

# Opposite\_Bias

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## 1 Opposite Bias Model

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```
[1]: from collections import defaultdict
import matplotlib.pyplot as plt
import numpy as np
```

Just a quick test of one agent with an agenda of 10 and one agent with an agenda of -5 both targeting a single naive agent.

### 1.1 Baseline, infinite time

```
[7]: A = np.array([
    [0.5],
], ndmin = 2)

B_1 = np.array([
    0.25,
], ndmin = 2).T

B_2 = np.array([
    0.25,
], ndmin = 2).T

B = [B_1, B_2]

X_0_1 = np.array([
    2.5 - 10, # somewhat in between, will vary it later
], ndmin = 2).T

X_0_2 = np.array([
    2.5 + 5,
], ndmin = 2).T
X_0 = [X_0_1, X_0_2]

delta = 0.8
n = 1
```

```

m = 1
L = 2
Q = [1 * np.identity(n), 1 * np.identity(n)]
R = [1 * np.identity(m), 1 * np.identity(m)]

x = [10, -5] # here we have difference in agendas
r = [0, 0] # a message of nonzero weight has cost
c_base = sum([B[l] @ np.array([[r[l]]], ndmin = 2) for l in range(L)])
c = [c_base + (A - np.identity(n)) @ (x[l] * np.ones((n, 1))) for l in range(L)]

```

```

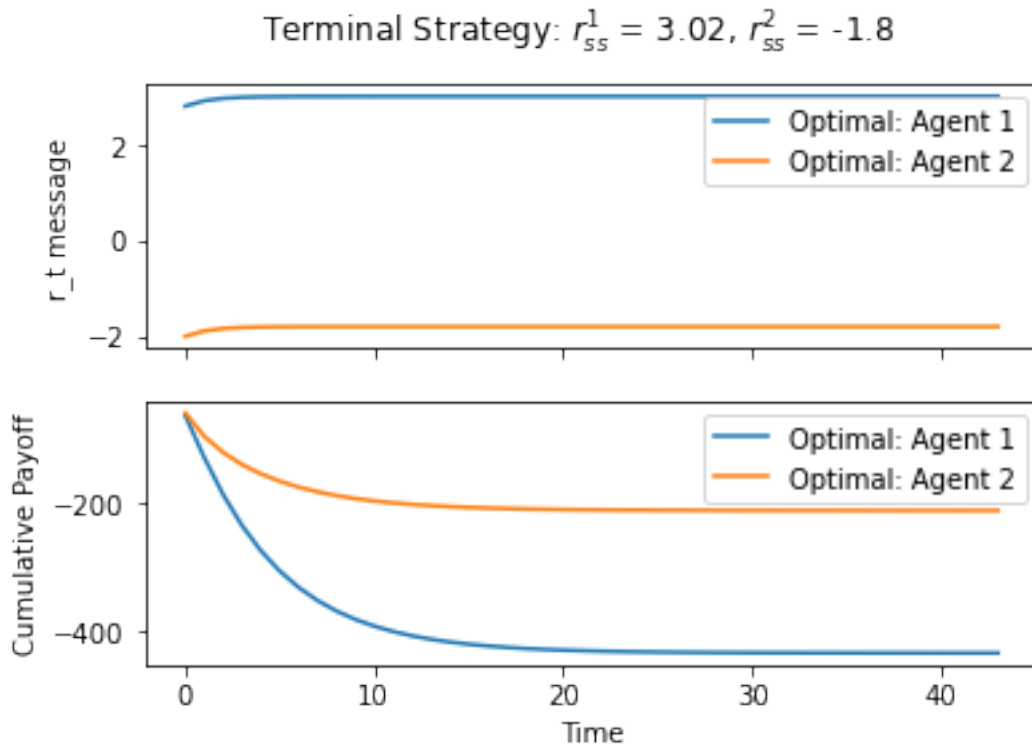
[8]: max_distances, historical_K, historical_k, historical_kappa = solve(Q, [np.
    ↪zeros((1, n)), np.zeros((1, n))], [0, 0], A, B, delta, n, m, L, Q, R, x, c,
    ↪tol = 1000)

```

