

Convex Optimization in Python

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I. INTRODUCTION

This article contains some of the exercises and examples from the book "**S. Boyd and L. Vandenberghe, Convex Optimization. Cambridge: Cambridge University Press, 2004**" that I have coded in Python3. The code can be downloaded from "<https://github.com/Shahrokh-Hamidi/Convex-Optimization>".

II. CHEBYSHEV CENTER

```
#Chebyshev Center
import numpy as np
import matplotlib.pyplot as plt
import scipy
import cvxpy as cp

n = 2
px = np.array([0, .5, 2, 3, 1])
py = np.array([0, 1, 1.5, .5, -.5])

px = np.hstack((px, px[0]))
py = np.hstack((py, py[0]))

px_diff = px[1:] - px[:-1]
py_diff = py[1:] - py[:-1]

px_avg = 0.5*(px[1:] + px[:-1])
py_avg = 0.5*(py[1:] + py[:-1])

A = []
for i in range(0, len(px)-1):
    p = np.array([px_diff[i], py_diff[i]])
    p = p/np.linalg.norm(p)
    A.append([-p[1], p[0]])

A = np.array(A)

b = []
for i in range(0, len(px)-1):
    p = np.array([px_avg[i], py_avg[i]])
    b.append(A[i,:].dot(p))

#plt.plot(px, py)

m = A.shape[-1]
x = cp.Variable(m)
r = cp.Variable(1)

constr = []
```

```

constr += [A0x + r <= b]

prob = cp.Problem(cp.Maximize(r), constr)
prob.solve(verbose = False)

x = x.value
r = r.value

#---- Display

N = 100

theta = np.linspace(0,2*np.pi, N).reshape(1,-1)

x1 = r*np.cos(theta).squeeze() + x[0]
x2 = r*np.sin(theta).squeeze() + x[1]

plt.plot(px, py)
plt.plot(x1, x2, 'r--')
plt.plot(x[0], x[1], 'ko')
plt.title('Chebyshev Center')
plt.axis('off')
plt.show()

```

Fig. 1 illustrates the result of the code for the *Chebyshev Center* code.

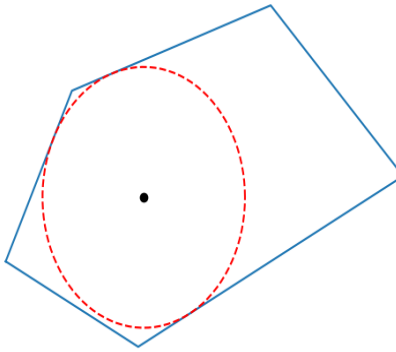


Fig. 1. The result for the *Chebyshev Center*.

III. CHEBYSHEV CENTER OF A 2D POLYHEDRON

```

#Chebyshev center of a 2D polyhedron
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%matplotlib qt

a1 = np.array([ 2, 1])
a2 = np.array([ 2, -1])
a3 = np.array([-1, 2])

```

```

a4 = np.array([-1, -2])
b = np.ones(4)

m = 2
c = cp.Variable(m)
r = cp.Variable(1)

constr = []

constr += [a1@c + np.linalg.norm(a1,2)*r <= b[0]]
constr += [a2@c + np.linalg.norm(a2,2)*r <= b[1]]
constr += [a3@c + np.linalg.norm(a3,2)*r <= b[2]]
constr += [a4@c + np.linalg.norm(a4,2)*r <= b[3]]

prob = cp.Problem(cp.Maximize(r), constr)
prob.solve(verbose = False)

c = c.value
r = r.value

#---- Display

N = 100

theta = np.linspace(0,2*np.pi, N).reshape(1,-1)
x = np.linspace(-2,2,100)

x1 = r*np.cos(theta).squeeze() + c[0]
x2 = r*np.sin(theta).squeeze() + c[1]

plt.plot(x, b[0]/a1[1] - a1[0]*x/a1[1], 'k')
plt.plot(x, b[1]/a2[1] - a2[0]*x/a2[1], 'k')
plt.plot(x, b[2]/a3[1] - a3[0]*x/a3[1], 'k')
plt.plot(x, b[3]/a4[1] - a4[0]*x/a4[1], 'k')
plt.plot(x1, x2, 'r--')
plt.plot(c[0], c[1], 'bo')
plt.title('Chebyshev center of a 2D polyhedron')
plt.ylim(-1,1)

plt.show()

```

Fig. 2 illustrates the result of the code for the *Chebyshev center of a 2D polyhedron* code.

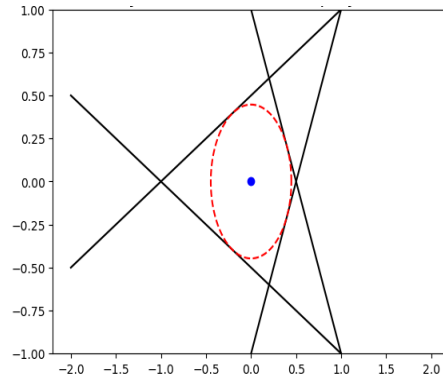


Fig. 2. The result for the *Chebyshev center of a 2D polyhedron*.

IV. FASTEST MIXING MARKOV CHAIN ON A GRAPH

```
#fastest mixing Markov chain on a graph
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%%matplotlib qt

n = 5
E = np.array([[0, 1, 0, 1, 1],
              [1, 0, 1, 0, 1],
              [0, 1, 0, 1, 1],
              [1, 0, 1, 0, 1],
              [1, 1, 1, 1, 0]])

P = cp.Variable((n,n), symmetric = True)

constr = []
constr += [P@np.ones(n) == np.ones(n)]
constr += [P >= 0]
constr += [P[E==0] == 0]

cost = cp.norm(P - np.ones((n,n))/n)
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = True)

print(f'the optimal value is {np.round(P.value,2)}')
```

V. FITTING A CONVEX FUNCTION TO GIVEN DATA

```
#Fitting a convex function to given data
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp
```

```

%matplotlib qt

lambda_ = 1

yuns = np.array([[ 5.2057354 ],
 [ 5.16852954],
 [ 4.46931747],
 [ 3.16764149],
 [ 3.21867268],
 [ 2.75587742],
 [ 1.63606279],
 [ 0.72527756],
 [ 0.24583927],
 [-0.58044829],
 [-0.87676552],
 [-0.82548372],
 [-0.79731423],
 [-0.05948396],
 [-0.04975525],
 [ 0.70500264],
 [ 0.82600211],
 [ 0.1403059 ],
 [ 0.51054544],
 [ 0.38582234],
 [ 0.83860086],
 [ 0.41632982],
 [ 0.81154682],
 [ 0.23060127],
 [ 0.84177419],
 [ 0.34454159],
 [ 0.37408514],
 [ 0.86597229],
 [ 0.2120701 ],
 [ 0.71788999],
 [ 0.80995603],
 [ 1.06910934],
 [ 0.64850169],
 [ 1.09248439],
 [ 0.76143045],
 [ 1.2122857 ],
 [ 1.17728916],
 [ 0.84659501],
 [ 0.95866895],
 [ 1.82113178],
 [ 1.80159358],
 [ 1.63543887],
 [ 1.77429526],
 [ 2.52647668],
 [ 2.65227764],
 [ 3.75011515],
 [ 4.05642222],
 [ 4.62476811],
 [ 4.91230273],
 [ 5.80689459],
 [ 7.02609346]])

u = np.array([[0. ],
 [0.04],
 [0.08],
 [0.12],
 [0.16],
 [0.2 ]],

```

```

[0.24],
[0.28],
[0.32],
[0.36],
[0.4 ],
[0.44],
[0.48],
[0.52],
[0.56],
[0.6 ],
[0.64],
[0.68],
[0.72],
[0.76],
[0.8 ],
[0.84],
[0.88],
[0.92],
[0.96],
[1.  ],
[1.04],
[1.08],
[1.12],
[1.16],
[1.2 ],
[1.24],
[1.28],
[1.32],
[1.36],
[1.4 ],
[1.44],
[1.48],
[1.52],
[1.56],
[1.6 ],
[1.64],
[1.68],
[1.72],
[1.76],
[1.8 ],
[1.84],
[1.88],
[1.92],
[1.96],
[2.  ]]

```

```

n = len(yns)
y = cp.Variable((n,1))
g = cp.Variable((n,1))

constr = []

constr += [y@np.ones((1,n)) >= np.ones((n,1))@y.T + cp.multiply((np.ones((n,1))@g.T), (u@np.
ones((1,n)) - np.ones((n,1))@u.T))]

cost = cp.norm(y - yns)
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = False)

y = y.value

```

```

plt.figure()
plt.plot(u, yns, 'o', mfc= 'none')
plt.plot(u, y, 'b')
plt.xlabel('u', fontsize = 16)
plt.ylabel('y', fontsize = 16)
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.title('Fitting a convex function to given data')
plt.xlim(-0.5,2.5)
plt.ylim(-1,8)
plt.grid()
plt.show()

```

Fig. 3 illustrates the result of the code for the *Fitting a convex function to given data* code.

