

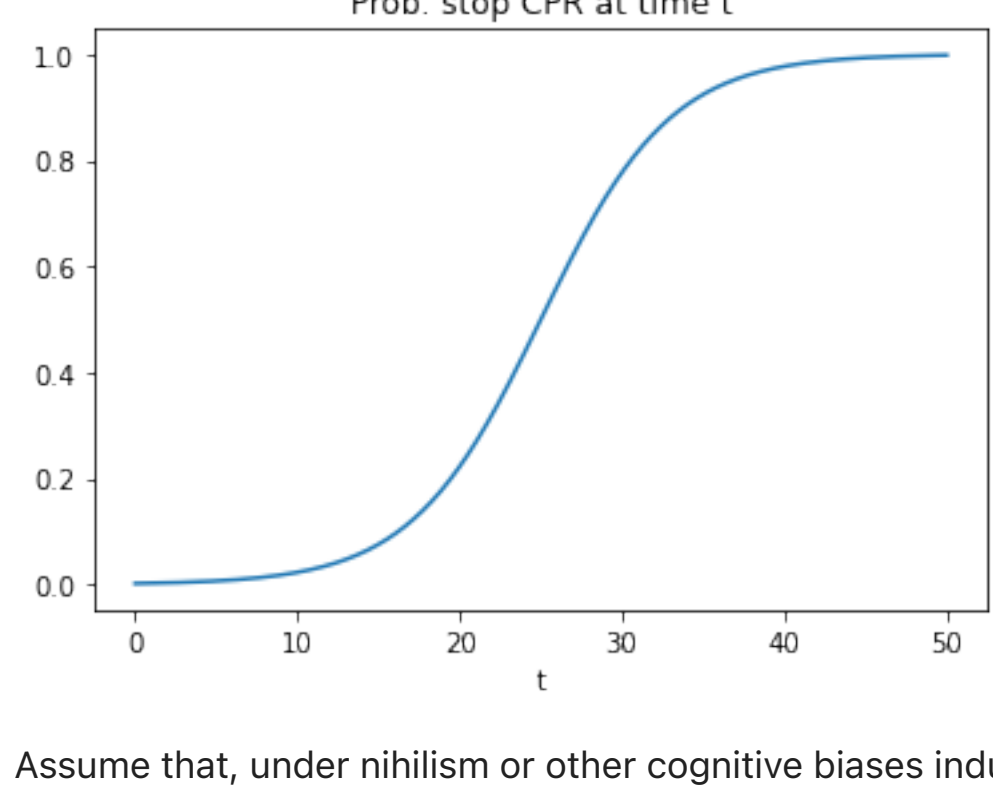
```
In [1]: import numpy as np
import matplotlib.pyplot as plt
import scipy.stats
import math
import random
random.seed(10)
```

## Simulate CPR decision

Assume that probability to stop CPR (in absence of policy) increases, following a sigmoid function. We simulate P(CPR\_stop | t)

```
In [2]: def sigm(t, a, b):
t = (t-a)/b
p = 1/(1 + np.exp(-t))
return p
```

```
In [3]: N=1000
x = np.linspace(0, 50, N)
plt.plot(x, [sigm(t, 25, 4) for t in x])
plt.xlabel("t")
plt.ylabel("")
plt.title("Probab. stop CPR at time t")
plt.show()
```



Assume that, under nihilism or other cognitive biases induced by presence of policy recommending stop of CPR, likelihood or stopping CPR increases linearly in the 2 min preceding the guideline-recommended time, reaching p=1 at the guideline-recommended time.

Define function that simulates probability of pausing CPR, receiving as input:

1. current time (t)
2. policy-recommended time (t\_stop). Initialized to Large number for simulations in absence of policy.
3. whether there is nihilism (higher likelihood of withdrawal when approaching policy-recommended time).

