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Encersise 2.1

a.
$$g(w) = \frac{1}{2} q w^2 + \tau w + d$$
 Where $q_1 \tau$, d are constants

1st derivative

 $g'(w) = \frac{1}{2} \times 2qw + \tau$

2nd derivative

 $g''(w) = q$

b.
$$g(w) = -\cos(2\pi w^2) + w^2$$

 $g'(w) = \sin(2\pi w^2) \times 2\pi \times 2w + 2w$
 $g'(w) = 4\pi w \sin(2\pi w^2) + 2w$
 $g''(w) = 4\pi \int \sin(2\pi w^2) + w 2\pi x 2w \cos(2\pi w^2) + 2$
 $= 4\pi \sin(2\pi w^2) + 16\pi^2 w^2 \cos(2\pi w^2) + 2$

$$C_{o} \qquad g(w) = \sum_{P=1}^{P} \log (1 + e^{-a_{P}w})$$

$$g'(w) = \sum_{P=1}^{P} \frac{-e^{-a_{P}w}}{1 + e^{-a_{P}w}} \propto a_{P}$$

$$g'(w) = \sum_{P=1}^{P} \frac{-a_{P}e^{-a_{P}w}}{(1 + e^{-a_{P}w})} \times \frac{e^{a_{P}w}}{e^{a_{P}w}}$$

$$g'(w) = -\sum_{p=1}^{p} \frac{a_p}{1 + e^{a_p w}}$$

$$g''(w) = \alpha_p \sum_{p=1}^{p} \frac{1}{(1+e^{\alpha_p w})^2} e^{\alpha_p w} \alpha_p$$

$$= \sum_{p=1}^{p} \frac{e^{\alpha_p w} \alpha_p^2}{(1+e^{\alpha_p w})^2}$$

$$\nabla g(\omega) = \frac{1}{2} Q 2 W + V^{T}$$

$$\nabla^2 g(w) = Q$$

b.
$$g(w) = -\cos(a\pi w^T w) + w^T w$$

 $\nabla g(w) = \sin(a\pi w^T w) a\pi aw + aw$
 $\nabla g(w) = 4\pi w \sin(a\pi w^T w) + aw$

 $\nabla^2 g(w) = 4\pi \int \sin(2\pi w^T w) + \sin(2\pi w^T w) \cdot \cos(2\pi w^T w) \cdot 2w + \frac{2}{2}$ $\nabla^2 g(w) = 4\pi \sin(2\pi w^T w) + 84\pi w^2 \cos(2\pi w^T w) + 2$

 $\nabla^2 g(w) = (4\pi \sin(2\pi w^T w) + 2) I_{NXN} + \cos(2\pi w^T w) (4\pi)^2 w \cdot w^T$

$$C_{o} g(w) = \sum_{P=1}^{P} \log \left(1 + e^{-ap^{T}w}\right)$$

$$\forall g(w) = \sum_{P=1}^{P} \frac{1}{1 + e^{-ap^{T}w}} - a_{P}e^{-ap^{T}w}$$

$$= -a_{P} \sum_{P=1}^{P} \frac{1}{\left(1 + e^{-ap^{T}w}\right)} \frac{e^{-ap^{T}w} \times e^{ap^{T}w}}{e^{ap^{T}w}}$$

$$= -a_{P} \sum_{P=1}^{P} \frac{1}{\left(e^{ap^{T}w} + 1\right)}$$

$$\nabla^2 g(w) = \sum_{P=1}^{P} \frac{a_P^T w}{(1 + e^{a_P^T w})^2} a_P a_P^T$$

Encersise 2.5

By 1st order taylor series approximation

$$h(w) = g(v) + \nabla^{T}g(v) (\overline{w} - \overline{v}) \qquad w = \begin{bmatrix} w_{1} & w_{2} & w_{N} \end{bmatrix}$$

$$h(w) = g(v) + \nabla^{T}g(v) \overline{w} - \nabla^{T}g(v) \overline{v} \qquad \nabla g(v) = 0$$