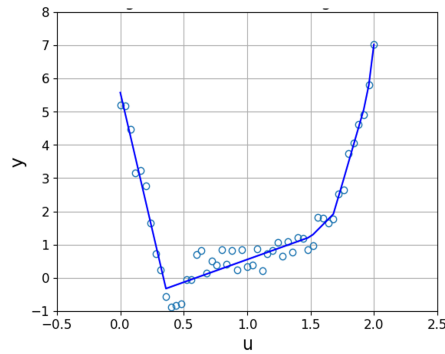


Fig. 3. The result for the *Fitting a convex function to given data*.

VI. MATRIX FRACTIONAL MINIMIZATION USING SOCP

```

#Matrix fractional minimization using SOCP
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%matplotlib qt

A = np.array([[[-0.432564811528221, 1.06676821135919, 0.815622288876143, -2.17067449430526,
0.428183273045163, 0.623233851138494, 0.
781181617878392, 1.47247993441992],
[-1.66558437823810, 0.0592814605236054, 0.711908323500893, -0.0591878245211912, 0.
895638471211752, 0.799048618147778, 0.
568960645723274, 0.0557438318378432],
[0.125332306474831, -0.0956484054836690, 1.29024975493248, -1.01063370647425, 0.
730957338429453, 0.940889940727780, -0.
821714291696256, -1.21731745370455],
[0.287676420358549, -0.832349463650023, 0.668600505682040, 0.614463048895481, 0.
577857346330798, -0.992091735543795, -0.
265606851332549, -0.0412271336864321],
[-1.14647135068146, 0.294410816392640, 1.19083807424337, 0.507740785341986, 0.
0403140316184403, 0.212035152165055, -1.
18777701646980, -1.12834386432023]]],

```

```

[1.19091546564300, -1.33618185793780, -1.20245711477394, 1.69242987019052, 0.
    677089187597305, 0.237882072875579, -2.
    20232071732344, -1.34927754310249],
[1.18916420165210, 0.714324551818952, -0.0197895577687705, 0.591282586924176, 0.
    568900205200723, -1.00776339167827, 0.
    986337391002023, -0.261101623061621],
[-0.0376332765933176, 1.62356206444627, -0.156717298831981, -0.643595202682526, -0.
    255645415631965, -0.742044752133604, -0.
    518635066344746, 0.953465445504819],
[0.327292361408654, -0.691775701702287, -1.60408556200116, 0.380337251713910, -0.
    377468955522361, 1.08229495315533, 0.
    327367564080834, 0.128644430046645],
[0.174639142820925, 0.857996672828263, 0.257304234677490, -1.00911552434079, -0.
    295887110003557, -0.131499702945274, 0.
    234057012847185, 0.656467513885396],
[-0.186708577681439, 1.25400142160253, -1.05647292808148, -0.0195106695302893, -1.
    47513450585526, 0.389880489687039, 0.
    0214661388790945, -1.16781936472664],
[0.725790548293303, -1.59372957644748, 1.41514148587234, -0.0482207891453123, -0.
    234004047656033, 0.0879871065797930, -1.
    00394446674772, -0.460605179506150],
[-0.588316543014189, -1.44096443190102, -0.805090404196880, 4.31918416255450e-05, 0.
    118444837054121, -0.635465225479316, -0.
    947146064738541, -0.262439952838333],
[2.18318581819710, 0.571147623658178, 0.528743010962225, -0.317859451247688, 0.
    314809043395056, -0.559573302196241, -0.
    374429195029166, -1.21315206849391],
[-0.136395883086596, -0.399885577715363, 0.219320672667622, 1.09500373878749, 1.
    44350824434982, 0.443653489503667, -1.
    18588621380853, -1.31943699810954],
[0.113931313520810, 0.689997375464345, -0.921901624355539, -1.87399025764096, -0.
    350974738327742, -0.949903798547645, -1.
    05590292352369, 0.931217514995436]])

b = np.array([0.0112448963841337, -0.645145815691170, 0.805728793112376, 0.231626010780437, -0.
    989759671682004, 1.33958570061039, 0.
    289502034538413,
    1.47891705768128, 1.13802801285837, -0.684138585136340, -1.29193604496594, -0.
    0729262762636467, -0.
    330598879892764, -0.
    843627639154800,
    0.497769664182782, 1.48849047090348])

B = np.array([[ -0.546475894767623, 0.469383119866330, 0.288807018730340, 1.95738475514751,
    -0.321004692181292, 1.22744798900972, 0.
    485497707312810, -1.27050020370838],
    [-0.846758163883060, -0.903566942617776, -0.429303004551915, 0.
    504542353592166, 1.
    23655565160192, -0.
    696204800032889, -0.
    00500507375553139, -1.
    66360645282977],
    [-0.246336528084900, 0.0358796387294769, 0.0558011901764726, 1.
    86452902048530, -0.
    631279656725146, 0.
    00752448652301445, -0.
    276217859354759, -0.
    703554261536755],
    [0.663024145855908, -0.627531219966832, -0.367873566740638, -0.
    339811777414964, -2.
    32521112888377, -0.
    782893044378287, 1.
    27645247367439, 0.

```



```

280880488523302],
[-0.854197374468980, 0.535397954249106, -0.464973367171118, -1.
13977940231323, -1.
23163653332502, 0.
586938559214431, 1.
86340061318454, -0.
541209329916194],
[-1.20131481533904, 0.552883517423822, 0.370960583848952, -0.
211123483380258, 1.
05564838790246, -0.
251207374568882, -0.
522559301636399, -1.
33353072973639],
[-0.119869428057387, -0.203690479567358, 0.728282931551495, 1.
19024493625120, -0.
113223989369025, 0.
480135822842601, 0.
103424446937315, 1.
07268626789014],
[-0.0652940148415865, -2.05432468055661, 2.11216016977150, -1.11620875778561
, 0.379223622685033, 0.
668155034433641, -0.
807649130897181, -0.
712085452494356],
[0.485295555916544, 0.132560731417280, -1.35729774309675, 0.635274134747122
, 0.944199726747308, -0.
0783211962734119, 0.
680438583748946, -0.
0112855612306856],
[-0.595490902619476, 1.59294070376602, -1.02261014433421, -0.
601412126269725, -2.
12042668822421, 0.
889172618412599, -2.
36458984794158, -0.
000817029195695836],
[-0.149667743824475, 1.01841178862471, 1.03783419871876, 0.551184711824902,
-0.644678915541937, 2.
30928748595239, 0.
990114872049490, -0.
249436284695434],
[-0.434751931152533, -1.58040249930316, -0.389799548476831, -1.
09984045471081, -0.
704301728433609, 0.
524638679771098, 0.
218899120881177, 0.
396575318711652],
[-0.0793302230234206, -0.0786619193594521, -1.38126562401984, 0.
0859905932937184, -1.
01813721639907, -0.
0117873239513068, 0.
261662460161402, -0.
264013354922243],
[1.53515226612215, -0.681656860002363, 0.315542632772365, -2.00456332159079
, -0.182081868411385, 0.
913140817761371, 1.
21344449497535, -1.
66401087693059],
[-0.606482859277266, -1.02455305742903, 1.55324256851535, -0.
493087917659697, 1.
52101323900559, 0.
0559406788884020, -0.
274666986456781, -1.
02897509954380],
[-1.34736267385024, -1.23435347798426, 0.707893884632476, 0.462048011799193
, -0.0384387638867116, -1.

