p_change = p_change
17
18
    # get current speed
19
    def get v(self):
20
      return self.v
21
    # get max speed
22
    def get v max(self):
23
      return self.v max
24
25
    # get probability slowing down
26
    def get p down(self):
27
      return self.p down
28
29
```

```
# number of spots can speed up each step
31
    def get acce(self):
32
       return self.acce
33
34
    # probability of changing lanes
    def get_p_change(self):
35
36
      return self.p change
37
    # change the current v
38
    def change v(self, new v):
39
      self.v = new v
40
       return self
41
1 class TrafficSimulator(object):
    # initialize the parameters. Only work for multi-lanes
    def init (self, length=100, density=0.1, v max=5, p down=0.5, p change = 1, interactive=False, lanes = 4):
       self.interactive = interactive
 4
       self.length = length
       self.density = density
       self.v max = v max
 8
       self.p down = p down
       self.p change = p change
 9
      # only work for multi lanes
10
11
       if lanes <= 1:
        raise ValueError("Lanes must be larger than 1")
12
13
       self.lanes = lanes
14
      # Arrays for storing the current state and the next state (when we are
15
      # busy doing a state update).
16
       self.lane = np.zeros((lanes, self.length))
17
       self.next lane = np.zeros((lanes, self.length))
18
19
20
    def initialize(self):
       . . .
21
      This will be called by the interactive pycxsimulator whenever the Reset
22
23
       button is clicked.
24
      # Set up a random initial state where the fraction of 1s in the array
25
      # equals the density parameter.
26
       self.lane = np.array(self.lane)
27
28
       self.lane.fill(-1)
```

```
self.lane = self.lane.tolist()
29
30
      # looping through each spot
31
      for x in range(self.lanes):
32
        for y in range(self.length):
33
          if RD.random() < self.density:</pre>
34
             # setting the basic parameter for each driver
35
             # max speed if random, with +- 2 from global cars settings
36
             car v max = RD.randint(self.v max - 2, self.v max + 1)
37
             # probability from uniform dist.
38
             car p down = RD.uniform(0.2, 0.8)
39
             # possible acceleration step
40
41
             car acc = RD.randint(1, 2)
42
             # current speed
             car v = RD.randint(0, car v max)
43
             # probability from uniform dist.
44
45
             car p change = RD.uniform(0.2, 0.8)
46
             # setting the car
             self.lane[x][y] = Car(v_max = car_v_max, p_down = car_p_down, acce = car_acc, v = car_v, p_change = car_p_change)
47
48
       self.time = 0
49
50
    # simple display using string
    def display 1(self):
51
      print(''.join('\cdot' if x == -1 else str(int(x.get v())) for x in self.lane[0]))
52
53
    def display all(self):
54
55
      for i in range(self.lanes):
        print(''.join('\cdot' if x == -1 else str(int(x.get v())) for x in self.lane[i]))
56
57
58
    # look ahead check function for the current lane
59
    # takes in the current lane and current position and output should we stay in lane and best speed can achieve
60
    def look ahead same(self, cur lane, cur pos):
      speed = cur_lane[cur_pos].get_v()
61
      optimal = True
62
      # each car has different best speed
63
      n_speed = min(speed + cur_lane[cur_pos].get_acce(), cur_lane[cur_pos].get_v_max())
64
65
      for i in range(int(min(speed + cur lane[cur pos].get acce(), cur lane[cur pos].get v max()))):
        # if there is car ahead -> not optimal
66
        if cur lane[(cur pos + i + 1)%len(cur lane)] != -1:
67
68
           optimal = False
          n \text{ speed} = i
69
```

