

In [1]:

```
import matplotlib.pyplot as plt
import numpy as np
import numpy.random
import numpy.linalg
import scipy.io
import scipy.stats
import sklearn.metrics

# setup plotting
from IPython import get_ipython
import psutil
inTerminal = not "IPKernelApp" in get_ipython().config
inJupyterNb = any(filter(lambda x: x.endswith("jupyter-notebook"), psutil.Process().parent().cmdline()))
get_ipython().run_line_magic("matplotlib", "" if inTerminal else "notebook" if inJupyterNb else "widget")
def nextplot():
    if inTerminal:
        plt.clf()      # this clears the current plot
    else:
        plt.figure()  # this creates a new plot
```

Load the data

In [2]:

```
data = scipy.io.loadmat("data/spamData.mat")
X = data["Xtrain"]
N = X.shape[0]
D = X.shape[1]
Xtest = data["Xtest"]
Ntest = Xtest.shape[0]
y = data["ytrain"].squeeze().astype(int)
ytest = data["ytest"].squeeze().astype(int)

features = np.array(
    [
        "word_freq_make",
        "word_freq_address",
        "word_freq_all",
        "word_freq_3d",
        "word_freq_our",
        "word_freq_over",
        "word_freq_remove",
        "word_freq_internet",
        "word_freq_order",
        "word_freq_mail",
        "word_freq_receive",
        "word_freq_will",
        "word_freq_people",
        "word_freq_report",
        "word_freq_addresses",
        "word_freq_free",
        "word_freq_business",
        "word_freq_email",
        "word_freq_you",
        "word_freq_credit",
        "word_freq_your",
        "word_freq_font",
        "word_freq_000",
        "word_freq_money",
        "word_freq_hp",
        "word_freq_hpl",
        "word_freq_george",
        "word_freq_650",
        "word_freq_lab",
        "word_freq_labs",
        "word_freq_telnet",
        "word_freq_857",
        "word_freq_data",
        "word_freq_415",
        "word_freq_85",
        "word_freq_technology",
        "word_freq_1999",
        "word_freq_parts",
        "word_freq_pm",
        "word_freq_direct",
        "word_freq_cs",
        "word_freq_meeting",
        "word_freq_original",
        "word_freq_project",
        "word_freq_re",
        "word_freq_edu",
        "word_freq_table",
        "word_freq_conference",
        "char_freq;",
        "char_freq(",
        "char_freq[",
        "char_freq!",
        "char_freq$",
        "char_freq#",
```

```

    "capital_run_length_average",
    "capital_run_length_longest",
    "capital_run_length_total",
  ]
)

```

1. Dataset Statistics

In [3]:

```
# look some dataset statistics
scipy.stats.describe(X)
```

Out[3]:

[illegible]

In [4]:

```
scipy.stats.describe(y)
```

Out[4]:

```
# plot the distribution of all features
nextplot()
```

```

densities = [scipy.stats.gaussian_kde(X[:, j]) for j in range(D)]
xs = np.linspace(0, np.max(X), 200)
for j in range(D):
    plt.plot(xs, densities[j](xs), label=j)
plt.legend(ncol=5)

```

Out[5]: <matplotlib.legend.Legend at 0x7fc0ae37f400>

```

In [6]: # this plots is not really helpful; go now explore further
# YOUR CODE HERE
nextplot()
densities = [scipy.stats.gaussian_kde(X[:, j]) for j in range(D)]
xs = np.linspace(-.3,.3)
for j in range(D):
    plt.plot(xs, densities[j](xs), label=j)
plt.legend(ncol=5)

```

Out[6]: <matplotlib.legend.Legend at 0x7fc0b07db970>

```

In [7]: import pandas as pd
df = pd.DataFrame(X)
print(df.describe())

```

| | 0 | 1 | 2 | 3 | 4 | \ |
|-------|-------------|-------------|-------------|-------------|-------------|---|
| count | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | |
| mean | 0.110819 | 0.228486 | 0.274153 | 0.062969 | 0.317788 | |
| std | 0.327252 | 1.373834 | 0.484063 | 1.334772 | 0.663570 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 75% | 0.000000 | 0.000000 | 0.410000 | 0.000000 | 0.390000 | |
| max | 4.540000 | 14.280000 | 5.100000 | 42.810000 | 9.090000 | |

| | 5 | 6 | 7 | 8 | 9 | ... | \ |
|-------|-------------|-------------|-------------|-------------|-------------|-----|---|
| count | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | ... | |
| mean | 0.095755 | 0.113546 | 0.107217 | 0.088923 | 0.241719 | ... | |
| std | 0.260613 | 0.373958 | 0.414731 | 0.264054 | 0.685420 | ... | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | |
| 50% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | ... | |
| 75% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.160000 | ... | |
| max | 3.570000 | 7.270000 | 11.110000 | 3.330000 | 18.180000 | ... | |

| | 47 | 48 | 49 | 50 | 51 | \ |
|-------|-------------|-------------|-------------|-------------|-------------|---|
| count | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | |
| mean | 0.031377 | 0.037954 | 0.138396 | 0.018183 | 0.265471 | |
| std | 0.273922 | 0.235502 | 0.278921 | 0.121674 | 0.871310 | |
| min | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 25% | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| 50% | 0.000000 | 0.000000 | 0.066000 | 0.000000 | 0.000000 | |
| 75% | 0.000000 | 0.000000 | 0.191000 | 0.000000 | 0.315000 | |
| max | 10.000000 | 4.385000 | 9.752000 | 4.081000 | 32.478000 | |

| | 52 | 53 | 54 | 55 | 56 |
|-------|-------------|-------------|-------------|-------------|--------------|
| count | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 | 3065.000000 |
| mean | 0.079128 | 0.053422 | 4.900629 | 52.675041 | 282.203915 |
| std | 0.259719 | 0.519230 | 27.245399 | 220.584047 | 607.414933 |
| min | 0.000000 | 0.000000 | 1.000000 | 1.000000 | 1.000000 |
| 25% | 0.000000 | 0.000000 | 1.600000 | 6.000000 | 35.000000 |
| 50% | 0.000000 | 0.000000 | 2.280000 | 15.000000 | 97.000000 |
| 75% | 0.056000 | 0.000000 | 3.737000 | 43.000000 | 272.000000 |
| max | 6.003000 | 19.829000 | 1102.500000 | 9989.000000 | 15841.000000 |

[8 rows x 57 columns]

```

In [8]: # Let's compute z-scores; create two new variables Xz and Xtestz.
Xz = (X - np.mean(X,axis=0))/np.std(X,axis=0)
Xtestz = (Xtest - np.mean(X,axis=0))/np.std(X,axis=0)

```

```

In [9]: # Let's check. Xz and Xtestz refer to the normalized datasets just created. We
# will use them throughout.
np.mean(Xz, axis=0) # should be all 0
np.var(Xz, axis=0) # should be all 1
np.mean(Xtestz, axis=0) # what do you get here?
np.var(Xtestz, axis=0)

np.sum(Xz ** 3) # should be: 1925261.15

```

Out[9]: 1925261.1560010156

```

In [10]: # Explore the normalized data
# YOUR CODE HERE

```

```

nextplot()
densities = [scipy.stats.gaussian_kde(Xz[:, j]) for j in range(D)]
xsz = np.linspace(-5,5)
for j in range(D):
    plt.plot(xsz, densities[j](xsx), label=j)

```

2. Maximum Likelihood Estimation

```

In [11]: import numpy as np
import matplotlib.pyplot as plt
def sigmoid(x):
    return 1/(1+np.exp(-x))

x = np.arange(-5.0,5.0,0.1)
y1 = sigmoid(x+0.5)
y2 = sigmoid(x+1)
y3 = sigmoid(x+1.5)

nextplot()
plt.plot(x,y1,'r', linestyle = '--') #x+0.5
plt.plot(x,y2,'g') #x+1
plt.plot(x,y3,'b', linestyle = '--') #x+1.5
plt.plot([0,0],[1.0,0.0],':') #add dotted line in the middle
plt.title('Sigmoid Function')
plt.show()
plt.savefig('Figure2.1.png')

```

Helper functions

```

In [12]: def logsumexp(x):
    """Computes log(sum(exp(x))).

    Uses offset trick to reduce risk of numeric over- or underflow. When x is a
    1D ndarray, computes logsumexp of its entries. When x is a 2D ndarray,
    computes logsumexp of each column.

    Keyword arguments:
    x : a 1D or 2D ndarray
    """
    offset = np.max(x, axis=0)
    return offset + np.log(np.sum(np.exp(x - offset), axis=0))

```

```

In [13]: # Define the logistic function. Make sure it operates on both scalars
# and vectors.
def sigma(x):
    # YOUR CODE HERE
    logistic_function = 1/(1+np.exp(-x))
    return logistic_function

```

```

In [14]: # this should give:
# [0.5, array([0.26894142, 0.5, 0.73105858])]
[sigma(0), sigma(np.array([-1, 0, 1]))]

```

```

Out[14]: [0.5, array([0.26894142, 0.5, 0.73105858])]

```

```

In [15]: # Define the logarithm of the logistic function. Make sure it operates on both
# scalars and vectors. Perhaps helpful: isinstance(x, np.ndarray).
def logsigma(x):
    # YOUR CODE HERE
    log_logistic_function = np.log(sigma(x))
    return log_logistic_function

```

```

In [16]: # this should give:
# [-0.69314718055994529, array([-1.31326169, -0.69314718, -0.31326169])]
[logsigma(0), logsigma(np.array([-1, 0, 1]))]

```

```

Out[16]: [-0.6931471805599453, array([-1.31326169, -0.69314718, -0.31326169])]

```

2b Log-likelihood and gradient

```

In [17]: def l(y, X, w):
    """Log-likelihood of the logistic regression model.

    Parameters
    -----

```

```

y : ndarray of shape (N,)
    Binary labels (either 0 or 1).
X : ndarray of shape (N,D)
    Design matrix.
w : ndarray of shape (D,)
    Weight vector.
"""
# YOUR CODE HERE
z = np.dot(X,w)
return np.sum(y*z - np.log(1+np.exp(z)))

```

```

In [18]: # this should give:
# -47066.641667825766
l(y, Xz, np.linspace(-5, 5, D))