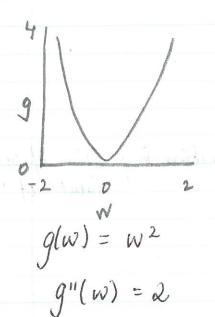
$$h(w) - \nabla^{T}g(v) \overline{w} - g(v) + \nabla^{T}g(v) \overline{v} = 0 \qquad \begin{bmatrix} \frac{\partial}{\partial w_{1}} g(v) \\ \frac{\partial}{\partial w_{2}} g(v) \end{bmatrix}^{T}$$

$$\int_{0}^{T} \int_{0}^{T} \int_{0}^{T}$$

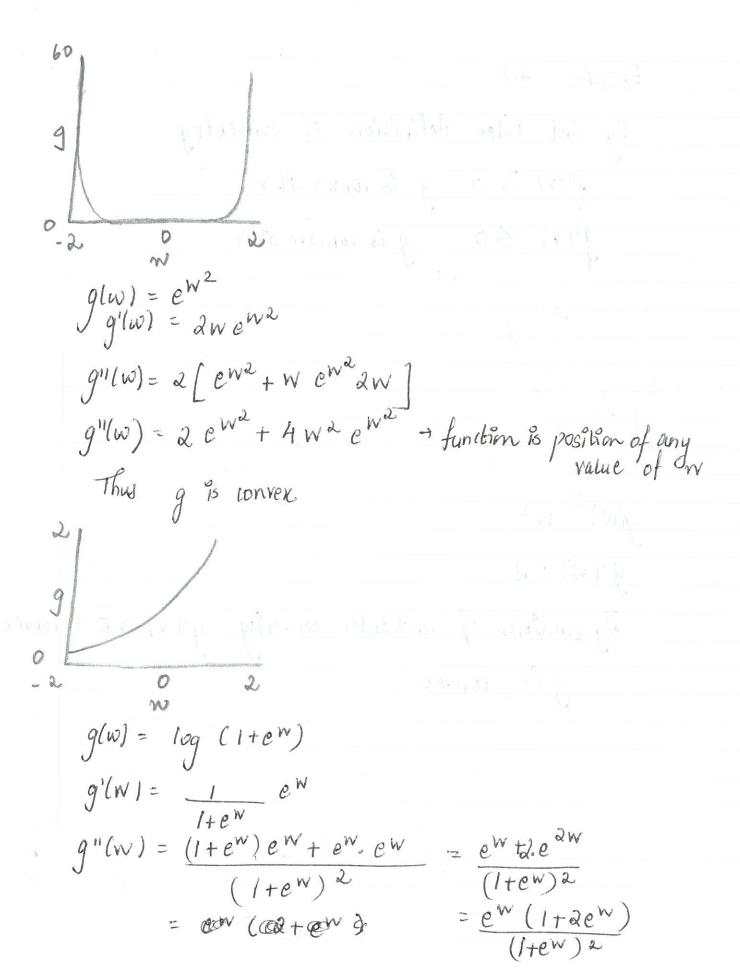
$$\sqrt{1}$$
 $\bar{n} = \begin{pmatrix} 1 \\ -\nabla g(v) \end{pmatrix}$

Exercise 207

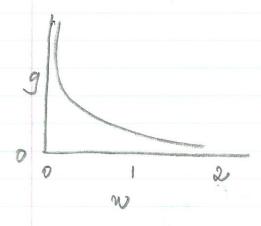
By and order definition of convexity $g''(v) \geq 0$ g is convex at v $g''(v) \leq 0$ g is concare at v