```
70
           break
       return optimal, n speed
71
72
73
     # look ahead check function for the other lane
     # takes in the next lane and current position and output should we stay change lane and best speed can achieve
74
75
     def look ahead other(self, cur lane, other lane, cur pos):
       speed = cur_lane[cur_pos].get_v()
76
77
       optimal = True
78
       # each car has different best speed
       n_speed = min(speed + cur_lane[cur_pos].get_acce(), cur_lane[cur_pos].get_v_max())
79
       for i in range(int(min(speed + cur_lane[cur_pos].get_acce(), cur_lane[cur_pos].get_v_max()))):
80
81
         # if there is car ahead -> not optimal
82
         if other lane[(cur pos + i + 1)%len(other lane)] != -1:
83
            optimal = False
84
           n \text{ speed} = i
85
           break
86
       return optimal, n speed
87
88
     # look behind and check function for the other lane
     # takes in the next lane and current position and output can we change lane so that no car behind that can crash us
89
     def look behind other(self, cur lane, other lane, cur pos):
90
91
       obstacle = False
92
       for i in range(self.v max + 2 + 2):
         # check all path: if there is obstacle: return True
93
94
         if other_lane[(cur_pos - i)%len(other_lane)] != -1:
95
            obstacle = True
96
       return obstacle
97
98
99
     # to NOT use period lanes (leftmost lane can turn left to go to rightmost lane):
     # a function to output all nearby lanes
100
     # for edge lane, will do the next lane twice (would change a bit of the result because the probability for edge lanes
101
     # to change is not p anymore, but 1 - (1-p)^2 = 2p - p^2.
102
     def next lanes(self, cur lane):
103
       # leftmost
104
       if cur lane == 0:
105
106
         return [1,1]
107
       #rightmost
108
       elif cur lane == self.lanes - 1:
         return [self.lanes - 2, self.lanes - 2]
109
110
       # left + right
```

```
else:
111
112
         return [cur lane - 1, cur lane + 1]
113
114
     # updating
115
     def step(self):
116
117
         Update the state of the cellular automaton.
118
119
         n = self.length
         lanes = self.lanes
120
121
122
         # initialize next state
         self.next lane = np.array(self.next lane)
123
124
         self.next lane.fill(-1)
         self.next lane = self.next lane.tolist()
125
126
         # loop through all cars
127
         for x in range(self.lanes):
128
129
           for i in range(self.length):
             # only consider non-empty cells
130
             if self.lane[x][i] != -1:
131
132
133
               # check the same lane first
134
               v = int(self.lane[x][i].get v())
               opt ahead same, n v same = self.look ahead same(self.lane[x], i)
135
136
               # check the nextby lanes
137
               left lane, right lane = self.next lanes(x)
138
139
               # optimal status and best speed
140
               opt ahead other 1, n v other 1 = self.look ahead other(self.lane[x], self.lane[left lane], i)
141
               opt ahead other 2, n v other 2 = self.look ahead other(self.lane[x], self.lane[right lane], i)
142
               opt_ahead_other_3, n_v_other_3 = self.look_ahead_other(self.lane[x], self.next_lane[left_lane], i)
143
144
               opt_ahead_other_4, n_v_other_4 = self.look_ahead_other(self.lane[x], self.next_lane[right_lane], i)
145
146
               # check obstacle
               obstacle 1 = self.look behind other(self.lane[x], self.lane[left lane], i)
147
               obstacle 2 = self.look behind other(self.lane[x], self.lane[right lane], i)
148
               obstacle 3 = self.look behind other(self.lane[x], self.next lane[left lane], i)
149
               obstacle 4 = self.look behind other(self.lane[x], self.next lane[right lane], i)
150
151
```

```
# if moving in same lane is not optimal and we have better option in the left lanes (optimal + no obstacle):
152
               if opt ahead same == False and opt ahead other 1 == True and opt ahead other 3 == True and obstacle 1 == False and obst
153
154
                  # random slowdown
155
                  if RD.random() < self.lane[x][i].get p down() and n v other 1 > 0:
156
                    n v other 1 -= 1
157
                  # update lane
158
                  self.next_lane[left_lane][int(i + n_v_other_1)%n] = self.lane[x][i].change_v(n_v_other_1)
159
160
                # if moving in same lane is not optimal and we have better option in the right lanes (optimal + no obstacle):
161
                elif opt ahead same == False and opt ahead other 2 == True and opt ahead other 4 == True and obstacle 2 == False and ob
162
                  # random slowdown
                 if RD.random() < self.lane[x][i].get p down() and n v other 2 > 0:
163
164
                    n v other 2 -= 1
                  # update lane
165
                  self.next lane[right lane][int(i + n v other 2)%n] = self.lane[x][i].change v(n v other 2)
166
167
               # stay in the same lane
168
                else:
169
                  # random slowdown
170
                 if RD.random() < self.lane[x][i].get p down() and n v same > 0:
171
172
                    n v same -= 1
173
                  # updaye
174
                  self.next_lane[x][int(i + n_v_same)%n] = self.lane[x][i].change_v(n_v_same)
175
176
         # update by swapping lanes
         for x in range(self.lanes):
177
178
            self.lane[x], self.next lane[x] = self.next lane[x], self.lane[x]
179
          self.time += 1
180
     # count the number of car pass the bar at each step
181
     # return a list of which lane has a car pass the bar
182
     def car pass(self):
183
184
       result = []
       # loop through each lane
185
186
       for x in range(self.lanes):
187
         added = False
         for i in range(self.v max):
188
189
           # if there is a car with speed > current position -> it passes the bar
           if self.lane[x][i] != -1 and self.lane[x][i].get v() > i:
190
191
              added = True
192
              result.annend(added)
```