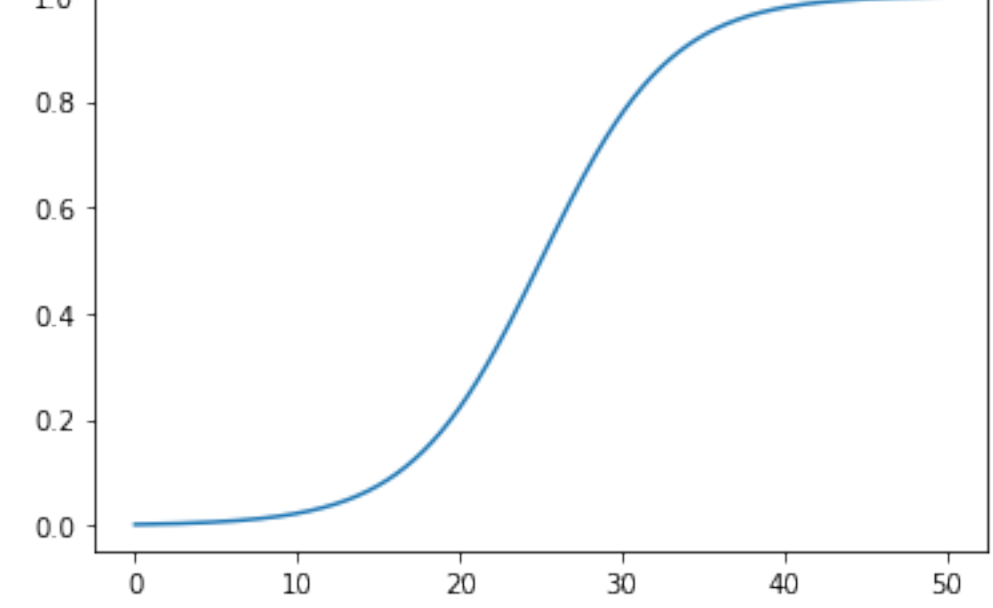
We assume that:

- Under no policy, the probability of withdrawal will be given by the above sigmoid.
- Under a policy-recommended time and no nihilism/biases, the probability of withdrawal will be given by the above sigmoid for times t<t\_stop, and will be equal to 1 for times t>=t\_stop.
- Under a policy-recommended time and presence of nihilism/biases, the probability of withdrawal will be given by the above sigmoid for times t<t\_stop-2, will increase linearly between t\_stop-2 and t\_stop (this constitute a sharper-than usual increase), and will be equal to 1 for times t>=t\_stop.

```
In [4]: def cpr_stop(t, t_stop = 100000, nihilism = False):
if t_stop<t:
    p=1
    stop = 1
elif not nihilism or t_stop-2<t:
    p = sigm(t, 25, 4)
    stop = np.random.binomial(1,p)
else:
    t_min = t_stop-2
    p_min = sigm(t_stop, 25, 4)
    p = ((t-t_stop+2)/2)*(1-p_min)+p_min
    stop = np.random.binomial(1,p)
return p, stop
```

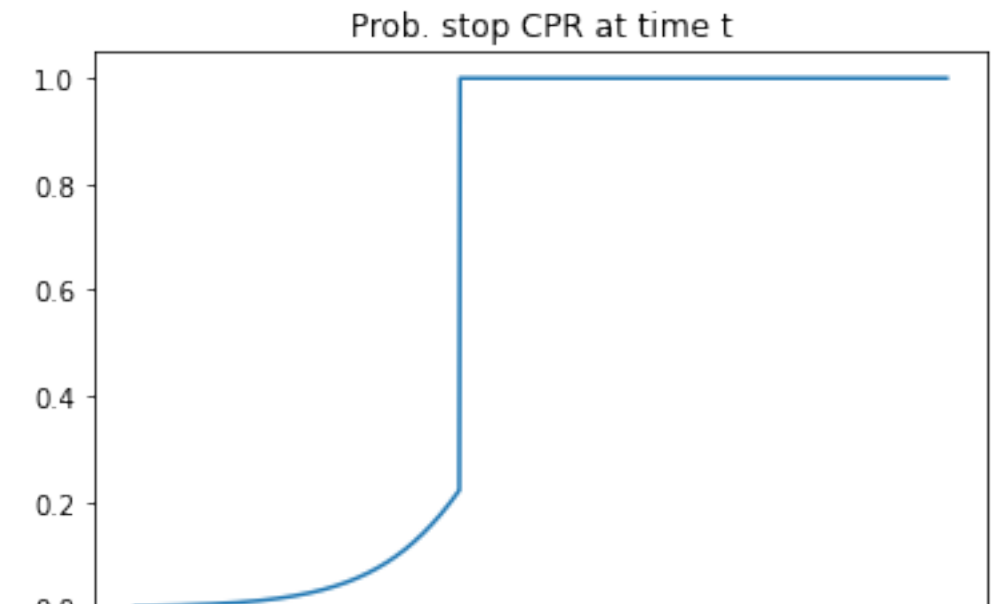
Visualization under no policy:

```
In [5]: x = np.linspace(0, 50, N)
plt.plot(x, [cpr_stop(t)[0] for t in x])
plt.xlabel("t")
plt.ylabel("")
plt.title("Probab. stop CPR at time t")
plt.show()
```



