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from __future__ import division
import numpy as np
import numpy.linalg as LA
from time import time
from itertools import count
from numpy.linalg import norm as LA_norm
import matplotlib.pyplot as plt
import builtins
import seaborn as sns
# Define proximal operators
def prox_norm_1(x, eps, u=0):
   Find proximal operator of function eps*||x-u||_1
   x1 = x + np.clip(u - x, -eps, eps)
   return x1
def f_conj(y):
   return 0.5*(y+b).dot(y+b)
def g(x):
   return la*LA.norm(x,1)
def prox_g(x, rho):
   return prox norm 1(x,la*rho)
def prox_f_conj(y, rho):
   return (y - rho*b)/(1+rho)
def prox f(y, rho):
   return (y + rho*b)/(1+rho)
# define energy
def J(x,y, min_val):
   t = A.dot(x)-b
   return np.abs(0.5* t.dot(t) + la* LA.norm(x,1) - min_val)
def J1(x,y):
   return J(x,y,0)
def VI_adaptive Golden(J, prox g, prox f conj, K, x0, y0, tau, theta, rho,min val, tau max, phi,numb iter=100):
   begin = time()
   x, y = x0, y0
   x1, y1 = x0, y0
   z_x, z_y = x0, y0
   values = [J(x0, y0, min_val)]
   func_value = [J(x0,y0,0)]
   iters = []
   stop_iter = numb_iter
   L n = None
   tau_prev = tau
   theta prev = theta
   tt = [0]
   for i in range(numb iter):
       z\theta = np.concatenate((x, y))
       z1 = np.concatenate((x1, y1))
       Fz_0 = np.concatenate((K.T.dot(y), -K.dot(x)))
       Fz_1 = np.concatenate((K.T.dot(y1), -K.dot(x1)))
       z_{norm} = LA.norm(z0 - z1)
       Fz_norm = LA.norm(Fz_0 - Fz_1)
       if Fz norm != 0:
           L_n = (phi * theta_prev / (4 * tau_prev)) * ((z_norm / Fz_norm) ** 2)
           tau_n = builtins.min(rho * tau_prev, L_n, tau_max)
           tau_n = builtins.min(rho * tau_prev, tau_max)
       z x = x1 - (1 / phi) * (x1 - z x)
       z_y = y1 - (1 / phi) * (y1 - z_y)
       x2 = prox g(z x - tau n * K.T.dot(y1), tau n)
       y2 = prox_f_conj(z_y + tau_n * K.dot(x1), tau_n)
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theta_n = phi * (tau_n / tau_prev)
                tau prev = tau n
                theta prev = theta n
                values.append(J(x2, y2, min_val))
                func_value.append(J(x2,y2,0))
                 print(f"Iteration \{i\}: J_gap = \{J(x2, y2, min\_val)\}, \ tau\_n = \{tau\_n\}, \ z\_norm = \{z\_norm\}, \ F\_z\_norm = \{Fz\_norm\}, \ L\_n = \{L\_norm\}, \ L\_norm\}, \ L\_n = \{L\_norm\}, \ L\_norm\}, \ L\_
                x, y = x1, y1
                x1, y1 = x2, y2
                tt.append(time() - begin)
                err = values[-1]
                end = time()
                if err <= 1e-9:
                       stop_iter = i+1
                        print ("Iter:", i+1)
                        print(f"Converged in {stop_iter} iters, {tt[-1]:.3f}s")
                        # print ("---- Adaptive Golden-Ratio Algorithm for VI ----")
                        print ("Time execution:", round(end - begin,2))
                        break
        if err > 1e-9:
         print ("Adaptive Golden-Ratio Algorithm for VI does not terminate after", round(end - begin,2), "seconds")
        return [values,func_value, x, y,iters, stop_iter, tt]
def pd adaptive Golden(J, prox g, prox f conj, K, x0, y0, tau, theta, beta, tau max, min val, rho val, phi, numb iter=100):
        begin = time()
        x, y, z = x0, y0, x0
        values = [J(x0, y0, min_val)]
        func value = [J(x0,y0,0)]
        tau prev = tau
        theta_prev = theta
        tt = [0]
       tau_values = []
        sigma values = []