```

[9]: xs2, rs2, payoffs2 = optimal(X_0, historical_K, historical_k, historical_kappa)
    do_plot(rs2, r, payoffs2, num_agents = 2)

```



```

[10]: payoffs2[0][-1] # agent 1 with the 10

```

```

[10]: -433.77327120528565

```

```

[11]: payoffs2[1][-1] # agent 2 with the -5

```

[11]: -212.00644422949424

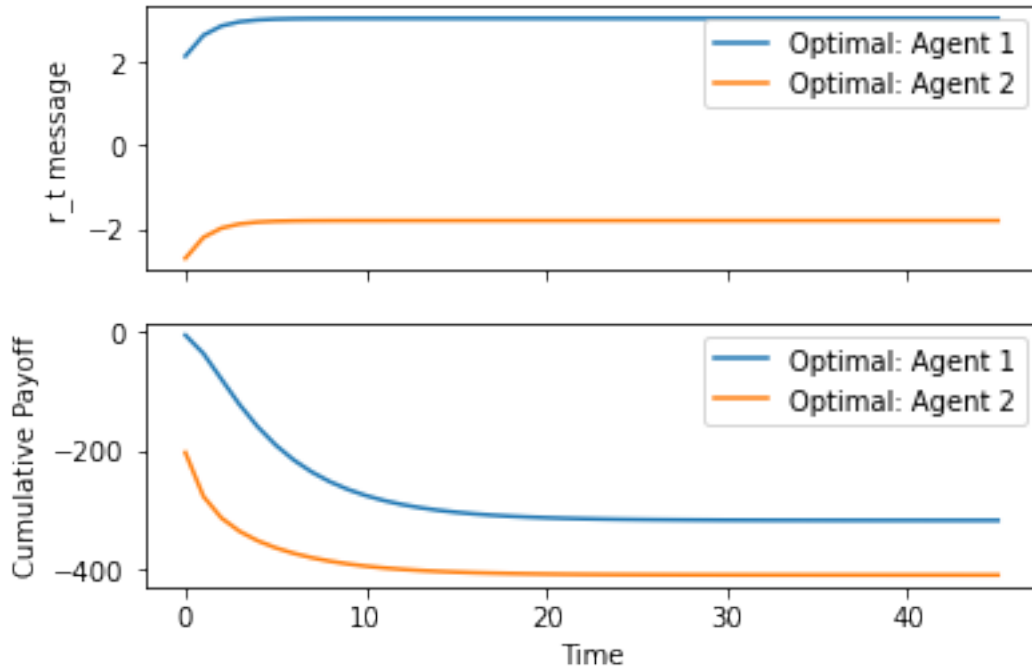
## 1.2 Baseline, infinite time, different starting opinion of naive agent

```
[12]: X_0_1 = np.array([
    9 - 10,
], ndmin = 2).T

X_0_2 = np.array([
    9 + 5,
], ndmin = 2).T
X_0 = [X_0_1, X_0_2]