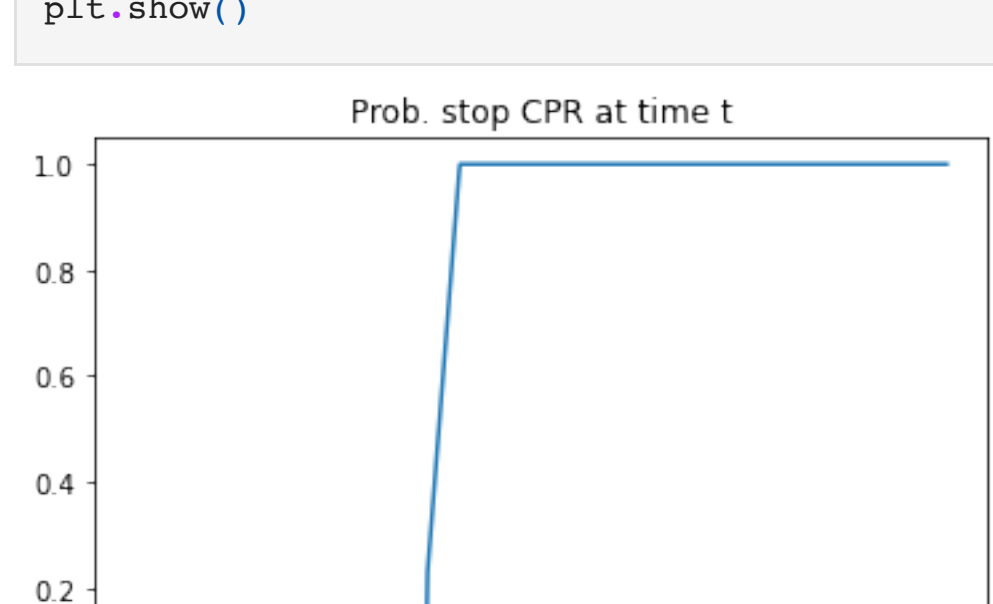
Visualization under a policy-recommended time and no nihilism/biases:

```
In [6]: x = np.linspace(0, 50, N)
plt.plot(x, [cpr_stop(t, 20)[0] for t in x])
plt.xlabel("t")
plt.ylabel("")
plt.title("Probab. stop CPR at time t")
plt.show()
```



Visualization under a policy-recommended time and presence of nihilism/biases

```
In [7]: x = np.linspace(0, 50, N)
plt.plot(x, [cpr_stop(t, 20, True)[0] for t in x])
plt.xlabel("t")
plt.ylabel("")
plt.title("Probab. stop CPR at time t")
plt.show()
```