```

```
10706989482601, -0.
133134450813529, 0.
243094700224565]])
```

```
def Form_I() :

    x = cp.Variable(n)

    constr = []

    constr += [x >= 0]

    cost = cp.matrix_frac(A*x + b, np.eye(m) + (B*cp.diag(x))*B.T)
    prob = cp.Problem(cp.Minimize(cost), constr)
    prob.solve(verbose = False)
```

```
x = x.value
print(f'Form_I Objective : {cost.value}')
```

```
def Form_II() :

    x = cp.Variable(n)
    Y = cp.Variable((n,n))

    constr = []

    constr += [x >= 0]
    constr += [Y == cp.diag(x)]

    cost = cp.matrix_frac(A*x + b, np.eye(m) + (B*Y)*B.T)
    prob = cp.Problem(cp.Minimize(cost), constr)
    prob.solve(verbose = False)
```

```
x = x.value
print(f'Form_II Objective : {cost.value}')
```

```
def Form_III() :

    x = cp.Variable(n)
    v = cp.Variable(m)
    w = cp.Variable(n)

    constr = []

    constr += [x >= 0]
    constr += [v + B*w == A*x + b]

    cost = cp.sum_squares(v) + cp.matrix_frac(w, cp.diag(x))
    prob = cp.Problem(cp.Minimize(cost), constr)
    prob.solve(verbose = False)
```

```
x = x.value
print(f'Form_II Objective : {cost.value}')
```

```

def Form_IV() :

    x = cp.Variable(n)
    v = cp.Variable(m)
    w = cp.Variable(n)
    Y = cp.Variable((n,n))

    constr = []

    constr += [x >= 0]
    constr += [v + B@w == A@x + b]
    constr += [Y == cp.diag(x)]
    cost = cp.sum_squares(v) + cp.matrix_frac(w, Y)
    prob = cp.Problem(cp.Minimize(cost), constr)
    prob.solve(verbose = False)

    x = x.value
    print(f'Form_II Objective : {cost.value}')
```

m, n = A.shape

Form_I()
Form_II()
Form_III()
Form_IV()

VII. MAXIMUM DETERMINANT PSD MATRIX COMPLETION

```

#Maximum determinant PSD matrix completion
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%matplotlib qt

n = 4

A = cp.Variable((n,n), PSD = True)

constr = []

constr += [A[0,0] == 3]
constr += [A[1,1] == 2]
constr += [A[2,2] == 1]
constr += [A[3,3] == 5]
constr += [A[0,1] == 0.5]
constr += [A[0,3] == 0.25]
constr += [A[1,2] == 0.75]

cost = -cp.log_det(A)
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = True)
```

```
print(f'A = {A.value}')
```

VIII. POLYNOMIAL FITTING

Fig. 1 illustrates the result of the code for the *Polynomial Fitting* code.

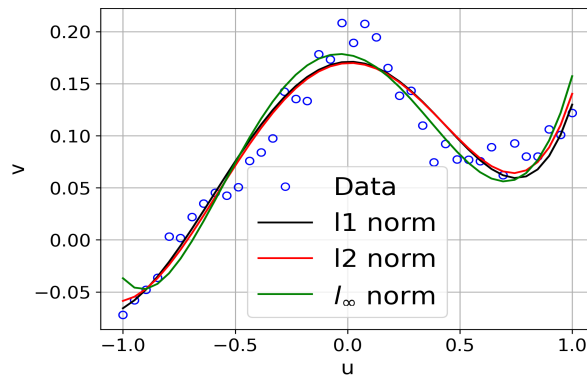


Fig. 4. The result for the *Polynomial Fitting*.

IX. QUADRATIC SMOOTHING

```
#Quadratic smoothing
import numpy as np
import matplotlib.pyplot as plt
import cvxpy as cp

#%matplotlib qt

n = 4000
t = np.arange(0, n)

signal = 0.5*np.sin((2*np.pi/n)*t)*np.sin(0.01*t)
noisy_signal = signal + np.random.normal(0,0.1,n)

lambda_ = 500
D = np.zeros((n,n))

for i in range(n-1):
    D[i, i:i+2] = [-1,1]

x = cp.Variable(n)

cost = cp.norm(noisy_signal - x, 2) + lambda_*cp.norm(D*x,2)
prob = cp.Problem(cp.Minimize(cost))
prob.solve()

denoised_signal = x.value

plt.subplot(311)
```

```

plt.plot(t, signal, 'k', lw = 2, label = 'signal')
plt.xlabel('x', fontsize = 12)
plt.ylabel('y', fontsize = 12)
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.grid()
plt.legend()
plt.title('Quadratic Smoothing', fontsize = 16)

plt.subplot(312)
plt.plot(t, noisy_signal, label = 'noisy_signal')
plt.xlabel('x', fontsize = 12)
plt.ylabel('y', fontsize = 12)
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.grid()
plt.legend()

plt.subplot(313)
plt.plot(t, denoised_signal, 'r', label = 'denoised_signal')
plt.xlabel('x', fontsize = 12)
plt.ylabel('y', fontsize = 12)
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.grid()
plt.legend()

plt.show()

```

Fig. 5 illustrates the result of the code for the *Quadratic smoothing* code.

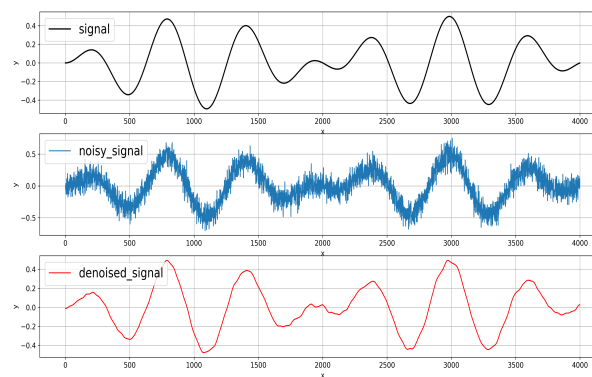


Fig. 5. The result for the *Quadratic smoothing*.

X. ROBUST REGRESSION USING THE L1 L2 HUBER PENALTY

```

#Robust regression using the l1 l2 huber penalty
import numpy as np
import matplotlib.pyplot as plt
import cvxpy as cp

```

```

#%matplotlib qt

def DATA_gen():

    x = np.linspace(-10, 10, 30)

    y = x + np.random.normal(0, 2, len(x))
    data = np.hstack((x.reshape(-1,1), y.reshape(-1,1)))
    data = np.vstack((data, np.array([-10, 10])))
    data = np.vstack((data, np.array([10, -10])))

    return data

def cvx_opt(penalty):

    m = cp.Variable(1)
    b = cp.Variable(1)

    if penalty == 'l2':
        cost = cp.norm(data[:,1] - (m*data[:,0] + b), 2)

    if penalty == 'l1':
        cost = cp.norm(data[:,1] - (m*data[:,0] + b), 1)

    if penalty == 'huber':
        cost = cp.sum(cp.huber(data[:,1] - (m*data[:,0] + b), M = 4))

    prob = cp.Problem(cp.Minimize(cost))
    prob.solve()

    b = b.value
    m = m.value

    return m, b

data = DATA_gen()

penalty = 'l2'
m2, b2 = cvx_opt(penalty)

penalty = 'l1'
m1, b1 = cvx_opt(penalty)

penalty = 'huber'
mh, bh = cvx_opt(penalty)

x = np.linspace(-10, 10, 100)
plt.plot(x, m2*x+b2, 'k--', label = 'l2 norm')
plt.plot(x, m1*x+b1, label = 'l1 norm')
plt.plot(x, mh*x+bh, label = 'huber')
plt.plot(data[:,0], data[:,1], 'ko', mfc = 'none')
plt.legend()

plt.title('Robust regression using the l1, l2, and huber penalty')

plt.xlabel('x', fontsize = 16)
plt.ylabel('y', fontsize = 16)

```

```

ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.grid()
plt.show()

```

Fig. 6 illustrates the result of the code for the Robust regression using the l1 l2 huber penalty code.