x = [10, -5] # here we have difference in agendas
r = [0, 0]
c_base = sum([B[l] @ np.array([[r[l]]], ndmin = 2) for l in range(L)])
c = [c_base + (A - np.identity(n)) @ (x[l] * np.ones((n, 1))) for l in range(L)]
max_distances, historical_K, historical_k, historical_kappa = solve(Q, [np.
    ↪ zeros((1, n)), np.zeros((1, n))], [0, 0], A, B, delta, n, m, L, Q, R, x, c,
    ↪ tol = 1000)
xs2, rs2, payoffs2 = optimal(X_0, historical_K, historical_k, historical_kappa)
do_plot(rs2, r, payoffs2, num_agents = 2)
```

Terminal Strategy:  $r_{ss}^1 = 3.02$ ,  $r_{ss}^2 = -1.8$



Terminal strategy is the same but the trajectory does differ because of the introduced shift in initial opinion.

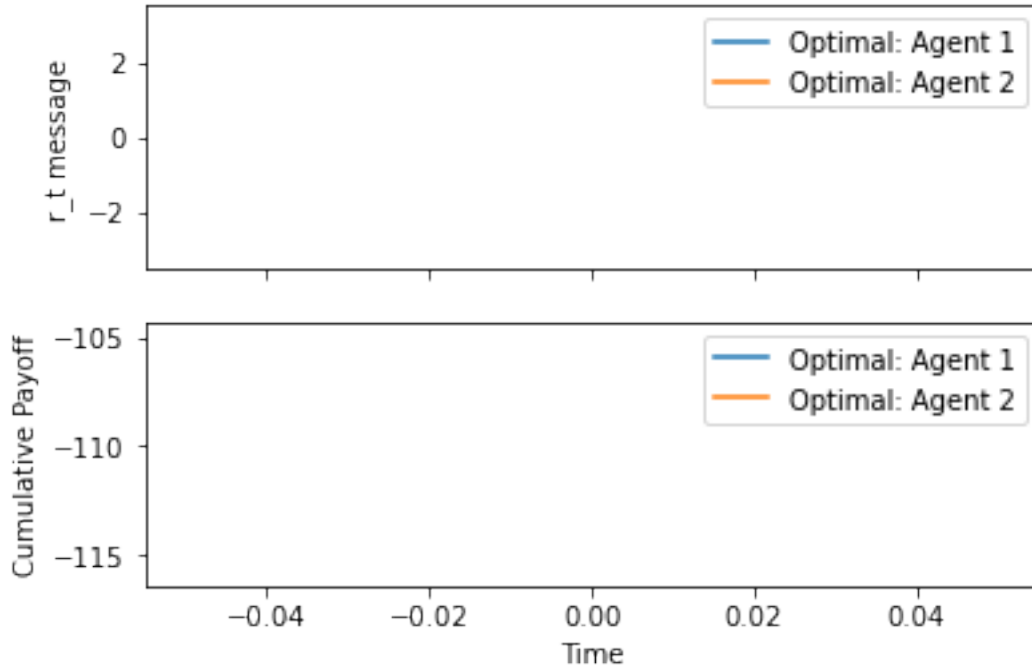
### 1.3 Exactly opposite agendas, infinite time

```
[13]: X_0_1 = np.array([
    0 - 10,
], ndmin = 2).T

X_0_2 = np.array([
    0 + 10,
], ndmin = 2).T
X_0 = [X_0_1, X_0_2]

x = [10, -10] # here we have difference in agendas
r = [0, 0]
c_base = sum([B[l] @ np.array([[r[l]]], ndmin = 2) for l in range(L)])
c = [c_base + (A - np.identity(n)) @ (x[l] * np.ones((n, 1))) for l in range(L)]
max_distances, historical_K, historical_k, historical_kappa = solve(Q, [np.
    ↪ zeros((1, n)), np.zeros((1, n))], [0, 0], A, B, delta, n, m, L, Q, R, x, c,
    ↪ tol = 1000)
xs2, rs2, payoffs2 = optimal(X_0, historical_K, historical_k, historical_kappa)
do_plot(rs2, r, payoffs2, num_agents = 2)
```

Terminal Strategy:  $r_{ss}^1 = 3.22$ ,  $r_{ss}^2 = -3.22$



