```
import numpy as np
# helper activation function
def activation(x):
    return np.tanh(x)
# helper loss function
def logistic_loss(y, f):
    return -f[y] + np.log(np.sum(np.exp(f)))
def prediction loss(x,y,W,V,b,c):
    # do stuff here
    \# activation function on the dot product of (x \text{ and } W) + b
    res = activation(np.dot(W,x) + b)
    # dot product of res and V and add c
    f = np.dot(V, res) + c
    # calculate the loss
    L = logistic loss(y, f)
    return L.squeeze()
```

```
def prediction_grad(x,y,W,V,b,c):
    # do stuff here
    f = np.dot(V, np.tanh(np.dot(W,x) + b)) + c
    unit vector = np.zeros(f.shape) # create a zero vector of the same
shape as f
    unit vector[y] = 1 # set the yth element to 1 to set the unit
vector in the y dim
    dLdf = -unit_vector + np.exp(f) / np.sum(np.exp(f))
    dLdc = dLdf
    # gradient of loss function relative to V
    a = np.tanh(np.dot(W,x) + b)
    dLdV = np.outer(dLdf, a.T)
    # gradient of loss function relative to b
    sigma prime = 1 - a^{**}2
    dLdb = sigma_prime * np.dot(V.T, dLdf)
    # gradient of loss function relative to W
    dLdW = np.outer(sigma prime * np.dot(V.T, dLdf), x.T)
```

```
return dLdW, dLdV, dLdb, dLdc
```

```
x = np.array([1, 2])
y = 1
W = np.array([[.5, -1],
               [-.5, 1],
               [1, .5]]
V = np.array([[-1, -1, 1],
               [1, 1, 1]]
b = np.array([0, 0, 0])
c = np.array([0, 0])
dLdW, dLdV, dLdb, dLdc = prediction grad(x,y,W,V,b,c)
print("dLdW:", dLdW)
print("dLdV:", dLdV)
print("dLdb:", dLdb)
print("dLdc:", dLdc)
dLdW: [[-0.18070664 -0.36141328]
 [-0.18070664 -0.36141328]
 [ 0.
               0.
                          ]]
dLdV: [[-0.45257413 0.45257413 0.48201379]
 [ 0.45257413 -0.45257413 -0.48201379]]
dLdb: [-0.18070664 -0.18070664 0.
dLdc: [ 0.5 -0.5]
```

### Question 4

```
import jax
from jax import numpy as np
from jax import grad

def prediction_grad_jax(x,y,W,V,b,c):
    # do stuff here

    dLdW, dLdV, dLdb, dLdc = grad(prediction_loss, argnums= (2,3,4,5))
    (x,y,W,V,b,c)
    return dLdW, dLdV, dLdb, dLdc
```

```
# Helper function
def logistic_loss_vectorized(Y, F):
```

```
# Gather the correct class scores for each sample
    correct class scores = F[np.arange(len(Y)), Y]
    # Compute the vector of losses for each sample
    losses = -correct class scores + np.log(np.sum(np.exp(F), axis=1))
    # Return the total loss (sum over all samples)
    return np.sum(losses)
# Helper function
def vectorized loss(X,Y,W,V,b,c):
    a = activation(np.dot(X, W.T) + b)
    pred = np.dot(a, V.T) + c
    return logistic loss vectorized(Y, pred)
############
# MAIN FUNCTION
###########
def prediction_loss_full(X,Y,W,V,b,c,λ):
    # do stuff here
    # X is now 2D array of inputs
    # Y is now 1D array of outputs
    L = vectorized loss(X,Y,W,V,b,c)
    # add the regularization
    L += \lambda * (np.sum(W**2) + np.sum(V**2))
    return L.squeeze() # include regularization
```

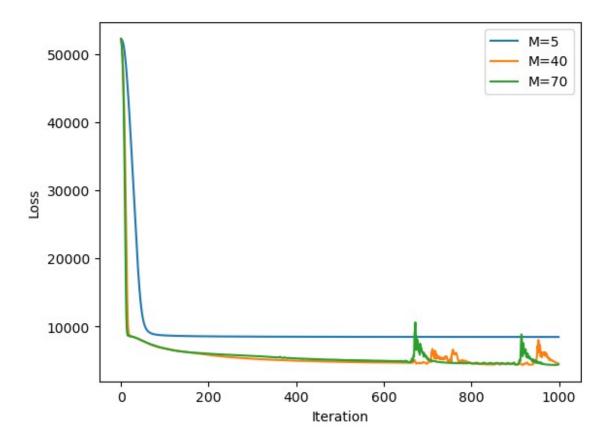
```
def prediction_grad_full(X,Y,W,V,b,c,λ):
    # do stuff here
    # X is now 2D array of inputs
    # Y is now 1D array of outputs

dLdW, dLdV, dLdb, dLdc = grad(prediction_loss_full, argnums=
(2,3,4,5))(X,Y,W,V,b,c,λ)
return dLdW, dLdV, dLdb, dLdc
```

```
from matplotlib import pyplot as plt
from numpy import random
import time
```

```
# load data
stuff=np.load("data.npz")
X_trn = stuff["X_trn"]
y trn = stuff["y trn"]
X tst = stuff["X tst"]