```
· courceappena (aaaca)
193
              break
194
         if not added:
            result.append(False)
195
        return result
196
197
198
     def check density(self, value=None):
199
       The density of cars on the road. Only affects initialization (reset) of
200
       the simulation. The density must be a value between 0 and 1.
201
202
203
       return np.mean(np.array(self.lane) != -1)
```

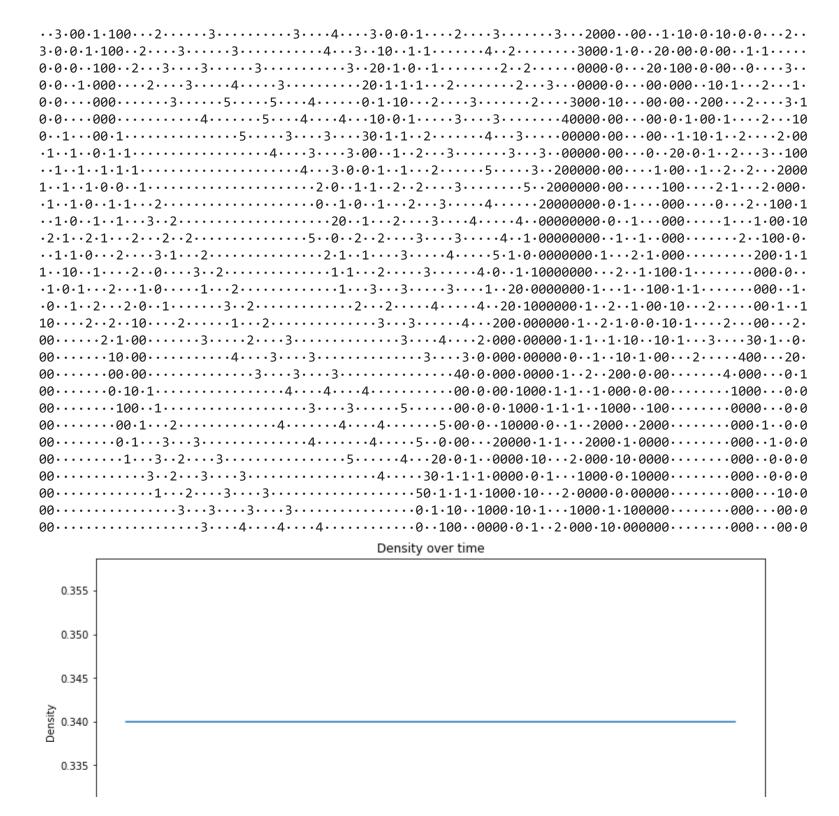

One key difference is each car having different property. Hence, from the figures below, there are cars with possibly very high p_down, which in case it stucks at the traffic jam and reach its turn to move, it will cost many step before it can move, which will create further traffic jam (thicker) in the latter of the road. This is depicted by bad driver/bad car, where when it stuck in traffic, the engine stops completely and takes some time to restart.

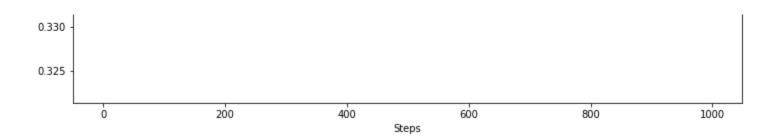
Also, traffic jams are created by differences in velocity. Hence, some cars with very high speed can be affected by vehicles at low speed. This result is even further reflected in this model comparing to the part-2 multi-lane models. Cars are running with max speed = 6 but then blocked by cars with speed = 4 (because its max speed is 4). This situation reflects the driver behavior: some prefers driving slow and safe, whereas others like driving fast. Hence, more traffic jams (and thicker jam) are created in the new models.