```

```
Out[18]: -47066.64166782577
```

```

In [19]: def dl(y, X, w):
        """Gradient of the log-likelihood of the logistic regression model.

        Parameters
        -----
        y : ndarray of shape (N,)
            Binary labels (either 0 or 1).
        X : ndarray of shape (N,D)
            Design matrix.
        w : ndarray of shape (D,)
            Weight vector.

        Returns
        -----
        ndarray of shape (D,)
        """
        # YOUR CODE HERE
        z = np.dot(X,w)
        prediction = sigma(z)
        errors = y - prediction
        gradients = np.dot(X.T,errors)
        return gradients

```

```

In [20]: # this should give:
# array([ 551.33985842, 143.84116318, 841.83373606, 156.87237578,
#         802.61217579, 795.96202907, 920.69045803, 621.96516752,
#         659.18724769, 470.81259805, 771.32406968, 352.40325626,
#         455.66972482, 234.36600888, 562.45454038, 864.83981264,
#         787.19723703, 649.48042176, 902.6478154 , 544.00539886,
#         1174.78638035, 120.3598967 , 839.61141672, 633.30453444,
#         -706.66815087, -630.2039816 , -569.3451386 , -527.50996698,
#         -359.53701083, -476.64334832, -411.60620464, -375.11950586,
#         -345.37195689, -376.22044258, -407.31761977, -456.23251936,
#         -596.86960184, -107.97072355, -394.82170044, -229.18125598,
#         -288.46356547, -362.13402385, -450.87896465, -277.03932676,
#         -414.99293368, -452.28771693, -167.54649092, -270.9043748 ,
#         -252.20140951, -357.72497343, -259.12468742, 418.35938483,
#         604.54173228, 43.10390907, 152.24258478, 378.16731033,
#         416.12032881])
dl(y, Xz, np.linspace(-5, 5, D))

```

```

Out[20]: array([ 551.33985842, 143.84116318, 841.83373606, 156.87237578,
                802.61217579, 795.96202907, 920.69045803, 621.96516752,
                659.18724769, 470.81259805, 771.32406968, 352.40325626,
                455.66972482, 234.36600888, 562.45454038, 864.83981264,
                787.19723703, 649.48042176, 902.6478154 , 544.00539886,
                1174.78638035, 120.3598967 , 839.61141672, 633.30453444,
                -706.66815087, -630.2039816 , -569.3451386 , -527.50996698,
                -359.53701083, -476.64334832, -411.60620464, -375.11950586,
                -345.37195689, -376.22044258, -407.31761977, -456.23251936,
                -596.86960184, -107.97072355, -394.82170044, -229.18125598,
                -288.46356547, -362.13402385, -450.87896465, -277.03932676,
                -414.99293368, -452.28771693, -167.54649092, -270.9043748 ,
                -252.20140951, -357.72497343, -259.12468742, 418.35938483,
                604.54173228, 43.10390907, 152.24258478, 378.16731033,
                416.12032881])

```

2c Gradient descent

```

In [21]: # you don't need to modify this function
def optimize(obj_up, theta0, nepochs=50, eps0=0.01, verbose=True):
    """Iteratively minimize a function.

    We use it here to run either gradient descent or stochastic gradient
    descent, using arbitrarily optimization criteria.

    Parameters
    -----
    obj_up : a tuple of form (f, update) containing two functions f and update.

```

```

        f(theta) computes the value of the objective function.
        update(theta,eps) performs an epoch of parameter update with step size
        eps and returns the result.
theta0 : ndarray of shape (D,)
        Initial parameter vector.
nepochs : int
        How many epochs (calls to update) to run.
eps0 : float
        Initial step size.
verbose : boolean
        Whether to print progress information.

Returns
-----
A triple consisting of the fitted parameter vector, the values of the
objective function after every epoch, and the step sizes that were used.
"""

f, update = obj_up

# initialize results
theta = theta0
values = np.zeros(nepochs + 1)
eps = np.zeros(nepochs + 1)
values[0] = f(theta0)
eps[0] = eps0

# now run the update function nepochs times
for epoch in range(nepochs):
    if verbose:
        print(
            "Epoch {:3d}: f={:10.3f}, eps={:10.9f}".format(
                epoch, values[epoch], eps[epoch]
            )
        )
    theta = update(theta, eps[epoch])

    # we use the bold driver heuristic
    values[epoch + 1] = f(theta)
    if values[epoch] < values[epoch + 1]:
        eps[epoch + 1] = eps[epoch] / 2.0
    else:
        eps[epoch + 1] = eps[epoch] * 1.05

# all done
if verbose:
    print("Result after {} epochs: f={}".format(nepochs, values[-1]))
return theta, values, eps

```

In [22]:

```

# define the objective and update function for one gradient-descent epoch for
# fitting an MLE estimate of logistic regression with gradient descent (should
# return a tuple of two functions; see optimize)
def gd(y, X):
    def objective(w):
        # YOUR CODE HERE
        p_i1 = logsigma(np.dot(X,w))
        p_i0 = logsigma(-np.dot(X,w))
        objective = -np.sum(y*p_i1 + (1-y)*p_i0)
        return objective

    def update(w, eps):
        # YOUR CODE HERE
        gradients = dl(y,X,w)
        w += eps * gradients
        return w

    return (objective, update)

```

In [23]:

```

# this should give
# [47066.641667825766,
# array([ 4.13777838e+01, -1.56745627e+01,  5.75882538e+01,
#        1.14225143e+01,  5.54249703e+01,  5.99229049e+01,
#        7.11220141e+01,  4.84761728e+01,  5.78067289e+01,
#        4.54794720e+01,  7.14638492e+01,  1.51369386e+01,
#        3.36375739e+01,  2.15061217e+01,  5.78014255e+01,
#        6.72743066e+01,  7.00829312e+01,  5.29328088e+01,
#        6.16042473e+01,  5.50018510e+01,  8.94624817e+01,
#        2.74784480e+01,  8.51763599e+01,  5.60363965e+01,
#        -2.55865589e+01, -1.53788213e+01, -4.67015412e+01,
#        -2.50356570e+00, -3.85357592e+00, -2.21819155e+00,
#        3.32098671e+00,  3.86933390e+00, -2.00309898e+01,
#        3.84684492e+00, -2.19847927e-01, -1.29775457e+00,
#        -1.28374302e+01, -2.78303173e+00, -5.61671182e+00,
#        1.73657121e+01, -6.81197570e+00, -1.20249002e+01,
#        2.65789491e+00, -1.39557852e+01, -2.01135653e+01,
#        -2.72134051e+01, -9.45952961e-01, -1.02239111e+01,
#        1.52794293e-04, -5.18938123e-01, -3.19717561e+00,
#        4.62953437e+01,  7.87893022e+01,  1.88618651e+01,
#        2.85195027e+01,  5.04698358e+01,  6.41240689e+01])