```
[14]: rs2
```

```
[14]: defaultdict(list, {0: [array([[3.21812075]])], 1: [array([[ -3.21812075]])]})
```

This is a standstill case and the blank graph is not an error. Neither agent has more influence than the other, so the opinion of the naive agent doesn't change, and convergence is immediate.

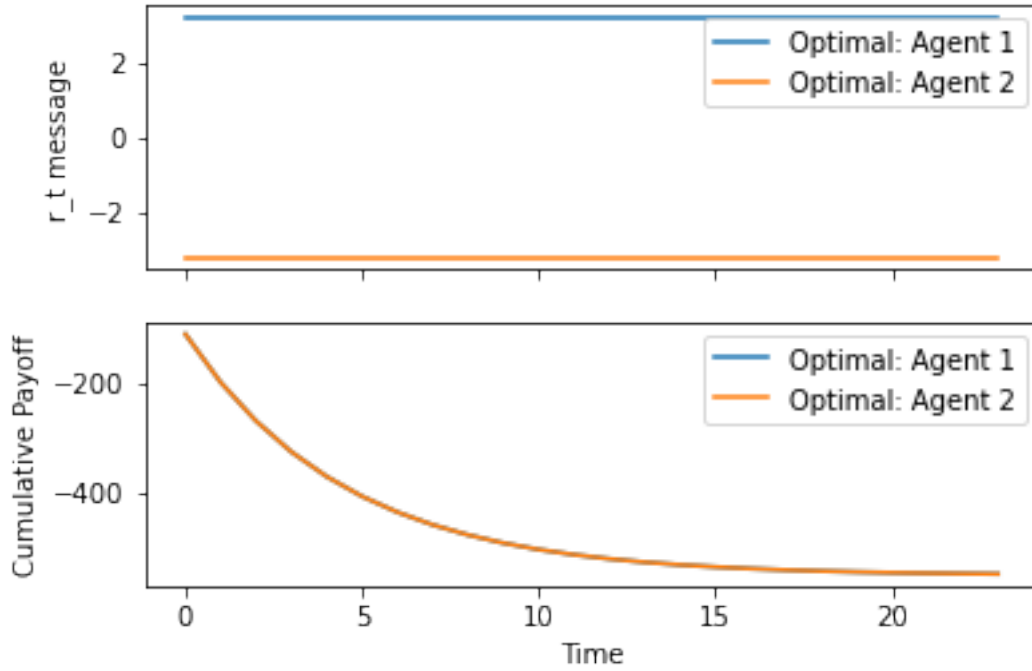
#### 1.4 Slight deviations from exactly opposite agendas, infinite time

```
[15]: X_0_1 = np.array([
    0 - 10,
], ndmin = 2).T

X_0_2 = np.array([
    0 + 9.999999,
], ndmin = 2).T
X_0 = [X_0_1, X_0_2]