```
1 sim = TrafficSimulator(length=100, density=0.350, v max=5, p down=0.5)
 2
 3 # initialize
 4 sim.initialize()
 5 density = []
 6 t = 1000
 7 for i in range(t):
    sim.step()
    if i >= 970:
       sim.display 1()
10
    density.append(sim.check density())
11
12
13 plt.figure(figsize = (12,6))
14 nl+ +i+lo/"Doncity oven +imo")
```

```
14 pit.title( Density Over time )
15 plt.xlabel("Steps")
16 plt.ylabel("Density")
17 plt.plot(range(t), density)
18 plt.show()
```

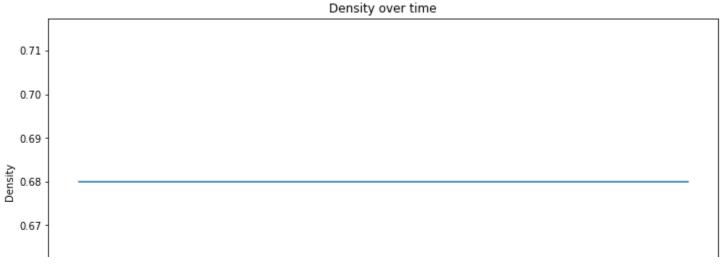


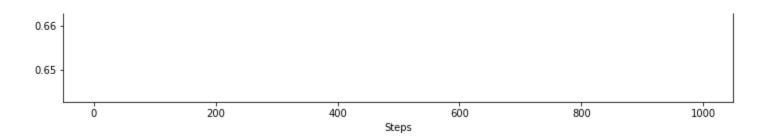