By condition of Indorder convexity g'll v) > 0 -> convex g 13 convex



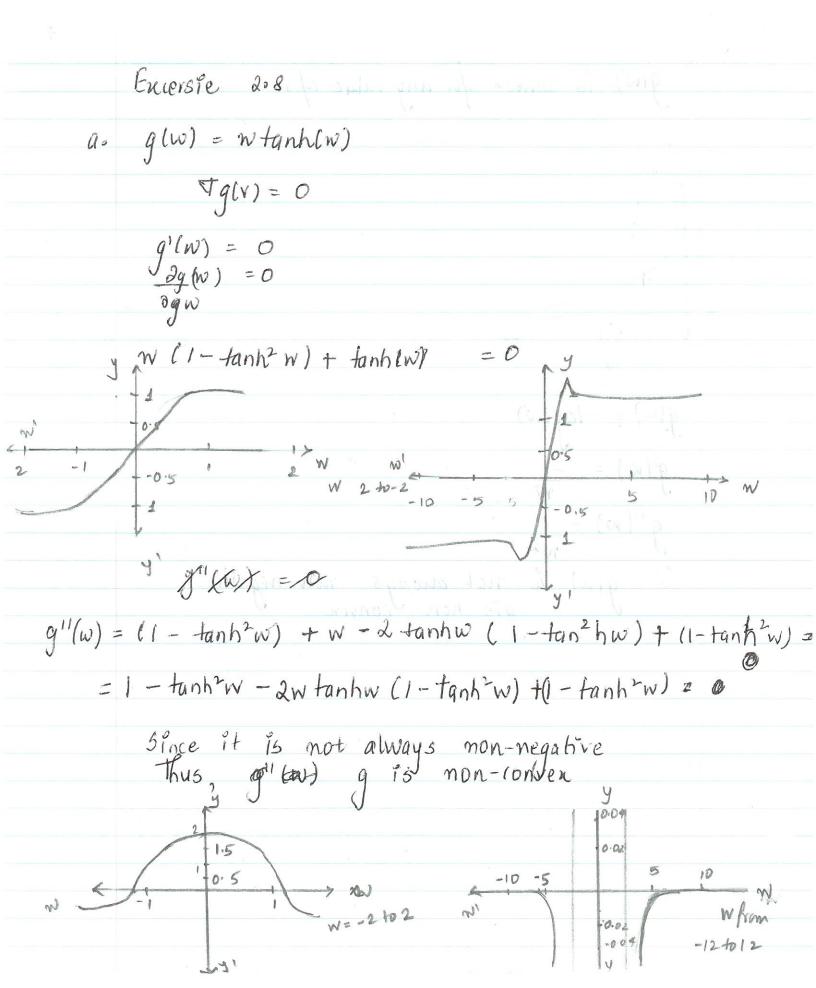
glw) is conven for any value of n



$$g(w) = -\log(w)$$

$$g'(w) = -\frac{1}{w}$$

glw) is not always non negative gis non-conven



$$N=2$$
 $W = [w_1, w_2]^T$

Exercise 2.13

```
from pylab import *
from mpl_toolkits.mplot3d import Axes3D
from autograd import grad
##### ML Algorithm functions ######
def gradient descent(w0,alpha):
  w = w0
  g_path = []
  w_path = []
  w_path.append(w)
  g_path.append(-cos(2*pi*dot(w.T,w)) + 2*dot(w.T,w))
  #grad=lambda w,w.T:-cos(2*pi*dot(w.T,w)) + 2*dot(w.T,w)
  # start gradient descent loop
  grad = 1
  iter = 1
  max_its = 50
  while linalg.norm(grad) > 10**(-5) and iter <= max_its:
    # take gradient step
    grad = 4 * w* pi*sin(2*pi *dot(w.T,w)) + 2*w # added this line
   w = w - alpha*grad
    # update path containers
    w_path.append(w)
    g path.append(-cos(2*pi*dot(w.T,w)) + 2*dot(w.T,w))
    iter+= 1
  g_path = asarray(g_path)
  g_path.shape = (iter,1)
  w_path = asarray(w_path)
  w_path.shape = (iter,2)
  # show final average gradient norm for sanity check
  s = dot(grad.T,grad)/2
  s = 'The final average norm of the gradient = ' + str(float(s))
  print(s)
  ## for use in testing if algorithm minimizing/converging properly
  # plot(asarray(obj_path))
  # show()
  return (w_path,g_path)
##### plotting functions ######
```

```
def make_function():
  global fig,ax1
  # prepare the function for plotting
  r = linspace(-1.15, 1.15, 300)
  s,t = meshgrid(r,r)
  s = reshape(s,(size(s),1))
  t = reshape(t,(size(t),1))
  h = concatenate((s,t),1)
  h = dot(h*h,ones((2,1)))
  b = -\cos(2*pi*h) + 2*h
  s = reshape(s,(int(sqrt(size(s))),int(sqrt(size(s)))))
  t = reshape(t,(int(sqrt(size(t))),int(sqrt(size(t)))))
  b = reshape(b,(int(sqrt(size(b))),int(sqrt(size(b)))))
  # plot the function
  fig = plt.figure(facecolor = 'white')
  ax1 = fig.add subplot(111, projection='3d')