x = [10, -9.999999]
r = [0, 0]
c_base = sum([B[l] @ np.array([[r[l]]], ndmin = 2) for l in range(L)])
c = [c_base + (A - np.identity(n)) @ (x[l] * np.ones((n, 1))) for l in range(L)]
max_distances, historical_K, historical_k, historical_kappa = solve(Q, [np.
    ↪zeros((1, n)), np.zeros((1, n))], [0, 0], A, B, delta, n, m, L, Q, R, x, c,
    ↪tol = 1000)
xs2, rs2, payoffs2 = optimal(X_0, historical_K, historical_k, historical_kappa)
do_plot(rs2, r, payoffs2, num_agents = 2)
```

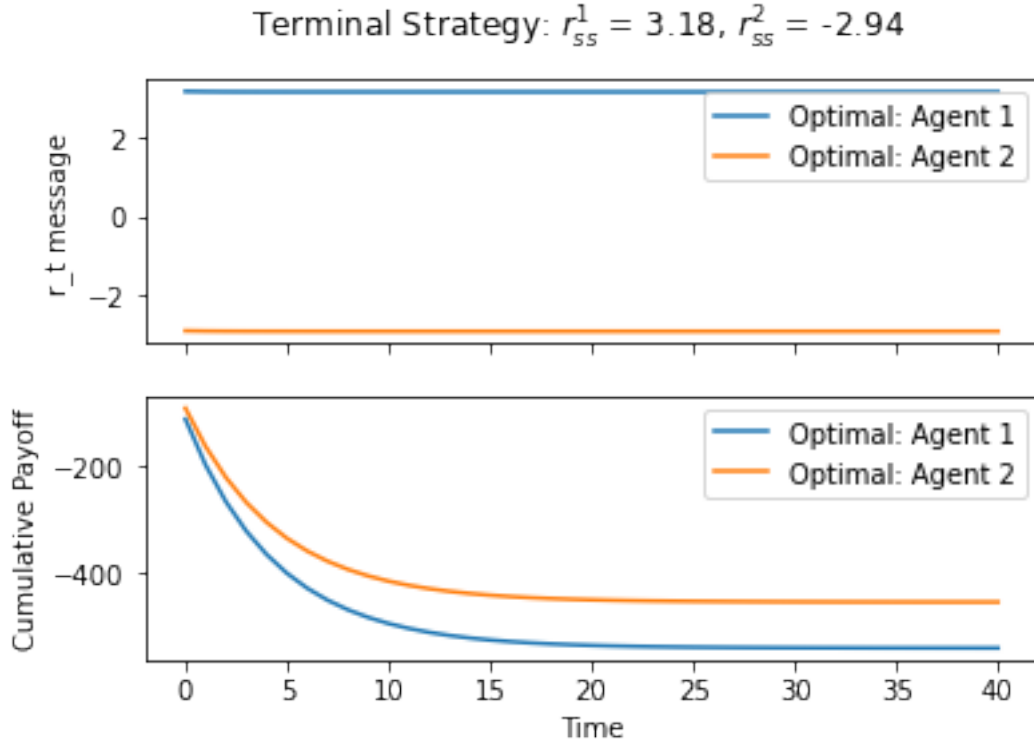
Terminal Strategy:  $r_{ss}^1 = 3.22$ ,  $r_{ss}^2 = -3.22$



```
[16]: X_0_1 = np.array([
    0 - 10,
], ndmin = 2).T

X_0_2 = np.array([
    0 + 9,
], ndmin = 2).T
X_0 = [X_0_1, X_0_2]

x = [10, -9]
r = [0, 0]
c_base = sum([B[l] @ np.array([[r[l]]], ndmin = 2) for l in range(L)])
c = [c_base + (A - np.identity(n)) @ (x[l] * np.ones((n, 1))) for l in range(L)]
max_distances, historical_K, historical_k, historical_kappa = solve(Q, [np.
    ↪ zeros((1, n)), np.zeros((1, n))], [0, 0], A, B, delta, n, m, L, Q, R, x, c,
    ↪ tol = 1000)
xs2, rs2, payoffs2 = optimal(X_0, historical_K, historical_k, historical_kappa)
do_plot(rs2, r, payoffs2, num_agents = 2)
```



When shifting one agenda closer to zero, the strategy follows moving closer to zero, and the strategy of the non-shifting agent also moves closer to zero but by a lesser amount.

### 1.5 Primary Code:

```
[2]: def M(K, B, R, L, delta):
    """Computes  $M_{t-1}$  given  $B_l$  for all  $l$ ,  $K_t$  for all  $l$ ,
         $R_l$  for all  $l$ , number of strategic agents  $L$ , and  $\delta$ ."""
    # handle the generic structure first, with the correct pairings:
    base = [[(B[l_prime].T @ K[l_prime] @ B[l]).item() for l in range(L)] for l_prime in range(L)]
    # then change the diagonals to construct  $M_{t-1}$ :
    for l in range(L): base[l][l] = (B[l].T @ K[l] @ B[l] + R[l]/delta).item()
    return np.array(base, ndmin = 2)

def H(B, K, A, L):
    """Computes  $H_{t-1}$  given  $B_l$  for all  $l$ ,  $K_t$  for all  $l$ ,
         $A$ , and number of strategic agents  $L$ ."""
    return np.concatenate(tuple(B[l].T @ K[l] @ A for l in range(L)), axis = 0)

def C_l(B, K, k, h, L, c, x, n):
    """Computes  $C_{t-1}^h$  (displayed as  $C_{t-1}^l$ ) given  $B_l$  for all  $l$ ,  $K_t$  for all  $l$ ,
         $c$ ,  $x$ , and  $n$ ."""
```