```
1 sim = TrafficSimulator(length=100, density=0.650, v_max=5, p_down=0.5)
 2
 3 # initialize
 4 sim.initialize()
 5 density = []
 6 t = 1000
 7 for i in range(t):
    sim.step()
    if i >= 970:
       sim.display_1()
10
    density.append(sim.check_density())
11
12
13 plt.figure(figsize = (12,6))
14 plt.title("Density over time")
15 plt.xlabel("Steps")
16 plt.ylabel("Density")
17 plt.plot(range(t), density)
18 plt.show()
```

 \Box





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```
1 sim = TrafficSimulator(length=100, density=0.5, v_max=5, p_down=0.5)
2
3 # initialize
4 sim.initialize()
5 density = []
6 t = 1000
7 for i in range(t):
8  sim.step()
9  if i >= 970:
10  sim.display_all()
11 density.append(sim.check_density())
```

```
\cdot 0 \cdot 0000 \cdot 0 \cdot \cdots \cdot 0 \cdot 0 \cdot 0 \cdot 1 \cdot 1 \cdot \cdots \cdot 0 \cdot \cdot 100 \cdot 1 \cdot 1 \cdot \cdots 2 \cdot \cdots 2 \cdot \cdots 3 \cdot \cdots 2 \cdot \cdots 2 \cdot \cdots 1 \cdot 0000 \cdot \cdots 20 \cdot 0 \cdot \cdots 1 \cdot \cdots 2 \cdot \cdots 0 \cdot 0 \cdot 10 \cdot 1 \cdot \cdots 2 \cdot 00000000000
\cdots \cdots 0 \cdot 00000 \cdot 10 \cdot 000 \cdot 1 \cdot 0000 \cdot 1 \cdot 0000 \cdot 1000 \cdot 10 \cdot 100 \cdot 00 \cdot 00 \cdot 00 \cdot 00 \cdot 1000 \cdot 100 \cdot 10 \cdot 100 \cdot 10 \cdot 1100 \cdot 00 \cdot 1000 \cdot 10000 \cdot 1000 \cdot 1000
00 \cdot \cdot 1 \cdot 1 \cdot \cdot \cdot \cdot 30 \cdot \cdot \cdot 2 \cdot \cdot 2 \cdot \cdot \cdot \cdot 300 \cdot 10 \cdot \cdot \cdot 1 \cdot \cdot \cdot \cdot 3 \cdot \cdot \cdot 3 \cdot \cdot 2 \cdot \cdot \cdot \cdot 10 \cdot \cdot 2000 \cdot \cdot 10 \cdot \cdot 2 \cdot \cdot \cdot 3 \cdot \cdot 1 \cdot 10 \cdot 0 \cdot \cdot \cdot 0 \cdot 1 \cdot \cdot \cdot 2000000000 \cdot 100
A A A A A A
               2 40 400 4
```

```
\cdot 10 \cdot \cdot 1 \cdot \cdot 0 \cdot \cdot \cdot 2 \cdot \cdot \cdot 3 \cdot \cdot 1 \cdot 00 \cdot 100 \cdot \cdot 1 \cdot \cdot \cdot \cdot 3 \cdot \cdot \cdot \cdot \cdot \cdot \cdot 1 \cdot \cdot 10 \cdot 1 \cdot 1000 \cdot 1 \cdot \cdot 1 \cdot \cdot \cdot 2 \cdot 0 \cdot \cdot 2 \cdot 100 \cdot \cdot 2 \cdot 1 \cdot \cdot \cdot 1 \cdot 000000000 \cdot 1000 \cdot 10
\cdots 00 \cdot 000 \cdot 1 \cdot \cdot 2 \cdot \cdots \cdot 30 \cdot \cdots \cdot 000 \cdot \cdots \cdot 1 \cdot \cdots \cdot 3 \cdot \cdot 2 \cdot \cdot 2 \cdot \cdots \cdot \cdots 0 \cdot 1 \cdot 0000000 \cdot 00 \cdot 1 \cdot 100000000 \cdot 00 \cdot \cdots 0000 \cdot 1 \cdot 1 \cdot \cdots \cdot 1 \cdot 1 \cdot \cdots \cdot 2
\cdots 20 \cdot 0 \cdot 1 \cdot \cdots \cdot 2 \cdot 1 \cdot 000 \cdot 0 \cdot 1 \cdot 0 \cdot 1 \cdot \cdots \cdots 3 \cdot 0 \cdot 00 \cdot 0 \cdot 000 \cdot 0 \cdot 1 \cdot \cdots 30 \cdot 1 \cdot 0 \cdot 00 \cdot 1 \cdot 1 \cdot 1 \cdot 1 \cdot 0 \cdot 0000000 \cdot 1000 \cdot
\cdots 00000000 \cdot 00 \cdot 00 \cdot 0000 \cdot \cdots 10 \cdot 100 \cdot 1 \cdot 00 \cdot 0 \cdot 000 \cdot \cdots \cdot 0 \cdot 100 \cdot 0 \cdot 0 \cdot 0 \cdot 00 \cdot \cdots 10 \cdot 00 \cdot \cdots 10000 \cdot \cdots 10 \cdot 000 \cdot 
\cdots 10000 \cdots 0000000 \cdot 10 \cdot 1 \cdot 1 \cdot 0 \cdots 200 \cdot 1 \cdot 100 \cdot 000 \cdot 1 \cdot 00000000 \cdot 0 \cdots 10 \cdot 1 \cdot 1 \cdot 1 \cdot \cdots \cdot 2 \cdot \cdots 30 \cdots 1 \cdot 100 \cdot 00 \cdot 1 \cdots 1 \cdot \cdots \cdot 3 \cdot \cdots \cdot 4
```