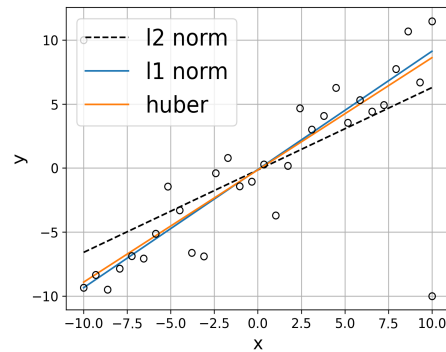


Fig. 6. The result for the *Robust regression using the l1 l2 huber penalty*.

XI. SIMPLE QP WITH INEQUALITY CONSTRAINTS

```

#simple QP with inequality constraints
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

P = np.array([[13, 12, -2], [12, 17, 6], [-2, 6, 12]])
q = np.array([-22, -14.5, 13])
r = 1
m = 3
#x_star = [1; 1/2; -1];

x = cp.Variable(m)

constr = []

constr += [x <= 1]
constr += [x >= -1]

cost = 0.5*cp.quad_form(x, P) + q@x + r
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = True)

x = x.value

print(f'x_optimal : {x}')

```

XII. TOTAL VARIATION RECONSTRUCTION EXAMPLE

```

#Total variation reconstruction example
import numpy as np
import matplotlib.pyplot as plt
import cvxpy as cp

#%matplotlib qt

n = 4000
t = np.arange(0, n)

signal = 0.5*np.sin(0.05*(2*np.pi/n)*t + np.pi/4)

for i in range(len(signal)):
    if n//4 <= i <= n//2:
        signal[i] = -signal[i]

    if 3*n//4 <= i:
        signal[i] = - signal[i]

noisy_signal = signal + np.random.normal(0,0.1,n)

lambda_ = 1
D = np.zeros((n,n))

for i in range(n-1):
    D[i, i:i+2] = [-1,1]

x = cp.Variable(n)

cost = cp.norm(noisy_signal - x, 2) + lambda_*cp.norm(D@x,1)
prob = cp.Problem(cp.Minimize(cost))
prob.solve()

denoised_signal = x.value

plt.subplot(311)
plt.plot(t, signal, 'k', lw = 2, label = 'signal')
plt.xlabel('x', fontsize = 12)
plt.ylabel('y', fontsize = 12)
plt.ylim(-0.6, 0.6)
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.grid()
plt.legend()
plt.title('Total variation reconstruction example', fontsize = 16)

plt.subplot(312)
plt.plot(t, noisy_signal, label = 'noisy_signal')
plt.xlabel('x', fontsize = 12)
plt.ylabel('y', fontsize = 12)
plt.ylim(-0.6, 0.6)
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)

```



```

plt.grid()
plt.legend()

plt.subplot(313)
plt.plot(t, denoised_signal, 'r', label = 'denoised_signal')
plt.xlabel('x', fontsize = 12)
plt.ylabel('y', fontsize = 12)
ax = plt.gca()
plt.ylim(-0.6, 0.6)
ax.xaxis.set_tick_params(labelsize=12)
ax.yaxis.set_tick_params(labelsize=12)
plt.grid()
plt.legend()

plt.show()

```

Fig. 7 illustrates the result of the code for the *total variation reconstruction example* code.

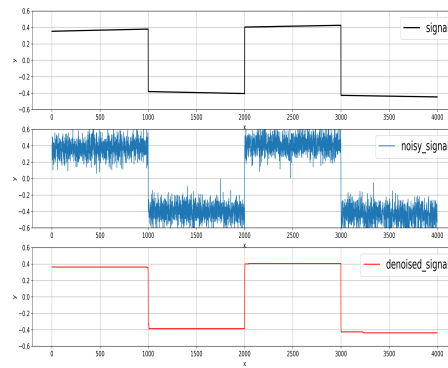


Fig. 7. The result for the *total variation reconstruction example*.

XIII. MAXIMUM ENTROPY DISTRIBUTION

```

#Maximum Entropy Distribution
import cvxpy as cp
import numpy as np
import scipy as scipy
import matplotlib.pyplot as plt

#%matplotlib qt

n = 100
u = np.linspace(-1,1,n)

A = np.array([[u], [-u], [u**2], [-u**2], [3 * ( u**3 ) - 2 * u], [-3 * ( u**3 ) + 2 * u], [
                                                    (u < 0)*1].tolist() ]]).squeeze()
b = np.array([0.1, 0.1, 0.5, -0.5, -0.2, 0.3, 0.4])

p = cp.Variable(n)
constr = []
constr += [A @ p <= b]
constr += [cp.sum(p) == 1]
constr += [p >= 0]

```

```

cost = cp.sum(cp.entr(p))
prob = cp.Problem(cp.Maximize(cost), constr)

prob.solve()

p = p.value

plt.plot(u, p)
plt.xlim(-1.3, 1.3)
plt.ylim(0, 0.05)
plt.xlabel('$u_i$', fontsize = 16)
plt.ylabel('$ Prob( X == u_i ) $', fontsize = 16)
#plt.rc('legend',fontsize=20) # using a size in points
#plt.rc('legend',fontsize='medium') # using a named size
ax = plt.gca()
ax.xaxis.set_tick_params(labelsize=14)
ax.yaxis.set_tick_params(labelsize=14)
plt.grid()
plt.legend()
#
plt.title('Maximum Entropy Distribution', fontsize = 16, color = 'k')
plt.tight_layout()
plt.show()

```

Fig. 8 illustrates the result of the code for the *Maximum Entropy Distribution* code.

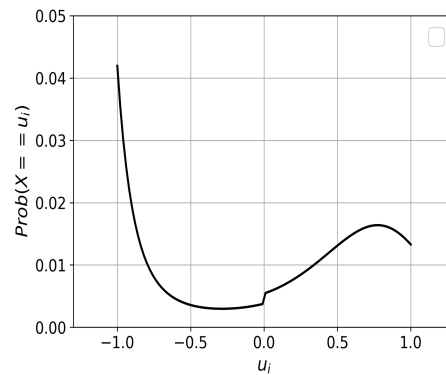


Fig. 8. The result for the *Maximum Entropy Distribution*.

XIV. ANALYTICAL CENTER OF A POLYTOPE

```

#Analytical Center of a Polytope
import numpy as np
import matplotlib.pyplot as plt
import scipy

import cvxpy as cp

#%matplotlib qt

n = 2
px = np.array([0, .5, 2, 3, 1])
py = np.array([0, 1, 1.5, .5, -.5])

px = np.hstack((px, px[0]))
py = np.hstack((py, py[0]))

```

```

px_diff = px[1:] - px[:-1]
py_diff = py[1:] - py[:-1]

px_avg = 0.5*(px[1:] + px[:-1])
py_avg = 0.5*(py[1:] + py[:-1])

A = []
for i in range(0, len(px)-1):
    p = np.array([px_diff[i], py_diff[i]])
    p = p/np.linalg.norm(p)
    A.append([-p[1], p[0]])

A = np.array(A)

b = []
for i in range(0, len(px)-1):
    p = np.array([px_avg[i], py_avg[i]])
    b.append(A[i,:].dot(p))

#plt.plot(px, py)

m = A.shape[-1]
x = cp.Variable(m)

constr = []
constr += [A@x <= b]

prob = cp.Problem(cp.Minimize(-cp.sum(cp.log(b - A@x))), constr)
prob.solve(verbose = False)

xp = x.value

#----- Display

plt.plot(px, py, 'k')
plt.plot(xp[0], xp[1], 'ro')
plt.title('Analytical Center of a Polytope')
plt.axis('off')
plt.show()

```

Fig. ?? illustrates the result of the code for the *Analytical Center of a Polytope* code.