        for i in range(numb iter):
                z = x - (1 / phi) * (x - z)
                x1 = prox_g(z - tau_prev * K.T.dot(y), tau_prev)
                Kx1 = K.dot(x1)
               Kx = K.dot(x)
               Kx_norm = LA.norm(Kx - Kx1)
               x norm = LA.norm(x - x1)
                if Kx norm != 0:
                        L_n = (theta_prev / (4 * beta * tau_prev)) * (x_norm / Kx_norm) ** 2
                        tau_n = builtins.min(rho_val * tau_prev, L_n, tau_max)
                else:
                        tau n = builtins.min(rho val * tau prev, tau max)
                sigma_n = beta * tau_n
                y1 = prox f conj(y + sigma n * Kx1, sigma n)
                print(f"Iteration {i}: J gap = {J(x1, y1, min val)}, tau n = {tau n}, x norm = {x norm}, Kx norm = {Kx norm}, L n = {L n}
                theta_n = phi * (tau_n / tau_prev)
                tau prev = tau n
                theta prev = theta n
                values.append(J(x1, y1, min_val))
                func_value.append(J(x1,y1,0))
                x, y = x1, y1
                tau values.append(tau n) # Store tau n value
                sigma_values.append(sigma_n) # Store sigma_n value
                tt.append(time() - begin)
                err = values[-1]
                end = time()
                if err <= 1e-9:
                        print ("Iter:", i+1)
                        print ("---- Adaptive Golden-Ratio PDA ----")
                        print ("Time execution:", round(end - begin,2))
                        break
        if err > 1e-9:
           print ("Adaptive Golden-Ratio PDA does not terminate after", round(end - begin,2), "seconds")
        return [values, func_value, x, y, tt, sigma_values, tau_values]
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print ("Primal-dual method does not terminate after", round(end - begin,2), "seconds")

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return [values, func_value, x, y,tt]
def pd_Golden(J, prox_g, prox_f_conj, K, x0, y0, sigma, tau, phi, min_val, numb_iter=100):
    Golden-Ratio Primal-dual algorithm for the problem min_x
    \max_{y} [<Kx,y> + g(x) - f*(y)]
    J denotes some function which we compute in every iteration to
    study perfomance. It may be energy, primal-dual gap, etc.
    begin = time()
    x, y, z = x0, y0, x0
    values = [J(x0, y0, min_val)]
    func_value = [J(x0,y0,0)]
    tt = [0]
    for i in range(numb iter):
        z = x-(1/phi)*(x - z)
        x = prox_g(z - tau * K.T.dot(y), tau)
        y = prox_f_conj(y + sigma * K.dot(x), sigma)
        values.append(J(x, y, min_val))
        func_value.append(J(x,y,0))
        print(f"Iteration {i}: J_gap = {J(x, y, min_val)}, tau = {tau}, phi = {phi}")
        tt.append(time() - begin)
        err = values[-1]
        end = time()
        if err <= 1e-9:
             print ("Iter:", i+1)
             print ("---- Golden-Ratio Primal-dual method -----")
             print ("Time execution:", round(end - begin,2))
            break
    if err > 1e-9:
      print ("Golden-Ratio Primal-dual method does not terminate after", round(end - begin,2), "seconds")
    return [values, func_value, x, y,tt]
\label{eq:conj} \texttt{def pd\_Golden\_linesearch(J, prox\_g, prox\_f\_conj, K, x0, y1, tau, beta, min\_val, numb\_iter=100, tol = 1e-8):}
    Golden-Ratio PDA with linesearch for problem min_x max_y [
    (Kx, y) + g(x) - f(y).
    beta denotes sigma/tau from a classical primal-dual algorithm.