# no Y_tst !
# helper function - training loop
def loss_training_loop(X_trn, y_trn, m, D, iters=1000, \lambda=1,
stepsize=0.000025, momentum=0.1):
    # initialize variables
    W = random.normal(0, 1, (m, D)) / np.sqrt(D)
    V = random.normal(0, 1, (len(y trn), m)) / np.sqrt(D)
    b = np.zeros(m)
    c = np.zeros(len(y trn))
    avg grad w = 0
    avg grad v = 0
    avg grad b = 0
    avg grad c = 0
    loss iter = []
    start time = time.time()
    # training loop
    for i in range(iters):
        # calculate loss
        loss iter.append(prediction loss full(X trn, y trn, W, V, b,
c, \lambda))
        # calculate gradients
        cur_grad_w, cur_grad_v, cur_grad_b, cur_grad_c =
prediction grad full(X trn, y trn, W, V, b, c, \lambda)
        # update variables with momentum
        avg_grad_w = (1 - momentum) * avg_grad_w + momentum *
cur grad w
        avg grad v = (1 - momentum) * avg grad <math>v + momentum *
cur grad v
        avg grad b = (1 - momentum) * avg grad b + momentum *
cur grad b
        avg_grad_c = (1 - momentum) * avg_grad_c + momentum *
cur_grad c
        W = W - stepsize * avg grad w
        V = V - stepsize * avg_grad_v
        b = b - stepsize * avg grad b
        c = c - stepsize * avg grad c
    end time = time.time()
```

```
print(f"{m} | {(end_time - start_time) * 1000}")
    return loss iter
#######################
# MAIN CODE
#########################
# reshape X trn
X \text{ trn} = X \text{ trn.reshape}(X \text{ trn.shape}[0], 2523)
M = [5, 40, 70]
D = X trn.shape[1]
# given params
iters = 1000
stepsize = .000025
momentum = .1
\lambda = 1
print("M | Training time (ms)")
for m in M:
    loss = loss_training_loop(X_trn, y_trn, m, D, iters, λ, stepsize,
momentum)
    plt.plot(range(iters), loss, label=f"M={m}")
    plt.xlabel("Iteration")
    plt.ylabel("Loss")
plt.legend()
plt.show()
M | Training time (ms)
5 | 219740.74411392212
40 | 243588.9778137207
70 | 270961.5559577942
```



```
# load data
stuff=np.load("data.npz")
X_trn = stuff["X_trn"]
y trn = stuff["y trn"]
X_{tst} = stuff["X_{tst}"]