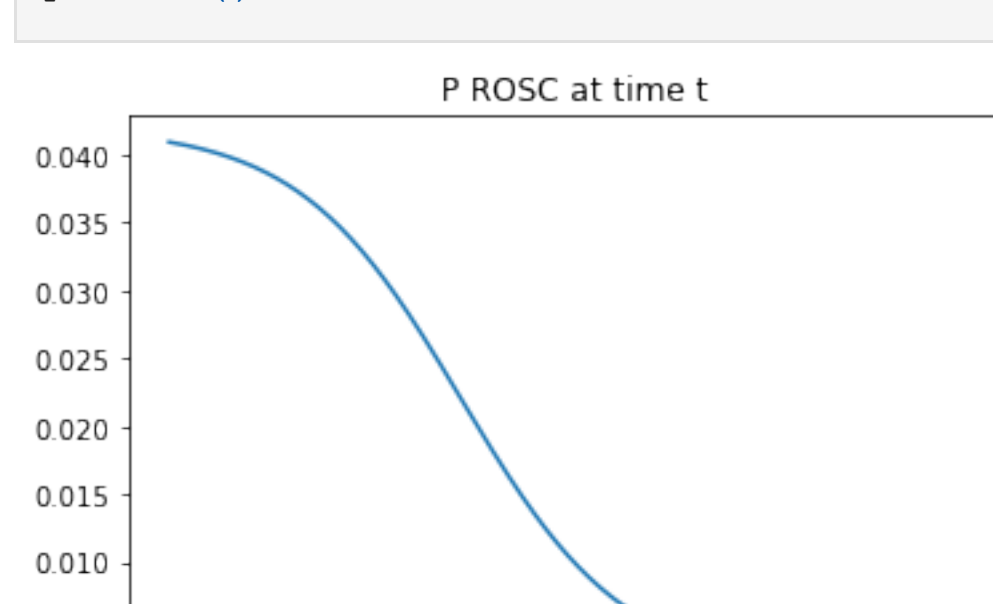
## Simulate ROSC

We simulate uncensored P(ROSC | t). The chosen shape of this distribution is informed by Reynolds et al., 2016 (ref below):

Reynolds JC, Grunau BE, Ritzenberger JC, Sawyer KN, Kurz MC, Callaway CW. Association Between Duration of Resuscitation and Favorable Outcome After Out-of-Hospital Cardiac Arrest: Implications for Prolonging or Terminating Resuscitation. Circulation. 2016;134(25):2084-2094.

```
In [8]: def rosc(t):
t = (t-18)/5
p = 1/(25*(1 + np.exp(t)))+0.002
rosc = np.random.binomial(1,p)
return p, rosc
```

```
In [9]: plt.plot(x, [rosc(t)[0] for t in x])
plt.xlabel("t")
plt.ylabel("")
plt.title("P ROSC at time t")
plt.show()
```



## Simulate outcomes considering probability that CPR is continued at a given time, and if continued, probability of ROSC.