    begin = time()
    values = [J(x0, y1, min_val)]
    func_value = [J(x0,y1,0)]
    tt = [0]
    phi = 1.5
    rho = 1/phi+1/phi**2
    mu = 0.7
    delta = 0.99
    iterates = [values, func_value, x0, x0, y1, tau] + [tt, 0]
    sqrt_b = np.sqrt(beta)
    # function T is an operator that makes one iteration of the algorithm:
    \# (x1, y1) = T(x,y, history)
    def T(values, func_value, z, x_old, y, tau_old, tt,l):
        z = ((phi-1)*x_old + z)/phi
        x = prox_g(z - tau_old * K.T.dot(y), tau_old)
        Kx = K.dot(x)
        tau = tau_old * rho
        for j in count(0):
             th = tau/tau old
             y1 = prox_f_conj(y + tau * beta * Kx, tau * beta)
             \text{if } \mathsf{sqrt\_b} \ * \ \mathsf{tau} \ * \ \mathsf{LA.norm}(\mathsf{K.T.dot}(\mathsf{y1} \ - \ \mathsf{y})) \ \lessdot \ \mathsf{delta*np.sqrt}(\mathsf{phi*th}) \ * \ \mathsf{LA.norm}(\mathsf{y1} \ - \ \mathsf{y}) \colon \\ 
                 break
             else:
                 tau *= mu
                 l +=1
```

#print(phi)

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values.append(J(x, y1, min_val))
       func_value.append(J(x,y1,0))
       #steps.append(l)
       tt.append(time() - begin)
       res = [values, func_value, z, x, y1, tau, tt,l]
       return res
   for i in range(numb_iter):
       iterates = T(*iterates)
       err = iterates[0][-1]
       x = iterates[3]
       v1 = iterates[4]
       tau = iterates[5]
       print(f"Iteration \ \{i\}: J\_gap = \{J(x, \ y1, \ min\_val)\}, \ tau = \{tau\}, \ phi = \{phi\}")
       end = time()
       if err <= tol:
           print ("Iter:", i+1)
           print ("---- Golden-Ratio Primal-dual method with linesearch-----")
           print ("Time execution:", round(end - begin,2))
           break
   if err > tol:
       print ("Golden-Ratio Primal-dual method with linesearch does not terminate after", round(end - begin,2), "seconds")
   print ("Number of linesearch:", iterates[-1])
   return [iterates[i] for i in [0, 1, -2,-1]]
n = 1000
m = 300
s = 10
la = 0.1
gen = 100
np.random.seed(gen)
A = np.random.normal(0,1,(m,n))
np.random.seed(gen)
w = np.random.uniform(-10,10, n)
w[s:] = 0
np.random.seed(gen)
w = np.random.permutation(w)
np.random.seed(gen)
nu = np.random.normal(0,0.1, m)
b = A.dot(w) + nu
\# s = 10
\# la = 0.1
\# gen = 100
# np.random.seed(gen)
\# B = np.random.normal(0,1, (m,n))
\# p = 0.5
\# A = np.zeros((m,n))
\# A[:,0] = B[:,0]/np.sqrt(1-p**2)
# for j in np.arange(1,n):
     A[:,j] = p*A[:,j-1] + B[:,j]
# np.random.seed(gen)
\# w = np.random.uniform(-10,10, n)
\# w[s:] = 0
# np.random.seed(gen)
\# w = np.random.permutation(w)
# np.random.seed(gen)
\# nu = np.random.normal(0, 0.1, m)
\# b = A.dot(w) + nu
# Starting points
x0 = np.zeros(n)
y0 = -b
L = np.sqrt(np.max(LA.eigh(A.dot(A.T))[0]))
beta = .05
beta1 = 1 #.5
phi_1 = 1.618
nhi2 = 1.76
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    beta2 = .01
    phi = 1.6
    s_p = np.sqrt(phi)
    rho_val = 1./ phi + 1./ phi **2
    theta = 2
    tau_2 = 1
    mu = .81
    tau max = 100000000
    tau = 1.0 / L
    sigma = 1.0 / L
   N = 20000
    c_= 0
    ans2 = pd_adaptive_Golden(J, prox_g, prox_f_conj, A, x0, y0, tau_2, theta, beta, tau_max, c_ , rho_val, phi, numb_iter=N)