# no Y_tst !
# reshape X trn
X \text{ trn} = X \text{ trn.reshape}(X \text{ trn.shape}[0], 2523)
# split training data into training and validation
X \text{ trn trn} = X \text{ trn}[:len(X \text{ trn})//2]
X_trn_val = X_trn[len(X_trn)//2:]
y_trn_trn = y_trn[:len(y_trn)//2]
y trn val = y trn[len(y trn)//2:]
# helper function - training loop and return variables
def loss_training_loop_variables(X_{trn}, y_{trn}, m, D, iters=1000, \lambda=1,
stepsize=0.000025, momentum=0.1):
    # initialize variables
    W = random.normal(0, 1, (m, D)) / np.sqrt(D)
    V = random.normal(0, 1, (len(y_trn), m)) / np.sqrt(D)
```

```
b = np.zeros(m)
    c = np.zeros(len(y trn))
    avg grad w = 0
    avg grad v = 0
    avg\_grad_b = 0
    avg grad c = 0
    loss iter = []
    for i in range(iters):
        # calculate loss
        loss iter.append(prediction loss full(X trn, y trn, W, V, b,
c, \lambda))
        # calculate gradients
        cur_grad_w, cur_grad_v, cur_grad_b, cur_grad_c =
prediction_grad_full(X_trn_trn, y_trn_trn, W, V, b, c, λ)
        # update variables with momentum
        avg_grad_w = (1 - momentum) * avg_grad_w + momentum *
cur grad w
        avg_grad_v = (1 - momentum) * avg_grad_v + momentum *
cur grad v
        avg grad b = (1 - momentum) * avg grad b + momentum *
cur grad b
        avg grad c = (1 - momentum) * avg grad c + momentum *
cur grad c
        W = W - stepsize * avg_grad_w
        V = V - stepsize * avg grad v
        b = b - stepsize * avg grad b
        c = c - stepsize * avg grad c
    # return final variables
    return W, V, b, c
def validation_prediction(X_val, y_val, W, V, b, c):
    # evaluate using trained variables
    a = activation(np.dot(X_val, W.T) + b)
    pred = np.dot(a, V.T) + c
    predicted classes = np.argmax(pred, axis=1) # predicted class for
each example
    # calculate classification error
    correct predictions = sum(predicted classes == y val)
    classification_error = 1 - correct_predictions / len(y_val)
```

```
return classification error
M = [5, 40, 70]
D = X trn.shape[1]
# given params
iters = 1000
stepsize = .000025
momentum = .1
\lambda = 1
print("M | classification error")
for m in M:
    final W, final V, final b, final c =
loss training loop variables (X trn trn, y trn trn, m, D, iters, \lambda,
stepsize, momentum)
    e = validation_prediction(X_trn_val, y_trn_val, final W, final V,
final b, final c)
    print(f"{m} | {e}")
M | classification error
5 | 0.7566666603088379
40 | 0.41633331775665283
70 | 0.359333336353302
# Re-train with best M on full training data
def train predict test data(X trn, y trn, X tst, m, D, iters=1000,
\lambda=1, stepsize=0.000025, momentum=0.1):
    X \text{ trn} = X \text{ trn.reshape}(X \text{ trn.shape}[0], 2523)
    D = X trn.shape[1]
    # given params
    iters = 1000
    stepsize = .000025
    momentum = .1
    \lambda = 1
    # best M from previous step
    m = 70
    # train with full training data
    W, V, b, c = loss_training_loop_variables(X_trn, y_trn, m, D,
iters, \lambda, stepsize, momentum)
    # predict on test data
    a = activation(np.dot(X tst, W.T) + b)
    pred = np.dot(a, V.T) + c
    predicted classes = np.argmax(pred, axis=1) # predicted class for
each example
```

```
return predicted classes
# import numpy as np
import csv
def write_csv(y_pred, filename):
    """Write a 1d numpy array to a Kaggle-compatible .csv file"""
    with open(filename, 'w') as csv_file:
        csv writer = csv.writer(csv file)
        csv_writer.writerow(['Id', 'Category'])
        for idx, y in enumerate(y_pred):
            csv writer.writerow([idx, y])
data = np.load('data.npz')
X trn = data['X trn'].reshape(X trn.shape[0], 2523)
y_trn = data['y_trn']
X_{tst} = data['X_{tst'}].reshape(X_{tst.shape}[0], 2523)
y_pred = train_predict_test_data(X_trn, y_trn, X_tst, m, D, iters, \lambda,
stepsize, momentum)
write_csv(y_pred, 'submission.csv')
```

## **REPORT:**

m value = 70 generalization error = 0.359333336353302