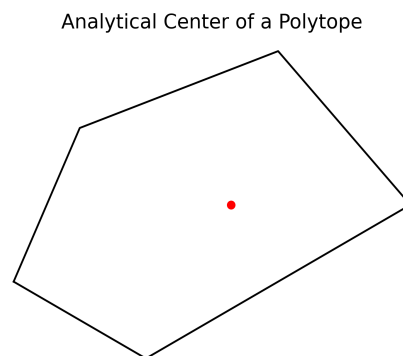


Fig. 9. The result for the *Analytical Center of a Polytope*.

XV. BOUNDING CORRELATION COEFFICIENTS

```
#Bounding correlation coefficients
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

##matplotlib qt

m = 4
p = cp.Variable((m,m), PSD = True)
constr = []
constr += [p[0][1] <= 0.9]
constr += [0.6 <= p[0][1]]
constr += [p[0][2] <= 0.9]
constr += [0.8 <= p[0][2]]
constr += [p[1][3] <= 0.7]
constr += [0.5 <= p[1][3]]
constr += [p[2][3] <= -0.4]
constr += [-0.8 <= p[2][3]]
for i in range(m):
    constr += [p[i][i] == 1.]

prob = cp.Problem(cp.Maximize(p[0][3]), constr)
prob.solve(verbose = False)

print(f'p.value = {p.value}')
```

XVI. EUCLIDEAN PROJECTION ON A HALFSPACE

```
#Euclidean projection on a halfspace
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

##matplotlib qt

n = 2
px = np.array([-5, 5])
py = np.array([-10, 10])

px_diff = px[1:] - px[:-1]
py_diff = py[1:] - py[:-1]

px_avg = 0.5*(px[1:] + px[:-1])
py_avg = 0.5*(py[1:] + py[:-1])

A = []
for i in range(0, len(px)-1):
```

```

    p = np.array([px_diff[i], py_diff[i]])
    p = p/np.linalg.norm(p)
    A.append([-p[1], p[0]])

A = np.array(A)

b = []
for i in range(0, len(px)-1):
    p = np.array([px_avg[i], py_avg[i]])
    b.append(A[i,:].dot(p))

x0 = [-5, 5]
m = 2
x = cp.Variable(m)

constr = []
constr += [A@x <= b]

prob = cp.Problem(cp.Minimize(cp.norm(x - x0, 2)), constr)
prob.solve(verbose = False)

xp = x.value

#----- Display

plt.plot(px, py, 'b', lw = 2)
plt.plot(xp[0], xp[1], 'k*', markersize = 10)
plt.plot(x0[0], x0[1], 'ro')
plt.xlim(-10,10)
plt.ylim(-10,10)
plt.title('Euclidean projection on a halfspace')
#plt.axis('off')
plt.show()

```

Fig. 10 illustrates the result of the code for the *Euclidean projection on a halfspace* code.

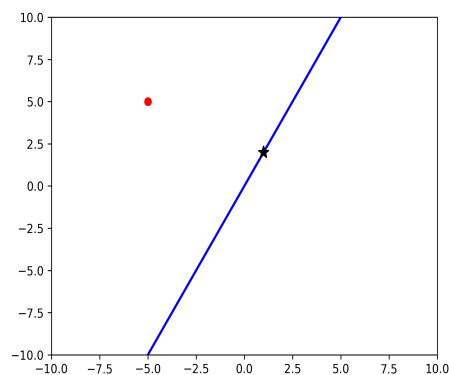


Fig. 10. The result for the *Euclidean projection on a halfspace*.

XVII. EUCLIDEAN PROJECTION ON NONNEGATIVE ORTHANT

```

#Euclidean projection on nonnegative orthant
import numpy as np
import matplotlib.pyplot as plt

```

```

import scipy

import cvxpy as cp

%matplotlib qt

x0 = np.array([5, -5])
m = 2
x = cp.Variable(m)

constr = []
constr += [x >= 0]

prob = cp.Problem(cp.Minimize(cp.norm(x - x0)), constr)
prob.solve(verbose = False)

xp = x.value

#----- Display

plt.plot(xp[0], xp[1], 'k*')
plt.plot(x0[0], x0[1], 'ro')
plt.xlim(-10,10)
plt.ylim(-10,10)
#plt.axis('off')

```

Fig. 11 illustrates the result of the code for the *Euclidean projection on nonnegative orthant* code.

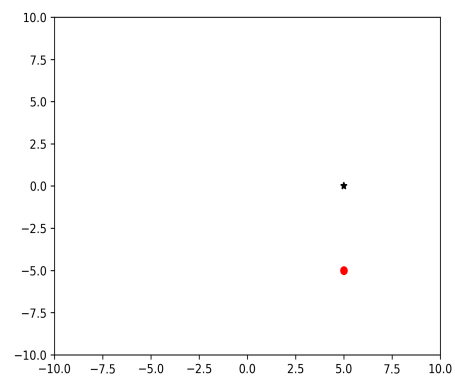


Fig. 11. The result for the *Euclidean projection on nonnegative orthant*.

XVIII. LINEAR DISCRIMINATION

```

#linear discrimination
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

```

```

#!/matplotliblib qt

x = np.random.multivariate_normal([-3,-3], [[1,0],[0,1]], 10)
y = np.random.multivariate_normal([3,3], [[1,0],[0,1]], 10)

a = cp.Variable((1,x.shape[-1]))
b = cp.Variable(1)

constr = []

for i in range(x.shape[0]):
    constr += [a*x[i,:].reshape(-1,1) - b >= 1]
    constr += [a*y[i,:].reshape(-1,1) - b <= -1]
cost = 0
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = False)

# ----- Display

z = np.linspace(-5,5,100)
plt.plot(z, (b.value - a.value.squeeze()[0]*z)/a.value.squeeze()[1])
plt.plot(x[:,0], x[:,1], 'k*')
plt.plot(y[:,0], y[:,1], 'ro')
plt.title('Linear Discrimination')
plt.show()

```

Fig. 12 illustrates the result of the code for the *linear discrimination* code.

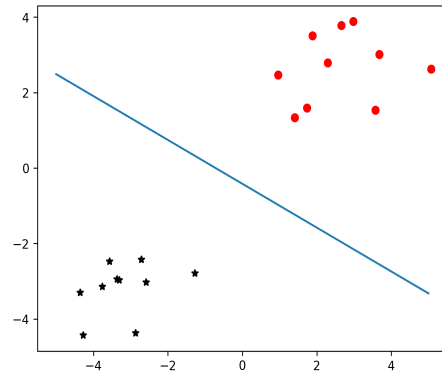


Fig. 12. The result for the *linear discrimination*.