```

```
f, update = gd(y, Xz)
[f(np.linspace(-5, 5, D)), update(np.linspace(-5, -5, D), 0.1)]
```

```
Out [23]: [47066.64166782577,
array([ 4.13777838e+01, -1.56745627e+01,  5.75882538e+01,  1.14225143e+01,
        5.54249703e+01,  5.99229049e+01,  7.11220141e+01,  4.84761728e+01,
        5.78067289e+01,  4.54794720e+01,  7.14638492e+01,  1.51369386e+01,
        3.36375739e+01,  2.15061217e+01,  5.78014255e+01,  6.72743066e+01,
        7.00829312e+01,  5.29328088e+01,  6.16042473e+01,  5.50018510e+01,
        8.94624817e+01,  2.74784480e+01,  8.51763599e+01,  5.60363965e+01,
       -2.55865589e+01, -1.53788213e+01, -4.67015412e+01, -2.50356570e+00,
       -3.85357592e+00, -2.21819155e+00,  3.32098671e+00,  3.86933390e+00,
       -2.00309898e+01,  3.84684492e+00, -2.19847927e-01, -1.29775457e+00,
       -1.28374302e+01, -2.78303173e+00, -5.61671182e+00,  1.73657121e+01,
       -6.81197570e+00, -1.20249002e+01,  2.65789491e+00, -1.39557852e+01,
       -2.01135653e+01, -2.72134051e+01, -9.45952961e-01, -1.02239111e+01,
        1.52794293e-04, -5.18938123e-01, -3.19717561e+00,  4.62953437e+01,
        7.87893022e+01,  1.88618651e+01,  2.85195027e+01,  5.04698358e+01,
        6.41240689e+01]])]
```

```
In [24]: # you can run gradient descent!
numpy.random.seed(0)
w0 = np.random.normal(size=D)
wz_gd, vz_gd, ez_gd = optimize(gd(y, Xz), w0, nepochs=500)
```

```
Epoch 0: f= 6636.208, eps=0.010000000
Epoch 1: f= 4216.957, eps=0.010500000
Epoch 2: f= 2657.519, eps=0.011025000
Epoch 3: f= 1926.135, eps=0.011576250
Epoch 4: f= 1449.495, eps=0.012155063
Epoch 5: f= 1207.529, eps=0.012762816
Epoch 6: f= 1052.489, eps=0.013400956
Epoch 7: f= 957.275, eps=0.014071004
Epoch 8: f= 899.610, eps=0.014774554
Epoch 9: f= 882.904, eps=0.015513282
Epoch 10: f= 1017.083, eps=0.007756641
Epoch 11: f= 840.760, eps=0.008144473
Epoch 12: f= 805.649, eps=0.008551697
Epoch 13: f= 822.108, eps=0.004275848
Epoch 14: f= 746.377, eps=0.004489641
Epoch 15: f= 735.803, eps=0.004714123
Epoch 16: f= 729.780, eps=0.004949829
Epoch 17: f= 724.467, eps=0.005197320
Epoch 18: f= 719.408, eps=0.005457186
Epoch 19: f= 714.564, eps=0.005730046
Epoch 20: f= 709.932, eps=0.006016548
Epoch 21: f= 705.514, eps=0.006317375
Epoch 22: f= 701.321, eps=0.006633244
Epoch 23: f= 697.373, eps=0.006964906
Epoch 24: f= 693.728, eps=0.007313152
Epoch 25: f= 690.591, eps=0.007678809
Epoch 26: f= 688.614, eps=0.008062750
Epoch 27: f= 688.607, eps=0.008465887
Epoch 28: f= 690.854, eps=0.004232944
Epoch 29: f= 679.967, eps=0.004444591
Epoch 30: f= 678.649, eps=0.004666820
Epoch 31: f= 677.447, eps=0.004900161
Epoch 32: f= 676.292, eps=0.005145169
Epoch 33: f= 675.182, eps=0.005402428
Epoch 34: f= 674.120, eps=0.005672549
Epoch 35: f= 673.114, eps=0.005956177
Epoch 36: f= 672.177, eps=0.006253986
Epoch 37: f= 671.334, eps=0.006566685
Epoch 38: f= 670.656, eps=0.006895019
Epoch 39: f= 670.397, eps=0.007239770
Epoch 40: f= 671.342, eps=0.003619885
Epoch 41: f= 668.932, eps=0.003800879
Epoch 42: f= 668.378, eps=0.003990923
Epoch 43: f= 668.027, eps=0.004190469
Epoch 44: f= 667.720, eps=0.004399993
Epoch 45: f= 667.433, eps=0.004619993
Epoch 46: f= 667.159, eps=0.004850992
Epoch 47: f= 666.897, eps=0.005093542
Epoch 48: f= 666.650, eps=0.005348219
Epoch 49: f= 666.417, eps=0.005615630
Epoch 50: f= 666.201, eps=0.005896411
Epoch 51: f= 666.008, eps=0.006191232
Epoch 52: f= 665.858, eps=0.006500794
Epoch 53: f= 665.812, eps=0.006825833
Epoch 54: f= 666.068, eps=0.003412917
Epoch 55: f= 665.424, eps=0.003583562
Epoch 56: f= 665.290, eps=0.003762741
Epoch 57: f= 665.204, eps=0.003950878
Epoch 58: f= 665.128, eps=0.004148421
Epoch 59: f= 665.054, eps=0.004355843
Epoch 60: f= 664.982, eps=0.004573635
Epoch 61: f= 664.911, eps=0.004802316
Epoch 62: f= 664.842, eps=0.005042432
Epoch 63: f= 664.773, eps=0.005294554
Epoch 64: f= 664.707, eps=0.005559282
Epoch 65: f= 664.641, eps=0.005837246
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|-------|------|----|----------|-----------------|
| Epoch | 66: | f= | 664.578, | eps=0.006129108 |
| Epoch | 67: | f= | 664.518, | eps=0.006435563 |
| Epoch | 68: | f= | 664.467, | eps=0.006757341 |
| Epoch | 69: | f= | 664.446, | eps=0.007095208 |
| Epoch | 70: | f= | 664.544, | eps=0.003547604 |
| Epoch | 71: | f= | 664.339, | eps=0.003724984 |
| Epoch | 72: | f= | 664.278, | eps=0.003911234 |
| Epoch | 73: | f= | 664.239, | eps=0.004106795 |
| Epoch | 74: | f= | 664.206, | eps=0.004312135 |
| Epoch | 75: | f= | 664.173, | eps=0.004527742 |
| Epoch | 76: | f= | 664.139, | eps=0.004754129 |
| Epoch | 77: | f= | 664.106, | eps=0.004991835 |
| Epoch | 78: | f= | 664.072, | eps=0.005241427 |
| Epoch | 79: | f= | 664.037, | eps=0.005503499 |
| Epoch | 80: | f= | 664.002, | eps=0.005778674 |
| Epoch | 81: | f= | 663.967, | eps=0.006067607 |
| Epoch | 82: | f= | 663.936, | eps=0.006370988 |
| Epoch | 83: | f= | 663.918, | eps=0.006689537 |
| Epoch | 84: | f= | 663.948, | eps=0.003344768 |
| Epoch | 85: | f= | 663.839, | eps=0.003512007 |
| Epoch | 86: | f= | 663.807, | eps=0.003687607 |
| Epoch | 87: | f= | 663.783, | eps=0.003871988 |
| Epoch | 88: | f= | 663.760, | eps=0.004065587 |
| Epoch | 89: | f= | 663.737, | eps=0.004268866 |
| Epoch | 90: | f= | 663.713, | eps=0.004482310 |
| Epoch | 91: | f= | 663.688, | eps=0.004706425 |
| Epoch | 92: | f= | 663.661, | eps=0.004941746 |
| Epoch | 93: | f= | 663.634, | eps=0.005188834 |
| Epoch | 94: | f= | 663.606, | eps=0.005448275 |
| Epoch | 95: | f= | 663.576, | eps=0.005720689 |
| Epoch | 96: | f= | 663.546, | eps=0.006006724 |
| Epoch | 97: | f= | 663.514, | eps=0.006307060 |
| Epoch | 98: | f= | 663.482, | eps=0.006622413 |
| Epoch | 99: | f= | 663.451, | eps=0.006953533 |
| Epoch | 100: | f= | 663.427, | eps=0.007301210 |
| Epoch | 101: | f= | 663.442, | eps=0.003650605 |
| Epoch | 102: | f= | 663.371, | eps=0.003833135 |
| Epoch | 103: | f= | 663.340, | eps=0.004024792 |
| Epoch | 104: | f= | 663.316, | eps=0.004226032 |
| Epoch | 105: | f= | 663.294, | eps=0.004437333 |
| Epoch | 106: | f= | 663.271, | eps=0.004659200 |
| Epoch | 107: | f= | 663.248, | eps=0.004892160 |
| Epoch | 108: | f= | 663.223, | eps=0.005136768 |
| Epoch | 109: | f= | 663.198, | eps=0.005393606 |
| Epoch | 110: | f= | 663.172, | eps=0.005663287 |
| Epoch | 111: | f= | 663.146, | eps=0.005946451 |
| Epoch | 112: | f= | 663.121, | eps=0.006243773 |
| Epoch | 113: | f= | 663.102, | eps=0.006555962 |
| Epoch | 114: | f= | 663.108, | eps=0.003277981 |
| Epoch | 115: | f= | 663.042, | eps=0.003441880 |
| Epoch | 116: | f= | 663.019, | eps=0.003613974 |
| Epoch | 117: | f= | 663.001, | eps=0.003794673 |
| Epoch | 118: | f= | 662.982, | eps=0.003984406 |
| Epoch | 119: | f= | 662.963, | eps=0.004183627 |
| Epoch | 120: | f= | 662.943, | eps=0.004392808 |
| Epoch | 121: | f= | 662.922, | eps=0.004612449 |
| Epoch | 122: | f= | 662.900, | eps=0.004843071 |
| Epoch | 123: | f= | 662.877, | eps=0.005085225 |
| Epoch | 124: | f= | 662.853, | eps=0.005339486 |
| Epoch | 125: | f= | 662.828, | eps=0.005606460 |
| Epoch | 126: | f= | 662.802, | eps=0.005886783 |
| Epoch | 127: | f= | 662.774, | eps=0.006181122 |
| Epoch | 128: | f= | 662.745, | eps=0.006490178 |
| Epoch | 129: | f= | 662.715, | eps=0.006814687 |
| Epoch | 130: | f= | 662.685, | eps=0.007155422 |
| Epoch | 131: | f= | 662.659, | eps=0.007513193 |
| Epoch | 132: | f= | 662.656, | eps=0.007888852 |
| Epoch | 133: | f= | 662.786, | eps=0.003944426 |
| Epoch | 134: | f= | 662.631, | eps=0.004141647 |
| Epoch | 135: | f= | 662.578, | eps=0.004348730 |
| Epoch | 136: | f= | 662.545, | eps=0.004566166 |
| Epoch | 137: | f= | 662.519, | eps=0.004794475 |
| Epoch | 138: | f= | 662.497, | eps=0.005034198 |
| Epoch | 139: | f= | 662.477, | eps=0.005285908 |
| Epoch | 140: | f= | 662.462, | eps=0.005550204 |
| Epoch | 141: | f= | 662.457, | eps=0.005827714 |
| Epoch | 142: | f= | 662.476, | eps=0.002913857 |
| Epoch | 143: | f= | 662.373, | eps=0.003059550 |
| Epoch | 144: | f= | 662.355, | eps=0.003212527 |
| Epoch | 145: | f= | 662.340, | eps=0.003373154 |
| Epoch | 146: | f= | 662.325, | eps=0.003541811 |
| Epoch | 147: | f= | 662.310, | eps=0.003718902 |
| Epoch | 148: | f= | 662.293, | eps=0.003904847 |
| Epoch | 149: | f= | 662.276, | eps=0.004100089 |
| Epoch | 150: | f= | 662.257, | eps=0.004305094 |
| Epoch | 151: | f= | 662.238, | eps=0.004520348 |
| Epoch | 152: | f= | 662.218, | eps=0.004746366 |
| Epoch | 153: | f= | 662.197, | eps=0.004983684 |
| Epoch | 154: | f= | 662.175, | eps=0.005232868 |
| Epoch | 155: | f= | 662.152, | eps=0.005494512 |
| Epoch | 156: | f= | 662.128, | eps=0.005769237 |
| Epoch | 157: | f= | 662.103, | eps=0.006057699 |

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Epoch 159: f= 662.048, eps=0.006678613
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Epoch 161: f= 661.989, eps=0.007363171
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Epoch 189: f= 661.388, eps=0.006545257
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Epoch 197: f= 661.133, eps=0.009670325
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Epoch 212: f= 660.837, eps=0.004558710
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Epoch 234: f= 660.254, eps=0.003023904
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Epoch 245: f= 660.092, eps=0.005171902
Epoch 246: f= 660.073, eps=0.005430497
Epoch 247: f= 660.052, eps=0.005702022
Epoch 248: f= 660.031, eps=0.005987123
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Epoch 366: f= 657.740, eps=0.005009577
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Epoch 390: f= 657.299, eps=0.003663580
Epoch 391: f= 657.287, eps=0.003846759
Epoch 392: f= 657.275, eps=0.004039097
Epoch 393: f= 657.263, eps=0.004241052
Epoch 394: f= 657.250, eps=0.004453104
Epoch 395: f= 657.236, eps=0.004675760
Epoch 396: f= 657.221, eps=0.004909548
Epoch 397: f= 657.206, eps=0.005155025
Epoch 398: f= 657.190, eps=0.005412776
Epoch 399: f= 657.173, eps=0.005683415
Epoch 400: f= 657.156, eps=0.005967586
Epoch 401: f= 657.138, eps=0.006265965
Epoch 402: f= 657.118, eps=0.006579263
Epoch 403: f= 657.098, eps=0.006908226
Epoch 404: f= 657.077, eps=0.007253638
Epoch 405: f= 657.054, eps=0.007616320
Epoch 406: f= 657.031, eps=0.007997136
Epoch 407: f= 657.007, eps=0.008396992
Epoch 408: f= 656.981, eps=0.008816842
Epoch 409: f= 656.954, eps=0.009257684
Epoch 410: f= 656.926, eps=0.009720568
Epoch 411: f= 656.896, eps=0.010206597
Epoch 412: f= 656.866, eps=0.010716927
Epoch 413: f= 656.838, eps=0.011252773
Epoch 414: f= 656.871, eps=0.005626387
Epoch 415: f= 656.908, eps=0.002813193
Epoch 416: f= 656.776, eps=0.002953853
Epoch 417: f= 656.765, eps=0.003101546
Epoch 418: f= 656.755, eps=0.003256623
Epoch 419: f= 656.745, eps=0.003419454
Epoch 420: f= 656.735, eps=0.003590427
Epoch 421: f= 656.724, eps=0.003769948
Epoch 422: f= 656.713, eps=0.003958445
Epoch 423: f= 656.701, eps=0.004156368
Epoch 424: f= 656.689, eps=0.004364186
Epoch 425: f= 656.676, eps=0.004582395
Epoch 426: f= 656.662, eps=0.004811515
Epoch 427: f= 656.648, eps=0.005052091
Epoch 428: f= 656.632, eps=0.005304695
Epoch 429: f= 656.617, eps=0.005569930
Epoch 430: f= 656.600, eps=0.005848427
Epoch 431: f= 656.583, eps=0.006140848
Epoch 432: f= 656.564, eps=0.006447890
Epoch 433: f= 656.545, eps=0.006770285