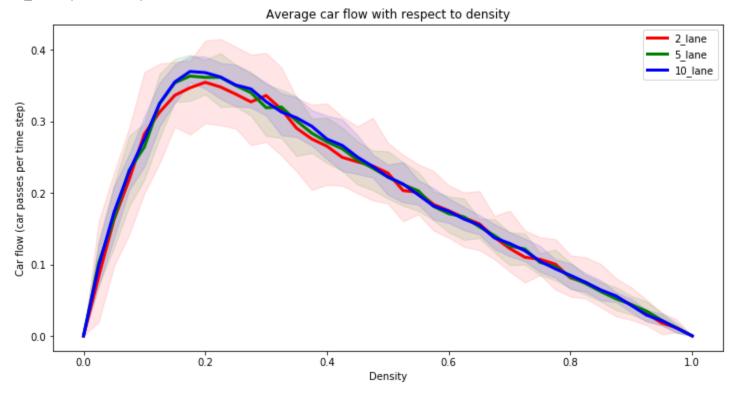
```
\cdots 1000 \cdot 1 \cdot \cdots 1 \cdot 100 \cdot \cdots \cdot 1 \cdot 10 \cdot 1 \cdot 0 \cdots 2 \cdot \cdots \cdots 2 \cdot \cdots \cdot 3000000000 \cdot 00 \cdot 00000000000 \cdot 10000 \cdot \cdots 20 \cdot \cdots 2 \cdot \cdots 2 \cdot \cdots 00 \cdot 1 \cdot 1 \cdot \cdots \cdots 2 \cdot \cdots 2 
0 \cdot \cdot \cdot \cdot \cdot 3 \cdot \cdot 2 \cdot \cdot \cdot 2 \cdot 1 \cdot 10000 \cdot \cdot \cdot \cdot 1 \cdot \cdot \cdot \cdot \cdot 4 \cdot \cdot \cdot 3 \cdot \cdot \cdot 200 \cdot \cdot \cdot 200000 \cdot \cdot 2 \cdot 0 \cdot \cdot 1 \cdot \cdot \cdot 1 \cdot \cdot \cdot 2 \cdot \cdot 20 \cdot \cdot 2000 \cdot 10 \cdot 000000 \cdot 1 \cdot 1 \cdot \cdot 1 \cdot 00
```

→ 3.3. Average car flow with respect to density

The patterns are similar to the multi-lane model above (more lane - better flow, less uncertainty, less dependent on random initialization). I will focus the analysis on the comparison between the standard multi-lane and this chaotic multi-lane in section 4.

```
ل بر ر ر ر با - vatues - د عاادی
 3 # keep track list
 4 track_mean, track_low, track_high = [[] for i in range(len(lanes_values))], [[] for i in range(len(lanes_values))], [[] for i in range(len(lanes_values))],
 5 densities = np.linspace(0, 1, 41)
 6 # running first few steps to avoid effect by random initialization
 7 init steps = 50
8 \text{ steps} = 100
 9 \text{ simulations} = 30
10
11 # looping through each number of lane
12 for k in range(len(lanes values)):
    num lanes = lanes values[k]
13
14
    for p in densities:
15
      # initialize the model
16
       sim = TrafficSimulator(length=100, density = p, v_max = 5, p_down = 0.5, lanes = num_lanes)
17
       tracking = []
18
19
       # start simulation
20
       for i in range(simulations):
21
         total = 0
22
         sim.initialize()
         for i in range(steps + init steps):
23
24
           sim.step()
           # only record after the first few steps
25
           if i >= init steps:
26
             total += np.sum(sim.car pass())
27
         # take the average
28
         tracking.append(total/num lanes/steps)
29
30
       # record into list
31
       track mean[k].append(np.mean(tracking, axis = 0))
       track low[k].append(np.quantile(tracking, 0.05, axis = 0))
32
       track high[k].append(np.quantile(tracking, 0.95, axis = 0))
33
 1 plt.figure(figsize = (12,6))
2 # plot the multi-lanes
 3 for i in range(len(track mean)):
    print(str(lanes_values[i]) + "_lane peak at: p =", densities[track_mean[i].index(max(track_mean[i]))])
    plt.plot(densities, track_mean[i], label = str(lanes_values[i]) + "_lane", color = coloring[i], linewidth = 3)
    plt.fill_between(densities, track_low[i], track_high[i], alpha=0.1, color = coloring[i])
 6
 8 # multiple lanes - different cars - the value:
```

```
9 multi_diff_mean, multi_diff_low, multi_diff_high = track_mean, track_low, track_high
10
11 plt.legend()
12 plt.title("Average car flow with respect to density")
13 plt.xlabel("Density")
14 plt.ylabel("Car flow (car passes per time step)")
15 plt.show()
```



▼ 4. Conclusions

1

How much more traffic can flow through a 2-lane road compared to a 1-lane road at the same traffic density? What about roads with more than 2 lanes? Either model 3 or more lanes and report on your results, or predict how much larger the traffic flow through a 3+ lane road will

be compared to a 1-lane road at the same traffic density.