XIX. LINEAR PLACEMENT PROBLEM

```

#!/Linear placement problem
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#!/matplotliblib qt

```

```

fixed = np.array([[ 1,   1,  -1, -1,   1,   -1,  -0.2,  0.1], [ 1,  -1,  -1,  1, -0.5, -0.2,
                                                             -1,   1]]) .T
M = fixed.shape[0]
N = 6

# first N columns of A correspond to free points,
# last M columns correspond to fixed points

A = np.array([[ 1,  0,  0, -1,  0,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [1,  0, -1,  0,  0,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [1,  0,  0,  0, -1,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [1,  0,  0,  0,  0,  0,  -1,  0,  0,  0,  0,  0,  0,  0],
               [1,  0,  0,  0,  0,  0,   0, -1,  0,  0,  0,  0,  0,  0],
               [1,  0,  0,  0,  0,  0,   0,  0,  0,  0, -1,  0,  0,  0],
               [1,  0,  0,  0,  0,  0,   0,  0,  0,  0,  0,  0, -1,  0],
               [0,  1, -1,  0,  0,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [0,  1,  0, -1,  0,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [0,  1,  0,  0,  0, -1,   0,  0,  0,  0,  0,  0,  0,  0],
               [0,  1,  0,  0,  0,  0,   0, -1,  0,  0,  0,  0,  0,  0],
               [0,  1,  0,  0,  0,  0,   0,  0, -1,  0,  0,  0,  0,  0],
               [0,  1,  0,  0,  0,  0,   0,  0,  0,  0,  0,  0, -1,  0],
               [0,  0,  1, -1,  0,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [0,  0,  1,  0,  0,  0,   0, -1,  0,  0,  0,  0,  0,  0],
               [0,  0,  1,  0,  0,  0,   0,  0,  0,  0, -1,  0,  0,  0],
               [0,  0,  0,  1, -1,  0,   0,  0,  0,  0,  0,  0,  0,  0],
               [0,  0,  0,  1,  0,  0,   0,  0, -1,  0,  0,  0,  0,  0],
               [0,  0,  0,  1,  0,  0,   0,  0,  0,  0, -1,  0,  0,  0],
               [0,  0,  0,  1,  0, -1,   0,  0,  0,  0,  0, -1,  0,  0],
               [0,  0,  0,  0,  1, -1,   0,  0,  0,  0,  0,  0,  0,  0],
               [0,  0,  0,  0,  1,  0,  -1,  0,  0,  0,  0,  0,  0,  0],
               [0,  0,  0,  0,  1,  0,   0,  0,  0, -1,  0,  0,  0,  0],
               [0,  0,  0,  0,  1,  0,   0,  0,  0,  0,  0,  0,  0, -1],
               [0,  0,  0,  0,  0,  1,   0,  0, -1,  0,  0,  0,  0,  0],
               [0,  0,  0,  0,  0,  1,   0,  0,  0,  0, -1,  0,  0,  0]])

x = cp.Variable((A.shape[-1], 2))
cost = cp.sum_squares(A @ x)

constr = []
for i in range(A.shape[0]):
    constr += [x[N:, :] == fixed]

prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = False)

x = x.value

#----- Display

plt.plot(x[:N,0], x[:N,1], 'gs', label = 'free points')
plt.plot(x[N:,0], x[N:,1], 'rs', label = 'fixed points')

for i in range(A.shape[0]):
    ind = np.nonzero(A[i,:])
    for idx in ind:
        plt.plot(x[idx,0], x[idx,1], 'k-.', lw = 0.2)

plt.legend()
plt.title('Linear Placement Problem')
plt.xlim(-1.2, 1.2)

```



```
plt.ylim(-1.2,1.2)
plt.show()
```

Fig. 13 illustrates the result of the code for the *Linear placement problem* code.

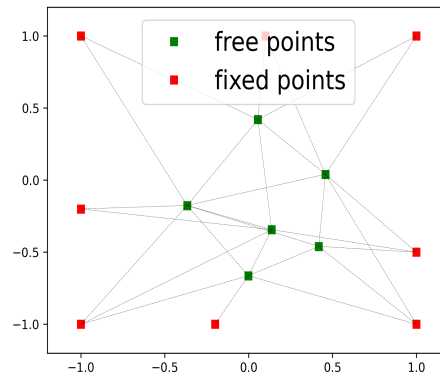


Fig. 13. The result for the *Linear placement problem*.

XX. MAX VOLUME INSCRIBED ELLIPSOID

```
#max volume inscribed ellipsoid

import numpy as np
import matplotlib.pyplot as plt
import scipy

import cvxpy as cp

n = 2
px = np.array([0, .5, 2, 3, 1])
py = np.array([0, 1, 1.5, .5, -.5])

px = np.hstack((px, px[:-1]))
py = np.hstack((py, py[:-1]))

px_diff = px[1:] - px[:-1]
py_diff = py[1:] - py[:-1]

px_avg = 0.5*(px[1:] + px[:-1])
py_avg = 0.5*(py[1:] + py[:-1])

A = []
for i in range(0, len(px)-1):
    p = np.array([px_diff[i], py_diff[i]])
    p = p/np.linalg.norm(p)
    A.append([-p[1], p[0]])

A = np.array(A)

b = []
for i in range(0, len(px)-1):
    p = np.array([px_avg[i], py_avg[i]])
    b.append(A[i,:].dot(p))

#plt.plot(px, py)

m = A.shape[-1]
```

```

X = cp.Variable((m,m), symmetric = True)
d = cp.Variable(m)

constr = []
for i in range(A.shape[0]):
    constr += [cp.norm( X@A[i,:].reshape(-1,1) , 2) + A[i,:].reshape(1,-1)@d <= b[i]]

prob = cp.Problem(cp.Maximize(cp.log_det(X)), constr)
prob.solve(verbose = False)

X = X.value
d = d.value

#---- Display

N = 100

theta = np.linspace(0,2*np.pi, N).reshape(1,-1)

ellipse = X@np.array([[np.cos(theta)], [np.sin(theta)]]).squeeze() + d.reshape(-1,1) @ np.
ones((1,N))

plt.plot(px, py, 'b', lw = 2)
plt.plot(ellipse[0,:], ellipse[1,:], 'r')
plt.title('Max Volume Inscribed Ellipsoid')
plt.axis('off')
plt.show()

```

Fig. 14 illustrates the result of the code for the *max volume inscribed ellipsoid* code.

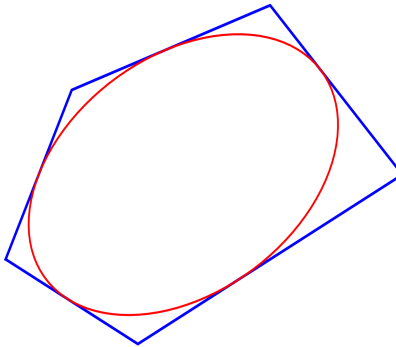


Fig. 14. The result for the max volume inscribed ellipsoid.

XXI. ONE FREE POINT LOCALIZATION

```

#One free point localization
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%matplotlib qt

```

```

p = np.random.multivariate_normal([0,0], [[10,0],[0,10]], 10)

x = cp.Variable((1,p.shape[-1]))

constr = []
cost = cp.sum(cp.norm(x - p ,1))
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = False)

xp = x.value

# ----- Display
plt.plot(p[:,0], p[:,1], 'k*')
plt.plot(xp[:,0], xp[:,1], 'ro')
plt.title('One free point localization')
plt.show()

```

Fig. 15 illustrates the result of the code for the *One free point localization* code.

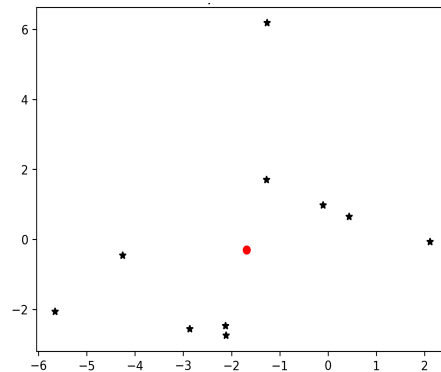


Fig. 15. The result for the *One free point localization*.