```

        k_t_l \forall \text{forall } l, \text{ a specific naive agent } h, \text{ number of strategic agents } \_
        \rightarrow L,
        c_l \forall \text{forall } l, x_l \forall \text{forall } l, \text{ and number of naive agents } n"""
        return np.concatenate(tuple(B[l].T @ K[l] @ A @ ((x[h] - x[l]) * np.
        \rightarrow ones((n, 1)))
                                + B[l].T @ K[l] @ c[l]
                                + 0.5 * B[l].T @ k[l].T for l in range(L)), axis = 0)

def E(M_, H_):
    """Computes the generic  $E_{t-1}$  given  $M_{t-1}$  and  $H_{t-1}$ ."""
    return np.linalg.inv(M_) @ H_

def F(M_, C_l_, l):
    """Computes  $F_{t-1}$  given  $M_{t-1}$ ,  $C_{t-1}$ , and specific naive agent  $l$ .
    \rightarrow """
    return (np.linalg.inv(M_) @ C_l_)[l:l+1, :]

def G(A, B, E_, L):
    """Computes the generic  $G_{t-1}$  given  $A$ ,  $B_l$  \forall \text{forall } l,
     $E_{t-1}$ , and number of strategic agents  $L$ ."""
    return A - sum([B[l] @ E_[l:l+1, :] for l in range(L)])

def g_l(B, E_, h, x, F_, L):
    """Computes  $g_{t-1}$  given  $B_l$  \forall \text{forall } l,  $E_{t-1}$ ,
    a particular naive agent  $h$ ,  $x_l$  \forall \text{forall } l,  $F_{t-1}$  \forall \text{forall } l,
    number of strategic agents  $L$ , number of naive agents  $n$ , and  $c_h$ ."""
    return - sum([B[l] @ (E_[l:l+1, :] @ ((x[h] - x[l]) * np.ones((n, 1))) + \_
    \rightarrow F_[l]) for l in range(L)]) + c[h]

```

```

[3]: def K_t_minus_1(Q, K, E_, R, G_, L, delta):
    return [Q[l] + E_[l:l+1, :].T @ R[l] @ E_[l:l+1, :]
            + delta * G_.T @ K[l] @ G_ for l in range(L)]

def k_t_minus_1(K, k, G_, g, E_, F_, R, L, delta):
    return [2*delta* g[l].T @ K[l] @ G_ + delta * k[l] @ G_
            + 2 * F_[l].T @ R[l] @ E_[l:l+1, :] for l in range(L)]

def kappa_t_minus_1(K, k, kappa, g_, F_, R, L, delta):
    return [-delta * (g_[l].T @ K[l] @ g_[l] + k[l] @ g_[l] - kappa[l])
            - (F_[l].T @ R[l] @ F_[l]) for l in range(L)]

```

```

[4]: def solve(K_t, k_t, kappa_t, A, B, delta, n, m, L, Q, R, x, c, tol = 300):
    historical_K = [K_t]
    historical_k = [k_t]
    historical_kappa = [kappa_t]
    max_distances = defaultdict(list)
    counter = 0

```