At p = 0.1 (peak of traffic flow), the 2-lane model can hold an additional 4% compared to the single-lane model. However, the 5-lane model can hold up to 11% increases to the single-lane model. The traffic flow for the 2-lane model and 3+ lane model is better than the single lane, with less dependence on the initial configuration. This result is demonstrated by the resulting line plus the narrower 95% interval, indicating the more certainty, or in the simulation case, less prone to the initial configuration. The model is flexibly adaptable to all number of lanes; hence, further testing out is feasible given more computing power. (The simulation here takes 1.5h to run each section - already with Colab free GPU). In conclusion, the multi-lane model can hold more traffic (more lane with the same density each lane), and better traffic flow. The 2-lane model only has a slight increase, whereas the 5-lane has significant increase of 11%.

How applicable is this model to traffic in Buenos Aires (BA)?

This model is quite reflective of traffic in BA because most vehicles are cars and have similar behavior. For BA, the small roads are usually single-lane, which is identical to section 1. Also, for bigger ways, BA has massive highways with 3+ lanes (some have five lanes), which is applicable for section 2. The results are also similar to what perceived in real life: backward traffic jams. BA traffic can be better depicts by the chaotic model, where each car has different behaviors. Finally, for the next step, to add more real-life components, I suggest adding traffic lights and intersections (as those two are among the reasons slowing down the traffic). This simulation is representative of highway situations.

Comparison between different multi-lane models (standard vs chaotic). What do your results imply about how self-driving cars should be programmed?

Interestingly, the chaotic version with the multi-lane is only peaked when density = 0.2, which implies it works better with a higher density road. The main reason is the max_speed component and the accelerating factor.

First, each car has its max speed, which on average, less than the preset v_max. Call a random vehicle with slow speed A. This means is a fast car (B) can speed up and pass A, no traffic jam would occur (as traffic jam is from the negative velocity difference between the car in front and at the back).

Second, half of the cars have accelerating step = 2, which makes them accelerate faster, making the traffic flow easier to increase.

With all such advantages, but the maximum traffic flow is not higher than of the standard model.

This result leads to a possible suggestion for self-driving cars: same behaviors and chaotic behaviors have its benefits: the standard model avoids noises and unexpected scenarios, whereas the chaotic model allows for freedom depends on the environment. Hence, the self-driving car should be an adaptive system on the environment: instead of having fixed behaviors, cars should accelerate/decelerate strategically. Furthermore, a possible benefit of self-driving cars is the chance of communicating with other cars, which might lead to better planning and coordination between systems, rather than each car as an independent component.

Next steps

I will add traffic lights, intersections turn, more noises in drivers' behaviors, simulate car accidents, and related obstacles. Also, I am very interested in having the system of coordinate vehicles (cars communicating to achieve the best outcome on average). These suggestions are all worth exploring.

```
1 plt.figure(figsize = (12,6))
2
3 # plot the single lane to compare
4 plt.plot(densities, single_lane_mean, label = "1_lane", color = coloring[3], linewidth = 3)
5
6 # plot the multi-lanes + same cars
7 for i in range(len(multi_same_mean)):
8    plt.plot(densities, multi_same_mean[i], label = str(lanes_values[i]) + "_lane + same car", color = coloring[i], linewidth = 3, li
9
10 # plot the multi-lanes + diff cars
11 for i in range(len(multi_diff_mean)):
12    plt.plot(densities, multi_diff_mean[i], label = str(lanes_values[i]) + "_lane + diff car", color = coloring[i], linewidth = 3, li
13
14 plt.legend()
15 plt.title("Average car flow with respect to density")
16 plt.xlabel("Density")
17 plt.ylabel("Car flow (car passes per time step)")
18 plt.show()
```

 \Box