XXII. POLYNOMIAL DISCRIMINATION

```

#polynomial discrimination
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp
import scipy.io

#%matplotlib qt

X = np.array([[ -2.95855623e-02,  1.95754105e-01,  9.38421496e-02,
-3.29467959e-02, -1.73989577e-01, -7.97793709e-01,
-1.11389191e-01, -7.42729742e-01, -1.29151943e-01,
-5.17979960e-01, -1.09758793e-01, -2.30802197e-01,
-7.73237398e-03,  7.09756728e-02, -3.52385404e-01,
-5.31747802e-01, -3.04772028e-01, -1.29998958e-01,

```

```

-4.48261427e-02, -3.27872167e-03, -4.41183114e-01,
-4.05461983e-01, -1.99804573e-01, 4.26455138e-03,
2.62474869e-03, -3.51403372e-01, -3.96796643e-01,
-2.97028945e-01, -1.39562473e-01, -5.57034030e-01,
-4.39141850e-01, 8.26766799e-04, -8.98575132e-02,
1.98784110e-01, 1.48327407e-01, -7.65239272e-01,
-1.64675275e-01, 1.46751529e-01, -6.94701156e-02,
-2.10891761e-01, -4.41468102e-01, -3.05412384e-01,
-4.84305217e-02, -2.79176289e-01, -5.10060070e-01,
-7.98311175e-02, -3.10935435e-01, -3.72311823e-01,
2.19521351e-01, -4.94892629e-01, 1.41049092e-01,
-3.87453856e-01, 1.34704940e-01, -3.12572867e-01,
-6.26808596e-01, -3.25919656e-01, -6.47490319e-01,
-1.60047770e-01, -1.02291418e-01, -2.23325151e-01,
1.01700226e-01, -5.31054659e-01, -4.42743514e-01,
3.72895510e-01, -2.93658107e-02],
[-3.27235847e-01, 4.95076766e-01, 5.29947667e-02,
-9.59639561e-03, 7.63301831e-01, -2.65502307e-01,
-9.16862531e-02, 2.55875621e-01, -1.70749169e-01,
2.63716029e-01, 8.63248949e-01, -5.52139923e-01,
4.47627192e-03, -1.00834217e-01, -5.59729838e-01,
3.16068644e-01, 6.43951955e-02, 7.36883561e-02,
1.32683793e-01, 3.80192236e-01, -5.87038834e-01,
8.70099909e-02, 3.12597219e-01, 2.65889204e-03,
4.41683197e-02, 5.15480333e-01, -4.29987771e-01,
-3.98981772e-01, 1.11941884e-01, -7.95167137e-02,
4.92736689e-01, -8.85028346e-03, -3.67032553e-01,
6.48520918e-01, 6.98918608e-01, -3.16115610e-01,
2.87103155e-01, -6.41579927e-01, -1.60079670e-01,
-5.80573323e-03, 2.21465550e-01, 7.80819944e-01,
3.49373009e-01, -2.23253724e-01, 2.95930684e-01,
-7.49587566e-01, -1.23183214e-01, -8.86820600e-02,
-4.88104745e-01, 1.19707947e-01, -6.29274097e-01,
-2.48284959e-01, -6.85654170e-01, 3.10257939e-01,
-6.87885168e-02, -8.22196336e-01, 3.28320725e-01,
4.06064597e-01, -1.32930751e-02, -2.41369680e-01,
-7.44523222e-02, -5.16360847e-01, -4.14590950e-01,
-8.18568152e-01, 4.40919531e-02]])

```

```

Y = np.array([[ -1.10929648, -1.19714993, -1.46155265, 0.54850428, 1.35098877,
-0.63978276, 1.02322679, 1.52509307, 0.61292653, 2.04638631,
1.82855895, 1.47921071, 0.30167283, 1.73791846, 0.7515328 ,
-1.25628825, -0.88484211, 0.53786931, 1.53502706, 1.18898028,
0.91609724, -1.54078336, 0.16536052, -1.19906352, -1.46105915,
1.27808057, -1.12648287, 0.3258603 , 1.14215806, 0.28618332,
1.47693679, 0.89203912, -0.68661538, -1.388819 , 1.73895725,
1.57556233, 1.28373784, -0.87911447, 1.40727042, -1.40937883,
-1.28074118, -1.48632542, 0.38125655, -1.52045199, -1.66213125,
-1.94551437, 0.21882479, 0.11292287, -1.41478813, -1.87993473,
-1.00727723, 0.02675306, -0.50369109, -1.39723257, -1.22424294,
1.30030558, -1.01635215, 1.0255251 , -0.08169464, -0.25732126,
1.40042328, -2.00438398, 1.36791438, -0.89550151, -1.55659656,
-0.70043184, 0.99463546, 1.61911896, -1.79102261, 0.82796362,
-1.17658101, 0.07050389, 1.21510545, -0.26214263, 1.28184009,
-1.80832372, 1.53041901, -0.66284338, -1.14343021, 0.8866055 ,
-1.22024598, -0.86028255, 0.44238846, -0.39174046, -0.33583426,
-1.0828518 , 0.22247235, 0.06527953, 1.66426983, 0.95034167,
0.29308652, -0.70090159, -0.7519563 , -1.04020311, -1.73012502,
1.17321142, -0.01267105, 0.44442947, 1.43795889, -0.96444755,
-1.61170243, 1.07293517, -1.390684 , 1.86297062, -1.17721976,
-0.85478808, 0.94232596, 0.90095948, 0.78233839, 0.6769013 ,
0.57207325, 1.07070613, 0.94326805, -0.88960536, -0.70306538,
0.49395402, -0.72786602, -1.88687969, -0.32508892, 1.30512574,
0.33981014, 0.30344273, 0.23495848, 0.34879119, 0.29813592,

```

```

0.7812839 , 0.61364035, 0.38713553, 0.75876337, 0.70237945,
0.39402689, 0.31522323, 0.39765858, 0.5236989 , 0.74799895,
0.28614548, 0.24846108, 0.64083345, 0.49758925, 0.48985264,
0.28120179, 0.42798242, 0.58821225, 0.41714166, 0.30514283,
0.62799254],
[ 0.3852498 , 0.48917503, 0.23041757, 1.26242449, 1.2942288 ,
1.26090287, -1.40510591, 1.42402683, -1.4810577 , 0.07343144,
-0.61127391, -1.37203234, -1.17497071, -0.79741137, -1.8623418 ,
-0.01485873, 0.84298797, -1.78331797, 0.98114637, 1.2863001 ,
-1.61188272, 0.85716211, -1.97658857, -0.6671302 , -0.41711143,
0.30076968, -0.14360928, -1.13532496, 1.58119757, -1.41148329,
0.52105578, -1.80541092, -1.13739852, 1.38593001, -0.24846801,
-1.21754355, 0.93499571, 1.89903227, 0.43621015, -0.82161215,
-0.03838718, -0.59754699, -1.47367586, 0.88731639, 0.61900299,
0.66901519, -1.27319787, 1.205941 , -0.87794017, -0.86446196,
-0.49818959, 1.97003418, -1.00804074, -0.81891045, 0.4138192 ,
-1.26725377, 0.88957589, 1.75638958, 1.23448912, 1.60107613,
-1.42114194, 0.3921614 , 0.43390617, -1.24962578, -0.21339644,
-1.03449096, 0.73352648, 0.20857677, 0.35460486, 1.2492346 ,
0.86176662, 1.3834841 , -1.54888459, -1.70639443, -0.39449858,
1.02390835, -0.82895152, 1.15288164, 1.36591446, 1.52710936,
-0.1884893 , 0.72104447, -1.28836322, 1.15171548, -1.12005379,
-1.62522906, -1.26085395, -1.13053544, -0.77038397, -1.33230553,
1.34445451, 1.29038998, -0.8204131 , 1.69555841, -0.93375822,
-0.67643161, -1.66943251, 1.17823186, 0.89618357, -1.0573024 ,
-0.7036574 , 1.64458793, 0.92030731, 0.92614406, 1.48093904,
0.9156026 , -1.68778436, 0.92584162, -1.55306823, -1.63437019,
1.7825389 , 1.02149349, -1.21931587, 1.30945838, 1.55670293,
-1.17650937, -0.82744872, 0.11239135, 1.58052194, 0.14566471,
-0.20296804, -0.03981107, 0.15737806, -0.06000793, 0.28542558,
0.05675917, -0.40796816, 0.00328204, -0.25757154, 0.31645786,
0.1985505 , -0.26469693, 0.07997021, -0.61982956, 0.47241106,
-0.21855985, -0.22959073, 0.40903737, -0.64462399, 0.28872615,
-0.10924733, -0.406085 , 0.2233023 , 0.4763915 , 0.40876068,
-0.59554049]]])