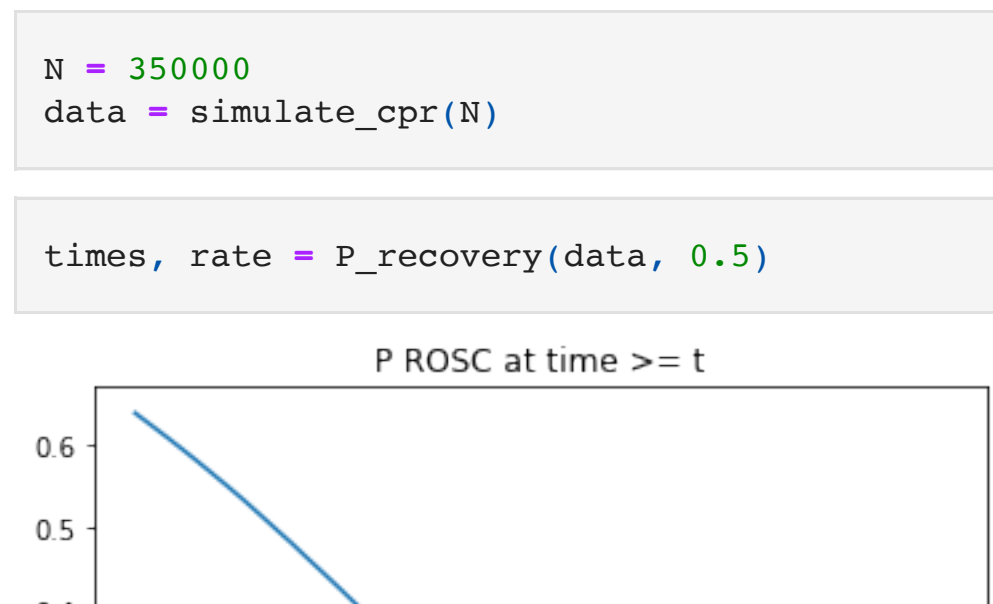
```
In [10]: def simulate_cpr(N_patients, t_policy=100000, nihilism = False, step = 0.5):
data = np.empty([N_patients,2])
for i in range(N_patients):
    cont_cpr = True
    t=step
    while cont_cpr:
        p, y = rosc(t)
        if y==1:
            data[i,:] = [t,1]
            #print('recovered', c)
            cont_cpr = False
        else:
            p = cpr_stop(t, t_policy, nihilism)
            if stop==1:
                data[i,:] = [t,0]
                cont_cpr = False
            t+=step
    return data
```

```
In [11]: def P_recovery(data, step= 1.0, plot_curve=True):
rate = []
times = np.arange(step, int(max(data[:,0])), step)
for t in times:
    idx = np.where(data[:,0]==t)
    rate.append(sum(data[idx,1])/sum(data[:,0]==t))
if plot_curve:
    plt.plot(list(times), rate)
    plt.xlabel("CPR duration")
    plt.ylabel("")
    plt.title("P ROSC at time >= t")
    plt.show()
return times, rate
```

Data for N = 350000 patients, under no policy

```
In [14]: N = 350000
data = simulate_cpr(N)
```

```
In [15]: times, rate = P_recovery(data, 0.5)
```



Data for N = 350000 patients, under policy-recommended time t\_stop=20 and unconscious tendencies

```
In [16]: data_2 = simulate_cpr(N, 20, True, 0.5)
```

```
In [17]: times2, rate_2 = P_recovery(data_2, 0.5, False)
```

Inferred policy when retraining with observational data

```
In [18]: th_idx = np.where(np.array(rate_2)<0.05)
t_learned=times[th_idx][0]
t_learned
```

```
Out[18]: 18.0
```

Data for N = 350000 patients, under new learned policy t\_stop = t\_learned and unconscious tendencies

```
In [19]: data_3 = simulate_cpr(N, t_learned, True, 0.5)
```

```
In [20]: times3, rate_3 = P_recovery(data_3, 0.5, False)
```

```
In [21]: th_idx = np.where(np.array(rate_3)<0.05)
t_learned=times[th_idx][0]
t_learned
```

```
Out[21]: 16.5
```