```

Epoch 434: f= 656.525, eps=0.007108799
Epoch 435: f= 656.504, eps=0.007464239
Epoch 436: f= 656.482, eps=0.007837451
Epoch 437: f= 656.459, eps=0.008229324
Epoch 438: f= 656.435, eps=0.008640790
Epoch 439: f= 656.410, eps=0.009072829
Epoch 440: f= 656.388, eps=0.009526471
Epoch 441: f= 656.406, eps=0.004763235
Epoch 442: f= 656.387, eps=0.005001397
Epoch 443: f= 656.379, eps=0.005251467
Epoch 444: f= 656.381, eps=0.002625734
Epoch 445: f= 656.303, eps=0.002757020
Epoch 446: f= 656.295, eps=0.002894871
Epoch 447: f= 656.286, eps=0.003039615
Epoch 448: f= 656.277, eps=0.003191596
Epoch 449: f= 656.268, eps=0.003351175
Epoch 450: f= 656.258, eps=0.003518734
Epoch 451: f= 656.248, eps=0.003694671
Epoch 452: f= 656.237, eps=0.003879404
Epoch 453: f= 656.226, eps=0.004073375
Epoch 454: f= 656.214, eps=0.004277043
Epoch 455: f= 656.202, eps=0.004490895
Epoch 456: f= 656.189, eps=0.004715440
Epoch 457: f= 656.175, eps=0.004951212
Epoch 458: f= 656.161, eps=0.005198773
Epoch 459: f= 656.145, eps=0.005458711
Epoch 460: f= 656.130, eps=0.005731647
Epoch 461: f= 656.113, eps=0.006018229
Epoch 462: f= 656.096, eps=0.006319141
Epoch 463: f= 656.077, eps=0.006635098
Epoch 464: f= 656.058, eps=0.006966853
Epoch 465: f= 656.038, eps=0.007315195
Epoch 466: f= 656.017, eps=0.007680955
Epoch 467: f= 655.995, eps=0.008065003
Epoch 468: f= 655.972, eps=0.008468253
Epoch 469: f= 655.948, eps=0.008891666
Epoch 470: f= 655.923, eps=0.009336249
Epoch 471: f= 655.896, eps=0.009803061
Epoch 472: f= 655.868, eps=0.010293215
Epoch 473: f= 655.841, eps=0.010807875
Epoch 474: f= 655.835, eps=0.011348269
Epoch 475: f= 656.135, eps=0.005674135
Epoch 476: f= 656.301, eps=0.002837067
Epoch 477: f= 655.760, eps=0.002978921
Epoch 478: f= 655.744, eps=0.003127867
Epoch 479: f= 655.735, eps=0.003284260
Epoch 480: f= 655.725, eps=0.003448473
Epoch 481: f= 655.716, eps=0.003620897
Epoch 482: f= 655.705, eps=0.003801941
Epoch 483: f= 655.695, eps=0.003992039
Epoch 484: f= 655.684, eps=0.004191640
Epoch 485: f= 655.672, eps=0.004401222
Epoch 486: f= 655.659, eps=0.004621284
Epoch 487: f= 655.646, eps=0.004852348
Epoch 488: f= 655.633, eps=0.005094965
Epoch 489: f= 655.619, eps=0.005349713
Epoch 490: f= 655.604, eps=0.005617199
Epoch 491: f= 655.588, eps=0.005898059
Epoch 492: f= 655.571, eps=0.006192962
Epoch 493: f= 655.554, eps=0.006502610
Epoch 494: f= 655.536, eps=0.006827741
Epoch 495: f= 655.517, eps=0.007169128
Epoch 496: f= 655.497, eps=0.007527584
Epoch 497: f= 655.476, eps=0.007903963
Epoch 498: f= 655.454, eps=0.008299161
Epoch 499: f= 655.432, eps=0.008714119
Result after 500 epochs: f=655.4134964699465

```

```

In [25]: # look at how gradient descent made progress
# YOUR CODE HERE
nextplot()
plt.plot(range(501),vz_gd)
plt.show()

```

2d Stochastic gradient descent

```

In [26]: def sgdepoch(y, X, w, eps):
    """Run one SGD epoch and return the updated weight vector. """
    # Run N stochastic gradient steps (without replacement). Do not rescale each
    # step by factor N (i.e., proceed differently than in the lecture slides).
    # YOUR CODE HERE
    # np.random.rand(2022)
    # np.random.shuffle(X)
    # np.random.shuffle(y)
    index_list = list(range(X.shape[0]))
    np.random.shuffle(index_list)
    for i in index_list :

```

```

gradient = dl(y[i],X[i],w)
w += eps * gradient
return w

```

In [27]:

```

# when you run this multiple times, with 50% probability you should get the
# following result (there is one other result which is very close):
# array([-3.43689655e+02, -1.71161311e+02, -5.71093536e+02,
#        -5.16478220e+01,  4.66294348e+02, -3.71589878e+02,
#        5.21493183e+02,  1.25699230e+03,  8.33804130e+02,
#        5.63185399e+02,  1.32761302e+03, -2.64104011e+02,
#        7.10693307e+02, -1.75497331e+02, -1.94174427e+02,
#        1.11641507e+02, -3.30817509e+02, -3.46754913e+02,
#        8.48722111e+02, -1.89136304e+02, -4.25693844e+02,
#        -1.23084189e+02, -2.95894797e+02, -2.35789333e+02,
#        -3.38695243e+02, -3.05642830e+02, -2.28975383e+02,
#        -2.38075137e+02, -1.66702530e+02, -2.27341599e+02,
#        -1.77575620e+02, -1.49093855e+02, -1.70028859e+02,
#        -1.50243833e+02, -1.82986008e+02, -2.41143708e+02,
#        -3.31047159e+02, -5.79991185e+01, -1.98477863e+02,
#        -1.91264948e+02, -1.17371919e+02, -1.66953779e+02,
#        -2.01472565e+02, -1.23330949e+02, -3.00857740e+02,
#        -1.95853348e+02, -7.44868073e+01, -1.11172370e+02,
#        -1.57618226e+02, -1.25729512e+00, -1.45536466e+02,
#        -1.43362438e+02, -3.00429708e+02, -9.84391082e+01,
#        -4.54152047e+01, -5.26492232e+01, -1.45175427e+02])
sgdePOCH(y[1:3], Xz[1:3, :], np.linspace(-5, 5, D), 1000)

```

Out [27]:

```

array([-3.43689655e+02, -1.71161311e+02, -5.71093536e+02, -5.16478220e+01,
        4.66294348e+02, -3.71589878e+02,  5.21493183e+02,  1.25699230e+03,
        8.33804130e+02,  5.63185399e+02,  1.32761302e+03, -2.64104011e+02,
        7.10693307e+02, -1.75497331e+02, -1.94174427e+02,  1.11641507e+02,
       -3.30817509e+02, -3.46754913e+02,  8.48722111e+02, -1.89136304e+02,
       -4.25693844e+02, -1.23084189e+02, -2.95894797e+02, -2.35789333e+02,
       -3.38695243e+02, -3.05642830e+02, -2.28975383e+02, -2.38075137e+02,
       -1.66702530e+02, -2.27341599e+02, -1.77575620e+02, -1.49093855e+02,
       -1.70028859e+02, -1.50243833e+02, -1.82986008e+02, -2.41143708e+02,
       -3.31047159e+02, -5.79991185e+01, -1.98477863e+02, -1.91264948e+02,
       -1.17371919e+02, -1.66953779e+02, -2.01472565e+02, -1.23330949e+02,
       -3.00857740e+02, -1.95853348e+02, -7.44868073e+01, -1.11172370e+02,
       -1.57618226e+02, -1.25729512e+00, -1.45536466e+02, -1.43362438e+02,
       -3.00429708e+02, -9.84391082e+01, -4.54152047e+01, -5.26492232e+01,
       -1.45175427e+02])

```

In [28]:

```

# define the objective and update function for one gradient-descent epoch for
# fitting an MLE estimate of logistic regression with stochastic gradient descent
# (should return a tuple of two functions; see optimize)
def sgd(y, X):
    def objective(w):
        # YOUR CODE HERE
        p_i0 = logsigma(-np.dot(X,w))
        p_i1 = logsigma(np.dot(X,w))
        objective = -np.sum(y*p_i1 + (1-y)*p_i0)
        return objective

    def update(w, eps):
        return sgdePOCH(y, X, w, eps)

    return (objective, update)

```

In [29]:

```

# with 50% probability, you should get:
# [40.864973045695081,
#  array([-3.43689655e+02, -1.71161311e+02, -5.71093536e+02,
#        -5.16478220e+01,  4.66294348e+02, -3.71589878e+02,
#        5.21493183e+02,  1.25699230e+03,  8.33804130e+02,
#        5.63185399e+02,  1.32761302e+03, -2.64104011e+02,
#        7.10693307e+02, -1.75497331e+02, -1.94174427e+02,
#        1.11641507e+02, -3.30817509e+02, -3.46754913e+02,
#        8.48722111e+02, -1.89136304e+02, -4.25693844e+02,
#        -1.23084189e+02, -2.95894797e+02, -2.35789333e+02,
#        -3.38695243e+02, -3.05642830e+02, -2.28975383e+02,
#        -2.38075137e+02, -1.66702530e+02, -2.27341599e+02,
#        -1.77575620e+02, -1.49093855e+02, -1.70028859e+02,
#        -1.50243833e+02, -1.82986008e+02, -2.41143708e+02,
#        -3.31047159e+02, -5.79991185e+01, -1.98477863e+02,
#        -1.91264948e+02, -1.17371919e+02, -1.66953779e+02,
#        -2.01472565e+02, -1.23330949e+02, -3.00857740e+02,
#        -1.95853348e+02, -7.44868073e+01, -1.11172370e+02,
#        -1.57618226e+02, -1.25729512e+00, -1.45536466e+02,
#        -1.43362438e+02, -3.00429708e+02, -9.84391082e+01,
#        -4.54152047e+01, -5.26492232e+01, -1.45175427e+02])]
f, update = sgd(y[1:3], Xz[1:3, :])
[f(np.linspace(-5, 5, D)), update(np.linspace(-5, 5, D), 1000)]

```

Out [29]:

```

[40.864973045695095,
 array([-3.43689655e+02, -1.71161311e+02, -5.71093536e+02, -5.16478220e+01,
        4.66294348e+02, -3.71589878e+02,  5.21493183e+02,  1.25699230e+03,
        8.33804130e+02,  5.63185399e+02,  1.32761302e+03, -2.64104011e+02,
        7.10693307e+02, -1.75497331e+02, -1.94174427e+02,  1.11641507e+02,

```

```

-3.30817509e+02, -3.46754913e+02, 8.48722111e+02, -1.89136304e+02,
-4.25693844e+02, -1.23084189e+02, -2.95894797e+02, -2.35789333e+02,
-3.38695243e+02, -3.05642830e+02, -2.28975383e+02, -2.38075137e+02,
-1.66702530e+02, -2.27341599e+02, -1.77575620e+02, -1.49093855e+02,
-1.70028859e+02, -1.50243833e+02, -1.82986008e+02, -2.41143708e+02,
-3.31047159e+02, -5.79991185e+01, -1.98477863e+02, -1.91264948e+02,
-1.17371919e+02, -1.66953779e+02, -2.01472565e+02, -1.23330949e+02,
-3.00857740e+02, -1.95853348e+02, -7.44868073e+01, -1.11172370e+02,
-1.57618226e+02, -1.25729512e+00, -1.45536466e+02, -1.43362438e+02,
-3.00429708e+02, -9.84391082e+01, -4.54152047e+01, -5.26492232e+01,
-1.45175427e+02]])]

```

In [30]:

```

# you can run stochastic gradient descent!
wz_sgd, vz_sgd, ez_sgd = optimize(sgd(y, Xz), w0, nepochs=500)

```

```

Epoch 0: f= 655.413, eps=0.010000000
Epoch 1: f= 655.413, eps=0.010500000
Epoch 2: f= 655.413, eps=0.011025000
Epoch 3: f= 655.413, eps=0.005512500
Epoch 4: f= 655.414, eps=0.002756250
Epoch 5: f= 655.439, eps=0.001378125
Epoch 6: f= 655.439, eps=0.000689063
Epoch 7: f= 655.439, eps=0.000344531
Epoch 8: f= 655.439, eps=0.000172266
Epoch 9: f= 655.439, eps=0.000086133
Epoch 10: f= 655.439, eps=0.000043066
Epoch 11: f= 655.439, eps=0.000045220
Epoch 12: f= 655.439, eps=0.000022610
Epoch 13: f= 655.439, eps=0.000023740
Epoch 14: f= 655.439, eps=0.000011870
Epoch 15: f= 655.439, eps=0.000005935
Epoch 16: f= 655.439, eps=0.000006232
Epoch 17: f= 655.439, eps=0.000006543
Epoch 18: f= 655.439, eps=0.000003272
Epoch 19: f= 655.439, eps=0.000001636
Epoch 20: f= 655.439, eps=0.000000818
Epoch 21: f= 655.439, eps=0.000000409
Epoch 22: f= 655.439, eps=0.000000429
Epoch 23: f= 655.439, eps=0.000000215
Epoch 24: f= 655.439, eps=0.000000107
Epoch 25: f= 655.439, eps=0.000000054
Epoch 26: f= 655.439, eps=0.000000027
Epoch 27: f= 655.439, eps=0.000000013
Epoch 28: f= 655.439, eps=0.000000014
Epoch 29: f= 655.439, eps=0.000000007
Epoch 30: f= 655.439, eps=0.000000004
Epoch 31: f= 655.439, eps=0.000000002
Epoch 32: f= 655.439, eps=0.000000001
Epoch 33: f= 655.439, eps=0.000000000
Epoch 34: f= 655.439, eps=0.000000000
Epoch 35: f= 655.439, eps=0.000000000
Epoch 36: f= 655.439, eps=0.000000000
Epoch 37: f= 655.439, eps=0.000000000
Epoch 38: f= 655.439, eps=0.000000000
Epoch 39: f= 655.439, eps=0.000000000
Epoch 40: f= 655.439, eps=0.000000000
Epoch 41: f= 655.439, eps=0.000000000
Epoch 42: f= 655.439, eps=0.000000000
Epoch 43: f= 655.439, eps=0.000000000
Epoch 44: f= 655.439, eps=0.000000000
Epoch 45: f= 655.439, eps=0.000000000
Epoch 46: f= 655.439, eps=0.000000000
Epoch 47: f= 655.439, eps=0.000000000
Epoch 48: f= 655.439, eps=0.000000000
Epoch 49: f= 655.439, eps=0.000000000
Epoch 50: f= 655.439, eps=0.000000000
Epoch 51: f= 655.439, eps=0.000000000
Epoch 52: f= 655.439, eps=0.000000000
Epoch 53: f= 655.439, eps=0.000000000
Epoch 54: f= 655.439, eps=0.000000000
Epoch 55: f= 655.439, eps=0.000000000
Epoch 56: f= 655.439, eps=0.000000000
Epoch 57: f= 655.439, eps=0.000000000
Epoch 58: f= 655.439, eps=0.000000000
Epoch 59: f= 655.439, eps=0.000000000
Epoch 60: f= 655.439, eps=0.000000000
Epoch 61: f= 655.439, eps=0.000000000
Epoch 62: f= 655.439, eps=0.000000000
Epoch 63: f= 655.439, eps=0.000000000
Epoch 64: f= 655.439, eps=0.000000000
Epoch 65: f= 655.439, eps=0.000000000
Epoch 66: f= 655.439, eps=0.000000000
Epoch 67: f= 655.439, eps=0.000000000
Epoch 68: f= 655.439, eps=0.000000000
Epoch 69: f= 655.439, eps=0.000000000
Epoch 70: f= 655.439, eps=0.000000000
Epoch 71: f= 655.439, eps=0.000000000
Epoch 72: f= 655.439, eps=0.000000000
Epoch 73: f= 655.439, eps=0.000000000
Epoch 74: f= 655.439, eps=0.000000000
Epoch 75: f= 655.439, eps=0.000000000

```

[illegible]

[illegible]

[illegible]

[illegible]

```

Epoch 444: f= 655.439, eps=0.000000000
Epoch 445: f= 655.439, eps=0.000000000
Epoch 446: f= 655.439, eps=0.000000000
Epoch 447: f= 655.439, eps=0.000000000
Epoch 448: f= 655.439, eps=0.000000000
Epoch 449: f= 655.439, eps=0.000000000
Epoch 450: f= 655.439, eps=0.000000000
Epoch 451: f= 655.439, eps=0.000000000
Epoch 452: f= 655.439, eps=0.000000000
Epoch 453: f= 655.439, eps=0.000000000
Epoch 454: f= 655.439, eps=0.000000000
Epoch 455: f= 655.439, eps=0.000000000
Epoch 456: f= 655.439, eps=0.000000000
Epoch 457: f= 655.439, eps=0.000000000
Epoch 458: f= 655.439, eps=0.000000000
Epoch 459: f= 655.439, eps=0.000000000
Epoch 460: f= 655.439, eps=0.000000000
Epoch 461: f= 655.439, eps=0.000000000
Epoch 462: f= 655.439, eps=0.000000000
Epoch 463: f= 655.439, eps=0.000000000
Epoch 464: f= 655.439, eps=0.000000000
Epoch 465: f= 655.439, eps=0.000000000
Epoch 466: f= 655.439, eps=0.000000000
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Epoch 468: f= 655.439, eps=0.000000000
Epoch 469: f= 655.439, eps=0.000000000
Epoch 470: f= 655.439, eps=0.000000000
Epoch 471: f= 655.439, eps=0.000000000
Epoch 472: f= 655.439, eps=0.000000000
Epoch 473: f= 655.439, eps=0.000000000
Epoch 474: f= 655.439, eps=0.000000000
Epoch 475: f= 655.439, eps=0.000000000
Epoch 476: f= 655.439, eps=0.000000000
Epoch 477: f= 655.439, eps=0.000000000
Epoch 478: f= 655.439, eps=0.000000000
Epoch 479: f= 655.439, eps=0.000000000
Epoch 480: f= 655.439, eps=0.000000000
Epoch 481: f= 655.439, eps=0.000000000
Epoch 482: f= 655.439, eps=0.000000000
Epoch 483: f= 655.439, eps=0.000000000
Epoch 484: f= 655.439, eps=0.000000000
Epoch 485: f= 655.439, eps=0.000000000
Epoch 486: f= 655.439, eps=0.000000000
Epoch 487: f= 655.439, eps=0.000000000
Epoch 488: f= 655.439, eps=0.000000000
Epoch 489: f= 655.439, eps=0.000000000
Epoch 490: f= 655.439, eps=0.000000000
Epoch 491: f= 655.439, eps=0.000000000
Epoch 492: f= 655.439, eps=0.000000000
Epoch 493: f= 655.439, eps=0.000000000
Epoch 494: f= 655.439, eps=0.000000000
Epoch 495: f= 655.439, eps=0.000000000
Epoch 496: f= 655.439, eps=0.000000000
Epoch 497: f= 655.439, eps=0.000000000
Epoch 498: f= 655.439, eps=0.000000000
Epoch 499: f= 655.439, eps=0.000000000
Result after 500 epochs: f=655.4392468949942

```

2e Compare GD and SGD