    ans29 = pd_Golden_linesearch(J, prox_g, prox_f_conj, A, x0, y0, tau_2, beta1,c_, numb_iter=N, tol = 1e-9)
    ans1 = VI_adaptive_Golden(J, prox_g, prox_f_conj, A, x0, y0, tau_2, theta, rho_val,c_,tau_max, phi, numb_iter=N)
    ans17 = pd(J, prox_g, prox_f_conj, A, x0, y0, .04*sigma, 25*tau,c_, numb_iter=N)
    ans 3 = pd\_Golden(J, prox\_g, prox\_f\_conj, A, x0, y0, s\_p*sigma, s\_p*tau, phi\_1, c\_, numb\_iter=N)
   ans4 = pd\_Golden\_Partial\_adaptive(J, prox\_g, prox\_f\_conj, A, x0, y0, mu, beta, phi2, c\_, tau\_2, numb\_iter=N)
    # ans23 = pd_Golden_Partial_adaptive(J, prox_g, prox_f, dist_sub, A, x0, y0, mu, beta, phi, la, b, tau_2, numb_iter=N)
    \# \text{ mu} = .15
    # ans24 = pd_Golden_Partial_adaptive(J, prox_g, prox_f, dist_sub, A, x0, y0, mu, beta, phi, la, b, tau_2, numb_iter=N)
    # phi = 2
    # rho1 = 1.49
    # ans19 = pd_Golden_relaxed(J, prox_g, prox_f_conj, A, x0, y0, .05*sigma, 20*tau, phi, rho1, numb_iter=N)
    \# \min \text{ val} = \text{builtins.min}(\text{ans29}[0]+\text{ans2}[0]+\text{ans1}[0])
    # print(min_val)
        Streaming output truncated to the last 5000 lines.
         Iteration 15001:J_gap = 5.109370164468624, tau_n = 0.04233466887984343, x_norm = 1.8921464009288593e-15, Kx_norm = 5.92843!
         Iteration 15003:J_{gap} = 5.109370164468623, tau_n = 0.04233466887984343, x_{norm} = 1.889596467802366e-15, Kx_{norm} = 6.178827!
         Iteration 15004:J_{gap} = 5.109370164468623, tau_n = 0.04233466887984343, x_{norm} = 1.8867629992116287e-15, Kx_{norm} = 5.983360
         Iteration 15010:J_{gap} = 5.109370164468623, tau_n = 0.04233466887984343, x_{norm} = 2.0889168141568215e-15, Kx_{norm} = 6.56696687984343, tau_n = 0.04233466887984343, tau_n = 0.0423346887984343, tau_n = 0.04233468879843
        Iteration 15011:J_{gap} = 5.109370164468622, tau_n = 0.04233466887984343, x_{norm} = 1.8911583070788454e-15, Kx_{norm} = 5.50679! Iteration 15012:J_{gap} = 5.109370164468622, tau_n = 0.04233466887984343, x_{norm} = 1.8885578436652368e-15, Kx_{norm} = 5.67232
         Iteration 15013:J_{gap} = 5.109370164468623, tau_n = 0.04233466887984343, x_{norm} = 1.8891604585765246e-15, Kx_{norm} = 6.180076
         Iteration 15018:J_{gap} = 5.109370164468622, tau_n = 0.04233466887984343, x_{norm} = 6.430146333645472e-16, Kx_{norm} = 4.630894e
         Iteration 15021:J gap = 5.109370164468623, tau n = 0.04233466887984343, x norm = 1.0947129149690507e-15, Kx norm = 5.744049
         \textbf{Iteration 15024:J\_gap = 5.109370164468622, tau\_n = 0.04233466887984343, x\_norm = 1.883619953043873e-15, Kx\_norm = 5.721172.}
        Iteration 15027:J_gap = 5.109370164468623, tau_n = 0.04233466887984343, x_norm = 1.881885562134672e-15, Kx_norm = 6.0185666887984343, tau_n = 0.04233466887984343, tau_n = 0.0423346887984343, tau_n = 0.0423346887984343, tau_n = 0.0423346887984343, tau_n = 0.0423346887984343, tau_n = 0.0423346887984
         Iteration 15030:J_{gap} = 5.109370164468622, tau_n = 0.04233466887984343, x_{norm} = 2.080521130653346e-15, Kx_{norm} = 5.728664. Iteration 15031:J_{gap} = 5.109370164468622, tau_n = 0.04233466887984343, x_{norm} = 1.8868598890635575e-15, Kx_{norm} = 6.14495.