  ax1.plot_surface(s,t,b,cmap = 'Greys',antialiased=False) # optinal surface-smoothing args rstride=1,
cstride=1.linewidth=0
  ax1.azim = 115
  ax1.elev = 70
  # pretty the figure up
  ax1.xaxis.set rotate label(False)
  ax1.yaxis.set_rotate_label(False)
  ax1.zaxis.set rotate label(False)
  ax1.get_xaxis().set_ticks([-1,1])
  ax1.get_yaxis().set_ticks([-1,1])
  ax1.set_xlabel('$w_0$',fontsize=20,rotation = 0,linespacing = 10)
  ax1.set ylabel('$w 1$',fontsize=20,rotation = 0,labelpad = 50)
  ax1.set_zlabel(' $g(\mathbf{w})$',fontsize=20,rotation = 0,labelpad = 20)
def plot_steps(w_path,g_path):
  # colors for points
  ax1.plot(w_path[:,0],w_path[:,1],g_path[:,0],color = [1,0,1],linewidth = 5) # add a little to output path
so its visible on top of the surface plot
  ax1.plot(w_path[-8:-1,0],w_path[-8:-1,1],g_path[-8:-1,0],color = [1,0,0],linewidth = 5) # add a little to
output path so its visible on top of the surface plot
def main():
  make_function()
                                    # plot objective function
```

```
# plot first run on surface
alpha = 10**-2
w0 = array([-0.7,0])
w0.shape = (2,1)
w_path,g_path = gradient_descent(w0,alpha) # perform gradient descent
plot_steps(w_path,g_path)

# plot second run on surface
w0 = array([0.8,-0.8])
w0.shape = (2,1)
w_path,g_path = gradient_descent(w0,alpha) # perform gradient descent
plot_steps(w_path,g_path)
show()
main()
```

The final average norm of the gradient = 0.011667426577188758 The final average norm of the gradient = 4.415498975795742e-11

Exercise 2.17 b.

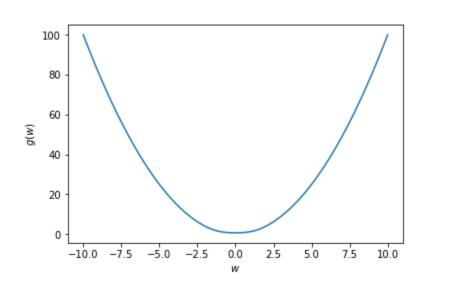
```
Plot g(w) = log(1+e^w^T.w)

import numpy as np
import matplotlib.pyplot as plt
import math as math
def f(t):
    return math.log1p(math.exp(np.dot(t,np.transpose(t))))

t = np.linspace(-10, 10, 100)
```

```
y = np.zeros(len(t))
for i in range(len(t)):
    y[i] = f(t[i])

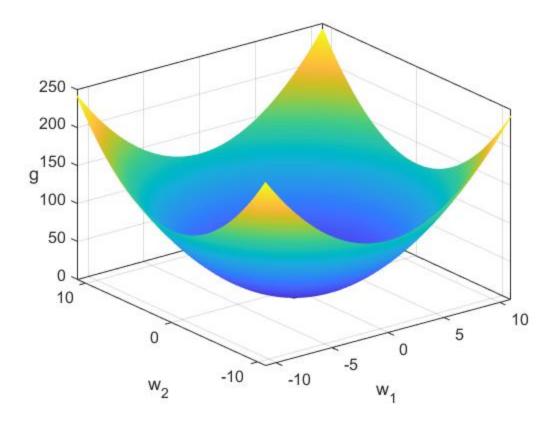
plt.plot(t,y)
plt.xlabel('$w$')
plt.ylabel('$g(w)$')
plt.show()
```