```

In [31]: # YOUR CODE HERE
nextplot()
plt.plot(range(501),vz_gd,label='Gradient Descent')
plt.plot(range(501),vz_sgd,label='Stochastic Gradient Descent')
plt.legend()
plt.show()
plt.savefig('Figure2.2.png')

```

```

In [32]: # YOUR CODE HERE
nextplot()
plt.plot(range(501),vz_gd,label='adj Gradient Descent')
plt.plot(range(501),vz_sgd,label='adj Stochastic Gradient Descent')
plt.xlim(0,50)
plt.legend()
plt.show()
plt.savefig('Figure2.3.png')

```

3 Prediction

```

In [33]: def predict(Xtest, w):
        """Returns vector of predicted confidence values for logistic regression with
        weight vector w."""

```

```

# YOUR CODE HERE
z = np.dot(Xtest, w)
prediction = sigma(z)
return prediction

def classify(Xtest, w):
    """Returns 0/1 vector of predicted class labels for logistic regression with
    weight vector w."""
    # YOUR CODE HERE
    return np.where(predict(Xtest,w) > 0.5 , 1, 0)

```

```

In [34]: # Example: confusion matrix
yhat = predict(Xtestz, wz_gd)
ypred = classify(Xtestz, wz_gd)
print(sklearn.metrics.confusion_matrix(ytest, ypred)) # true x predicted

[[887  54]
 [ 71 524]]

```

```

In [35]: # Example: classification report
print(sklearn.metrics.classification_report(ytest, ypred))

```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.93 | 0.94 | 0.93 | 941 |
| 1 | 0.91 | 0.88 | 0.89 | 595 |
| accuracy | | | 0.92 | 1536 |
| macro avg | 0.92 | 0.91 | 0.91 | 1536 |
| weighted avg | 0.92 | 0.92 | 0.92 | 1536 |

```

In [36]: # Example: precision-recall curve (with annotated thresholds)
nextplot()
precision, recall, thresholds = sklearn.metrics.precision_recall_curve(ytest, yhat)
plt.plot(recall, precision)
for x in np.linspace(0, 1, 10, endpoint=False):
    index = int(x * (precision.size - 1))
    plt.text(recall[index], precision[index], "{:3.2f}".format(thresholds[index]))
plt.xlabel("Recall")
plt.ylabel("Precision")

```

```

Out[36]: Text(0, 0.5, 'Precision')

```

```

In [37]: # Explore which features are considered important
# YOUR CODE HERE
nextplot()
plt.plot(range(len(wz_gd)),wz_gd,'-o')
plt.xlabel('Index Feature')
plt.ylabel('Weight')
plt.savefig('Figure2.4.png')

```

```

In [38]: max(wz_gd)
np.argmax(wz_gd)
min(wz_gd)
np.argmin(wz_gd)

```

```

Out[38]: 24

```

4 Maximum A posteriori Estimation

4a Gradient Descent

```

In [39]: def l_l2(y, X, w, lambda_):
    """Log-density of posterior of logistic regression with weights w and L2
    regularization parameter lambda_"""
    # YOUR CODE HERE
    pos_logistic_regression = l(y,X,w) - (lambda_/2)*(np.dot(w,w))
    #(np.linalg.norm(w,ord=2))
    return pos_logistic_regression

```

```

In [40]: # this should give:
# [-47066.641667825766, -47312.623810682911]
[l_l2(y, Xz, np.linspace(-5, 5, D), 0), l_l2(y, Xz, np.linspace(-5, 5, D), 1)]

```

```

Out[40]: [-47066.64166782577, -47312.62381068291]

```

```
In [41]: def dl_l2(y, X, w, lambda_):
        """Gradient of log-density of posterior of logistic regression with weights w
        and L2 regularization parameter lambda_."""
        # YOUR CODE HERE
        gradient = dl(y,X,w) - (lambda_)*w
        return gradient
```

```
In [42]: # this should give:
# [array([ 551.33985842, 143.84116318, 841.83373606, 156.87237578,
#          802.61217579, 795.96202907, 920.69045803, 621.96516752,
#          659.18724769, 470.81259805, 771.32406968, 352.40325626,
#          455.66972482, 234.36600888, 562.45454038, 864.83981264,
#          787.19723703, 649.48042176, 902.6478154 , 544.00539886,
#          1174.78638035, 120.3598967 , 839.61141672, 633.30453444,
#          -706.66815087, -630.2039816 , -569.3451386 , -527.50996698,
#          -359.53701083, -476.64334832, -411.60620464, -375.11950586,
#          -345.37195689, -376.22044258, -407.31761977, -456.23251936,
#          -596.86960184, -107.97072355, -394.82170044, -229.18125598,
#          -288.46356547, -362.13402385, -450.87896465, -277.03932676,
#          -414.99293368, -452.28771693, -167.54649092, -270.9043748 ,
#          -252.20140951, -357.72497343, -259.12468742, 418.35938483,
#          604.54173228, 43.10390907, 152.24258478, 378.16731033,
#          416.12032881]),
# array([ 556.33985842, 148.66259175, 846.4765932 , 161.33666149,
#          806.89789007, 800.06917193, 924.61902946, 625.71516752,
#          662.75867626, 474.20545519, 774.5383554 , 355.43897054,
#          458.52686767, 237.04458031, 564.95454038, 867.16124121,
#          789.34009417, 651.44470748, 904.43352968, 545.61254171,
#          1176.21495178, 121.6098967 , 840.68284529, 634.19739158,
#          -705.95386516, -629.66826731, -568.98799574, -527.33139555,
#          -359.53701083, -476.82191975, -411.9633475 , -375.65522015,
#          -346.08624261, -377.11329972, -408.38904835, -457.48251936,
#          -598.29817327, -109.57786641, -396.60741472, -231.14554169,
#          -290.60642261, -364.45545242, -453.37896465, -279.71789819,
#          -417.85007654, -455.32343122, -170.76077664, -274.29723194,
#          -255.77283808, -361.47497343, -263.05325885, 414.25224198,
#          600.25601799, 38.63962335, 147.59972763, 373.34588176,
#          411.12032881)])
[dl_l2(y, Xz, np.linspace(-5, 5, D), 0), dl_l2(y, Xz, np.linspace(-5, 5, D), 1)]
```

```
Out[42]: [array([ 551.33985842, 143.84116318, 841.83373606, 156.87237578,
          802.61217579, 795.96202907, 920.69045803, 621.96516752,
          659.18724769, 470.81259805, 771.32406968, 352.40325626,
          455.66972482, 234.36600888, 562.45454038, 864.83981264,
          787.19723703, 649.48042176, 902.6478154 , 544.00539886,
          1174.78638035, 120.3598967 , 839.61141672, 633.30453444,
          -706.66815087, -630.2039816 , -569.3451386 , -527.50996698,
          -359.53701083, -476.64334832, -411.60620464, -375.11950586,
          -345.37195689, -376.22044258, -407.31761977, -456.23251936,
          -596.86960184, -107.97072355, -394.82170044, -229.18125598,
          -288.46356547, -362.13402385, -450.87896465, -277.03932676,
          -414.99293368, -452.28771693, -167.54649092, -270.9043748 ,
          -252.20140951, -357.72497343, -259.12468742, 418.35938483,
          604.54173228, 43.10390907, 152.24258478, 378.16731033,
          416.12032881]),
 array([ 556.33985842, 148.66259175, 846.4765932 , 161.33666149,
          806.89789007, 800.06917193, 924.61902946, 625.71516752,
          662.75867626, 474.20545519, 774.5383554 , 355.43897054,
          458.52686767, 237.04458031, 564.95454038, 867.16124121,
          789.34009417, 651.44470748, 904.43352968, 545.61254171,
          1176.21495178, 121.6098967 , 840.68284529, 634.19739158,
          -705.95386516, -629.66826731, -568.98799574, -527.33139555,
          -359.53701083, -476.82191975, -411.9633475 , -375.65522015,
          -346.08624261, -377.11329972, -408.38904835, -457.48251936,
          -598.29817327, -109.57786641, -396.60741472, -231.14554169,
          -290.60642261, -364.45545242, -453.37896465, -279.71789819,
          -417.85007654, -455.32343122, -170.76077664, -274.29723194,
          -255.77283808, -361.47497343, -263.05325885, 414.25224198,
          600.25601799, 38.63962335, 147.59972763, 373.34588176,
          411.12032881)])]
```

```
In [43]: # now define the (f,update) tuple for optimize for logistic regression, L2
# regularization, and gradient descent
def gd_l2(y, X, lambda_):
    # YOUR CODE HERE
    def objective(w):
        p_i0 = logsigma(-np.dot(X,w))
        p_i1 = logsigma(np.dot(X,w))
        objective = -np.sum(y*p_i1 + (1-y)*p_i0)
        l2 = (lambda_/2)*(np.dot(w,w))
        return objective+l2
    def update(w,eps) :
        gradient = dl_l2(y,X,w,lambda_)
        w += eps * gradient
        return w
    return (objective,update)
```

```
In [44]: # let's run!
```

```
lambda_ = 100
wz_gd_l2, vz_gd_l2, ez_gd_l2 = optimize(gd_l2(y, Xz, lambda_), w0, nepochs=500)
```