```

```

m = 2
P = cp.Variable((m,m), PSD = True)
q = cp.Variable(m)
r = cp.Variable(1)

cost = 0

constr = []
for i in range(X.shape[-1]):
    constr += [(X[:,i].reshape(1,-1)@P)@X[:,i].reshape(-1,1) + q.T@X[:,i].reshape(-1,1) + r <
               = -1]
    constr += [(Y[:,i].reshape(1,-1)@P)@Y[:,i].reshape(-1,1) + q.T@Y[:,i].reshape(-1,1) + r >
               = 1]

prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = True)

P = P.value
q = q.value
r = r.value

points = np.vstack((np.linspace(-1,1,100).reshape(1,-1), np.linspace(-1,1,100).reshape(1,-1))
                    )
discr = (points.T@P)@points + points.T@q.reshape(-1,1) + r

```

```
#plt.plot(X[0,:], X[1,:], 'ro')
#plt.plot(Y[0,:], Y[1,:], 'go')
```

XXIII. ROBUST LINEAR DISCRIMINATION

```
#Robust Linear Discrimination
import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%matplotlib qt

x = np.random.multivariate_normal([-2,-2], [[1,0],[0,1]], 10)
y = np.random.multivariate_normal([2,2], [[1,0],[0,1]], 10)

a = cp.Variable((1,x.shape[-1]))
b = cp.Variable(1)
t = cp.Variable(1)

constr = []

for i in range(x.shape[0]):
    constr += [a*x[i,:].reshape(-1,1) - b >= t]
    constr += [a*y[i,:].reshape(-1,1) - b <= -t]
constr += [cp.norm(a,2) <= 1]
cost = t
prob = cp.Problem(cp.Maximize(cost), constr)
prob.solve(verbose = False)

a = a.value.squeeze()
b = b.value
t = t.value
# ----- Display

z = np.linspace(-5,5,100)
plt.plot(z, (b - a[0]*z)/a[1])
plt.plot(z, (t + b - a[0]*z)/a[1], 'r--')
plt.plot(z, (-t + b - a[0]*z)/a[1], 'r--')
plt.plot(x[:,0], x[:,1], 'k*')
plt.plot(y[:,0], y[:,1], 'ro')
plt.title('Robust Linear Discrimination')
plt.show()
```

Fig. 16 illustrates the result of the code for the *Robust Linear Discrimination* code.

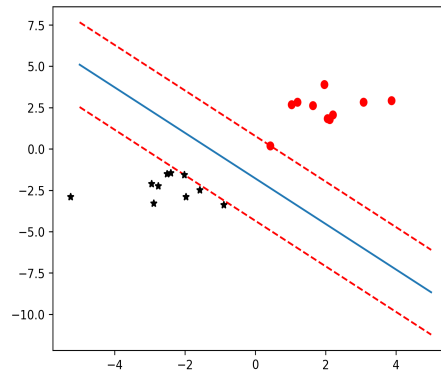


Fig. 16. The result for the *Robust Linear Discrimination*.

XXIV. SEPARATING ELLIPSOIDS IN 2D

```
#Separating ellipsoids in 2D

import numpy as np
import matplotlib.pyplot as plt
import scipy
import sys
import cvxpy as cp

#%matplotlib qt

n = 2
A = np.eye(n)
b = np.zeros(n)
C = np.array([[2, 1], [-.5, 1]])
d = np.array([-3, -3])

x = cp.Variable(n)
y = cp.Variable(n)
w = cp.Variable(n)

constr = []

constr += [cp.norm(A*x + b, 2) <= 1]
constr += [cp.norm(C*y + d, 2) <= 1]
constr += [x - y == w]
cost = cp.norm(w, 2)
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = False)

w = w.value
x = x.value
y = y.value
# ----- Display

angle = np.linspace(0, 2*np.pi, 100).reshape(1, -1)
points = np.vstack((np.cos(angle), np.sin(angle)))

ellipse_1 = np.linalg.inv(A) @ (points - b.reshape(-1, 1))
ellipse_2 = np.linalg.inv(C) @ (points - d.reshape(-1, 1))

z = (x+y)/2.
m = (y[1] - x[1])/(y[0] - x[0])
```

```

m_ = (-90 + np.arctan(m)*180/np.pi)*np.pi/180
b_ = z[1] - m_*z[0]

t = np.linspace(-1.5, 2, 100)
plt.plot(t, m_*t + b_, 'm')
plt.plot([x[0], y[0]], [x[1], y[1]])
plt.plot(x[0], x[1], 'kx', markersize = 10)
plt.plot(y[0], y[1], 'rx', markersize = 10)
plt.plot(ellipse_1[0,:], ellipse_1[1,:], 'b--')
plt.plot(ellipse_2[0,:], ellipse_2[1,:], 'g--')
plt.xlim(-2,4)
plt.ylim(-2,4)
plt.title('Separating Ellipsoids in 2D')
plt.show()

```

Fig. 17 illustrates the result of the code for the *Separating ellipsoids in 2D* code.

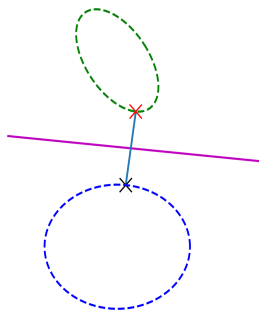


Fig. 17. The result for the *Separating ellipsoids in 2D*.

XXV. TIME SERIES ANALYSIS

```

#time series analysis

import numpy as np
import matplotlib.pyplot as plt
import cvxpy as cp
import matplotlib

#
# the data has been generated based on an AR model of order 1
# when A0 = 1, the model describes random walk
# in order to get an AR model A0 should be chosen as A0 < 1

n = 2000
y = np.zeros(n)
A0 = 1
for i in range(1,n):
    y[i] = A0*y[i-1] + np.random.normal(0,0.05)

n = len(y)

A = np.hstack((np.array([1, -2, 1]), np.zeros(n-3)))

```



```

D = []
for i in range(len(A)):
    D.append(np.roll(A,i))

D = np.array(D)

lambda_ = 10
x = cp.Variable(n)

cost = cp.norm(y - x, 2) + lambda_* cp.sum(cp.abs(D@x))      #cp.tv(x)
constr = []
prob = cp.Problem(cp.Minimize(cost), constr)
prob.solve(verbose = True)

x = x.value

plt.rcParams['savefig.dpi'] = 300

plt.plot(y, 'k-', lw = 0.3)
plt.plot(x, 'r')
matplotlib.rc('font', size=14)
plt.title('Time Series Analysis')

plt.xlabel('t', fontsize = 16)
plt.ylabel('y[t]', fontsize = 16)
matplotlib.style.use('ggplot')
plt.show()

```

Fig. 18 illustrates the result of the code for the *time series analysis* code.

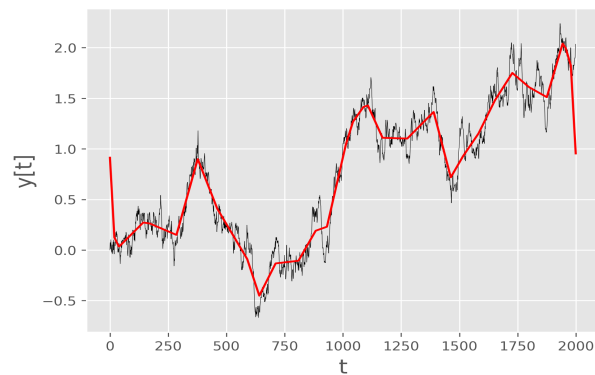


Fig. 18. The result for the *time series analysis*.



Shahrokh Hamidi was born in Iran, in 1983. He received his B.Sc., M.Sc., and Ph.D. degrees all in Electrical and Computer Engineering. He is with the faculty of Electrical and Computer Engineering at the University of Waterloo, Waterloo, Ontario, Canada. His current research areas include statistical signal processing, mmWave imaging, Terahertz imaging, image processing, system design, multi-target tracking, wireless and digital communication systems, machine learning, optimization, and array processing.