```

while True:
    M_ = M(K_t, B, R, L, delta)
    H_ = H(B, K_t, A, L)
    E_ = E(M_, H_)
    G_ = G(A, B, E_, L)
    K_new = K_t_minus_1(Q, K_t, E_, R, G_, L, delta)
    F_ = [F(M_, C_l(B, K_t, k_t, l, L, c, x, n), l) for l in range(L)]
    g = [g_l(B, E_, h, x, F_, L) for h in range(L)]
    k_new = k_t_minus_1(K_t, k_t, G_, g, E_, F_, R, L, delta)
    kappa_new = kappa_t_minus_1(K_t, k_t, kappa_t, g, F_, R, L, delta)
    cd_K = [np.max(np.abs(K_t[l] - K_new[l])) for l in range(L)]
    cd_k = [np.max(np.abs(k_t[l] - k_new[l])) for l in range(L)]
    cd_kappa = [np.max(np.abs(kappa_t[l] - kappa_new[l])) for l in range(L)]
    K_t = K_new
    k_t = k_new
    kappa_t = kappa_new
    historical_K.insert(0, K_t)
    historical_k.insert(0, k_t)
    historical_kappa.insert(0, kappa_t)
    for l in range(L):
        max_distances[(l+1, "K")].append(cd_K[l])
        max_distances[(l+1, "k")].append(cd_k[l])
        max_distances[(l+1, "kappa")].append(cd_kappa[l])
    counter += 1
    if sum(cd_K + cd_k + cd_kappa) == 0 or counter > tol:
        return max_distances, historical_K, historical_k, historical_kappa

```

```

[5]: def optimal(X_init, historical_K, historical_k, historical_kappa, infinite = _
↪ True):
    X_t = [a.copy() for a in X_init]
    xs = defaultdict(list)
    for l in range(L):
        xs[l].append(X_t[l])

    rs = defaultdict(list)
    payoffs = defaultdict(list)
    payoff = defaultdict(lambda: 0)
    i = 0
    while [i < len(historical_K), True][infinite]:
        K_t = historical_K[[i, 0][infinite]]
        k_t = historical_k[[i, 0][infinite]]
        M_ = M(K_t, B, R, L, delta)
        H_ = H(B, K_t, A, L)
        E_ = E(M_, H_)
        G_ = G(A, B, E_, L)
        F_ = [F(M_, C_l(B, K_t, k_t, l, L, c, x, n), l) for l in range(L)]
        g = [g_l(B, E_, h, x, F_, L) for h in range(L)]

```

```

        for l in range(L):
            Y_new = -1 * E_[l:l+1, :] @ X_t[l] - F(M_, C_l(B, K_t, k_t, l, L,
↪c, x, n), l)
            rs[l].append(Y_new)
            payoff[l] += (-1 * delta**i * (X_t[l].T @ Q[l] @ X_t[l])).item() +
↪(-1 * delta**i * (Y_new.T @ R[l] @ Y_new)).item()
            payoffs[l].append(payoff[l])
            X_new = G_ @ X_t[l] + g[l]
            xs[l].append(X_new)
            if l == L - 1 and infinite == True and np.max(X_t[l] - X_new) == 0:
                return xs, rs, payoffs
            X_t[l] = X_new
        i += 1

    return xs, rs, payoffs

```

```

[6]: def do_plot(rs, r, payoffs, num_agents = 1, set_cap = np.inf, flag = False,
↪legend = True):
    fig, sub = plt.subplots(2, sharex=True)
    if legend:
        fig.suptitle(f"Terminal Strategy: {'', '.join(['$r_{ss}^{' + str(l+1) +
↪'$ = ' + str(round(rs[l][:min(len(rs[l]), set_cap)][-1].item() + r[l], 2))
↪for l in range(num_agents)])}")

    for l in range(num_agents):
        sub[0].plot(range(min(len(rs[l]), set_cap)), [a.item() + r[l] for a in
↪rs[l][:min(len(rs[l]), set_cap)]], label = f"Optimal: {'Agent',
↪'Channel'}[flag]} {l+1}")
        sub[0].set(ylabel = "r_t message")

    for l in range(num_agents):
        sub[1].plot(range(min(len(payoffs[l]), set_cap)), payoffs[l][:
↪min(len(payoffs[l]), set_cap)], label = f"Optimal: {'Agent',
↪'Channel'}[flag]} {l+1}")
        sub[1].set(xlabel = "Time", ylabel = "Cumulative Payoff")
    if legend:
        sub[0].legend()
        sub[1].legend()
    plt.show()

```