```
Epoch 0: f= 5484.455, eps=0.010000000
Epoch 1: f= 2137.652, eps=0.010500000
Epoch 2: f= 30782.824, eps=0.005250000
Epoch 3: f= 6484.999, eps=0.005512500
Epoch 4: f= 1504.659, eps=0.005788125
Epoch 5: f= 1141.295, eps=0.006077531
Epoch 6: f= 1771.465, eps=0.003038766
Epoch 7: f= 1585.487, eps=0.003190704
Epoch 8: f= 1075.240, eps=0.003350239
Epoch 9: f= 1073.052, eps=0.003517751
Epoch 10: f= 1116.047, eps=0.001758876
Epoch 11: f= 1017.587, eps=0.001846819
Epoch 12: f= 990.329, eps=0.001939160
Epoch 13: f= 988.737, eps=0.002036118
Epoch 14: f= 988.563, eps=0.002137924
Epoch 15: f= 988.528, eps=0.002244820
Epoch 16: f= 988.518, eps=0.002357061
Epoch 17: f= 988.514, eps=0.002474914
Epoch 18: f= 988.513, eps=0.002598660
Epoch 19: f= 988.513, eps=0.002728593
Epoch 20: f= 988.513, eps=0.002865023
Epoch 21: f= 988.513, eps=0.001432511
Epoch 22: f= 988.512, eps=0.001504137
Epoch 23: f= 988.512, eps=0.001579344
Epoch 24: f= 988.512, eps=0.001658311
Epoch 25: f= 988.512, eps=0.001741227
Epoch 26: f= 988.512, eps=0.001828288
Epoch 27: f= 988.512, eps=0.001919702
Epoch 28: f= 988.512, eps=0.002015687
Epoch 29: f= 988.512, eps=0.002116472
Epoch 30: f= 988.512, eps=0.002222295
Epoch 31: f= 988.512, eps=0.002333410
Epoch 32: f= 988.512, eps=0.002450081
Epoch 33: f= 988.512, eps=0.002572585
Epoch 34: f= 988.512, eps=0.002701214
Epoch 35: f= 988.512, eps=0.002836275
Epoch 36: f= 988.512, eps=0.002978088
Epoch 37: f= 988.512, eps=0.003126993
Epoch 38: f= 988.512, eps=0.003283342
Epoch 39: f= 988.512, eps=0.003447510
Epoch 40: f= 988.512, eps=0.003619885
Epoch 41: f= 988.512, eps=0.003800879
Epoch 42: f= 988.512, eps=0.003990923
Epoch 43: f= 988.512, eps=0.004190469
Epoch 44: f= 988.512, eps=0.002095235
Epoch 45: f= 988.512, eps=0.002199996
Epoch 46: f= 988.512, eps=0.002309996
Epoch 47: f= 988.512, eps=0.002425496
Epoch 48: f= 988.512, eps=0.002546771
Epoch 49: f= 988.512, eps=0.001273385
Epoch 50: f= 988.512, eps=0.001337055
Epoch 51: f= 988.512, eps=0.001403907
Epoch 52: f= 988.512, eps=0.001474103
Epoch 53: f= 988.512, eps=0.001547808
Epoch 54: f= 988.512, eps=0.000773904
Epoch 55: f= 988.512, eps=0.000812599
Epoch 56: f= 988.512, eps=0.000406300
Epoch 57: f= 988.512, eps=0.000426615
Epoch 58: f= 988.512, eps=0.000213307
Epoch 59: f= 988.512, eps=0.000223973
Epoch 60: f= 988.512, eps=0.000235171
Epoch 61: f= 988.512, eps=0.000246930
Epoch 62: f= 988.512, eps=0.000123465
Epoch 63: f= 988.512, eps=0.000129638
Epoch 64: f= 988.512, eps=0.000136120
Epoch 65: f= 988.512, eps=0.000068060
Epoch 66: f= 988.512, eps=0.000071463
Epoch 67: f= 988.512, eps=0.000075036
Epoch 68: f= 988.512, eps=0.000078788
Epoch 69: f= 988.512, eps=0.000039394
Epoch 70: f= 988.512, eps=0.000041364
Epoch 71: f= 988.512, eps=0.000043432
Epoch 72: f= 988.512, eps=0.000045603
Epoch 73: f= 988.512, eps=0.000022802
Epoch 74: f= 988.512, eps=0.000023942
Epoch 75: f= 988.512, eps=0.000011971
Epoch 76: f= 988.512, eps=0.000012569
Epoch 77: f= 988.512, eps=0.000013198
Epoch 78: f= 988.512, eps=0.000013858
Epoch 79: f= 988.512, eps=0.000006929
Epoch 80: f= 988.512, eps=0.000003464
Epoch 81: f= 988.512, eps=0.000003638
Epoch 82: f= 988.512, eps=0.000001819
Epoch 83: f= 988.512, eps=0.000001910
Epoch 84: f= 988.512, eps=0.000000955
Epoch 85: f= 988.512, eps=0.000001003
Epoch 86: f= 988.512, eps=0.000000501
Epoch 87: f= 988.512, eps=0.000000526
```

| | | | |
|------------|----|----------|-----------------|
| Epoch 88: | f= | 988.512, | eps=0.000000553 |
| Epoch 89: | f= | 988.512, | eps=0.000000276 |
| Epoch 90: | f= | 988.512, | eps=0.000000290 |
| Epoch 91: | f= | 988.512, | eps=0.000000305 |
| Epoch 92: | f= | 988.512, | eps=0.000000320 |
| Epoch 93: | f= | 988.512, | eps=0.000000160 |
| Epoch 94: | f= | 988.512, | eps=0.000000168 |
| Epoch 95: | f= | 988.512, | eps=0.000000176 |
| Epoch 96: | f= | 988.512, | eps=0.000000185 |
| Epoch 97: | f= | 988.512, | eps=0.000000093 |
| Epoch 98: | f= | 988.512, | eps=0.000000097 |
| Epoch 99: | f= | 988.512, | eps=0.000000102 |
| Epoch 100: | f= | 988.512, | eps=0.000000051 |
| Epoch 101: | f= | 988.512, | eps=0.000000054 |
| Epoch 102: | f= | 988.512, | eps=0.000000028 |
| Epoch 103: | f= | 988.512, | eps=0.000000028 |
| Epoch 104: | f= | 988.512, | eps=0.000000033 |
| Epoch 105: | f= | 988.512, | eps=0.000000031 |
| Epoch 106: | f= | 988.512, | eps=0.000000033 |
| Epoch 107: | f= | 988.512, | eps=0.000000034 |
| Epoch 108: | f= | 988.512, | eps=0.000000036 |
| Epoch 109: | f= | 988.512, | eps=0.000000038 |
| Epoch 110: | f= | 988.512, | eps=0.000000040 |
| Epoch 111: | f= | 988.512, | eps=0.000000042 |
| Epoch 112: | f= | 988.512, | eps=0.000000044 |
| Epoch 113: | f= | 988.512, | eps=0.000000022 |
| Epoch 114: | f= | 988.512, | eps=0.000000023 |
| Epoch 115: | f= | 988.512, | eps=0.000000024 |
| Epoch 116: | f= | 988.512, | eps=0.000000025 |
| Epoch 117: | f= | 988.512, | eps=0.000000013 |
| Epoch 118: | f= | 988.512, | eps=0.000000013 |
| Epoch 119: | f= | 988.512, | eps=0.000000007 |
| Epoch 120: | f= | 988.512, | eps=0.000000007 |
| Epoch 121: | f= | 988.512, | eps=0.000000007 |
| Epoch 122: | f= | 988.512, | eps=0.000000008 |
| Epoch 123: | f= | 988.512, | eps=0.000000008 |
| Epoch 124: | f= | 988.512, | eps=0.000000008 |
| Epoch 125: | f= | 988.512, | eps=0.000000004 |
| Epoch 126: | f= | 988.512, | eps=0.000000004 |
| Epoch 127: | f= | 988.512, | eps=0.000000002 |
| Epoch 128: | f= | 988.512, | eps=0.000000002 |
| Epoch 129: | f= | 988.512, | eps=0.000000002 |
| Epoch 130: | f= | 988.512, | eps=0.000000003 |
| Epoch 131: | f= | 988.512, | eps=0.000000001 |
| Epoch 132: | f= | 988.512, | eps=0.000000000 |
| Epoch 133: | f= | 988.512, | eps=0.000000001 |
| Epoch 134: | f= | 988.512, | eps=0.000000001 |
| Epoch 135: | f= | 988.512, | eps=0.000000002 |
| Epoch 136: | f= | 988.512, | eps=0.000000002 |
| Epoch 137: | f= | 988.512, | eps=0.000000002 |
| Epoch 138: | f= | 988.512, | eps=0.000000002 |
| Epoch 139: | f= | 988.512, | eps=0.000000002 |
| Epoch 140: | f= | 988.512, | eps=0.000000002 |
| Epoch 141: | f= | 988.512, | eps=0.000000002 |
| Epoch 142: | f= | 988.512, | eps=0.000000001 |
| Epoch 143: | f= | 988.512, | eps=0.000000001 |
| Epoch 144: | f= | 988.512, | eps=0.000000001 |
| Epoch 145: | f= | 988.512, | eps=0.000000001 |
| Epoch 146: | f= | 988.512, | eps=0.000000001 |
| Epoch 147: | f= | 988.512, | eps=0.000000001 |
| Epoch 148: | f= | 988.512, | eps=0.000000001 |
| Epoch 149: | f= | 988.512, | eps=0.000000001 |
| Epoch 150: | f= | 988.512, | eps=0.000000000 |
| Epoch 151: | f= | 988.512, | eps=0.000000001 |
| Epoch 152: | f= | 988.512, | eps=0.000000001 |
| Epoch 153: | f= | 988.512, | eps=0.000000000 |
| Epoch 154: | f= | 988.512, | eps=0.000000000 |
| Epoch 155: | f= | 988.512, | eps=0.000000000 |
| Epoch 156: | f= | 988.512, | eps=0.000000000 |
| Epoch 157: | f= | 988.512, | eps=0.000000000 |
| Epoch 158: | f= | 988.512, | eps=0.000000001 |
| Epoch 159: | f= | 988.512, | eps=0.000000000 |
| Epoch 160: | f= | 988.512, | eps=0.000000000 |
| Epoch 161: | f= | 988.512, | eps=0.000000000 |
| Epoch 162: | f= | 988.512, | eps=0.000000000 |
| Epoch 163: | f= | 988.512, | eps=0.000000000 |
| Epoch 164: | f= | 988.512, | eps=0.000000000 |
| Epoch 165: | f= | 988.512, | eps=0.000000000 |
| Epoch 166: | f= | 988.512, | eps=0.000000000 |
| Epoch 167: | f= | 988.512, | eps=0.000000000 |
| Epoch 168: | f= | 988.512, | eps=0.000000000 |
| Epoch 169: | f= | 988.512, | eps=0.000000000 |
| Epoch | | | |

[illegible]

[illegible]

[illegible]