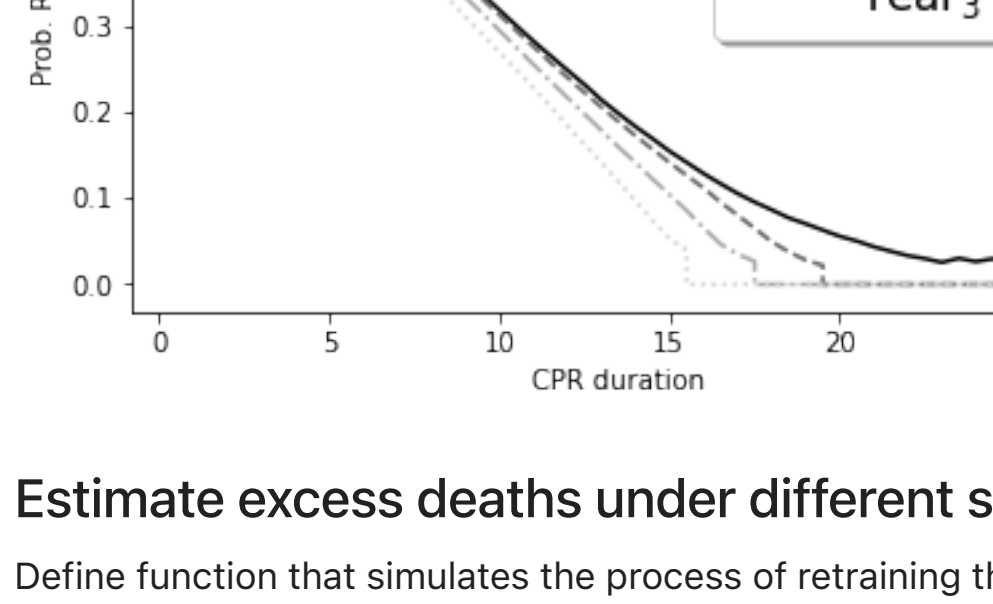
Data for N = 350000 patients, under new learned policy t\_stop = t\_learned and unconscious tendencies

```
In [22]: data_4 = simulate_cpr(N, t_learned, True, 0.5)
```

```
In [23]: times4, rate_4 = P_recovery(data_4, 0.5, False)
```

```
In [24]: def time_range(times, times_1):
return list(times_1)+[times_i-1]+[times[-1]]
```

```
In [25]: fig, ax = plt.subplots()
plt.plot(times, rate, color = "black", label = "No policy")
plt.plot(time_range(times, times2), rate_2*(0)+2, color = "dimgray", label = "Year1$", linestyle = "-.-")
plt.plot(time_range(times, times3), rate_3*(0)+2, color="darkgray", label = "Year2_2$", linestyle = "-.-")
plt.plot(time_range(times, times4), rate_4*(0)+2, color = "lightgray", label = "Year3_3$", linestyle = "dotted")
plt.xlabel("CPR duration")
plt.ylabel("Prob. ROSC")
plt.rc('font', size=14)
legend = ax.legend(loc='upper right', shadow=True, fontsize='large')
plt.tight_layout()
plt.savefig('rosc.jpg')
plt.show()
```



## Estimate excess deaths under different settings

Define function that simulates the process of retraining the policy k times (one per year), starting with observational data in the absence of policy.

```
In [32]: def iterate_policy(N, k, nihil, step=1.0):
data_nopolicy = simulate_cpr(N, 20, False, step)
excess = [0]*k
th = 20
th_list = [20]+[0]*(k-1)
for i in range(k):
    data_i = simulate_cpr(N, th, nihil, step)
    times, rate_i = P_recovery(data_i, step, False)
    th_idx = np.where(np.array(rate_i)<0.05)
    if len(th_idx[0])>0:
        th=times[th_idx][0]
    else:
        th = th
    th_list[i] = th
    excess[i] = sum(data_nopolicy[:,1])-sum(data_i[:,1])
return excess, th_list
```

```
In [33]: random.seed(10)
excess_nih, th_nih = iterate_policy(350000, 8, True, 0.5)
```

```
In [34]: random.seed(10)
excess_no_nih, th_no_nih = iterate_policy(350000, 8, False, 0.5)
```

```
In [36]: def calc_cum():
cum = [0]*len(l)
for i in range(len(l)):
    for j in range(i+1):
        cum[i] += l[j]
return cum
```

```
In [37]: excess_cum = calc_cum(excess_nih)
excess_cum_no = calc_cum(excess_no_nih)
```

```
In [38]: fig, ax = plt.subplots()
plt.plot(itr:[8], excess_cum[8], color = "black", label = "Unconscious tendencies") # "Guidelines alone"
plt.plot(itr:[8], excess_cum_no[8], color = "dimgray", label = "Perfect compliance", linestyle = "-.-") # "Guidelines + human tendencies"
plt.xlabel("Years post-implementation")
plt.ylabel("Cumulative excess deaths")
plt.rc('font', size=13.5)
legend = ax.legend(loc='upper left', shadow=True, fontsize='large')
plt.tight_layout()
plt.savefig('excess_cum.jpg')
plt.show()
```