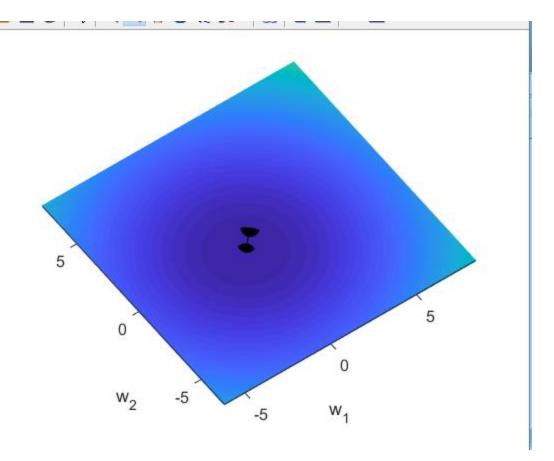


```
2 ....
 3 Created on Mon Apr 9 18:13:17 2018
 5 @author: dhana
 6 """
 7
 8
9
10 import numpy as np
11 import matplotlib.pyplot as plt
12 import math as math
13
14
15 def f(t):
16
      return math.log1p(math.exp(np.dot(t,np.transpose(t))))
17
18 t = np.linspace(-10, 10, 100)
19 y = np.zeros(len(t))
20 for i in range(len(t)):
21
      y[i] = f(t[i])
22
23 plt.plot(t,y)
24 plt.xlabel('$w$')
25 plt.ylabel('$g(w)$')
26 plt.show()
27
28
```

Exercise 2.17 c

```
set(get(gca, 'ZLabel'), 'Rotation', 0)
 set(gca, 'FontSize', 12);
 set(gcf,'color','w');
 grad stop = 10^-3;
max_its = 10;
 iter = 1;
 grad eval = 1;
 in = [w];
 out = [b];
 while iter <= max its</pre>
        % take gradient step
     grad eval= (2*exp(w'*w)*w)/(exp(w'*w) + 1)
     z11 = ((2*exp(w'*w)/(exp(w'*w) + 1)) -
(((4*exp(2*(w'*w))*w(1)^2/(exp(w'*w) +
1)^2)))+((((4*exp((w'*w))*w(1)^2/(exp(w'*w) + 1)))));
     z21 = -(((4*exp(2*(w'*w))*w(1)*w(2)/(exp(w'*w)) +
1)^2)))+((((4*exp((w'*w))*w(1)*w(2)/(exp(w'*w) + 1)))));
     z12 = z21;
     z22 = ((2*exp(w'*w)/(exp(w'*w) + 1)) -
(((4*exp(2*(w'*w))*w(2)^2/(exp(w'*w) +
1)^2)))+((((4*exp((w'*w))*w(2)^2/(exp(w'*w) + 1)))));
     z = [z11 \ z12 ; z21 \ z22];
     u = pinv(z);
     w1(iter) = w(1,:);
     w2(iter) = w(2,:);
     gp(iter) = log (1+exp(w'* w));
     grad1(iter) = grad eval(1,:);
     grad2(iter) = grad_eval(2,:);
     w = w - u * grad_eval;
        % update containers
        in = [in w];
        out = [out b];
        % update stopers
        iter = iter + 1;
  end
    hold on
    plot3(w1,w2,gp,'.-k','MarkerSize',50)
```