         Iteration 15038:J gap = 5.109370164468622, tau n = 0.04233466887984343, x norm = 6.362611235656658e-16, Kx norm = 4.977465!
        Iteration 15039:J_{gap} = 5.109370164468622, tau_n = 0.04233466887984343, x_norm = 6.393556298576347e-16, Kx_norm = 4.4463281 Iteration 15040:J_{gap} = 5.109370164468621, tau_n = 0.04233466887984343, x_norm = 6.407332136201325e-16, Kx_norm = 4.4827726
         Iteration 15041:J_{gap} = 5.109370164468621, tau_n = 0.04233466887984343, x_{norm} = 1.0938466660876331e-15, Kx_{norm} = 4.95990:
         Iteration 15045:J_{gap} = 5.109370164468623, tau_n = 0.04233466887984343, x_{norm} = 6.350628131786475e-16, Kx_{norm} = 4.615217
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Iteration 15048:J_{gap} = 5.109370164468623, tau_n = 0.04233466887984343, x_{norm} = 6.244727433481201e-16, Kx_{norm} = 4.489860!
    Iteration 15051:J_gap = 5.109370164468621, tau_n = 0.04233466887984343, x_norm = 6.137122159569311e-16, Kx_norm = 4.526402! Iteration 15052:J_gap = 5.109370164468621, tau_n = 0.04233466887984343, x_norm = 6.094356637030326e-16, Kx_norm = 4.763206.
    Iteration 15056:J_gap = 5.109370164468622, tau_n = 0.04233466887984343, x_norm = 5.894876507010693e-16, Kx_norm = 4.9356999
min values = [] # Create a list to store minimum values from each list
for v in [ans29[0], ans3[0], ans4[0], ans17[0]]:
   # Get the minimum value of the list 'v' and append it to min values
   min_values.append(builtins.min(v))
# Now, find the overall minimum from the collected minimum values
min val = min(min values)
print(f'{min_val:.30f}') # Print with 30 decimal places
5.109370164468620245656893530395
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from google.colab import files
# --- 1) Set seaborn style ---
sns.set style('darkgrid')
plt.rcParams['legend.facecolor'] = plt.rcParams['axes.facecolor']
# --- 2) Update Matplotlib parameters ---
plt.rcParams.update({
    'font.size':
   'figure.figsize':
                     (7, 5),
   'legend.fontsize': 16,
   'lines.linewidth': 2,
   'axes.labelsize':
   'xtick.labelsize': 16,
   'ytick.labelsize': 16,
   'xtick.major.pad': 4,
   'ytick.major.pad': 4,
})
# —— 3) Compute the common minimum for vertical shift ——
min_val = min(np.min(ans[0]) for ans in [ans1, ans3, ans4, ans17, ans29])
# —— 4) Define your plots: (iters, error, label, marker, color) ——
plots = [
   (np.arange(len(ans17[0])), np.array(ans17[0]) - min_val, 'PDHG',
                                                                 '^', 'red'),
   (np.arange(len(ans29[0])), np.array(ans29[0]) - min val, 'GRPDA-L', 'o', 'limegreen'),
                                                                'D', 'black'),
   (np.arange(len(ans3[0])), np.array(ans3[0]) - min_val, 'GRPDA',
   (np.arange(len(ans1[0])), np.array(ans1[0]) - min_val, 'aGRAAL', 'd', '#CD853F'),
(np.arange(len(ans4[0])), np.array(ans4[0]) - min_val, 'P-GRPDA', 's', '#8A2BE2'),
1
# --- 5) Plot each with markers every ~10% of iterations ---
for x, y, lbl, mk, col in plots:
   me = max(1, len(x)//11)
   plt.plot(x, y,
           color=col,
           marker=mk.
           markersize=7,
           markevery=me,
           label=lbl)
plt.yscale('log')
plt.xlabel('Iterations')
plt.ylabel('$F(x_n)-F^*$')
# --- 6) Semi-transparent legend ---
plt.legend(framealpha=1.0, loc='upper right')
plt.tight layout()
plt.savefig('log_scale_plot_comparison1.eps', dpi=600)
files.download('log_scale_plot_comparison1.eps')
```