```

Epoch 456: f= 988.512, eps=0.000000000
Epoch 457: f= 988.512, eps=0.000000000
Epoch 458: f= 988.512, eps=0.000000000
Epoch 459: f= 988.512, eps=0.000000000
Epoch 460: f= 988.512, eps=0.000000000
Epoch 461: f= 988.512, eps=0.000000000
Epoch 462: f= 988.512, eps=0.000000000
Epoch 463: f= 988.512, eps=0.000000000
Epoch 464: f= 988.512, eps=0.000000000
Epoch 465: f= 988.512, eps=0.000000000
Epoch 466: f= 988.512, eps=0.000000000
Epoch 467: f= 988.512, eps=0.000000000
Epoch 468: f= 988.512, eps=0.000000000
Epoch 469: f= 988.512, eps=0.000000000
Epoch 470: f= 988.512, eps=0.000000000
Epoch 471: f= 988.512, eps=0.000000000
Epoch 472: f= 988.512, eps=0.000000000
Epoch 473: f= 988.512, eps=0.000000000
Epoch 474: f= 988.512, eps=0.000000000
Epoch 475: f= 988.512, eps=0.000000000
Epoch 476: f= 988.512, eps=0.000000000
Epoch 477: f= 988.512, eps=0.000000000
Epoch 478: f= 988.512, eps=0.000000000
Epoch 479: f= 988.512, eps=0.000000000
Epoch 480: f= 988.512, eps=0.000000000
Epoch 481: f= 988.512, eps=0.000000000
Epoch 482: f= 988.512, eps=0.000000000
Epoch 483: f= 988.512, eps=0.000000000
Epoch 484: f= 988.512, eps=0.000000000
Epoch 485: f= 988.512, eps=0.000000000
Epoch 486: f= 988.512, eps=0.000000000
Epoch 487: f= 988.512, eps=0.000000000
Epoch 488: f= 988.512, eps=0.000000000
Epoch 489: f= 988.512, eps=0.000000000
Epoch 490: f= 988.512, eps=0.000000000
Epoch 491: f= 988.512, eps=0.000000000
Epoch 492: f= 988.512, eps=0.000000000
Epoch 493: f= 988.512, eps=0.000000000
Epoch 494: f= 988.512, eps=0.000000000
Epoch 495: f= 988.512, eps=0.000000000
Epoch 496: f= 988.512, eps=0.000000000
Epoch 497: f= 988.512, eps=0.000000000
Epoch 498: f= 988.512, eps=0.000000000
Epoch 499: f= 988.512, eps=0.000000000
Result after 500 epochs: f=988.511839602703

```

4b Effect of Prior

In [45]: `# YOUR CODE HERE`

4c Composition of Weight Vector

In [46]: `# YOUR CODE HERE`

5 Exploration (optional)

5 Exploration: PyTorch

In [47]:

```

# if you want to experiment, here is an implementation of logistic
# regression in PyTorch
import math
import torch
import torch.nn as nn
import torch.utils.data
import torch.nn.functional as F

# prepare the data
Xztorch = torch.FloatTensor(Xz)
ytorch = torch.LongTensor(y)
train = torch.utils.data.TensorDataset(Xztorch, ytorch)

# manual implementation of logistic regression (without bias)
class LogisticRegression(nn.Module):
    def __init__(self, D, C):
        super(LogisticRegression, self).__init__()
        self.weights = torch.nn.Parameter(
            torch.randn(D, C) / math.sqrt(D)
        ) # xavier initialization
        self.register_parameter("W", self.weights)

    def forward(self, x):
        out = torch.matmul(x, self.weights)
        out = F.log_softmax(out)
        return out

```

```

# define the objective and update function. here we ignore the learning rates
# and parameters given to us by optimize (they are stored in the PyTorch model
# and optimizer, resp., instead)
def opt_pytorch():
    model = LogisticRegression(D, 2)
    criterion = nn.NLLLoss(reduction="sum")
    # change the next line to try different optimizers
    # optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

    def objective(_):
        outputs = model(Xztorch)
        return criterion(outputs, ytorch)

    def update(_1, _2):
        for i, (examples, labels) in enumerate(train_loader):
            outputs = model(examples)
            loss = criterion(outputs, labels)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

        W = model.state_dict()["W"]
        w = W[:, 1] - W[:, 0]
        return w

    return (objective, update)

```

In [48]:

```

# run the optimizer
learning_rate = 0.01
batch_size = 100 # number of data points to sample for gradient estimate
shuffle = True # sample with replacement (false) or without replacement (true)

train_loader = torch.utils.data.DataLoader(train, batch_size, shuffle=True)
wz_t, vz_t, _ = optimize(opt_pytorch(), None, nepochs=100, eps0=None, verbose=True)

```

/var/folders/j5/tqm3_jydlmz9mmb920s62hlm0000gn/T/ipykernel_31523/2194961090.py:26: UserWarning: Implicit dimension choice for log_softmax has been deprecated. Change the call to include dim=X as an argument.

```

out = F.log_softmax(out)
Epoch 0: f= 2815.387, eps= nan
Epoch 1: f= 907.160, eps= nan
Epoch 2: f= 791.752, eps= nan
Epoch 3: f= 749.509, eps= nan
Epoch 4: f= 726.905, eps= nan
Epoch 5: f= 712.422, eps= nan
Epoch 6: f= 700.858, eps= nan
Epoch 7: f= 693.756, eps= nan
Epoch 8: f= 689.438, eps= nan
Epoch 9: f= 683.860, eps= nan
Epoch 10: f= 680.829, eps= nan
Epoch 11: f= 678.680, eps= nan
Epoch 12: f= 676.080, eps= nan
Epoch 13: f= 673.790, eps= nan
Epoch 14: f= 672.939, eps= nan
Epoch 15: f= 671.321, eps= nan
Epoch 16: f= 670.018, eps= nan
Epoch 17: f= 668.922, eps= nan
Epoch 18: f= 668.005, eps= nan
Epoch 19: f= 667.138, eps= nan
Epoch 20: f= 666.417, eps= nan
Epoch 21: f= 665.473, eps= nan
Epoch 22: f= 664.786, eps= nan
Epoch 23: f= 664.258, eps= nan
Epoch 24: f= 664.024, eps= nan
Epoch 25: f= 663.821, eps= nan
Epoch 26: f= 662.374, eps= nan
Epoch 27: f= 661.638, eps= nan
Epoch 28: f= 661.149, eps= nan
Epoch 29: f= 660.570, eps= nan
Epoch 30: f= 659.699, eps= nan
Epoch 31: f= 659.075, eps= nan
Epoch 32: f= 658.703, eps= nan
Epoch 33: f= 659.024, eps= nan
Epoch 34: f= 658.135, eps= nan
Epoch 35: f= 657.954, eps= nan
Epoch 36: f= 657.135, eps= nan
Epoch 37: f= 656.981, eps= nan
Epoch 38: f= 661.007, eps= nan
Epoch 39: f= 656.330, eps= nan
Epoch 40: f= 655.512, eps= nan
Epoch 41: f= 656.052, eps= nan
Epoch 42: f= 656.766, eps= nan
Epoch 43: f= 654.745, eps= nan
Epoch 44: f= 654.919, eps= nan
Epoch 45: f= 654.419, eps= nan
Epoch 46: f= 654.004, eps= nan
Epoch 47: f= 653.326, eps= nan
Epoch 48: f= 653.825, eps= nan

```

| | | | |
|--|--------|---------------|-----|
| Epoch | 49: f= | 652.837, eps= | nan |
| Epoch | 50: f= | 654.266, eps= | nan |
| Epoch | 51: f= | 652.222, eps= | nan |
| Epoch | 52: f= | 652.556, eps= | nan |
| Epoch | 53: f= | 651.495, eps= | nan |
| Epoch | 54: f= | 652.032, eps= | nan |
| Epoch | 55: f= | 651.843, eps= | nan |
| Epoch | 56: f= | 651.155, eps= | nan |
| Epoch | 57: f= | 652.042, eps= | nan |
| Epoch | 58: f= | 651.112, eps= | nan |
| Epoch | 59: f= | 650.247, eps= | nan |
| Epoch | 60: f= | 649.718, eps= | nan |
| Epoch | 61: f= | 649.735, eps= | nan |
| Epoch | 62: f= | 649.545, eps= | nan |
| Epoch | 63: f= | 650.149, eps= | nan |
| Epoch | 64: f= | 649.221, eps= | nan |
| Epoch | 65: f= | 648.994, eps= | nan |
| Epoch | 66: f= | 648.491, eps= | nan |
| Epoch | 67: f= | 649.297, eps= | nan |
| Epoch | 68: f= | 648.230, eps= | nan |
| Epoch | 69: f= | 647.323, eps= | nan |
| Epoch | 70: f= | 648.162, eps= | nan |
| Epoch | 71: f= | 647.615, eps= | nan |
| Epoch | 72: f= | 648.275, eps= | nan |
| Epoch | 73: f= | 647.234, eps= | nan |
| Epoch | 74: f= | 647.504, eps= | nan |
| Epoch | 75: f= | 646.416, eps= | nan |
| Epoch | 76: f= | 646.570, eps= | nan |
| Epoch | 77: f= | 646.780, eps= | nan |
| Epoch | 78: f= | 646.195, eps= | nan |
| Epoch | 79: f= | 645.592, eps= | nan |
| Epoch | 80: f= | 647.076, eps= | nan |
| Epoch | 81: f= | 645.706, eps= | nan |
| Epoch | 82: f= | 645.943, eps= | nan |
| Epoch | 83: f= | 645.132, eps= | nan |
| Epoch | 84: f= | 646.135, eps= | nan |
| Epoch | 85: f= | 645.635, eps= | nan |
| Epoch | 86: f= | 644.592, eps= | nan |
| Epoch | 87: f= | 645.028, eps= | nan |
| Epoch | 88: f= | 643.853, eps= | nan |
| Epoch | 89: f= | 644.554, eps= | nan |
| Epoch | 90: f= | 643.217, eps= | nan |
| Epoch | 91: f= | 643.370, eps= | nan |
| Epoch | 92: f= | 643.681, eps= | nan |
| Epoch | 93: f= | 643.722, eps= | nan |
| Epoch | 94: f= | 643.842, eps= | nan |
| Epoch | 95: f= | 643.359, eps= | nan |
| Epoch | 96: f= | 643.754, eps= | nan |
| Epoch | 97: f= | 642.871, eps= | nan |
| Epoch | 98: f= | 643.087, eps= | nan |
| Epoch | 99: f= | 642.780, eps= | nan |
| Result after 100 epochs: f=643.2067260742188 | | | |