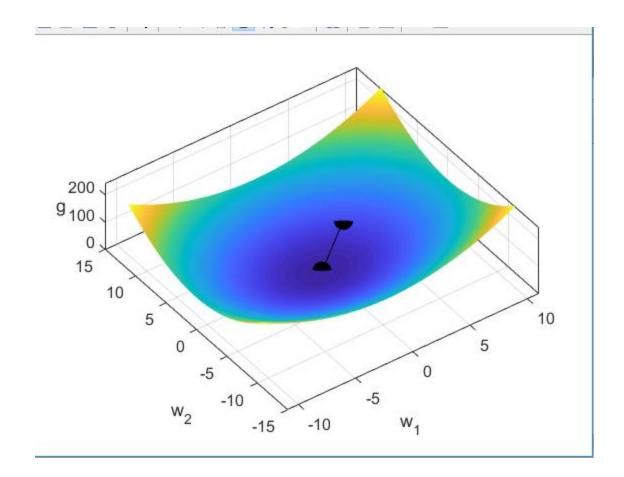




Exercise 2.17 d

```
w = 4 * [1, 1]'
range = 1.1;
x = [-range*10:0.01:range*10];
y = [-range*10:0.01:range*10];
z= zeros(length(x),length(y));
for i=1: length(x)
     for j=1: length(y)
         z(i,j) = log(1+exp(x(i)^2+y(j)^2));
     end
end
mesh(x,y,z)
box on
 xlabel('w 1', 'Fontsize', 18, 'FontName', 'cmmi9')
 ylabel('w 2', 'Fontsize', 18, 'FontName', 'cmmi9')
 zlabel('g','Fontsize',18,'FontName','cmmi9')
 set(get(gca, 'ZLabel'), 'Rotation', 0)
 set(gca, 'FontSize', 12);
 set(gcf,'color','w');
 grad stop = 10^-3;
 max_its = 10;
 iter = 1;
 grad_eval = 1;
 in = [w];
 out = [b];
```

```
while iter <= max its</pre>
        % take gradient step
     grad eval= (2*exp(w'*w)*w)/(exp(w'*w) + 1)
     z11 = ((2*exp(w'*w)/(exp(w'*w) + 1)) -
(((4*exp(2*(w'*w))*w(1)^2/(exp(w'*w) +
1)^2)))+((((4*exp((w'*w))*w(1)^2/(exp(w'*w) + 1)))));
     z21 = -(((4*exp(2*(w'*w))*w(1)*w(2)/(exp(w'*w)) +
1)^2))+((((4*exp((w'*w))*w(1)*w(2)/(exp(w'*w) + 1)))));
     z12 = z21;
     z22 = ((2*exp(w'*w)/(exp(w'*w) + 1)) -
(((4*exp(2*(w'*w))*w(2)^2/(exp(w'*w) +
1)^2)))+((((4*exp((w'*w))*w(2)^2/(exp(w'*w) + 1)))));
     z = [z11 \ z12 ; z21 \ z22];
     u = pinv(z);
     w1(iter) = w(1,:);
     w2(iter) = w(2,:);
     gp(iter) = log (1+exp(w'* w));
    grad1(iter) = grad eval(1,:);
    grad2(iter) = grad eval(2,:);
    w = w - u * grad eval;
        % update containers
       in = [in w];
        out = [out b];
        % update stopers
        iter = iter + 1;
  end
    hold on
    plot3(w1, w2, qp, '.-k', 'MarkerSize', 50)
```



Exercise 2.17

d. Reason behind why minimum of second order taylor series approximation of g(w) centered at w=4*[1,1] gives minimum of g(w) is because $log(1+e^{t})$ approximately equal to ti.e. there is w^{t} . Also, the second order Taylor series approximation is more closely resembles the underlying function around w, given that second derivative contains curvature information i.e the quadratic function itself.